First-Degree Price Discrimination: Evidence from Informal Markets in India

Rishab Srivastava*

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Abstract

Person-specific pricing has rarely been observed in an empirical setting. However. first-degree price discrimination is common in informal markets all around the world, where sellers practice flexible pricing and conclude sales through bilateral bargaining. Using transaction-level data from an observational study, this paper analyzes the dynamics of pricing and bargaining in an informal market. The observational data is supplemented with survey data from an online experiment. These complementary experiments deliver surprisingly consistent results. The degree of price discrimination is primarily influenced by the buyer's observable characteristics of gender, appearance, and race. These observables are correlated with income, due to which buyers with higher incomes are asked and pay higher prices. Bargaining is found to have a strong downward effect on the final price markup. A model that uses buyers' observables to tailor prices can raise profits by as much as 82% relative to a counterfactual uniform price model. These results have important implications for welfare, fairness, and competition.

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1 Introduction

Person-specific pricing, or first-degree price discrimination, allows firms to tailor prices to different consumers to maximize their profits. In theory, perfect price-discrimination allows firms to extract all market surplus.[1] However, price discrimination, perfect or imperfect, is rarely seen in practice. Waldfogel (2015) argues that this is because person-specific pricing is often illegal, unethical, or circumventable. Additionally, profitable price discrimination requires firms to accurately estimate the buyer's reservation price from their private information, which is often unavailable.

Yet, first-degree price discrimination is common in informal markets all over the world. Price discrimination, combined with bilateral bargaining, has been the foundation for many ancient markets and can be seen in local flea markets in the US, open-air markets in Europe, and informal *bazaars* in India (List, 2009). Despite the continued prevalence and importance of these marketplaces, little is known about the rules that govern the transactions in these markets. These markets are attractive since they create a centralized location with low rental costs for small-business owners to sell their wares, and for buyers to purchase a diverse array of goods without high search costs. Typically, these markets are highly competitive, with a flexible pricing model. This means that there are often no posted prices, which allows sellers to price discriminate amongst prospective customers. This allows sellers to generate more revenue, and service demographic groups with different reservation prices. Prices are often agreed to by haggling for the product, during which a buyer and seller engage in several rounds of bargaining.

There exist rich descriptive accounts of pricing and negotiation practices in informal markets from all around the world (Geertz, 1978; Alexander and Alexander, 1987). These cite anecdotal evidence on price discrimination and bargaining but have been less helpful in providing an analytical framework to study these markets. On the other hand, price discrimination and bargaining have also been studied extensively from a theoretical perspective

[1]Perfect first-degree P.D. refers to charging every consumer their exact reservation price (Shiller, 2013).

(Varian, 1989; Arnold and Lippman, 1998). Using transaction-level data from an observational study conducted in an informal market in India, I bridge the gap between theory and evidence. I explore the dynamics of pricing and bargaining in these informal markets and develop structural models to answer several questions. First, I test whether sellers price discriminate against buyers. If yes, what observables do they use to price discriminate? Second, I examine the accuracy of the sellers' beliefs about the buyers' willingness to pay. Third, I estimate the effect of bargaining on lowering the price. Finally, I present models for perfect and imperfect price discrimination and compare their profits against a counterfactual single price model. This observational study is supplemented with survey data from an online experiment conducted on Amazon MTurk. These complementary experiments provide surprisingly consistent insights.

I find that sellers primarily price discriminate based on a buyer's appearance and race. Females also tend to pay slightly lower prices as compared to males. Complementary data from the survey suggests that this is a consequence of statistical discrimination rather than animus. Although survey respondents tend to offer lower prices to older people, I find no evidence that sellers in the market price discriminate based on age. Since these observables predict income, high-income individuals are asked and pay prices that are 5% higher. Bargaining has a strong downward effect on the price markup, and can lower the final price by 19 percentage points relative to the marginal cost of the good. A model of imperfect price discrimination that tailors prices to the buyers' observable characteristics raises expected profits by as much as 82% relative to a counterfactual uniform price model.

The remainder of this paper is organized as follows. In Section 2, the relevant literature on price discrimination and informal markets is reviewed. Section 3 details the market background and experimental design. Section 4 describes the observational and survey data. Section 5 presents the empirical model used. Section 6 discusses the results, and Section 7 concludes. The appendix includes materials used in the observational study and the online survey experiment.

2 Literature Review

By exploring models of price discrimination in an informal market, this paper will fit into the broader literature on pricing mechanisms, bargaining, and the economics of informal markets. Price discrimination has been extensively explored as a topic of theoretical interest. Varian (1989) proves that first-degree price discrimination extracts *all* consumer surplus since the seller offers a take-it or leave-it price exactly equal to the buyer's willingness to pay. In my study, sellers do not have perfect information about the buyers' reservation price, and use heuristics such as gender, race, age, and appearance to estimate it. Bargaining with imperfect information has also received its fair share of theoretical literature. Arnold and Lippman (1998) compare social welfare under bargaining and posted price mechanisms. My paper is similar to these theoretical papers in that it presents a model of price discrimination and bargaining; however, I focus on the profits of the seller rather than welfare costs to the buyer. An early empirical paper by Ayres and Siegelman (1995) shows that car dealers in Chicago offer higher prices to black and female test drivers than white males. Graddy (1995) finds that Asian buyers pay lower prices as compared to white buyers in the seemingly competitive Fulton Fish market. Similarly, this paper uses the buyer's race and gender to predict the extent of price discrimination. I expand the buyers' observable characteristics to include age and perceived affluence as well.

Personalized pricing has become an area of empirical research more recently. Graddy and Hall (2011) develop a dynamic profit-maximizing model of price discrimination in the Fulton Fish market and compare it to the single price model; they find that price discrimination increases revenue by an insignificant amount. Shiller (2013) uses consumers' web-browsing data to estimate their willingness to pay for Netflix subscriptions; a model that increases profits by 12.2%. Waldfogel (2015) explores price-discrimination in the context of higher education and finds that tailoring prices to student quality and state residency raises revenue by 8.4%. Similar to these papers, I develop a model for price discrimination practiced by a seller in the informal market. However, my model differs in that it incorporates bargaining and gives the seller two opportunities to offer a price to the buyer.

There also exists literature on bilateral bargaining in informal markets. An early paper by Geertz (1978) gives a descriptive account of asymmetric information, negotiation, and bargaining in a *bazaar* economy in Morocco. He observes that extensive search for a good across different sellers is second to intensive bargaining with the same seller. *Clientalization* (continuing relationships between buyers and sellers) and bargaining are thus the two most important search procedures in such markets. My analysis includes bargaining but omits clientalization, since it is not commonly witnessed with the sellers included in the observational study. Similarly, Alexander and Alexander (1987) describe rich accounts of negotiation strategies and bargaining patterns in Indonesian markets. They find that most transactions follow a common pattern as shown in Figure 1. Recent work by List (2009) explores the pricing and allocation mechanism in open-air markets, focusing specifically on collusion between sellers. List mentions that these markets are popular as there exists opportunity for buyers to "strike a deal" due to bargaining, and for sellers to gain from price discrimination on individual sales.

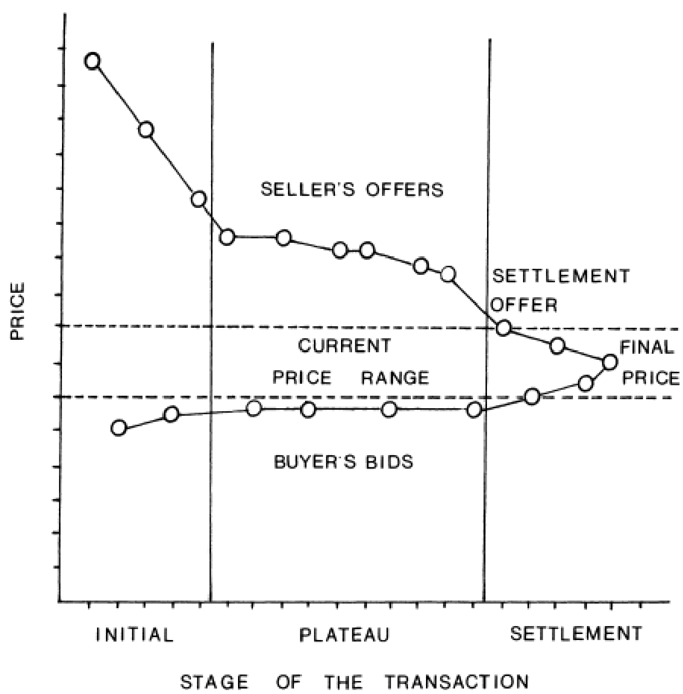


Figure 1: A three-stage model of bargaining. Source: Alexander and Alexander (1987)

Price discrimination is also tied to discrimination in the marketplace. List (2004) uses two complimentary field experiments to explore racial and gender discrimination in the market for second-hand sportscards. He finds that minorities, including females, non-white, and older dealers, tend to receive inferior initial and final offers as compared to their majority counterparts. He concludes that this is a consequence of statistical discrimination rather than animus towards minorities. Delecourt and Ng (2019) conduct a randomized field experiment in a vegetable market in India to test for discrimination against female sellers. My approach in the field experiment will be similar to those in these two studies; however, I will test for supply-side price discrimination rather than demand-side discrimination.

3 Market Background and Experimental Design

3.1 Informal Markets

I collect data using an observational field study conducted in Sarojini Nagar market in New Delhi, India. The sellers in these stores are small business owners, who work in their stalls 10 hours a day and 6 days a week. Goods frequently sold in these stores are clothes, purses, bags, jewelry, shoes, etc. These micro-businesses are extremely common in developing countries such as India due to low fixed and rental costs for sellers and low search costs for buyers (List, 2009). The key feature of these markets is the high competition among sellers, as well as the flexible pricing mechanism that exists. Sellers can quote any first-ask price from the buyer, who has the opportunity to drive down the price through bargaining. Buyers can search for similar goods in the market, gathering quotes from various sellers before making a purchase. However, in a bazaar economy, extensive search is second to intensive bargaining due to the scarcity of information in the marketplace (Geertz, 1978). This means that buyers prefer to bargain for a good that they wish to purchase rather than utilize the competitiveness of the market by searching for the same good across multiple stores.

Once a buyer enters a store and picks out a good, the sellers quotes a first-ask price for the good. This price is based on the seller's estimate of the buyer's willingness to pay for that good. Sellers also "highball" the price, in order to ensure that there is enough room in case the buyer tries to bargain. The buyer then quotes their first-ask price and the buyer-seller go back-and-forth bargaining. Eventually, they agree to an equilibrium price that the buyer is willing to pay and the seller is willing to accept. If no such understanding can be made, the transaction ends without the sale being made and the buyer leaves. Interactions can also involve some callback from the seller with a lower price if the buyer leaves. Due to their historical and cultural significance of many of these bazaars, they are often frequented by foreign tourists.

3.2 Amazon M-Turk

I conduct an online survey experiment to collect data that supplements the observational study. The data is collected using Amazon Mechanical Turk (mTurk) - a rapidly growing online labor market platform on which workers can complete short tasks such as surveys, data entry, image classification for modest compensation. Amazon mTurk is increasingly being used to carry out public goods games, behavioral and social experiments quickly and inexpensively (Walker et al., 2018; Dellavigna and Pope, 2017). On the other hand, mTurk has also been used for informational surveys, in order to elicit respondents' opinions on issues such as policy, government, and taxes (Kuziemko et al., 2015). Small stakes economic games on mTurk have been shown to replicate the same results as those conducted in a traditional lab setting (Amir, Rand and Gal, 2011). These games can often be made dynamic and interactive using a survey platform such as Qualtrics, which has functions that enable the surveyor to change the survey flow based on in-game responses, similar to a decision tree. Online surveys also naturally lend themselves to conducting a series of experiments with the same sample.

About 57% of mTurk workers are from the US and 32% are from India. The median annual reported income on mTurk is somewhere between $20,000 and $30,000. About one-third of workers have at least a college degree, and the population has an average age of 31 (Ross et al., 2009).

3.3 Experimental Design

3.3.1 Observational study

Volunteers (undergraduates from the University of Delhi) are grouped into pairs assigned to observe different sellers at Sarojini Nagar market. The volunteers spend 2 hours every week at their allotted seller for 4 weeks from January to February. The volunteers sit in the sellers' shops and observe buyers attempting to purchase a variety of goods, mostly apparel, accessories, and jewellery. The marginal cost and willingness to accept for various categories of goods is collected from the sellers in advance. Once a buyer enters the store, the surveyor collects data about the transaction on a spreadsheet. They record variables such as seller's first-ask price, buyer's first-ask price, final price, bargaining effort or intensity, and the buyer's demographic characteristics such as age, gender, perceived affluence etc.

After the transaction has culminated, the surveyor elicits private information such as income level, reservation price, age, market experience from the buyer in an exit interview using an online form. This enables us to tie the price-level data from the transaction to the buyer's demographic characteristics. To maintain consistency across pairs, the volunteers were required to follow a strict data collection rubric. The online form and data collection rubric are given in the appendix.

Figure 2: A set of stalls in Sarojini Nagar market, New Delhi

3.3.2 Survey Experiment

The experiment was conducted on Amazon MTurk using a survey that simulated seller-side decision making. The survey was posted with the title "Pricing Survey" and a description stating that the survey was on prices and decision-making and paid \$1 for approximately 5 minutes, i.e. an hourly wage of \$12. The respondents' location was limited to India. Additionally, respondents were required to have completed 5000 prior tasks with an approval rating of at least 95%. They were also informed that they could earn an extra bonus based on their decisions in the survey. The survey can be divided into four sections.

The first section elicited demographic information from the buyer with basic questions on gender, age, education, income level, and employment status. The second section showed an image of the market in Figure 2 and a shirt that the respondent had been assigned to sell. The respondent is also informed that the shirt's marginal cost to them is Rs. 175, and that they should aim to sell it for a higher amount. After reading this information, the survey asks the lowest price the respondents are willing to accept for the shirt, i.e. their willingness to accept (WTA) price. Note that the respondents' WTA is obtained before they are shown customers. This ensures that the respondents are not able to change their WTA after the bargaining game has started.

The third section gives instructions to the respondent for selling the good to incoming customer. Respondents get two attempts to bargain with a customer, who has a hidden but fixed willingness to pay for the shirt. If at any point the respondent quotes a price that is less than or equal to this willingness to pay, the customer accepts and the respondent is paid a bonus equal to the percentage difference between the price and their willingness to accept. For instance, if a respondent's willingness to accept was Rs. 200 and they offer a price of Rs. 250, which the customer accepts, they receive a payoff of (250-200)/200 = $0.25. However, if the customer declines both offers of the seller, the game ends and the respondent does not earn any bonus. In this scenario, a terminal question elicits the respondents' willingness to accept, termed lowest-ask price, for that customer.

The fourth section shows the respondent a randomly chosen image of a customer out of 10 possible customers. The customers have different observable characteristics of gender, age, race, and perceived affluence. The customer has a willingness to pay (WTP) price that is consistent with these observed characteristics. The respondent then gets an opportunity to sell the good (shirt) to the customer, as described above. This process is repeated for 2 more randomly chosen customers. To ensure quality of the responses, three attention check questions were added which the respondents were required to pass. The complete survey, including the attention check questions, can be found in the appendix.

4 Data

4.1 Observational Study

Table 1 shows the demographic characteristics of the 240 buyers in the informal market. About 20% of the buyers were foreigners and 72% of them were female. Around 18% of the sample population is above 40 years of age and 39% of buyers were classified as affluent in appearance by the surveyors. Income is measured as a categorical variable on a scale of 1 to

3. The average income category was 2.06, where 2 represents a monthly income in the range Rs. 50,000 - Rs. 1,00,000. The average experience of buyers in informal markets as reported is 7.79 years. The bargaining intensity or effort is measured on a scale of 1 to 3, where 3 is the most effort.

Table 1: Demographic Characteristics: Buyers (Observational Data)

Characteristic	Mean	SD	Min	Max	Count
Foreigner	0.20	0.35	0.0	1.0	48
Female	0.72	0.45	0.0	1.0	173
Above40	0.18	0.38	0.0	1.0	43
Affluent	0.39	0.49	0.0	1.0	94
Income	2.06	0.76	1.0	3.0	240
Buyer Experience (in years)	7.79	7.26	0.0	25.0	240
Bargaining Intensity	1.92	0.85	1.0	3.0	240

Notes: Income denotes categorical variable (1-3). 1) Less than Rs. 50, 000, 2) Rs. 50,000 - Rs. 1,00,000, 3) Greater than Rs. 1,00,000.

Table 2 shows the summary statistics of the transactions conducted by the buyers with the sellers in the informal market. Due to heterogeneity of marginal costs and prices across goods, I convert the first ask prices and final prices into proportion markups from the marginal cost. For instance, a first ask markup of 1.5 represents a first ask price that was 150% more than the good's marginal cost, or 2.5 times marginal cost. The first two columns suggest that women are quoted lower first-ask prices from the sellers as compared to men. On average, the females' first ask price is marked up by 104% more than marginal cost, as compared to 124% more for males. This difference is persistent in the final price markup as well.

Another significant difference in two demographic groups is between foreigners and Indians. Foreigners are first-asked a price that are 126% more than marginal cost, as compared to 106% for Indians. People above 40 years of age tend to be offered and pay a slightly lower price as well. As expected, perceived affluence has a large effect on the seller's first ask markup. An affluent-looking individual is asked a price that is 124% higher than marginal cost, as compared to about 100% (2 times marginal cost) for those who do not look affluent.

An interesting observation is that foreigners tend to complete 98% of their purchases. A possible explanation is that foreigners tend to visit these markets once or twice during their visit, and are more attached to the goods they select. Another explanation is that foreigners have a higher willingness to pay for these goods due to purchasing power differences between their home countries and India. In terms of income, males, foreigners, people above 40, and those that look affluent tend to earn higher incomes than their counterparts.

Figure 3 shows the distribution of mean first-ask markups across demographic groups. These observed differences across multiple demographic groups motivate my use of multivariate regressions.

Figure 4 shows the kernel density estimates of the first-ask markup and the final-price markup. I only collect the first-ask and final prices for a transaction, which causes the sharp leftward shift of the density function. The actual transition might be smoother due to multiple rounds of bargaining that are not collected in the observational data. The final-price markup has non-zero density below 0.0, which indicates that sellers might not have disclosed their true marginal costs.

Table 2: Summary Statistics: Transactions (Observational Data)

		Female		Foreigner		Above40		Affluent		Overall
		No	Yes	No	Yes	No	Yes	No	Yes	
Seller First Ask	Mean	147.16	142.66	139.32	162.29	145.03	138.84	138.42	152.45	143.92
F_t	SD	38.64	41.82	38.15	46.60	41.25	39.47	37.91	44.08	40.84
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
First Ask Markup	Mean	1.24	1.04	1.06	1.26	1.10	1.08	1.00	1.24	1.10
M_t	SD	0.26	0.23	0.22	0.31	0.25	0.27	0.19	0.27	0.25
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
Final price	Mean	122.84	121.33	118.80	133.54	122.34	119.07	117.26	128.72	121.75
P_t	SD	36.13	39.63	35.51	47.78	39.05	36.89	35.98	41.64	38.54
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
Final Price Markup	Mean	0.88	0.74	0.76	0.85	0.78	0.78	0.71	0.90	0.78
Z_t	SD	0.37	0.34	0.32	0.43	0.36	0.30	0.33	0.35	0.35
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
Seller Marginal Cost	Mean	66.27	70.12	68.23	72.29	69.34	67.67	69.52	68.30	69.04
c	SD	17.65	20.20	19.39	20.13	19.43	20.33	19.73	19.38	19.52
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
Purchased	Mean	0.79	0.69	0.65	0.98	0.73	0.67	0.58	0.93	0.72
y_t	SD	0.41	0.46	0.48	0.14	0.45	0.47	0.49	0.26	0.45
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00
Income	Mean	2.15	2.02	1.91	2.65	2.00	2.33	1.98	2.18	2.06
$income_i$	SD	0.84	0.72	0.74	0.48	0.76	0.71	0.79	0.69	0.76
	Count	67.00	173.00	192.00	48.00	197.00	43.00	146.00	94.00	240.00

Figure 3: Effect of observables on first-ask markup (Observational)

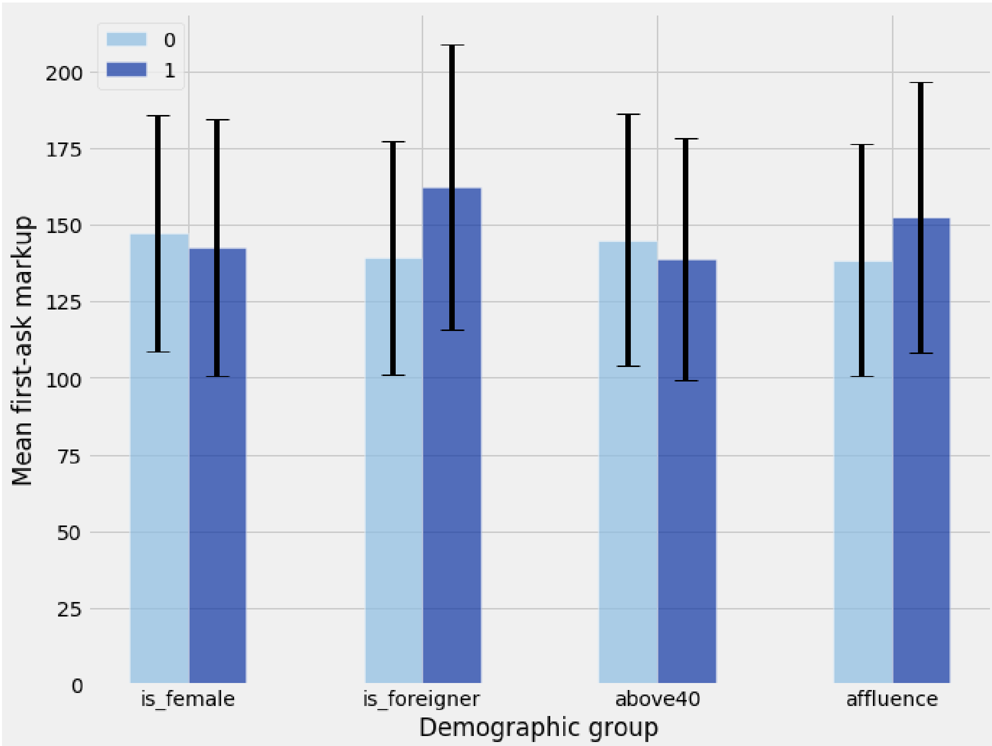


Figure 4: Kernel densities for the first-ask markup and the final price markup (Observational)

4.2 Survey Experiment

Table 3 shows the demographic characteristics of the 304 respondents that were included in the study. At 72%, the majority of the respondents are male. The average age of the respondents is approximately 34 years. Ages in the overall sample range from 20 years to 77 years.

In terms of education, about 90% of the sample has obtained a bachelor's degree or higher. In terms of income, 96% of the sample falls in the low-income to middle-income group with a monthly income between Rs. 10,000 to Rs. 25,000. About 80% of respondents hold full-time or part-time employment.

Table 3: Demographic Characteristics (Survey Respondents)

Characteristic	Mean	Standard Deviation	Count
Age	33.56	8.92	304
Gender			
Female	0.28	0.45	85
Male	0.72	0.45	219
Education			
Less than high school degree	0.01	0.10	3
High school degree or equivalent	0.03	0.18	10
Some college but no degree	0.04	0.19	11
Vocational degree	0.02	0.14	6
Bachelor's degree	0.62	0.48	190
Graduate degree	0.28	0.45	84
Monthly Household Income			
Less than Rs. 10,000	0.08	0.27	24
Rs. 10,000 - Rs. 25,000	0.38	0.49	115
Rs. 25,000 - Rs. 50,000	0.33	0.47	100
Rs. 50,000 - Rs. 75,000	0.12	0.33	37
Rs. 75,000 - Rs. 1,00,000	0.07	0.12	22
Greater than Rs. 1,00,000	0.02	0.07	6
Employment			
Employed (full time)	0.78	0.42	236
Employed (part time)	0.17	0.38	53
Unemployed (looking for work)	0.03	0.16	8
Unemployed (not looking for work)	0.02	0.13	5
Retired	0.01	0.08	2
Observations			304

Table 4 presents the summary statistics for the transaction level data. Since each respondent had to review 3 images of buyers, the sample contains 912 transaction-level observations. The first two columns suggest that women are often quoted lower prices from the sellers as compared to men. This is consistent with findings from the observational data. On average, the women are first-asked a price of about Rs. 394 as compared to Rs. 422 for males.

Another large difference in two demographic groups is between foreigners and Indians. Foreigners are asked a first price of Rs. 462 as compared to Rs. 381 for Indians, a difference of about Rs. 81. People above 40 years of age also tend to be asked a price Rs. 42 lesser than young buyers; however, this difference tends to decrease as the transaction progresses. As expected, perceived appearance is a big factor that determines the seller's ask prices. An increase in appearance from 1 (working-class) to 2 (middle-class) increases the ask prices by more than Rs. 30. Similarly, an increase in appearance from 2 (middle-class) to 3 (upper-class) increases the first-ask prices by about Rs. 90. These differences are consistent with those seen in the observational data.

Mean first-ask prices across demographic groups are shown in Figure 5. The differences across demographic groups persist throughout the bargaining game, and can be seen in the seller's second-ask, lowest-ask, and the final transaction price as well. These observed differences across multiple demographic groups motivate my use of multivariate regressions.

Figure 6 plots a histogram of the seller's willingness to accept (WTA) in rupees. The marginal cost of the good is fixed at Rs. 175 and revealed to the seller *before* bargaining with the buyer proceeds. A large proportion of sellers prefer Rs. 200 as the lowest price they are willing to accept from any buyer. The prices range from 175 to 300. As expected, sellers prefer round numbers such as 175, 200, 225, 250 as their WTA.

Figure 7 shows kernel density estimates of the sellers' first, second, and lowest-ask prices. Sellers get only 2 rounds to bargain with a buyer; so, the lowest-ask price is a hypothetical third ask price elicited from the seller after the buyer has decided not to purchase the good. As bargaining progresses, the histograms show a leftward shift.

Table 4: Summary Statistics: Transactions (Survey Data)

		Female		Foreigner		Above40		Appearance			Overall
		No	Yes	No	Yes	No	Yes	1	2	3	
Willingness to Pay	Mean	394.38	372.82	350.08	450.49	390.42	367.90	300.00	341.69	425.30	383.55
WTP_i	SD	52.60	60.82	32.31	35.06	59.32	51.13	0.00	11.79	41.85	57.83
	Count	454.00	458.00	608.00	304.00	634.00	278.00	101.00	304.00	507.00	912.00
Seller's first ask	Mean	421.85	393.80	380.67	461.94	420.50	378.73	329.26	361.24	451.30	407.76
F_t	SD	70.97	71.70	64.50	55.90	70.25	69.80	49.85	50.39	55.37	72.63
	Count	454.00	458.00	608.00	304.00	634.00	278.00	101.00	304.00	507.00	912.00
Seller's second ask	Mean	390.32	355.35	354.29	437.79	379.73	352.43	299.12	338.53	410.10	372.77
S_t	SD	55.99	65.22	53.44	50.86	62.36	61.50	35.71	38.53	53.71	63.15
	Count	252.00	254.00	394.00	112.00	377.00	129.00	58.00	174.00	274.00	506.00
Seller's lowest ask	Mean	362.43	331.99	337.43	405.60	350.57	338.73	284.95	323.02	372.06	348.25
L_t	SD	63.60	57.36	50.66	85.39	62.28	63.33	27.61	37.54	64.63	62.33
	Count	101.00	88.00	159.00	30.00	152.00	37.00	19.00	58.00	112.00	189.00
Final price	Mean	373.29	347.69	326.08	429.15	368.00	343.19	282.12	318.38	401.25	360.43
P_t	SD	62.98	68.07	43.46	50.21	68.15	60.21	25.76	30.31	58.25	66.75
	Count	454.00	458.00	608.00	304.00	634.00	278.00	101.00	304.00	507.00	912.00
Bargaining	Mean	1.78	1.75	1.91	1.47	1.83	1.60	1.76	1.76	1.76	1.76
E_t	SD	0.79	0.76	0.78	0.67	0.79	0.71	0.75	0.75	0.79	0.77
	Count	454.00	458.00	608.00	304.00	634.00	278.00	101.00	304.00	507.00	912.00
Purchased	Mean	0.78	0.81	0.74	0.90	0.76	0.87	0.81	0.81	0.78	0.79
y_t	SD	0.42	0.39	0.44	0.30	0.43	0.34	0.39	0.39	0.42	0.41
	Count	454.00	458.00	608.00	304.00	634.00	278.00	101.00	304.00	507.00	912.00

Figure 5: Effect of observables on first-ask price (Survey)

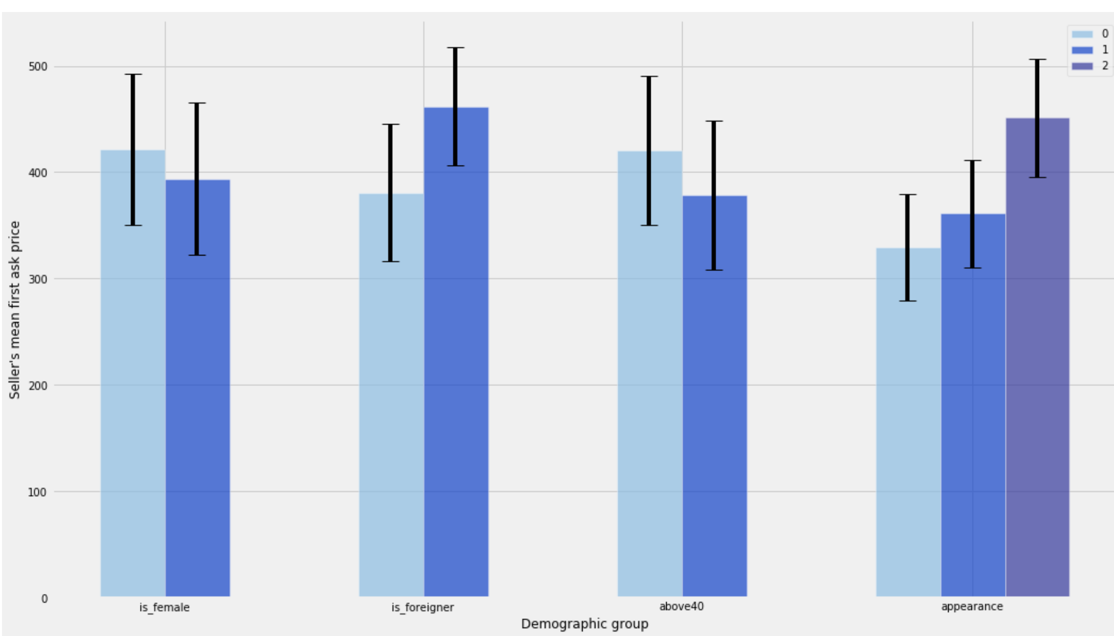


Figure 6: Seller's willingness to accept (Survey)

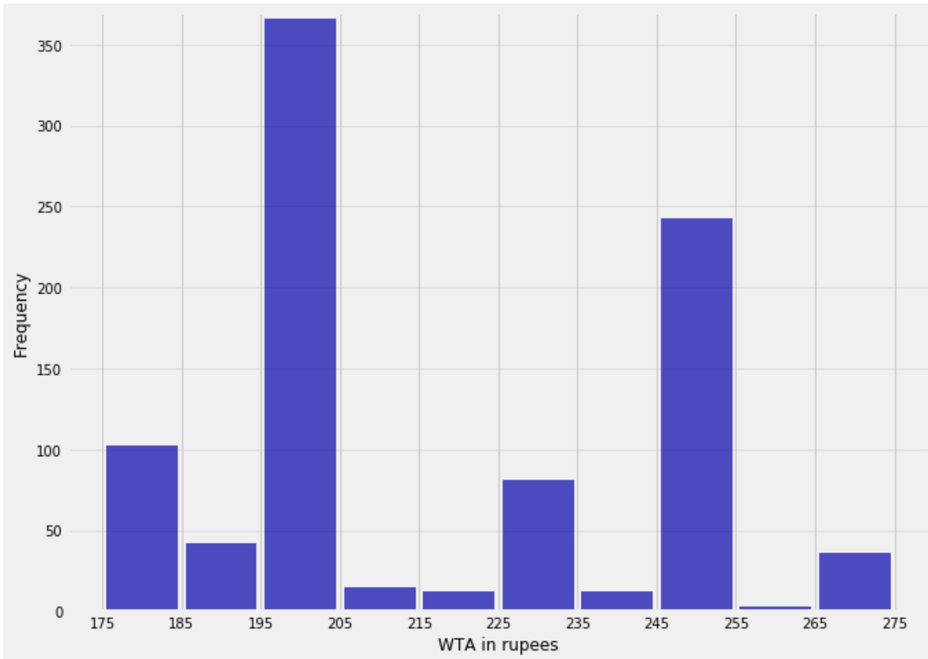


Figure 7: Kernel densities for the first, second, and lowest-ask prices (Survey)

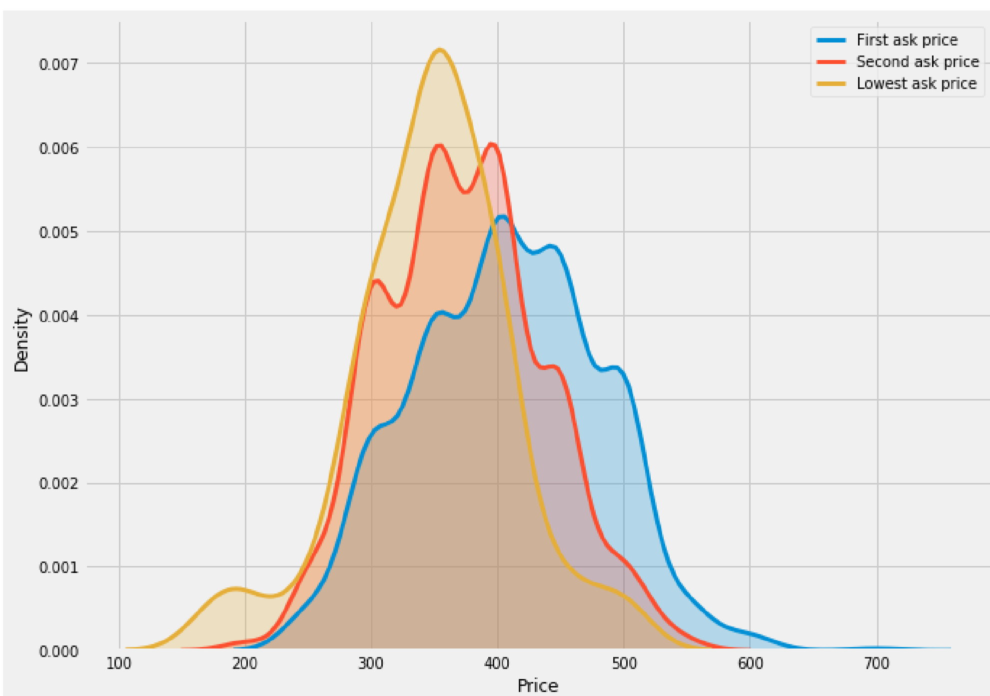


Figure 8 estimates a logit model that predicts the probability that a good is purchased given a first-ask price in rupees. This model will be extended in section 4.2 to include the buyer demographic type and predict the optimal first-ask and second-ask prices to maximize sellers' expected profits. Figure 9 plots the probability of a purchase with the final price. Since the buyers have a fixed *prior* (probability of entering the store) and willingness to pay, the cumulative density function is a piece-wise constant decreasing function.

Figure 8: Probability of purchase given first-ask price

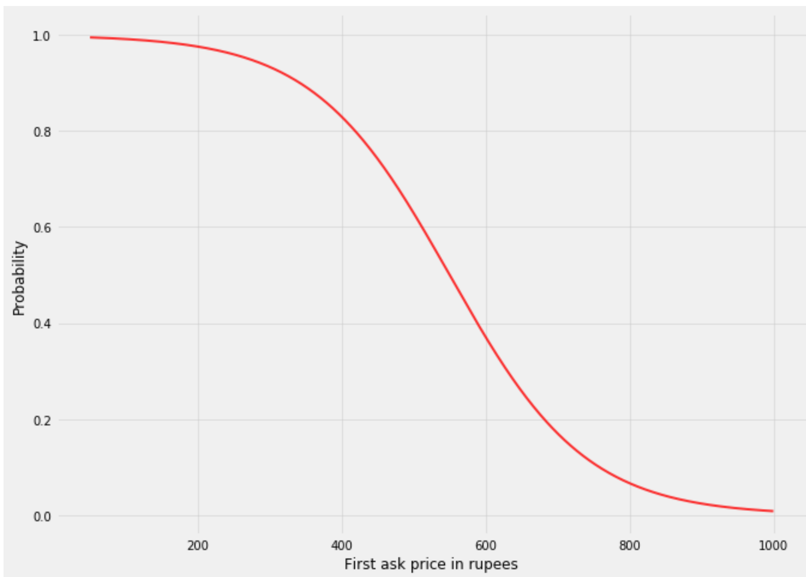
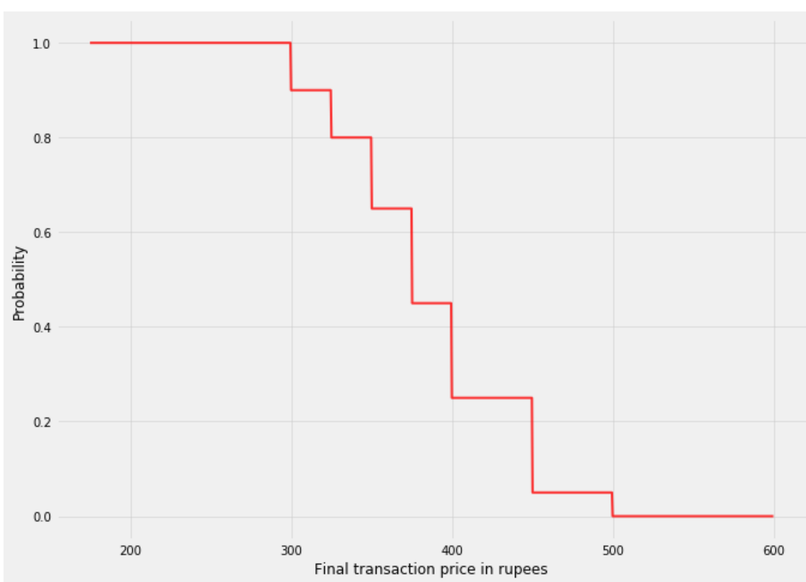


Figure 9: Probability of purchase given final price



5 Empirical Model

5.1 Observational Study

What observables do sellers use to price discriminate?

Let F_{sig} be the first-ask price of seller s to buyer i for good g. c_{sg} is the marginal cost of good g for seller s. I abbreviate sig as t since a seller s, buyer i, and good g together constitute a transaction t. So, the *first-ask markup* is defined as:

$$M_t = M_{sig} = \frac{F_{sig} - c_{sg}}{c_{sg}}$$

The structural model is given as:

$$M_{sig} = x_i'\beta + v_{sig}$$

where x_i includes the observable features of buyer i such as gender, age, perceived affluence, is_foreigner, and a constant.

I make the modeling assumption that the unobserved error v_{sig} can be decomposed into two parts: a permanent component α_s that captures the fixed effects of seller s and the transaction-varying component ϵ_{sig}. The model can be written as:

$$M_{sig} = x_i'\beta + \alpha_s + \epsilon_{sig}$$
$$M_t = x_i'\beta + \alpha_s + \epsilon_t$$

I estimate the following OLS model, that includes dummy variables for $S - 1$ sellers to capture the seller fixed effects.

$$M_t = x_i'\beta + (D_{2t}, D_{3t}, ..., D_{St})\theta + \epsilon_t$$

What does the buyer's willingness to pay depend on?

Since the observational data on willingness to pay are sparse and inaccurate, I use income as a proxy for the buyer's affluence and their willingness to pay for the good.

I estimate the following structural model using an OLS regression:

$$income_i = x_i'\beta + \epsilon_t$$

where x_i contains observable characteristics of buyer i and a constant. The variable $income_i$, collected as a categorical variable, is the income level (on a scale of 1-3, where 3 is the highest) of the buyer.

How good are the sellers' beliefs about the buyer's willingness to pay?

I use buyer's income as a proxy for income as done in the previous part.

The structural model is given as:

$$M_t = \beta_0 + \beta_1 income_i + u_t$$

I once again decompose u_t into two parts: a permanent component α_s and a transaction-varying component ϵ_t. I estimate the following OLS model, with seller fixed effects:

$$M_t = \beta_0 + \beta_1\, income_i + (D_{2t}, D_{3t}, ..., D_{St})\theta + \epsilon_t$$

where the coefficient β_1 gives us the degree to which the seller's beliefs are correct.

Does bargaining help drive down the price?

Let P_{sig} be the final price of seller s to buyer i for good g. I can abbreviate sig as t for transaction. I define Z_t as a proportion of the marginal cost c, termed the *final price markup.*

The final price markup is calculated as:

$$Z_t = \frac{P_t - c}{c}$$

I also define the *final price markup from the first-ask price*, which measures the proportion difference of the final price from the seller's first-ask price. This is defined as:

$$Z_{F_t} = \frac{P_t - F_t}{F_t}$$

The structural models with seller fixed effects are given as:

$$Z_t = \beta_0 + \beta_1 E_t + \alpha_s + \epsilon_t$$
$$Z_t = \beta_0 + \beta_1 E_t + \beta_2 M_t + \alpha_s + \epsilon_t$$
$$Z_{F_t} = \beta_0 + \beta_1 E_t + \alpha_s + \epsilon_t$$

A positive relationship between Z_t and M_t is expected due to *anchoring* effects. To control for this, I use the second and third structural models which include the first-ask price F_t or first-ask markup M_t.

I estimate the following OLS models, that include dummy variables for $S-1$ sellers to capture the seller fixed effects.

$$Z_t = \beta_0 + \beta_1 E_t + (D_{2t}, D_{3t}, ..., D_{St})\theta + \epsilon_t$$
$$Z_t = \beta_0 + \beta_1 E_t + \beta_2 M_t + (D_{2t}, D_{3t}, ..., D_{St})\theta + \epsilon_t$$
$$Z_{F_t} = \beta_0 + \beta_1 E_t + (D_{2t}, D_{3t}, ..., D_{St})\theta + \epsilon_t$$

Does the model of price discrimination increase profits?

In this section, I present a profit maximization model of a seller who price discriminates using buyer observables. I compare two scenarios of this imperfect price discrimination: 1) the seller only has one attempt to offer a price, 2) the seller has two attempts to offer a price. I then test how these models compare to a counterfactual profit-maximizing uniform price model.

Imperfect price discrimination case (only first-ask)

A one-ask price discrimination model abstracts from bargaining and allows the seller to quote a single take-it-or-leave-it price to the buyer. The seller's profit markup for a transaction t in which a good g is sold at price p_t:

$$\pi_t = \left(\frac{p_t - c_g}{c_g}\right)$$

The buyer is first offered a price of F_t by the seller at a first ask markup of M_t. The expected profits in transaction t can be written as:

$$\mathbb{E}[\pi_t] = Pr(y_t = 1|x_i, M_t)\,\hat{Z}(M_t)$$

where y_t is the indicator variable $\mathbb{1}\{\text{good is purchased in transaction } t\}$, x_i are characteristics of buyer i, and M_t is the seller's first-ask markup as defined previously. Z_t is the final price markup as defined previously.

$\hat{Z}_t$ is calculated using a OLS regression of the final price markup Z_t on the first-ask markup M_t as defined previously.

The probability $Pr(y_t = 1|x_i, M_t)$ represents that the consumer i purchases the good given the seller's first-ask price. I will estimate this using a logit model as detailed below.

Logit model

$Pr(y_t = 1|x_i, M_t)$ is calculated by training a logit model of y_t on x_i, M_t, and a constant for all observed transactions. This allows us to compute the probability that buyer i purchases the good with price markup M_t. I use a model of the following specification:

$$Pr(y_t = 1|x_i, M_t) = \frac{1}{1 + e^{-(x_i\theta + M_t\beta)}}$$

where x_i includes the buyer's gender, race, affluence, age, and a constant term. Therefore, the seller's optimization problem to maximize expected profits can be written as:

$$\begin{aligned} \max\ \mathbb{E}[\pi] &= \sum_{transaction\, t} \max_{M_t}\ \mathbb{E}[\pi_t(M_t)] \\ &= \sum_t \max_{M_t}\ Pr(y_t = 1|x_i, M_t)\, \hat{Z}(M_t) \end{aligned}$$

Imperfect price discrimination case (first-ask and second-ask)

I extend the expression in the previous question to include one more round and incorporate bargaining. This time, the seller has two attempts to bargain with a buyer to sell his good. Let p_1 be $Pr(y_t = 1|x_i, M_t)$ i.e. the probability that buyer i purchases the good given the seller's first-ask markup M_t. Let p_2 be $Pr(y_t = 1|x_i, N_t)$ i.e. the probability that buyer i purchases the good given the seller's second-ask markup N_t. The second-ask markup, similar to the first-ask markup, is defined as:

$$N_t = \frac{S_t - c}{c}$$

where S_t is the seller's second ask price and c is the marginal cost of the good. The seller's optimization problem in this case can be written as:

$$\begin{aligned} \max\ \mathbb{E}[\pi] &= \sum_{transaction\, t} \max_{M_t, N_t}\ \mathbb{E}[\pi_t(M_t, N_t)] \\ &= \sum_t \max_{M_t, N_t}\ p_1\, \hat{Z}(M_t) + (1 - p_1)\, p_2\, \hat{Z}(N_t) \end{aligned}$$

where p_1 and p_2 are estimated using two different logit models. $\hat{Z}(M_t)$ and $\hat{Z}(N_t)$ are the estimated final prices given the first-ask markup and the second-ask markup respectively.

Uniform pricing case

The seller's profit maximization problem can be written as:

$$\begin{aligned}
\max \mathbb{E}[\pi] &= \sum_{transaction\, t} \max_p \mathbb{E}[\pi_t(p)] \\
&= \sum_t \max_p Pr(y_t = 1|x_i, \bar{p}) \left(\frac{p - c_g}{c_g}\right) \\
&= \max_p \sum_t Pr(y_t = 1|x_i, \bar{p}) \left(\frac{p - c_g}{c_g}\right)
\end{aligned}$$

A logit model is used to estimate $Pr(y_t = 1|x_i, \bar{p})$ similar to the previous cases.

OLS Model case

I use an OLS model to predict the buyer's willingness to pay for a certain good using the final transaction price markup. The OLS model is given as:

$$Z_t = x_i'\beta + \epsilon_t$$

I then use the below expression to find expected profits:

$$\begin{aligned}
\mathbb{E}[\pi] &= \sum_{transaction\, t} \mathbb{E}[\pi_t] \\
&= \sum_t Pr(y_t = 1|x_i, \hat{Z}_t)\, \hat{Z}_t \\
&= \sum_t Pr(y_t = 1|x_i, \hat{Z}_t)\, \hat{Z}_t
\end{aligned}$$

where $\hat{Z}_t$ is the final transaction price markup calculated from the OLS model above. $Pr(y_t = 1|x_i, \hat{Z}_t)$ is calculated using a logit model as detailed previously.

Note: Since the observational dataset is small at 240 observations, I use bootstrap sampling with replacement to calculate the expected profits in all 4 cases. I use a sample size of 50 transactions and run 100 iterations. In order to maximize the objective function for a given resample in the case of imperfect price discrimination, I use a gradient ascent based optimization function.

5.2 Survey Experiment

What observables do sellers use to price discriminate?

In order to maximize expected profits, the respondent, in the position of a seller, runs the following optimization problem in their head:

$$\max_{p} \quad \frac{p - WTA_s}{WTA_s} \quad \text{subject to:} \quad p \leq W\hat{T}P_i$$

where $W\hat{T}P_i$ is the seller's estimate of the buyer's willingness to pay.

We subtract the ask prices by the sellers' willingness to accept to remove any heterogeneity in WTA price that might bias the true extent of price discrimination. I estimate the following OLS models, similar to the one in the observational study but omitting the seller fixed effects due to random assignment:

$$F_t - WTA_s = x_i'\beta + \epsilon_t$$

$$S_t - WTA_s = x_i'\beta + \epsilon_t$$

$$L_t - WTA_s = x_i'\beta + \epsilon_t$$

where F_t and S_t are the first-ask price and second-ask price of the seller respectively. L_t is the lowest price the seller is willing to take from the buyer in the image after both his bids have been rejected. I call this the lowest-ask price.

What does the buyers' willingness to pay depend on?

I run a OLS regression of the following form to predict the buyers' WTP from their observable characteristics:

$$WTP_i = x_i'\beta + \epsilon_i$$

where x_i contains the observable features for buyer i and a constant.

How good are the sellers' beliefs about the buyers' willingness to pay?

The seller's estimate of the buyer's willingness to pay can be ascertained from their ask prices during bargaining. Additionally, I assume that the sellers first-ask price is a scalar multiple of the buyers' WTP. To test how the seller's ask prices estimate the buyer's willingness to pay, I run the following (hypothetical) OLS regressions:

$$F_t = WTP_i\,\theta_1 + \epsilon_t$$

$$S_t = WTP_i\,\theta_2 + \eta_t$$

$$L_t = WTP_i\,\theta_3 + u_t$$

where the parameters $\theta_1, \theta_2, \theta_3$, estimated using the OLS regressions, represent the accuracy of the sellers' beliefs. F_t, S_t, and L_t are the sellers first-ask, second-ask, and lowest-ask prices respectively.

I compare the sellers' beliefs to my model's estimates of the buyers' WTP from the previous section. I also calculate the root mean squared error (RMSE) from the buyers' true WTP to compare the estimates of the sellers' ask prices to my model's predictions. The RMSE is calculated as follows:

$$\sqrt{\sum_{i=1}^{n} \frac{(W\hat{T}P_i - WTP_i)^2}{n}}$$

Does bargaining help drive down the price?

To estimate the effect of bargaining on lowering the price, I use the following structural model:

$$F_t - P_t = \beta_0 + \beta_1 E_t + u_t$$

where F_t is the seller's first-ask price and P_t is the final transaction price after the three rounds of bargaining. E_t represents the bargaining intensity, which is quantified as the number of rounds of bargaining that took place (on a scale of 1-3).

However, due to the heterogeneity in the buyers' willingness to pay, the number of times the buyer says no might be systematically correlated with their WTP. To control for this, I add dummy variables for demographic types, which capture *fixed effects* within each buyer type. This gives us the second structural model:

$$F_t - P_t = \beta_0 + \beta_1 E_t + (D_{2t}, D_{3t}, ..., D_{Bt})\theta + \epsilon_t$$

Both models are estimated using an OLS regression.

Does this model of price discrimination increase profits?

Uniform pricing case

Similar to Graddy and Hall (2011), I use the prior probabilities of the 7 buyers entering the store frequenting the market from the observational data. For buyer i, let this prior be $\hat{\lambda}_i$ such that:

$$\sum_i \hat{\lambda}_i = 1$$

The seller sets a fixed price p to maximize the expected profits given as:

$$\mathbb{E}[\pi] = \sum_{i=1}^{7} \max_{p} \hat{\lambda}_i \,(p - c) \quad s.t. \quad c \leq p \leq WTP_i$$

The optimal price p^* is given as:

$$p^* = \sum_{i=1}^{7} \hat{\lambda}_i \, WTP_i \quad \forall i : WTP_i \geq c$$

Then, we can calculate expected profits.

Perfect Price Discrimination case

In a situation where the seller can perfectly estimate the buyer's willingness to pay, the seller runs the following optimization to maximize expected profits:

$$\mathbb{E}[\pi] = \sum_{i=1}^{7} \max_{p_i} \hat{\lambda}_i \,(p_i - c) \quad s.t. \quad c \leq p_i \leq WTP_i$$

The optimal price p_i to ask buyer i that solves this optimization is given as:

$$p_i = WTP_i \quad \forall i : WTP_i \geq c$$

Then, we can calculate expected profits.

Imperfect Price discrimination case

In the online experiment, we have data for the seller's first-ask price F_t as well as their second-ask price S_t. Thus, the seller's expected profits for an individual in buyer demographic group i who engages in a transaction can be written as:

$$\mathbb{E}[\pi_i] = p_1 \,(\hat{Z}(F_i) - c) + (1 - p_1) \, p_2 \,(\hat{Z}(S_i) - c)$$

where $p_1 = Pr(y = 1|x_i, F_i)$ and $p_2 = Pr(y = 1|x_i, S_i)$. These represent probabilities that the purchase is made, given that the seller quotes the first-ask price F_i or the second-ask price S_i respectively. As done before, I use logit models to estimate $p_1(F_i)$ and $p_2(S_i)$ and an OLS model to predict the final transaction prices $\hat{Z}$ for both bargaining rounds.

Therefore, the seller's optimization problem to maximize expected profits is:

$$\begin{aligned}
\max \mathbb{E}[\pi] &= \sum_{group\, i} \hat{\lambda}_i \max_{F_i,\, S_i} \mathbb{E}[\pi_i(F_i, S_i)] \\
&= \sum_{i} \hat{\lambda}_i \max_{F_i,\, S_i} p_1\,(\hat{Z}(F_i) - c) + (1 - p_1)\, p_2\,(\hat{Z}(S_i) - c)
\end{aligned}$$

where $\mathbb{E}[\pi_i]$ has been substituted from the previous equation and $\hat{\lambda}_i$ is the prior likelihood of buyer group i frequenting the informal market.

6 Results

6.1 What observables do sellers use to price discriminate?

Observational

Table 5 shows the results of the OLS regression of seller's first-ask markup M_t on the buyer's observable characteristics from the observational data. Appearance is an indicator variable for perceived affluence. The first regression does not include the interaction between is_foreigner and appearance. I find that appearance has a strong effect on the extent of price discrimination, and sellers raise prices by 23.44 percentage points to those who appear affluent. Females are also quoted prices that are lower by about 17.71 percentage points. This result is different than that of List (2004), in which females and males tend to receive similar bids and pay similar prices for the same good conditional on the execution of the purchase. As expected, foreigners are quoted prices that are on average 19.26 percentage points higher. All these results are statistically significant at the 1% level. I do not find a strong effect of age on the extent of price discrimination. This result is inconsistent with List (2004), which found that older buyers receive offers that are 10% higher as compared to the baseline of young white males.

After including the interaction term between is_foreigner and appearance to capture affluent-looking foreigners, the effect of foreigner on the first-ask markup decreases to 9.66 percentage points. The effect of appearance falls by about 5 percentage points from 23.44 to 18.60 percentage points.

Survey

Table 6 shows results from the survey of the OLS regressions of the ask prices F_t, S_t, and L_t on the buyer's observable characteristics. I find that, controlling for the other observables, foreigners are quoted a price that is about Rs. 45 - Rs. 60 more for the same good, which translates to about 20 - 30 percentage points higher for a willingness to accept of Rs. 200. *Ceteris paribus*, females and people older than 40 years of age also tend to be asked lower prices, especially in the first round. This translates to females being offered prices that are lower by about 10 - 15 percentage points, which is consistent with the observational data. However, the result that older people are asked lower prices is not supported by results from the observational study. This suggests that the price discrimination observed in the field is a consequence of statistical discrimination - the belief that different demographic groups have different distribution of reservation prices - rather than animosity against certain demographic groups. This result is consistent with the findings of List (2004). These differences are statistically significant at the 1% level. The characteristic with the biggest effect, as expected, is the buyer's appearance. Appearance is measured on a scale of 1-3, where 3 is the most affluent-looking. A 1 point increase in appearance represents a jump from working-class to middle-class or middle-class to upper-class in perceived affluence. For a 1 point increase in appearance, there is approximately a Rs. 56 increase in the seller's first-ask price. These differences persist, but become narrower in the next two rounds of the bargaining game. In the case for the variable *above*40, the difference also loses its statistical significance, which implies that sellers do not continue price discriminating based on age as bargaining continues.

Table 5: OLS Regression of first-ask markup M_t on observables (Observational)

	M_t (1)	M_t (2)
const	1.0982***	1.1080***
	(0.0269)	(0.0263)
appearance	0.2344***	0.1860***
	(0.0256)	(0.0277)
is_female	-0.1771***	-0.1623***
	(0.0280)	(0.0274)
above40	-0.0179	-0.0270
	(0.0328)	(0.0319)
is_foreigner	0.1926***	0.0966**
	(0.0312)	(0.0389)
is_foreigner × appearance		0.2449***
		(0.0625)
N	240	240
R^2	0.42	0.46

Notes: Standard errors in parentheses. *** denotes significance at the 1% level.

Table 6: OLS Regression of (ask price - seller's WTA) on observables (Survey)

	$F_t - WTA_s$	$S_t - WTA_s$	$L_t - WTA_s$
const	61.6796***	49.2893***	32.3649**
	(7.1155)	(8.5146)	(15.2355)
is_foreigner	45.7179***	60.0831***	53.7991***
	(4.1607)	(5.4379)	(10.4223)
appearance	56.4757***	46.6574***	41.0749***
	(2.9142)	(3.3417)	(5.7461)
female	-21.8286***	-30.6165***	-24.5614***
	(3.6201)	(4.4405)	(7.6441)
above40	-27.1334***	-12.1212**	4.7280
	(3.9506)	(5.1091)	(9.7585)
N	912	506	189
R^2	0.52	0.51	0.37

Notes: Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels respectively.

6.2 What does the buyers' willingness to pay depend on?

Observational

In the observational dataset, I use income as a proxy for the buyers' willingness to pay. After running a regression of income on the buyers' observables, I find that foreigners and older people tend to have higher incomes, as expected. Appearance is also positively correlated with income, statistically significant at the 5% level. Gender is not correlated with income. The results of the OLS regression are given in Table 7.

Table 7: OLS Regression of income on observables (Observational)

	income
const	1.8768***
	(0.0956)
is_foreigner	0.7247***
	(0.1106)
appearance	0.1826**
	(0.0907)
is_female	-0.1291
	(0.0994)
above40	0.3245***
	(0.1163)
N	240
R^2	0.20

Notes: Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels respectively.

Survey

In order to prevent overfitting to the training data, the survey dataset is first divided into a training set and a test set, with a 60/40 split.

Using the training data, I run a regression to estimate the buyer's willingness to pay from their observable characteristics. The results, given in Table 8, are similar to those found in the previous section. Controlling for other variables, foreigners' WTP tends to be higher by about Rs. 71. Similarly, females are willing to pay about Rs. 18 lesser than males for the same good. A 1 point increase in appearance, which is a rough proxy for the buyer's affluence, increases the buyer's WTP by Rs. 47. These differences are statistically significant at the 1% level. On the other hand, age does not seem to have a large effect on WTP. Older people tend to have a WTP that is about Rs. 5 lower; however, this is significant only at the 10% level.

Table 8: OLS Regression to predict buyer's WTP from observables (Survey)

	buyer_WTP
const	258.4804***
	(2.0359)
is_foreigner	70.8379***
	(1.2029)
appearance	47.2699***
	(0.8499)
female	-17.9429***
	(1.0481)
above40	-5.4046***
	(1.1394)
N	547
R^2	0.96

Notes: Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels respectively.

6.3 How good are the sellers' beliefs about the buyers' willingness to pay?

Observational

I find a weak positive relationship between the income and the seller's first-ask markup. A 1 point increase in income level category increases the seller's first ask markup by about 4.5 percentage points. This is statistically significant at the 5% level, but only has an R^2 of 0.02. This effect persists until the final transaction price, but decreases in statistical significance. This might be because income is not strongly correlated with the buyer's willingness to pay for a particular good. The buyer's willingness to pay for inexpensive goods might be correlated with unobserved characteristics such as body language, amount of interest shown in the good rather than observables. These characteristics may not be correlated with income. This cannot be confirmed since we do not have information about the buyer's willingness to pay for a good.

Table 9: OLS Regression of M_t and Z_t on income (Observational)

	M_t	Z_t
const	1.0061***	0.6764***
	(0.0468)	(0.0651)
income	0.0445**	0.0508*
	(0.0213)	(0.0297)
N	240	240
R^2	0.02	0.01

Notes: Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels respectively.

Survey

The OLS model from Table 8 is used on the test data to calculate the buyer's predicted WTP, given as $\hat{WTP}$. I then calculate the root mean squared error (RMSE) using the model's predictions and the buyer's true WTP from the test data.

On the same test data, I also calculate the RMSE for the seller's ask prices. The results are given in Table 10. I find that my model does a much better job of predicting the buyer's willingness to pay given their observables than the seller's ask prices. Amongst the ask prices, the seller's second-ask price is the most accurate in predicting the buyer's willingness to pay. This is because this is the seller's final opportunity to make the sale before the buyer walks, and thus, it's imperative that their estimate is accurate. As expected, the seller's first-ask price systematically overestimates the buyer's WTP. On the other hand, their lowest-ask price, which is only elicited if the seller fails to make the sale after two attempts, systematically underestimates the buyer's WTP. To show this pattern, the results of a hypothetical regression of ask prices on the buyer's WTP are given in Table 11. All three results are statistically significant at the 1% level.

Table 10: Comparing the model's predictions with the sellers' ask prices (Survey)

	Model	Seller's First Ask F_t	Seller's Second Ask S_t	Seller's Lowest Ask L_t
RMSE	22.03	51.56	39.99	45.61
N	365.00	365.00	185.00	66.00

Notes: To calculate the RMSE error for the second ask and lowest ask prices, we exclude all the observations where these variables are missing i.e. where the transaction terminated at the first round. This is the reason why the number of observations N varies across the last 3 columns.

Table 11: A hypothetical regression to find estimate of WTP (Survey)

	seller_first_ask (1)	seller_second_ask (2)	seller_lowest_ask (3)
buyer_WTP	1.0602***	0.9941***	0.9299***
	(0.0042)	(0.0046)	(0.0089)
N	912	506	189
R^2	0.99	0.99	0.98

Notes: Standard errors in parentheses. *** denotes significance at the 1% level.

6.4 Does bargaining help drive down the price?

Observational

Table 12 shows the results of the three OLS regressions of the *final price markup* Z_t on bargaining intensity E_t. As expected, bargaining intensity is negatively correlated with the final price markup. Table 10 column (1) shows that a 1 point increase in bargaining intensity decreases the final price markup by 18 percentage points. In column (2), after controlling for first-ask markup M_t to rule out anchoring effects, I find that the magnitude of this effect increases by 1 percentage point. In column (3), I regress the *final price markup from the first-ask price* Z_{F_t} on bargaining intensity. The bargaining intensity has a weaker effect on this measure; a 1 point increase in E_t decreases the final price below the first-ask price by about 9 percentage points. The coefficients on all three ask prices are significant at the 1%

level. Thus, bargaining is found to have a strong effect on lowering the final price below the seller's first ask price. However, our result might be an overestimate of the true effect of bargaining since the bargaining intensity is decided by the observer ex-post the completion of the transaction.

Table 12: OLS Regression of price markup on bargaining intensity (Observational)

	Z_t (1)	Z_t (2)	Z_{F_t} (3)
const	1.1274***	0.3015***	0.0242
M_t		0.7723***	
		(0.0638)	
bargaining_intensity	-0.1803***	-0.1917***	-0.0905***
	(0.0240)	(0.0189)	(0.0088)
N	240	240	240
R^2	0.19	0.50	0.31

Notes: Standard errors in parentheses. *** denotes significance at the 1% level.

Survey

Table 13 shows the results of the OLS regression of the difference between the first-ask F_t and final transaction price Z_t, termed as the ask markup, on the bargaining intensity variable. The bargaining intensity variable captures the number of times the buyer says no to a seller's ask, i.e. the number of rounds in the bargaining process.

I find that every time the buyer declines the seller's ask, the seller reduces the price by Rs. 54. After including fixed effects, I find that bargaining still lowers the price below the first-ask by about Rs. 53. Both these coefficients are statistically significant at the 1% level. This supports our findings from the observational study, which suggests that bargaining has a strong downward influence on the price markup above the first-ask price.

Table 13: **OLS Regression of price difference on bargaining intensity (Survey)**

	$F_t - P_t$ (1)	$F_t - P_t$ (2)
const	-47.2758***	-41.3893***
	(3.0247)	(2.9057)
bargaining	53.6904***	52.7718***
	(1.5723)	(1.7034)
buyer fixed effects	no	yes
N	912	912
R^2	0.56	0.57

Notes: Standard errors in parentheses. *** denotes significance at the 1% level.

6.5 Does this model of price discrimination increase profits?

Observational

Due to heterogeneity of marginal costs and prices across goods, I calculate the profit as a profit markup defined as:

$$\pi_t = \frac{p_t - c_t}{c_t}$$

where p_t is the final price of the good and c is the marginal cost of the good. The prices are also defined as percentages of marginal cost. So, a price of 1.50 represents $p_t = 1.50c$.

Table 14 shows the expected prices, probabilities of purchase, and profits under the four estimated models. The data shows the following trends:

Price:

Model $<$ Imperfect(F_t) $=$ Imperfect(F_t, S_t) $price_2$ $<$ Imperfect(F_t, S_t) $price_1$ $<$ Uniform

Pr(purchase):

Imperfect(F_t, S_t) p_1 $<$ Uniform $<$ Imperfect(F_t, S_t) p_2 $=$ Imperfect(F_t) $<$ Model

Profits:

Model $<$ Uniform $<$ Imperfect(F_t) $<$ Imperfect(F_t, S_t)

As expected, the maximum price is obtained under the uniform price model at about 1.77c or 1.77 times marginal cost. The first ask price of the two-ask price discrimination model Imperfect(F_t, S_t) is about 1.70c, higher than the first ask price of the one-ask price discrimination model Imperfect(F_t) of 1.57c. Additionally, the second-ask price of the two-ask model is about the same as the first-ask price of the one-ask model. This makes sense, since at the last attempt in any price discriminating model, the seller wants to quote a price to maximize profits as well as the probability of purchase to ensure that the sale is completed.

The OLS model has the highest expected probability of purchase at 0.58. Since the prices of the one-ask model's first bid and two-ask model's second bid are the same, they have the same mean probability of purchase at 0.36. The two-ask model's first bid has the lowest probability at 0.26. A potential explanation is that since sellers have two attempts to convince a buyer, they quote a high first bid which has a lower probability of success to maximize their profits and then return to a baseline lower price that increases the probability that the good is purchased.

The two-ask price discrimination model has the highest expected profits at 40%. On the other hand, the one-ask model gives us the second highest profit at 28%. As expected, the uniform price model fares worse than the two price discrimination models and yields mean profits of 22%. Despite taking into account the buyers' observables into the price, the OLS model performs very poorly at 10% expected profits.

Table 14: Prices, Pr(purchase), and Profits under various models (Observational)

	Uniform				**Imperfect (F_t)**				**Imperfect (F_t, S_t)**				**Model**			
	Mean	SD	95% CI		Mean	SD	95% CI		Mean	SD	95% CI		Mean	SD	95% CI	
$price_1$	1.77	0.09	(1.66,	1.99)	1.57	0.05	(1.48,	1.68)	1.70	0.06	(1.58,	1.82)	1.10	0.02	(1.05,	1.14)
$price_2$									1.57	0.05	(1.48,	1.67)				
p_1	0.29	0.03	(0.23,	0.36)	0.36	0.04	(0.28,	0.42)	0.26	0.03	(0.21,	0.30)	0.58	0.05	(0.50,	0.67)
p_2									0.35	0.04	(0.28,	0.42)				
Profit %	0.22	0.04	(0.17,	0.29)	0.28	0.05	(0.19,	0.39)	0.40	0.06	(0.29,	0.52)	0.10	0.02	(0.07,	0.14)

Notes: Profits and prices are calculated as a proportion of marginal cost.
Mean, standard deviation, and confidence interval are calculated using bootstrap sampling.

Survey

In this section, since the good is fixed in the survey and has a marginal cost of 175, profits are calculated per good as:

$$\pi_t = p_t - 175$$

Uniform pricing

The profits calculated under the uniform price model for different prices p are given in Figure 10 below. I find that the $p = 350$ results in the maximum expected profit of Rs. 140, but prices out two demographic groups from the market with low reservation prices. The calculation is given in Table 15.

Figure 10: Profits vs Fixed Price

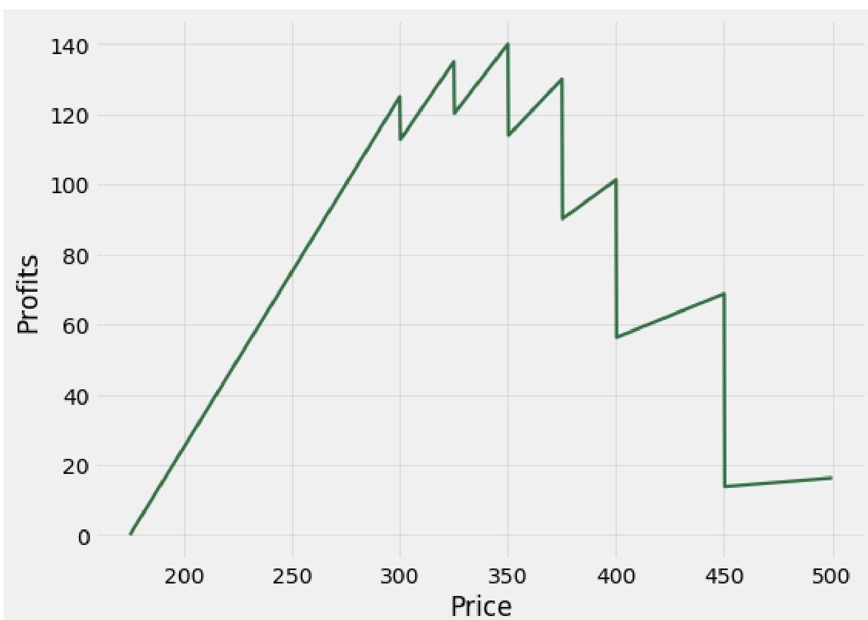


Table 15: Expected profits with optimal uniform price ($p = 350$) (Survey)

	Prior $\hat{\lambda}_i$	Willingness to pay WTP_i	Profit π_i
Male affluent foreigner	0.05	500	175
Female affluent foreigner	0.15	450	175
Female old foreigner	0.05	450	175
Male middle-class foreigner	0.10	400	175
Male affluent Indian	0.10	400	175
Female affluent Indian	0.20	375	175
Male middle-class Indian	0.10	350	175
Female working-class Indian	0.10	300	0
Female old Indian	0.10	325	0
Male old Indian	0.05	350	175
Expected Profits			140

Notes: $\pi_i = max\{(WTP_i - 175), 0\}$.
$E[\pi] = \sum_i \hat{\lambda}_i \pi_i$

Perfect price discrimination

Under perfect price discrimination, the seller has perfect information about the buyers' willingness to pay and sets price for buyer group i exactly equal to their willingness to pay.

$$p_i = WTP_i$$

This gives the maximum expected profit of the three cases at Rs. 210. This model of price discrimination extracts all consumer surplus and maximizes producer surplus.

Table 16: **Expected profits under perfect price discrimination (Survey)**

	Prior $\hat{\lambda}_i$	Price WTP_i	Profit π_i
Male affluent foreigner	0.05	500	325
Female affluent foreigner	0.15	450	275
Female old foreigner	0.05	450	275
Male middle-class foreigner	0.10	400	225
Male affluent Indian	0.10	400	225
Female affluent Indian	0.20	375	200
Male middle-class Indian	0.10	350	175
Female lower-class Indian	0.10	300	125
Female old Indian	0.10	325	150
Male old Indian	0.05	350	175
Expected Profits			210

Notes: $\pi_i = WTP_i - 175$.
$E[\pi] = \sum_i \hat{\lambda}_i \pi_i$

Imperfect price discrimination

Under imperfect price discrimination, the seller has a noisy estimate of the buyer's willingness to pay through their observable characteristics. The seller has two attempts to sell the good to the customer. If both attempts are above the buyer's true WTP, then the good is not sold and the seller makes 0 profits. At each attempt, there is some probability p_1 or p_2 that the sale is completed at a final transaction price of $\hat{Z}(F_i)$ or $\hat{Z}(S_i)$ where F_i and S_i are the seller's first-ask and second-ask prices respectively.

The probabilities $p_1 = Pr(\text{purchase} = 1|F_i, x_i)$ and $p_2 = Pr(\text{purchase} = 1|S_i, x_i)$ are calculated using a logit model on the ask prices and the buyer's observables x_i. The estimated final prices based on these transaction prices are calculated using an OLS regression of final price Z_t on the observables x_i and ask price. I then try to maximize the profit objective function in the model section using a gradient ascent algorithm.

Table 17 shows the variables used to calculate the profits. As expected, the first-ask prices F_i to the different demographic groups are higher than their corresponding second-ask prices S_i. As a consequence of this, the probability of a purchase at the first-ask p_1 is lower than the probability of a purchase at the second-ask price p_2. The probability p_2 is extremely high (> 0.85) since the seller only has two attempts to bargain before the buyer walks away. Under this model, we obtain expected profits of Rs. 198.01, about 41% higher than the uniform price model. With a marginal cost of Rs. 175, this model yields a profit markup percentage of 113%. This is consistent with our result from the observational study but larger in magnitude. One potential explanation might be that sellers in the observational study did not reveal their true marginal cost. Another explanation is that sellers might face lower profit percentages on certain categories of goods such as leather goods and jewellery. This heterogeneity in profits across goods might lower the average profit percentage in the observational setting.

Thus, our findings suggest that price discrimination raises profits as compared to a profit-maximizing uniform price model. Amongst the price discriminating models, the two-ask model raises profits by 81% while a one-ask take-it-or-leave-it pricing model raises profits by 27% relative to the single price model.

Table 17: Expected profits under imperfect price discrimination (Survey)

	Prior $\hat{\lambda}_i$	First ask F_i	Second ask˜ S_i	Price 1 $\hat{Z}(F_i)$	Price 2 $\hat{Z}(S_i)$	Prob 1 p_1	Prob 2 p_2	Profit π_i
Male affluent foreigner	0.05	558.07	503.34	455.50	420.89	0.65	0.93	262.12
Female affluent foreigner	0.15	531.54	478.19	438.72	404.98	0.65	0.92	245.34
Female old foreigner	0.05	528.41	475.23	436.74	403.10	0.65	0.92	243.36
Male middle-class foreigner	0.10	527.81	474.66	436.36	402.74	0.65	0.92	242.98
Male affluent Indian	0.10	452.58	403.87	388.78	357.97	0.63	0.90	195.39
Female affluent Indian	0.20	426.40	379.47	372.22	342.54	0.62	0.89	178.84
Male middle-class Indian	0.10	422.72	376.06	369.89	340.38	0.62	0.89	176.51
Female lower-class Indian	0.10	367.21	324.92	334.79	308.03	0.59	0.86	141.40
Female old Indian	0.10	393.63	349.15	351.49	323.36	0.60	0.88	158.11
Male old Indian	0.05	419.64	373.20	367.94	338.57	0.62	0.89	174.56
Expected Profits								198.01

Notes: $\pi_i = p_1(F_i)\,(\hat{Z}(F_i) - 175) + (1 - p_1(F_i))\,p_2(S_i)\,(\hat{Z}(S_i) - 175)$
$E[\pi] = \sum_i \hat{\lambda}_i \pi_i$

7 Conclusion

The tailoring of prices in informal markets provides a rare and observable instance of first-degree price discrimination in the marketplace. Using observational data collected from an informal market, I find that sellers price discriminate primarily based on observable characteristics of gender, appearance, and race. Males, foreigners, and affluent-looking individuals tend to pay higher prices as opposed to their counterparts. The survey data confirms that this is a consequence of statistical discrimination rather than taste-based discrimination. Since some of these observables predict income, buyers with higher incomes are asked and pay prices that are 5% higher. However, buyers can lower the price through bargaining, which has a strong downward effect on the final price markup. A model based on imperfect price discrimination increases expected profits by as much as 82% as compared to a uniform price model. These results are consistent with the those from the survey experiment; the difference being that the effects from the survey are larger in magnitude.

This paper contributes to a small but growing body of research on first-degree price discrimination. The study takes advantage of the unique dynamics of this informal market to explore economic phenomena in a naturally-occurring marketplace. However, the models in this paper present a simplification of the multidimensional nature of the informal market. On the seller side, I omit dimensions such as quantity sold, inventory management and heterogeneity in quality of goods. On the buyer side, I abstract from the effect of unobservable characteristics, bargaining in groups, and differences in buyer search costs & opportunity costs. Another limitation of the model is that it does not capture existing relationships between buyers and sellers, which might have downstream effects on bargaining intensity and the extent of price manipulation. Further research should explore these aspects of informal markets.

Price discrimination also incurs costs that are difficult to measure. In terms of welfare, price discrimination transfers surplus from the consumer to the producer and increases total welfare. A person-specific pricing model might also improve distributional outcomes by charging low-income groups affordable prices. In comparison, a single price model often prices these consumers out of the market. However, flexible pricing increases search costs for buyers and may decrease demand. Price discrimination across homogeneous goods can intensify competition between sellers in the marketplace. Tailoring prices to buyers' observable characteristics can result in different prices charged to different demographic groups for similar goods, which can have important implications on the public perception of market fairness. These fairness concerns can constrain the profit-seeking behavior of the sellers.[2] Haggling for a good can also impose psychological costs to the buyer, which can be detrimental for sellers in the long-run. In conclusion, my results have important implications for welfare, fairness, and competition.

[2] See Kahneman, Knetsch and Thaler (1986).

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A Appendix

A.1 Observational Study

Figure A.1: Part of data collection rubric for volunteers

Data Collection Rubric

Goal of rubric:
A complete guide on how to collect observational data for the field experiment

Required variables we need to collect:

1. Private information from the seller
    a. Seller's marginal cost
    b. Seller's willingness to accept (the minimum price the seller is willing to take for the good)
2. Private information from the buyer
    a. Buyer's willingness to pay (the maximum price the buyer is willing to pay for the good)
    b. Buyer's monthly income (range)
    c. Market experience (years)
    d. Age
3. Transactional data
    a. Good transacted
    b. Buyer's first ask
    c. Seller's first ask
    d. Was the good purchased?
    e. Final equilibrium price for good
    f. Bargaining intensity or effort (5 is maximum)
    g. Producer gender
    h. Buyer gender
    i. Buyer is_foreigner
    j. Buyer appearance (on a scale of 1-5)
        i. 5 is most affluent/wealthy, 1 is very poor

Procedure:

1. Establish your presence in the allotted store/shop with your partner
    a. Explain that you're part of a school research project and want to observe their store for a couple of hours in a non-interfering way
    b. Use financial incentives if necessary (Rs. 100 to observe for 1 hour)
2. Elicit the seller's private information (variables given above), which can be collected on the Excel sheet
3. During a certain transaction, one person can start collecting the transactional data in this Google Sheet
4. After the transaction has completed and the buyer is about to leave the store, elicit private information from the buyer (variables given above) using this Google Form
5. At the end of the day, add the information from the buyer's Google Form to the Excel sheet. To do this, go to the Google Form link you received in your email and click on **Responses**

Figure A.2: Excel Sheet for data collection

A	B	C	D	E	F	G	H	I	J	K	M	N	O
Observer	good	buyer_first_ask	seller_first_ask	equilibrium_price	purchased?	bargain_intensity (1-5)	seller_gender	buyer_gender	buyer_is_foreigner	buyer_appearance (1-5)	buyer_income	buyer_experience (yrs)	buyer_age
Jahnvi and Kriti	Top	250	250	250	yes	0	M	F	no	4	Above 150000	10	45
Jahnvi and Kriti	Dress	150	450	150	yes	2	M	F	no		Below 50000	5	22
Jahnvi and Kriti	Skirt	250	350	250	yes	0	M	F	no	2	50000-150000	10	27
Jahnvi and Kriti	Dress	300	600	300	yes	5	M	F	no	5	Above 150000	16	40
Jahnvi and Kriti	Dress	150	450	200	yes	2	M	F	no	3	Below 50000	4	23
Jahnvi and Kriti	Cami	80	175	100	yes	4	M	F	no	3	Below 50000	4	23
Somansh and Lakshay	watch	250	420	300	yes	3	M	M	no	4	below 50000	0	20
Somansh and Lakshay	t-shirt	200	250	250	yes	0	M	M	no	3	below 50000	0	21
Somansh and Lakshay	top	150	300	150	yes	5	M	F	no	4	Above 150000	5	26
Somansh and Lakshay	sneakers	350	350	350	yes	0	M	M	no	5	Above 150000	0	20
Somansh and Lakshay	sneakers	300	350	320	yes	2	M	M	no	3	Above 150000	1	22
Somansh and Lakshay	jacket	840	900	840	Yes	3	M	M	No	4	Above 50000	2	21

Figure A.3: Google Form to elicit buyer's private information

Buyer Demographic Information

This form is completely anonymous and is part of a behavioral economics study conducted at UC Berkeley.

*Required

Good Transacted *

Your answer

Maximum willingness to pay (in rupees) *

Your answer

Monthly Income Level *

- Below Rs. 10,000 or Student
- Rs. 10,000 - Rs. 25,000
- Rs. 25,000 - Rs. 50,000
- Rs. 50,000 - 1,00,000
- Rs. 1,00,000 and above

Age *

Your answer

Experience in the market (in number of years) *

Your answer

Submit

A.2 Randomized Survey Experiment

Figure A.4: Demographic Questions and Instructions

Q0.
Thank you for interest in the survey.

We check responses carefully in order to make sure that people have read the instructions for the task and responded carefully. We will only accept participants who clearly demonstrate that they have read and understood the survey.

There will be some simple questions that test whether you are reading the instructions. If you get these wrong, you will not be eligible for participation.

You have a maximum of 15 minutes to complete the survey, so please focus on quality of responses. You are also eligible for a bonus based on your responses.

- I understand
- I do not understand

Q1. Gender

- Male
- Female

Q2. Age

Q3. Education (completed)

- Less than high school degree
- High school degree or equivalent
- Some college but no degree
- Vocational degree
- Bachelor's degree (4 year)
- Graduate degree

Q4. Monthly household income

- Less than Rs. 10,000
- Rs. 10,000 - Rs. 25,000
- Rs. 25,000 - Rs. 50,000
- Rs. 50,000 - Rs. 75,000
- Rs. 75,000 - Rs. 1,00,000
- Greater than Rs. 1,00,000

Q5. Employment

- Student
- Employed (full time)
- Employed (part time)
- Unemployed (looking for work)
- Unemployed (not looking for work), e.g. homemaker
- Retired

.
Imagine yourself in this street vendor's shoes, who has a store in an Indian open-air market that looks something like this:

.
You are a vendor selling shirts similar to the one given in the picture below to incoming buyers.
You can ask for any price you want for the good to a buyer, who also has the opportunity to bargain for the good based on his/her preferences.
The shirt costed you Rs. 175, and so you want to **sell it for a little more than that amount.**

Figure A.5: Survey questions on Price Discrimination

Q6. What is the lowest price you would be willing to accept for this shirt?

Read these instructions very carefully - Chance to win a bonus!

Now, you will get two attempts to bargain with a customer who wants to purchase a shirt from your store.

- If at any point you quote a price and the customer **decides to accept (says Yes)**, you will get a bonus equal to the proportional difference between this price and your answer in the **previous Q6 (the lowest price you were willing to accept)**. Bonus will be paid in dollars ($).
  - For example, if your answer to Q6 was Rs. 200 and you offer Rs. 250, which the customer accepts, you will be paid (250-200)/(200) = $0.25 = 25 cents.
- Otherwise, if your price is higher than the maximum price the customer is willing to pay, the customer will say **No.**
- If the customer says **No twice**, the game will end and you will not not earn any additional bonus.

Note: The maximum price a customer is willing to pay might be linked to their affluence/appearance.

Q9. Here is your customer.

What is the first price you would ask from this customer?

Q10.
Customer is not willing to pay your offered price of 500. Please ask for a lower price.

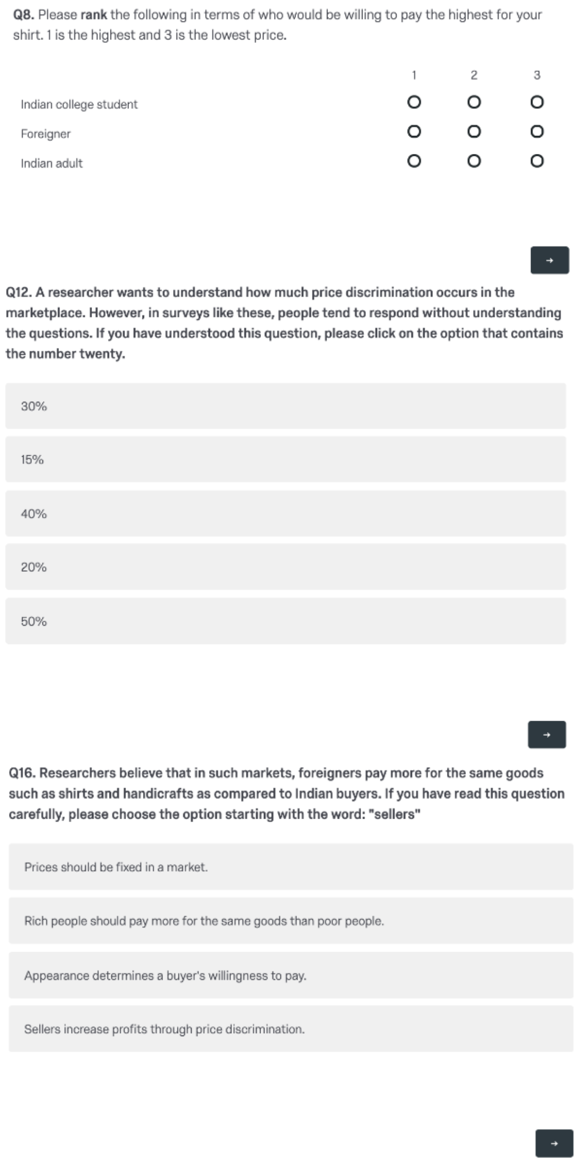
What is the second price you would ask from the customer?

Customer accepted your price of 400.

Q11.
Customer is not willing to pay your second price of 475.

What is the lowest price you would have accepted from this customer?

Figure A.6: Attention Check Questions



Q8. Please **rank** the following in terms of who would be willing to pay the highest for your shirt. 1 is the highest and 3 is the lowest price.

	1	2	3
Indian college student	O	O	O
Foreigner	O	O	O
Indian adult	O	O	O

Q12. A researcher wants to understand how much price discrimination occurs in the marketplace. However, in surveys like these, people tend to respond without understanding the questions. If you have understood this question, please click on the option that contains the number twenty.

- 30%
- 15%
- 40%
- 20%
- 50%

Q16. Researchers believe that in such markets, foreigners pay more for the same goods such as shirts and handicrafts as compared to Indian buyers. If you have read this question carefully, please choose the option starting with the word: "sellers"

- Prices should be fixed in a market.
- Rich people should pay more for the same goods than poor people.
- Appearance determines a buyer's willingness to pay.
- Sellers increase profits through price discrimination.