Journal of Economic Psychology 101 (2024) 102707

Contents lists available at ScienceDirect

Journal of Economic Psychology

journal homepage: www.elsevier.com/locate/joep

An empirical study of sequential offer bargaining during the Festival of Sacrifice[☆]

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ARTICLE INFO

Keywords:
Bargaining
Negotiation
Field data
Process
Communication
Gender

ABSTRACT

We report results from a unique data set of real-life bargaining transactions collected from the market for livestock (sheep) before the Festival of Sacrifice (Eid al-Adha) in Izmir, Turkey. This market is characterized by frequent and aggressive bargaining, which occurs in the form of sequential price offers. We record bargaining transactions as they occur, and collect detailed information on the bargaining environment, as well as on the characteristics of buyers and sellers. We also elicit each seller's outside option by means of an incentive compatible mechanism and obtain a reported maximum willingness to pay from buyers. We particularly focus on aspects of the bargaining process, such as non-price communication. In different types of empirical analysis, results robustly indicate that the presence and content of communication matters, for the likelihood of a sale as well as concessions made. Specifically, buyer-side communication is associated with larger concessions from the seller and a higher probability of sale. The presence of a mediator during the negotiation is associated with a higher probability of sale as well, while it has no effect on prices. We also provide results on the relative importance of groups of variables for predicting bargaining outcomes, which can provide directions for further research in bargaining.

1. Introduction

Bargaining has predominantly been a theoretical and experimental area of study within economics. Laboratory experiments, which permit in-depth analysis of bargaining by inducing costs and values and controlling for institutional features, have been very useful for studying questions on surplus division. At the other end of the spectrum, studies on naturally occurring bargaining transactions are rare, and tend to contain scant information on the details of the bargaining process. Field experiments have provided a middle ground, by achieving a degree of control in actual market settings through scripted bargaining by hired agents or lab-in-the-field studies.

In this paper, we report results from the analysis of a unique data set that contains naturally-occurring, alternating-offer bargaining transactions during the sale of sheep for the Festival of Sacrifice (Eid-al-Adha) in Turkey, combined with data on valuations, coming from the same sellers and buyers for whom we observe the bargaining transactions. Using data on a rich set of variables relating to the bargaining process, our goal is to explore which factors on the buyer and seller side, and which characteristics of the bargaining environment predict intermediate and final bargaining outcomes such as the probability of a sale, how much each side concedes on their initial offer, and final sale prices.

☆ We would like to thank our team of field research assistants for their hard work, and seminar participants at Bilkent University for helpful comments.

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https://doi.org/10.1016/j.joep.2024.102707
Received 5 June 2022; Received in revised form 29 January 2024; Accepted 7 February 2024
Available online 10 February 2024

Most Muslims sacrifice an animal (often a sheep, cow, or similar livestock) in order to distribute meat to the poor and to relatives once a year as part of their religious observance. The tradition goes back to the accounts of Abraham in the Old Testament. In the week leading up to the Festival, temporary marketplaces are set up across the country, where sellers form tents to sell their livestock. The market is one of a few in a modern economy where "textbook" alternating offer bargaining is still the dominant trading mechanism in a directly observable environment. In a tradition that has survived until today, almost all transactions occur through aggressive bargaining via face-to-face, sequential price offers, with the alternating-offer process sometimes accompanied by a continual handshake between the buyer and the seller until a deal is struck.[1] This makes the sale of sheep before the Festival a unique and valuable setting to observe real-life, real-time bargaining events.

We visited a marketplace located in Izmir, Turkey, every day for eight days leading up to the first day of the Festival to collect data on negotiations for sheep. The design of our study allows us to record all offers, responses, counter-offers, and bargaining outcomes, along with detailed information about the bargaining process (e.g., duration, communication, negotiation points mentioned in communication, the presence of a mediator) during bargaining transactions in this marketplace. We combine this naturally-occurring bargaining data with detailed buyer and seller data. Specifically, through surveys, we elicit self-reported willingness to pay from the buyers, along with a rich set of buyer and seller characteristics (e.g., demographics and costs) that we hypothesize to affect bargaining outcomes. We also elicit sellers' outside options, by actually purchasing sheep from them through an incentive compatible, random-price mechanism.[2] We consider the association of several process variables in addition to a rich set of buyer and seller characteristics with bargaining outcomes. In terms of buyer characteristics, we record gender, socioeconomic status, and whether bargaining is undertaken as a group or on behalf of another person, among others. In terms of seller characteristics, we have information on factors such as how far they come from and their real-time inventory, which we update every morning we were present in the market. In terms of process variables, we focus on whether there was communication between the buyer and the seller apart from exchanging offers, and whether there was a mediator involved. In particular, we study the communication process in some detail by distinguishing which buyer, seller or product characteristics are mentioned during conversation, such as the sheep's quality, the buyer's budget and the seller's cost, and conversation points invoking association between the buyer and the seller.

Our field records contain a large set of variables some of which are correlated with each other, which makes it difficult to establish causality. For our empirical analysis, we use an approach that combines OLS regressions with machine learning algorithms, and attempt to study which variables and groups of variables are robust predictors of bargaining outcomes.[3] Our results highlight the importance of two process variables, communication and mediation. We find that the presence and content of communication among parties are strongly associated with bargaining outcomes, both in terms of the probability of reaching an agreement, as well as the concessions made. Buyer-side communication is predictive of both probability of sale and seller concessions. Specifically, conversation that invokes association (the buyer mentioning being from the same hometown as the seller) or signals a longer relationship (the buyer mentioning having made a previous purchase from the same seller) increases the probability of sale. The previous purchase argument is also associated with higher seller concessions, along with the "cheap talk" strategy of the buyer mentioning his/her budget constraint. The presence of a third-party mediator during the bargaining process is associated with a higher chance of sale as well as larger concessions from both buyers and sellers, likely increasing the efficiency of the market.

In our field records we keep track of whether there is a woman in the buyer party, as well as whether women are actively involved in bargaining. This allows us to study bargaining outcomes of women in comparison to men, contributing to a major line of literature on gender differences in bargaining (Andersen et al., 2018; Babcock & Laschever, 2003; Leibbrandt & List, 2015; among others). We do not find that buyer parties containing women or actively negotiating women obtain significantly worse (or better) outcomes.[4]

A unique feature of our study is that we collect a large set of naturally-occurring and experimentally elicited variables concurrently for the same bargains, allowing us to draw some inferences on which groups of variables better predict outcomes. Group-based machine learning and variance decomposition analyses suggest that collecting detailed information on bargaining process variables such as communication, content of communication and mediation can be particularly useful for predicting which types of negotiations will end with a sale. Experimental and survey based elicitation of seller and buyer valuations are also valuable for predicting the probability of sale, but while they are strongly predictive of prices by themselves, they have limited incremental explanatory value for prices if one can condition on a rich set of other bargaining characteristics.

In its use of naturally occurring data, our work relates to the empirical literature that uses real-life bargaining transactions from the field or from existing data on bargaining outcomes in non-experimental settings. Sieg (2000) uses Canadian malpractice data, Morton et al. (2011) data from auto retail records, and Backus et al. (2020a) data from online bargaining transactions and find that many features of the data agree with theoretical predictions from existing bargaining models. The latter study emphasizes that bargaining outcomes are more strongly affected by buyer rather than product characteristics. Larsen et al. (2021) uses sequential-offer bargaining data from the wholesale used-car market in the US to study the welfare implications of bargaining, while Keniston

[1] While the bargaining is free-form, in the sense that there is no formal constraint on the type of offers or transactions, alternating-offer bargaining is a strong empirical regularity.

[2] This latter part of our study is therefore a framed field experiment in the classification of Harrison and List (2004).

[3] Specifically, we use the Least Absolute Shrinkage and Selection Operator, i.e., LASSO (Hastie et al., 2017; Tibshirani, 1996), along with Least Angle Regression (LARS) (Efron et al., 2004; Hastie et al., 2017) and a Group LASSO algorithm (Yuan & Lin, 2006).

[4] Lack of significant gender effects in our setup is consistent with a recent stream of papers on bargaining that document null effects on gender. For example, in a study of dynamic unstructured bargaining, Xue et al. (2023) find that the gender composition of pairs does not have a significant effect in the incidence of conflict, and Ren et al. (2022) show that women are not less likely to initiate negotiations in a context where negotiation is not costly.

(2011) studies bargaining vis-a-vis conventional fixed-price setting using data gathered from the auto-rickshaw market in India. Ambrus et al. (2018) study bargaining with pirates for ransom payments in 16th and 17th century Somalia, and find that increased bargaining duration reduces ransom payments, in accordance with theoretical predictions. Mateen et al. (2021) demonstrate that buyer bid characteristics significantly affect bargaining outcomes in the housing market. Keniston et al. (2021) study real-life bargaining transactions from multiple contexts to demonstrate the prevalence of the split-the-pie strategy in bargaining, which they argue to also act as a norm of fairness. This growing line of work has also attempted to test various hypotheses using other interesting and creative data sources such as GATT negotiations (Bagwell et al., 2020) and procurement of coronary stents by hospitals (Grennan, 2014).

Field experiments, another major method used to study bargaining, usually create bargaining transactions in semi-structured form, where behavior on one side of the market is pre-determined, to study the causal effects of specific treatment variables on outcomes.[5] Most relevant to our paper is the line of research that sends confederates to bargain in a natural market (e.g., Andersen et al., 2018; Ayres & Siegelman, 1995; Castillo et al., 2013, among others), either with pre-specified strategies or free-form bargaining with incentives to negotiate. Through this method, Ayres and Siegelman (1995) and List (2004a) study gender discrimination in bargaining, for new cars and collectible sports cards, respectively. Castillo et al. (2013) and Michelitch (2015) study taxi markets in Lima (Peru) and Ghana, to study gender and ethnicity based discrimination.[6] In a similar market in Cape Town (South Africa), Bengtsson (2015) studies the efficiency of informal trade within a field experiment. Iyer and Schoar (2015) perform two sets of field experiments that use hired subjects to study bargaining by tailoring stores and wholesale markets for pens to test hypotheses about the effects of reputational concerns. Bhattacharya and Dugar (2020, 2022, 2023), in a set of closely-related papers to the current one, focus on bargaining in fish markets in India, and study questions on the effect of buyer-side strategies such as (different types of) communication and asking for a discount, on outcomes such as price and the incidence of fraud on the part of sellers.

Our study differs from most existing field studies in that we do not use confederates with predetermined strategies, but rather observe and record naturally-occurring transactions, both on the buyer and the seller side. Our approach relies on collecting detailed information on the features of the bargaining process as well as the characteristics of buyers and sellers through surveys and an incentive compatible mechanism, making several unobserved characteristics of the participants and the process observable.[7] While the setup would potentially be amenable to a natural field experiment manipulating a specific aspect of bargaining (e.g. communication or mediation), resource constraints imposed by the high price of the product, the difficulty of using confederates in repeated transactions in a single market, and our desire to create a unique dataset on bargaining transactions that includes process variables as well as information from both sides of the bargaining transaction (including valuations) led us to opt for collecting observational data rather than experimental. We view our study instead as a first step that explores the predictive power of several variables of interest such as mediation, communication, and gender in a rich set of free-form, naturally-occurring negotiation data. We provide support from a new market for existing experimental studies manipulating bargaining process variables such as communication (Bhattacharya & Dugar, 2023), and suggest further directions for field experiments that would put forward causal evidence for the relationships observed.

The rest of the paper is structured as follows. Section 2 provides background information on the bargaining setup for the Festival of Sacrifice. Section 3 puts forward our study design and procedures. Section 4 introduces the data set. Section 5 describes our empirical strategy. Section 6 presents our results, and Section 7 provides a final discussion and concluding remarks.

2. Background

Livestock markets are constructed specifically for the Festival of Sacrifice and remain open for multiple days before the first day of the Festival. Sellers construct tents under which they keep their flock, and also live in the same location during the time they are there. The livestock market before the Festival has a unique feature in the sense that the value to the buyer is realized on the day of the Festival, and the seller also has strong incentives to sell the sheep by then, as the alternative would be to transport the flock back to the seller's hometown or sell to butchers at a reduced rate. In this sense, there is growing pressure both to sell and to buy as the Festival approaches, i.e., the setting is one of bargaining with a deadline.

We chose a marketplace in the Bayraklı district of Izmir as our study site. This marketplace hosted sellers of sheep alone (and some goat), as opposed to other marketplaces that host sheep varieties and large cattle together, and the relative homogeneity of the product was conducive to our data collection strategy. While there was some heterogeneity across sellers with respect to the type of sheep they sell, the flock of a given seller was usually of the same type, and animals were distinguishable mainly with respect to their weights.

[5] Field experiments that have used bargaining mechanisms for price determination have also allowed testing fundamental predictions of classical economic theory. List (2004b) studies convergence of the market price to market equilibrium, while List and Price (2005) study collusive incentives and strategies. Dindaroğlu and Ertac (2022) provide a recent survey of the existing literature.

[6] A related line of work creates artificial bargaining transactions using mail inquiries, commonly known as the correspondence method. This method has been used by Zussmann (2013) and Hanson and Hawley (2011) to study ethnicity-based discrimination in automobiles and rental housing, respectively.

[7] From a methodological perspective, a closely related study is Andersen et al. (2018), who recruit buyer subjects and make them residual claimants of bargaining gains in the tomato market. In a second study, they implement an alternating offer bargaining game with induced valuations and costs, within a lab-in-the-field setup. Our study combines features of both settings: we collect rich observational data from naturally occurring negotiations, and complement this with elicited data through surveys and an incentivized mechanism, to achieve greater observability of factors not normally observed in natural transaction data.

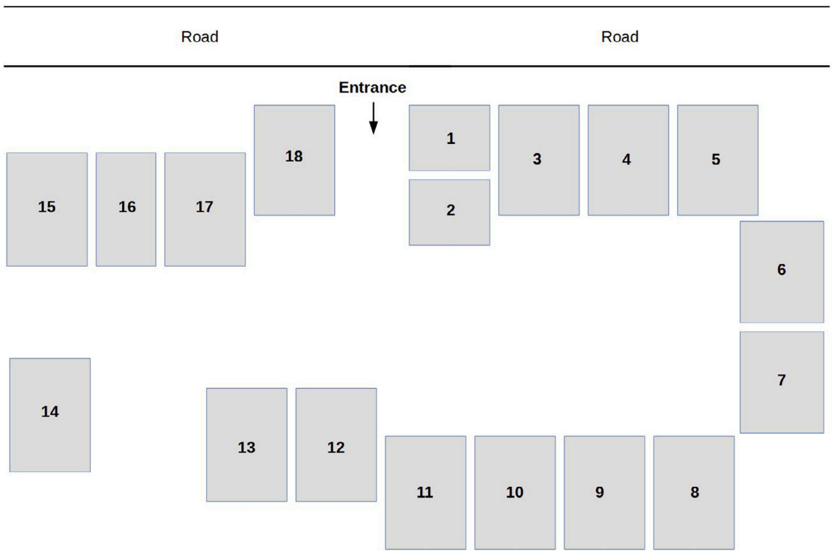

Fig. 1. An aerial plan of the marketplace, each rectangle representing a different seller's tent.

The marketplace was situated in a relatively poor district, so that bargaining strategies would not be satiated, and even small differences in price would matter. There were 18 sellers, all located in close proximity in a roughly rectangular setup, which allowed us keep track of changes in sellers' inventories with ease. Another advantage was that the market had a single entrance and exit, which made it easier to keep track of the buyers in the market at any given time, to be able to observe multiple transactions of the same buyer. Fig. 1 shows an aerial plan of the marketplace where each seller's tent is represented by a rectangle.

3. Study design and procedures

Our data collection strategy has three main components: (1) recording actual bargaining transactions by following buyers throughout their visit to the market, (2) collecting information on the valuations and costs of the sellers, (3) collecting information on buyers.

We were in the marketplace from early morning to late evening for 8 days, a period that covers the time from the second day the market had been open, till the first day of the Festival, at which time the market was closed.[8] The timeline of our data collection activities is as follows:

- Day 0: Market opens.
- Day 1: First visit to the market.
- Days 2, 3 and 4: Visit.
- Day 5: Visit, first elicitation of sellers' minimum willingness to accept (WTA, during the evening).
- Day 6: Visit, second WTA elicitation (during the evening).
- Day 7: Visit, third WTA elicitation (during the evening).
- Day 8: Final visit (first day of the Festival).

On each visit day, the main data collection activities consisted of observing and noting transactions by buyers, and then asking buyers of their willingness to fill an anonymous survey for research purposes. Below, we explain each component of our data collection strategy in detail.

3.1. Recording bargaining transactions

Our strategy for recording bargaining transactions is based on following a buyer or a buyer party (with their consent), upon their entrance into the market till their exit, and recording information on their negotiations with different sellers.

We collect data on bargaining transactions using a fixed paper–pencil template.[9] This template included all offers, rejection/acceptance responses, all counter-offers (or lack thereof), the outcome and (if relevant) the sales price. In each bargain, we

[8] Data were collected between October 30th, 2011 and November 6th, 2011.

[9] On the first three days of our presence in the market, we collected data on bargaining transactions through voice records, after which we switched to using the fixed template, as it became clear that transcription would be difficult with the amount of noise around. We extract all relevant information from the existing voice records to make these records consistent with the paper-based recording procedure for the analysis.

kept records of each offer and counter-offer until either a deal was struck, or one of the parties rejected an offer without making a counter-proposal and walked away. In addition, we included several variables about the bargaining process that we hypothesized could have an effect on bargaining behavior and outcomes. Specifically, we recorded the duration of the bargain, number of people in the buyer party, the number of people actively bargaining, whether there were women in the buyer party, whether women took an active role in bargaining, whether there was a mediator, and whether certain attributes or characteristics of the sheep, the seller or the buyer were mentioned. These were (i) the weight/quality of the sheep, (ii) the buyer being from the same hometown as the seller, (iii) the cost to the seller, (iv) the buyer's budget, (v) the buyer being a repeat customer, having purchased from the same buyer the previous year or earlier this year.[10] We had one sheet for every bargain, and assistants used a booklet of sheets. We kept track of buyer and seller IDs in repeated transactions, as buyers typically visit multiple sellers' tents, and sometimes go back to a previous seller.

We were very careful to prevent our presence from interfering with bargaining events. We briefly introduced ourselves as researchers when the buyers noticed us, and asked for permission to be around during their time in the market and record information about their transactions.[11] We observed bargaining transactions from a distant place as possible, and never communicated with the buyers or the sellers during transactions. In most cases, the buyers seemed to forget about our presence, as the place is small and already quite crowded and there tend to be many bystanders at any given point in time.

3.2. Collecting data on sellers

We collect detailed information on sellers through different methods. The first is an (anonymous) questionnaire that collects information on a number of factors that can affect the seller's cost or reservation price. These include whether the seller is a "breeder" or a "feeder" (with breeders having lower cost), the distance they traveled to reach the market (due to the heterogeneity in hometowns), and previous experience in the same marketplace. In addition, on each day that we collected bargaining data, we performed a "morning survey" before the market opened, through which we updated the remaining inventory of the seller.

A unique feature of our data is that we elicit the minimum willingness to accept (WTA) of the sellers through an incentive compatible mechanism, the Becker–DeGroot–Marschak (BDM) mechanism commonly used in experimental economics (Becker et al., 1964). We adapted the mechanism to elicit the minimum willingness to accept from every seller, separately for every type of sheep under their possession. Specifically, we purchased three sheep from the sellers through a random-price mechanism, after asking for the minimum price they would be willing to sell at (details and the full set of instructions are available in Appendix C).[12]

Because of the pressure of selling the stock before the Festival, and because of updates on expectations as market information is dynamically revealed, sellers' perceived outside option (and therefore WTA) is likely to change over the course of the days leading up to the Festival. We therefore implemented this elicitation procedure three times, during nights 5, 6 and 7, the former two being the nights before the busiest days of the market (and the days on which we collected the bulk of our data). The third one coincided with the first day of the festival (day 8).[13] Additionally, we obtained the same "minimum price" information retrospectively into the past, for the first day we began data collection. While this information was not collected via an incentive compatible mechanism, the sellers had no reason to lie to us. For the remaining days for which we do not have field information on WTA measures, we interpolate the WTA values for each animal type in the seller's stock.

3.3. Collecting data on buyers

Upon their exit from the market (either following a purchase or otherwise), we asked the buyers for whom we observed any bargaining transactions whether they would be willing to fill a short, anonymous survey for research on understanding the bargaining process. We presented a small gift item (pen, keychain) for participation. We obtained questionnaire responses from 327 buyers (corresponding to 79.4% of buyers in our data set), corresponding to 247 purchases we could record.

This survey included information on demographics such as age, gender and household income, as well as questions on whether a sale occurred, the number of sheep purchased, whether the purchase was being made for oneself or someone else, search experience in this market and elsewhere (for this particular period), and general experience with bargaining. In addition, we elicited self-reported willingness to pay and the buyer's perceived cost to the seller, in order to get a measure of the actual and perceived surplus in recorded bargaining transactions. These questions differed for those who purchased a sheep and those who did not. The buyers who purchased a sheep were asked (1) the maximum price they would have been willing to pay for the specific sheep they purchased, i.e. the minimum ask price that would have made them walk away from that seller's tent, (2) the maximum price that they would be willing to pay for an animal in general, i.e., the minimum ask price that would make them choose not to buy and sacrifice this year. Those who did not purchase were asked only the latter maximum willingness-to-pay question.

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10 The reason why we particularly record being from the same hometown is because this is a strong social tie in Turkey, that is likely to have an effect on economic interactions as well.

11 The sellers also knew that we were researchers, collecting data in the market for analyzing the nature of livestock transactions.

12 The purchased sheep were not sacrificed but entrusted to a small family farm that keeps a small number of sheep/goat for felt and milk.

13 We did not begin implementation earlier since the BDM procedure elicits market-relevant information from the sellers, and truthful reports could require establishing sufficient trust with them. By the time we implemented the procedure, all sellers were convinced that we did not have any financial motives nor any incentives to share information with third parties.

A particularly important demographic variable for bargaining would be the socioeconomic status of the buyer, especially as it can be a proxy for willingness to pay. In order to account for cases where the buyers would not want to take the survey, we also had helpers note on the record sheet if the buyer(s) appeared particularly wealthy or poor from the outside. The way the helpers were instructed about this was as follows: "if there are characteristics about the bargaining party/group that makes you think that they are particularly wealthy or poor as compared to the general buyer population you see in the market (not from what they say, but from attire, demeanor etc.), please note this". This information may be relevant particularly because it represents the visual cues the seller obtains about buyer income, hence may contain information used by sellers to estimate a perceived bargaining surplus and select a bargaining strategy.

4. Data

Our data set contains a total of 1077 bargains between 412 distinct buyers (either individuals or groups) and the 18 sellers in the marketplace.[14] 247 of these bargains ended up with a purchase. Only 18.5% of buyers are single individuals, whereas the rest come to the market as a dyad or group. While there are only 6 single female buyers, 47.8% of the buyer groups contain at least one female, which correspond to 49.4% of all bargains (summary statistics for all variables are provided in Table 1).

Determining exactly which transactions can be deemed as bargains is a nontrivial task. Any transaction in which a potential buyer gave a counter-offer as a response to the seller's initial offer is deemed a "bargain". However, a particular issue is categorizing transactions that end with immediate rejection of the (first visited) seller's initial offer. Potential buyers often walk away without giving a counter-offer. Whether these transactions are rejections in the bargaining game, or whether these are unlikely buyers browsing the market for other purposes (e.g. sellers from other marketplaces fishing for price information, or people curious about current prices after they have purchased a sheep) is unclear. In these cases, we approached the buyers and asked whether they were planning to purchase at least one sheep during that day. If the response was affirmative, we included these buyers (and their transactions) in our data set as first-round rejections. If not, we excluded them from the data set.

4.1. Sellers

12 of the 18 sellers in our data were feeders, while 4 were breeders, with two having both sheep that they bred and also bought. The average seller had been in the business of selling livestock before the Festival for 16 years, and came to the market with 95 animals. 10 sellers had been in the same marketplace the year before. All sellers were male, with the exception of a couple working together.

In our analyses, we use seller cost variables (breeder vs. feeder and the distance of the seller's hometown to Izmir) as potential predictors of bargaining outcomes. While the distance variable relates to transportation costs, it is also a proxy for the bargaining power of the seller since the sellers coming from far away are harder-pressed to sell their animals in the marketplace, as the alternative could be to transport them back to their hometown.

4.2. Buyers

Our final data set contains bargains from 412 distinct buyers or buyer groups, 327 of which responded to our questionnaire. Recall that we have two distinct sources of information on the wealth of buyers, i.e., whether the buyer was noted as particularly wealthy or particularly poor by the field assistants based on their appearance, and another via questionnaire responses. For buyers who did not fill the survey, we only have access to the former, appearance-based information. Two pieces of analysis give credence to the appearance-based information: First, for people for whom we have both self-reports on income from the buyer survey and helpers' notes, there is a positive correlation between the two measures. In an ordered logit regression of the categorical income variable obtained via the buyer survey on the dummy variables "buyer identifiably wealthy" and "buyer identifiably poor", clustered at the buyer level, we find that both covariates are statistically significant in the expected directions ($p < 0.001$ for wealthy and $p < 0.01$ for poor, see Appendix Table A.1). Second, the machine learning algorithms (LASSO/LARS) commonly pick the identifiable wealth variables instead of reported income coming from the buyer survey (Table 2). We should also note that any visual cue available to our helpers is also available to the seller, and in that sense, our measure may be a more realistic measure of how buyers' wealth affects the seller's response, e.g., initial offers and concessions.

4.3. Willingness to accept and willingness to pay

Our experimental procedure elicits willingness to accept values on three distinct days from sellers. As expected, we observe that the daily WTA values decline as the Festival draws near. For example, for a medium-sized animal, the average WTA falls from 748 Turkish Liras (TL) on the first day, to 700 TL on the 6th day to 670 TL on the final day.[15]

Recall that we elicit two different WTP variables from the buyers, one capturing a reported WTP for the actual animal they purchased, and the other how much they are willing to pay for a sheep overall. As the Festival draws near, we observe that both

[14] The largest sample we use includes 1046 observations due to missing values.

[15] Note, however, that since we collect data naturally in discrete time, we are not able to precisely capture adjustments to WTA during a particular day, especially towards the final days of the market where such drops can happen faster as market uncertainty is resolved.

measures of willingness to pay also decline.[16] This suggests that buyers who have lower willingness to pay come to the market later, as they may care less about the type of sheep they buy or are aware that sellers will lower prices as the Festival draws near, an expectation that is borne out in our sales price data.

4.4. The bargaining environment

Each buyer engages in an average of 2.62 unique negotiations, with 2 (1.997) distinct sellers on average.[17] 58.2% of the buyers we observe leave the market having made at least one purchase. The first offer is almost always by the seller, following price solicitation from the buyer.

We were told by the sellers that they tend to quote a standard opening price for three categories of weight (small, medium, large), with small adjustments for product characteristics (e.g., a particularly good-looking animal) and buyers. Indeed, on a given day, initial offers by sellers are concentrated around three values: one for small, one for medium, and one for large animals.

In our data, the average final sales price is 675 Turkish Liras, often more than or close to one month's income for the buyers in our sample at the time. Bargaining rounds are clearly non-satiated, that is, price differences of 5–10 TL matter.

5. Empirical strategy

5.1. Outcomes and covariates

In the following, we study the correlates of two main bargaining outcomes: (1) the probability of sale, (2) the final sales price for successful transactions ending in a sale. In addition, we study several intermediate bargaining variables/negotiation characteristics that are important for understanding the bargaining process. These are: initial offers, the concessions made by the seller and buyer in their final offers, and bargaining duration/number of rounds.

In analyzing the determinants of these bargaining outcomes and characteristics, we focus on:

1. Process variables: Existence of non-price communication, scope of communication (number of talking points mentioned during communication), buyer-related communication (budget, previous purchase, same hometown), seller-related communication (cost, animal characteristics), the presence of a mediator.
2. Situational variables: Days left to the Festival, which creates time pressure.
3. Seller characteristics: Whether seller is a feeder or a breeder, whether seller is coming from a far city, remaining stock of the seller at the beginning of the day.
4. Observable buyer characteristics: Buyer being identifiably rich or identifiably poor, number of people in the buyer party, presence of a woman, active involvement by a woman, buyer age for the person leading the bargain.
5. Buyer characteristics unobservable to the seller: Buyer experience, buyer's stated income, whether buyer is bargaining on behalf of someone else.
6. Valuations: WTA, WTP (Overall), WTP (Purchased).

This categorization also reflects a natural grouping of all variables, which we use in Group LASSO analysis in Section 6.4. A complete list of the variables used in the study are given in Table 1, which also shows the type of each variable, its description and summary statistics. In what follows, we go over these variables in more detail in light of the data.

5.1.1. Buyer characteristics

As noted above, we study the effects of a number of buyer characteristics. Gender is an important characteristic for bargaining outcomes, as there is a large literature studying gender effects in bargaining, which generally finds that women are at a disadvantage, both because they avoid negotiation and because they are given worse offers. Bargaining for sheep is traditionally a male activity. Still, we have a significant number of negotiations in which a woman is present in the buyer group; 47.8% of buyer groups include at least one woman. These buyer groups take part in 49.4% of all bargains.[18] In 46.5% of the bargains where they are present, women are actively involved in the negotiation, which consists of 22.9% of all negotiations. In what follows, we will study whether women get better or worse offers, whether they concede more themselves or get sellers to concede more than men do.

Another buyer-related variable is whether the buyer is bargaining on behalf of someone else. It is well-known that individuals may bargain differently when the purchase is for themselves versus someone else; 23% of buyers that complete our survey state that they are buying a sheep on behalf of someone else (this corresponds to 24% of all bargains).

A related variable is whether bargaining is done as a group or individually. Groups are known to make different decisions than individuals, and it is possible to hypothesize that groups would bargain differently than individuals, or that the presence of others alongside would make a buyer negotiate in a tougher fashion. In our sample, 18.5% of buyers come to the market individually. We

[16] For example, the overall WTP declines from 766 to 615 TL.

[17] Note that it is possible for buyers to have more than one negotiation with the same seller.

[18] It should be noted that Izmir is one of the most modern cities in Turkey in terms of gender equality. However, considering the location of the study site (a low-SES district) and selection into the bargaining context (the demand for a product related to religious observance), we could expect patriarchal gender norms to still be relevant.

are particularly interested in whether bargaining as a group and bargaining on behalf of others increase the probability of sale, and concessions on the part of the seller/buyer.

In addition, we have variables coming from the (voluntary) buyer's questionnaire, such as buyer age, whether the buyer sees herself as experienced in bargaining, and buyer's reported income.

5.1.2. Bargaining process variables

Communication

A potentially important aspect of bargaining transactions is the presence of non-price-related communication. In order to study the effects of this, we record the incidence of communication, apart from just making offers, responding to offers and making counter-offers. In our sample, non-price communication takes place in 65.5% of the bargains. Among bargains where there is such communication, 46% includes communication points from both parties, 42% includes communication from the seller side only, and 12% includes communication from the buyer side only. Bargains with communication include an average of 2.04 "talking points", while the sample average of the same is 1.33. We use the number of talking points mentioned during the negotiation as a measure of the scope of the communication between the buyer and the seller.

Recall that we also take note of whether seller-side variables (cost, quality of the sheep, weight of the sheep) and buyer-side variables (budget, buyer being from the same hometown of the seller, buyer being a repeat customer) are mentioned during the negotiations. In what follows, we explore the effects of buyer-side and seller-side communication variables on the probability of sale and prices, as well as concessions by the opposing side.

Mediation

The presence of a mediator was traditionally common in livestock bargaining for the Festival of Sacrifice. In fact, a well-known, almost comical image regarding the Festival is a third party bringing the buyer's and seller's hands together in the handshake process and not letting go until a deal is struck, thereby effectively forcing an agreement. In more recent times, in an urban area such as our study site, the tradition may have become much less common, as we observe only 78 instances of bargaining in which a mediator was involved. We should note that the mediator is not an institutional part of the setup. Mediators do not get payment, nor are they called upon explicitly. The market is a crowded place, and in many negotiations, there are onlookers and bystanders. Sometimes one steps in and acts as a mediator. The role is that of an objective helper, with the goal of inducing an agreement.[19]

5.2. Empirical strategy

The large set of variables collected in the field poses challenges in determining the correct specifications to explain bargaining outcomes observed in our dataset. One complicating factor is that we have a number of potentially correlated variables—for example, seller's remaining stock will be correlated with the days left until the festival. It is also difficult to establish the causal effects of a specific variable on a bargaining outcome, as our design is based on collecting detailed naturally-occurring data on many characteristics of bargaining rather than exogenously manipulating a subset of variables through confederates.

Given this, our goal is to obtain insights into the predictive power of variables and sets of variables on bargaining outcomes, and identify variables that have particularly robust associations, as shown by different methodologies and using different specifications. To this end, we use an empirical strategy that uses machine learning algorithms as well as regression models.

We take a structured approach to determine the predictive relevance of variables: we present regression results using variables that are theoretically relevant to a particular dependent variable to be studied. Here, we pay particular attention to and study in detail certain process variables that are the focus of this paper. We complement these regression results with an analysis that uses machine learning algorithms to select the best predictors of each of our dependent variables, from among the set of all variables (Table 1). Specifically, we use the Least Absolute Shrinkage and Selection Operator (LASSO) algorithm (Tibshirani, 1996) and Least Angle Regression (LARS) (Efron et al., 2004) in order to determine the complete set of variables most relevant for each bargaining outcome. LASSO and LARS give us the ordinal relevance of each variable for predicting each outcome, which has independent value for addressing predictive power.

Finally, given the potential endogeneity of variables, we also examine the relative predictive power of natural groupings of all variables. To this end, we apply a Group LASSO algorithm (Breheny, 2015; Breheny & Huang, 2009; Yuan & Lin, 2006), a generalization of the LASSO procedure for grouped selection, which provides a similar ordering of relevance among variable groups. We use the group definitions described in Table 1 in the Group LASSO analysis (Section 6.4), where we also study the explanatory power of each variable category.[20]

In the following section, we discuss both regression and LASSO results for each of our bargaining outcomes separately. As a summary of our results, we also present the variables that are robustly significant in both OLS/logit and LASSO regressions for each outcome, in Table 9.

[19] The presence of a mediator is potentially endogenous, as a mediator may emerge only in bargains where there is a small difference in what the seller wants and what the buyer wants, and/or when negotiation has taken a long time and the parties are having difficulty reaching an agreement. In fact, the number of rounds and the duration in minutes are both higher when there is a mediator ($p < 0.0001$ and $p < 0.001$ in t-tests), and this also supports the "emergence" view of the mediator. Also supporting this view is that most sellers in our data set were involved in bargains in which a mediator was present, indicating that mediators are not implicit partners of some sellers. The maximum incidence of mediation is 13.21% of bargains among different sellers.

[20] The entire variable set is used in all LASSO procedures except those that explain initial offers. The specification for this variable requires using a subset of the variable list, as many variables are not realized at the time the initial offer is made.

Table 1
Variable descriptions and descriptive statistics.

Group	Name in tables	Type	Variable description	Mean	St.Dev
E	Sale occurs	D	1 if sale occurred at the end of bargain	0.23	0.42
E	Final sale price	N	Final agreed upon sale price for successful bargains	673.56	107.36
E	Seller's initial offer	N	Opening offer by the seller	750.98	118.82
E	Seller's concession	N	Seller's percentage concession from initial offer	3.50	5.34
E	Buyer's concession	N	Buyer's percentage concession from initial offer	3.48	6.36
E	Duration of bargain (Min.)	N	Total duration of the bargain in minutes	2.84	3.23
E	Number of rounds in bargain	CT	Number of offer rounds in bargain	2.60	2.25
OS	Initial offer	N	The first offer made in the bargain	748.51	121.33
St	Days remaining	CT	Number of days remaining till the last day of market	2.47	1.69
P	Mediation	D	1 if there is mediating third party	0.07	0.26
P	Non-price communication	D	1 if there is any non-price conversation between buyer and seller	0.65	0.48
P	Communication scope	CT	Number of talking points, in (budget, product char., seller cost, previous purchase, townsmanship).	1.33	1.28
P	Communication by buyer	D	1 if there is conversation by the buyer	0.38	0.49
P	Communication by seller	D	1 if there is conversation by the seller	0.57	0.49
P	Communication -Buyer's budget	D	1 if there is conversation about the budget of the buyer	0.25	0.44
P	Communication -Seller's cost	D	1 if there is conversation about the cost of the seller	0.16	0.37
P	Communication -Prev. Purchase	D	1 if there is conversation about previous transaction	0.02	0.13
P	Communication -Sheep. Char.	D	1 if there is conversation about the animal	0.52	0.50
P	Communication -Same hometown	D	1 if there is conversation about townsmanship	0.18	0.39
S	Seller distance greater than 500 km	D	1 if seller's distance to hometown is greater than 500 km	0.27	0.45
S	Seller is feeder	D	1 if seller is a feeder (rather than breeder)	0.66	0.47
S	Seller's remaining stock	N	Remaining stock of seller in the morning, as % of initial stock.	37.46	25.97
B1	Buyer group size	CT	The number of buyers in the group (1–7)	2.30	0.98
B1	Female presence in group	D	1 if there is at least one female in the buyer group	0.49	0.50
B1	Female active in bargain	D	1 if at least one woman actively engages in bargaining	0.23	0.42
B1	Buyer identifiably rich	D	1 if buyer is identifiably Rich	0.08	0.26
B1	Buyer identifiably poor	D	1 if buyer is identifiably Poor	0.30	0.46
B1	Buyer age	CT	Buyer age	50.29	14.09
B2	Buyer bargains for someone else	D	1 if buyer is bargaining for someone else	0.24	0.43
B2	Buyer income	OC	Income level of buyer (1–4)	3.10	1.36
B2	Buyer experience	OC	Buyer experience in the animal market (1–4)	3.02	0.99
V	WTA	N	Seller's experimentally elicited willingness to accept	693.58	85.28
V	WTP (Overall)	N	Buyer's reported overall maximum willingness to pay	747.38	177.39
V	WTP (Purchase)	N	Buyer's reported max. willingness to pay for the purchased animal	691.13	118.08

CT stands for Count, D for Dummy (Indicator), OC for Ordered Categorical, and N for Numeric variables. Group definitions are as follows. E: Dependent (explained) variables, including bargaining outcomes and intermediate bargaining variables, OS: Opening strategy, St: Situational variable, P: Process variables, S: Seller characteristics, B1: Observable buyer characteristics, B2: Unobservable buyer characteristics, V: Valuations.

To account for multiple hypothesis testing, we calculate and present Romano–Wolf p-values in all regressions (Romano & Wolf, 2005).[21] The Romano–Wolf correction provides strong control of the family-wise error rate asymptotically, i.e., controls for the probability of rejecting at least one true null among the set of hypotheses performed.

One issue that we face in the data we collect is missing observations in some variables, due to the set of buyers who are unwilling to complete the survey but whose bargaining outcomes we observe. Specifically, we obtain questionnaire responses from 79.4% of the buyers in our data set (327 out of 412), which correspond to 86.5% of all recorded bargaining transactions. However, individual variables obtained from questionnaire responses are inevitably subject to different rates and patterns of non-response, which leads to analyses being performed on a different (and smaller) sample as more variables are included in regressions. In Appendix A, we present details on the patterns of non-response (Table A.5), and show that our main results are robust in a regression that uses an imputed sample (Table A.6).

6. Results

We begin by presenting a single table (Table 2) that contains LASSO/LARS regression results for all our variables of interest. The table reports the LASSO output for the primary as well as intermediate bargaining outcomes of interest, as well as the Least Angular Regression selection order for each variable. In what follows, we sequentially go over the dependent variables in this table and refer to Table 2 to talk about the match between OLS/logit regressions and the LASSO results.[22] We first study two primary bargaining outcomes, probability of sale and price conditional on sale, and then analyze the intermediate bargaining variables of initial offer and buyer and seller concessions, as well as duration, to get better insight into the relationships observed in the data.

[21] Romano–Wolf p-values are obtained using the rwolf package (Clarke, 2016) in Stata.

[22] More information on the application of LASSO and LARS in our context can be found in Appendix B, and all LASSO, LARS and Group LASSO outputs for all outcomes are available as a Supplementary File.

Table 2
LASSO (Least Absolute Shrinkage and Selection Operator) and LARS (Least Angle Regression) analysis.

Group	Variables	IO	#	PS	#	SC	#	BC	#	DUR	#	NR	#	FSP	#
OS	Initial offer	.		−0.001	5	0		0		0		0		0.800	1
St	Days remaining	0		0		−0.103	6	0		0		0		2.862	2
P	Mediation	.		1.255	1	1.979	2	1.037	1	0		1.068	1	0	
P	Non-price communication	.		0.268	3	0.432	3	0		0		0.281	2	0	
P	Communication scope	.		0		0		0.049	2	0.262	1	0		0	
P	Communication by buyer	.		0		1.185	1	0		0.417	2	0.318	3	−1.826	10
P	Communication by seller	.		0		0		0		0		0		3.031	8
P	Communication -Buyer's budget	.		0		0.340	5	0		0		0		−0.894	11
P	Communication -Seller's cost	.		0.054	9	0		0		0		0.161	4	0	
P	Communication -Prev. Purchase	.		2.189	2	0.913	8	0		0		0		0	
P	Communication -Sheep. Char.	.		0		0		0		0		0		0	
P	Communication -Same hometown	.		0.199	4	0		0		0		0		0	
S	Seller distance greater than 500 km	−122.21	1	0		0.361	7	0		0		0		−11.04	3
S	Seller is feeder	43.83	3	0.015	10	0		0		0		0		0	
S	Seller's remaining stock	1.908	2	0		−0.005	10	0		0		0		0.122	5
B1	Buyer group size	0		0		0		0		0		0		0	
B1	Female presence in group	0		0		0		0		0		0		−1.459	7
B1	Female active in bargain	.		0		0.136	9	0		0		0		−3.409	6
B1	Buyer identifiably rich	16.42	4	0.178	6	0		0		0		0		3.652	9
B1	Buyer identifiably poor	−5.98	5	−0.074	7	0		0		0		0		0	
B1	Buyer age	0		−0.0004	11	0		0		0		0		−0.009	12
B2	Buyer bargains for someone else	.		0		0		0		0		0		0	
B2	Buyer Income	.		0		0		0		0		0		0	
B2	Buyer experience	.		−0.035	8	−0.280	4	0		0		0		3.515	4
	Intercept	690.04		−0.765		3.627		1.960		2.350		2.196		69.45	
	Number of variables chosen	5		11		10		2		2		4		12	

The Table reports LASSO coefficients and LARS selection order for each dependent variable. Zero values indicate coefficients that are suppressed by LASSO in the "one standard error" solution (Hastie et al., 2017) for cross-validation over the tuning parameter, and "." indicates that the variable is left out of the LASSO procedure (only for Initial offer, IO). Columns marked with # give the order of selection by the LARS process for the column on their left, lower numbers indicating earlier (higher priority) selection as the LASSO tuning parameter changes. The LARS procedure uses LASSO regression for prioritization, i.e., the process is identical to the selection order by LASSO as the tuning parameter is reduced for selecting additional variables. Abbreviations for dependent variables are; IO: Seller's Initial Offer, PS: Probability of Sale, SC: Seller's Concession, BC: Buyer's Concession, DUR: Bargaining Duration, NR: Number of Rounds, FSP: Final Sale Price. Group definitions are as follows. E: Bargaining outcomes (explained variables), OS: Opening strategy, St: Situational variable, P: Process variables, S: Seller characteristics, B1: Observable buyer characteristics, B2: Unobservable buyer characteristics, V: Valuations.

6.1. Primary bargaining outcomes

6.1.1. Probability of sale

We start by studying the determinants of a negotiation ending successfully, with a sale (Table 3). We use all characteristics that would be theoretically relevant to the probability of sale in the regression, but start from the set that gives us the largest sample given missing observations in some variables, particularly those about buyer characteristics (please see the discussion in Appendix A). We place particular emphasis on the process characteristics of communication and mediation, and study the former in detail.

Using the largest possible sample, Column 1 shows that when there is non-price communication (of any kind) in a negotiation, the probability of sale is higher. The corresponding marginal effect indicates that, controlling for the initial offer, when the buyer and seller engage in communication (beyond exchanging offers), the probability of sale is 9.4 percentage points higher compared to bargains in which no such communication takes place.

We then study the communication process in more detail, using recorded field information on the communication points that were mentioned. First, the more talking points mentioned in communication, the higher the probability of sale (Column 2). Classifying types of communication points according to whether they are seller-related or buyer-related, we find that buyer-related communication is associated with a significantly higher probability of sale but seller-related communication is not. Breaking this down further, we find that the buyer mentioning coming from the same hometown as the seller, and having made a previous purchase are associated with a significantly higher probability of agreement (Column 4).

Another major variable associated with the probability of sale is the presence of a third party that acts as a mediator. When a mediator is present, the likelihood of a sale is 24.4 percentage points higher, and this variable is statistically significant in all specifications. As expected, higher initial offers are generally associated with a lower probability of sale. Having a woman present or active in the negotiation has no significant effect.

These results are consistent with the LASSO/LARS prioritization; Table 2, Column PS shows that our process variables, communication and mediation, are among the best predictors of the probability of sale: mediation is the best predictor, followed by communication variables, selected in orders of second, third, fourth. In addition to initial offer (selected 5th), the machine learning algorithm also selects some variables that were not significant in the regression model, at lower ranks (such as buyer wealth variables, selected 6th and 7th).

Table 3
Probability of sale.

	(1)	(2)	(3)	(4)	(5)
Initial offer	−0.0003* (0.018)	−0.0003* (0.022)	−0.0003* (0.010)	−0.0003* (0.018)	−0.0003 (0.107)
Days remaining	−0.004 (0.670)	−0.005 (0.647)	−0.005 (0.591)	−0.009 (0.323)	−0.004 (0.826)
Mediation	0.244** (0.002)	0.240** (0.002)	0.250** (0.002)	0.265** (0.002)	0.319** (0.002)
Non-price communication	0.094** (0.002)				
Communication scope		0.030** (0.004)			
Communication by buyer			0.078** (0.008)		
Communication by seller			0.007 (0.792)		
Communication -Buyer's budget				0.007 (0.842)	0.026 (0.603)
Communication -Seller's cost				0.059 (0.106)	0.073 (0.202)
Communication -Prev. Purchase				0.491** (0.002)	0.527** (0.004)
Communication -Sheep. Char.				−0.012 (0.712)	−0.021 (0.685)
Communication -Same hometown				0.073* (0.044)	0.108* (0.046)
Seller distance greater than 500 km	−0.002 (0.950)	0.0016 (0.966)	0.003 (0.926)	−0.004 (0.912)	−0.018 (0.737)
Seller is feeder	0.035 (0.274)	0.034 (0.287)	0.033 (0.289)	0.030 (0.353)	0.048 (0.309)
Seller's remaining stock	0.0006 (0.270)	0.0007 (0.220)	0.0009 (0.170)	0.0008 (0.174)	0.0005 (0.587)
Buyer group size	0.004 (0.763)	0.007 (0.627)	0.004 (0.832)	0.002 (0.902)	−0.005 (0.828)
Female presence in group	0.012 (0.741)	0.013 (0.703)	0.015 (0.671)	0.021 (0.541)	0.043 (0.387)
Female active in bargain	−0.0004 (0.994)	−0.0026 (0.940)	−0.004 (0.926)	−0.006 (0.888)	−0.028 (0.621)
Buyer identifiably rich					0.089 (0.190)
Buyer identifiably poor					−0.051 (0.297)
Buyer bargains for someone else					0.023 (0.674)
Buyer age					−0.001 (0.440)
Buyer experience					−0.038 (0.076)
Constant	−0.793 (0.166)	−0.656 (0.236)	−0.637 (0.259)	−0.616 (0.281)	0.608 (0.511)
Observations	1046	1046	1046	1046	589
Pseudo R^2	0.050	0.049	0.049	0.074	0.098

The dependent variable is Sale, the indicator variable for a bargain ending with a purchase. All regressions are from logit specifications with standard errors clustered at the seller and buyer levels. Reported coefficients are marginal effects. Romano–Wolf multiple testing adjusted *p*-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Overall, robust results on the probability of sale can be summarized as follows: (1) communication by the buyer that invokes association between the buyer and the seller is associated with a higher probability of sale, and (2) the presence of a mediator is conducive to bargains ending in a sale. We next turn to analyzing the second major outcome, sales price in negotiations that end in a sale.

Table 4
Final sale prices in successful bargains.

	(1)	(2)	(3)	(4)	(5)
Initial offer	0.816**	0.816**	0.814**	0.813**	0.744**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Days remaining	6.084**	6.003**	6.443**	5.935*	8.960**
	(0.004)	(0.006)	(0.002)	(0.012)	(0.010)
Mediation	−1.904	−1.648	−4.677	−3.976	−1.769
	(0.826)	(0.794)	(0.527)	(0.603)	(0.828)
Non-price communication	2.494				
	(0.757)				
Communication scope		0.497			
		(0.840)			
Communication by buyer			−8.529		
			(0.104)		
Communication by seller			11.343		
			(0.148)		
Communication -Buyer's budget				−7.878	−8.229
				(0.277)	(0.301)
Communication -Prev. Purchase				3.514	0.495
				(0.733)	(0.962)
Communication -Sheep. Char.				7.752	6.248
				(0.303)	(0.503)
Communication -Same hometown				−2.568	−1.917
				(0.683)	(0.820)
Communication -Seller's cost				2.628	1.886
				(0.661)	(0.816)
Seller distance greater than 500 km	−22.668*	−22.413*	−21.848*	−22.315*	−37.926**
	(0.016)	(0.034)	(0.028)	(0.026)	(0.008)
Seller is feeder	−0.098	−0.218	0.576	0.130	10.786
	(0.986)	(0.980)	(0.918)	(0.984)	(0.146)
Seller's remaining stock	0.094	0.096	0.045	0.065	0.112
	(0.538)	(0.501)	(0.737)	(0.627)	(0.563)
Buyer group size	−1.304	−1.266	−0.584	−1.394	−2.436
	(0.800)	(0.735)	(0.884)	(0.726)	(0.675)
Female presence in group	−6.160	−5.951	−5.380	−4.148	−2.157
	(0.387)	(0.433)	(0.467)	(0.581)	(0.769)
Female active in bargain	−12.421	−12.437	−12.612	−13.212	−14.531
	(0.150)	(0.140)	(0.114)	(0.128)	(0.102)
Buyer identifiably rich					9.570
					(0.287)
Buyer identifiably poor					−8.014
					(0.467)
Buyer bargains for someone else					1.093
					(0.902)
Buyer age					−0.812*
					(0.024)
Buyer experience					8.583*
					(0.020)
Constant	70.036*	70.689*	68.991*	72.500*	132.281**
	(0.018)	(0.015)	(0.017)	(0.015)	(0.003)
Observations	241	241	241	241	160
Adjusted R^2	0.828	0.828	0.830	0.827	0.809

The dependent variable is the final agreed upon sale price for bargains ending with a sale. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

6.1.2. Final sales price

Table 4 reports regression results explaining the variation in final sale prices for successful bargains. 23% of the negotiations we observe end in a sale. Our hypotheses here are that bargains with higher opening prices, if they end in a sale, will end with a higher final price. In addition, as the Festival draws near, prices are expected to fall, as the pressure to sell increases. We expect sellers coming from further away to accept lower final prices, while feeders, who have higher costs, to demand higher prices. Column 1 shows that all the relationships hypothesized above are borne out in the data, with the exception of that on feeders. Interestingly, neither communication, nor mediation or any buyer characteristics have significant associations with final sale prices.

Consistently with the regression, initial offer, days remaining till the Festival, and seller cost characteristics are among the first group of covariates selected by machine learning algorithm (Table 2, Column FSP). However, machine learning algorithms select more variables than the regression in the case of final sale prices. These are plausible associations; for example, final prices being higher for wealthy-looking buyers, or lower when female buyers are present/active, with signs consistent with regression results. However, these variables do not reach statistical significance in regressions, possibly due to the small sample size for these analyses that condition on a sale.

We next turn to analyzing bargaining characteristics such as initial offers, buyer and seller concessions, and duration, which can shed more light into the association of seller/buyer characteristics and process variables with bargaining outcomes.

6.2. Intermediate bargaining variables

6.2.1. Initial offers

We begin by studying the relationship between the seller's initial offer and seller and (observable) buyer characteristics when bargaining is initiated by the seller (Table 5). Theoretically, three sets of variables are relevant to initial offers: seller characteristics, buyer characteristics that are observable to the seller, and variables such as days left until the Festival. Our hypotheses here are as follows: (1) buyer wealth as observed by the seller matters; more wealthy-looking buyers are quoted higher initial prices, (2) sellers' cost structure and bargaining power affects initial offers: sellers who are coming from far away and have to sell the product quote lower offers; sellers who are breeders quote lower offers as they have lower costs and can also internalize inventory costs, (3) as the Festival approaches and time pressure to sell increases, quoted initial prices fall. In addition, while it is not possible to sign these hypotheses beforehand, it is conceivable that initial offers made to larger vs. smaller groups, or groups including women, could be different. We therefore include these variables as well.

In Table 5, we start with a specification based on the above structure that uses as much data as possible (Column 1). We then add the buyer characteristics that reduce the sample (column 2). Variables that are not realized at the time the initial offer is made are excluded from variable selection and analysis, such as communication (see Table 2).

Column 1 shows that sellers who are coming from further away quote lower prices. The coefficient is significant at the %1 level and corresponds to a 122–125 TL fall in opening prices for a seller that brings livestock from more than 500 km. away. Note that even though travel costs of such sellers are higher, these sellers also have lower bargaining power compared to sellers living nearby. Sellers who are feeders (as opposed to breeders) quote higher initial prices (46–49 TL more than breeders), indicating that the cost structure of sellers is reflected in initial offers. As the day of the Festival draws near, initial quoted prices decline, as expected. The remaining (percentage) stock of the seller has a positive relationship with initial offer, suggesting that this variable also captures some aspect of time.[23] Column 2 adds the variables for buyer being identifiably rich or poor, and buyer age, which are buyer characteristics observable to the seller.[24] As expected, in transactions where the bargaining party looks wealthy, the opening price quoted by the seller is higher.

Initial prices quoted to buyer parties that include women are lower, but this difference does not reach statistical significance. Seller's remaining stock turns out to be highly positively significant, as this variable may capture the approaching deadline better than the "days left" variable, as stocks also diminish, and the variable may capture the bargaining power and time pressure in a more seller-specific way.

These results are consistent with results from the machine learning algorithm (LASSO). Table 2 shows that the most important predictors of initial offers are seller characteristics capturing costs and bargaining power, followed by the buyer's identifiable wealth. The directions of the effects are also consistent with the regression analysis. Overall, our hypotheses about initial offers are borne out by the data: initial offers reflect variations in seller bargaining power, seller costs, and observable buyer wealth. We next turn to how much sellers and buyers concede.

6.2.2. Concessions

We define concession at the negotiation level as the percentage reduction (increase) from the initial offer of the seller (buyer) at the end of the negotiation, either through a purchase or the buyer walking away (Tables 6 and 7). Here, our main hypotheses concern the role of communication and mediation: we expect that in the presence of communication and mediation, there will be larger concessions from initial offers in general. In addition, we would again expect seller characteristics related to the seller's bargaining power (e.g., coming from further away) to be associated with larger concessions.

We begin by studying the seller's concession (Table 6). We again start with the specification that includes theoretically-relevant variables and makes the most use of observations. Column 1 shows that, controlling for initial offer, communication and the presence of a mediator are two process variables that are strongly predictive of behavior: when there is communication during the negotiation, or when there is a mediator involved, the seller's concession percentage is significantly higher. Sellers that come from far away concede more, while being a feeder or breeder does not have any effect. A seller that needs to travel at least 500 km to return

[23] Results reported are robust to using the absolute value of the remaining stock rather than percentage.

[24] This reduces the number of observations to 593 due to information on identified wealth being missing in field records and the non-response on the buyer survey on age.

Table 5
Initial offer by the seller.

	(1)	(2)
Days remaining	2.276	5.385
	(0.371)	(0.120)
Seller distance greater than 500 km	−122.301**	−125.649**
	(0.002)	(0.002)
Seller is feeder	49.159**	46.349**
	(0.002)	(0.002)
Seller's remaining stock	1.673**	1.738**
	(0.002)	(0.002)
Buyer group size	−2.454	−7.070
	(0.513)	(0.160)
Female presence in group	−4.492	−4.431
	(0.605)	(0.711)
Buyer identifiably rich		48.109*
		(0.026)
Buyer identifiably poor		−8.192
		(0.387)
Buyer age		−0.183
		(0.581)
Constant	688.953***	706.118***
	(0.000)	(0.000)
Observations	1013	593
Adjusted R^2	0.236	0.286

The dependent variable is the opening price of the seller. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted *p*-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

home concedes 1.7 to 2.4 percentage points more compared to sellers living in closer locations. Finally, as the Festival draws near and the pressure to sell increases, the concession percentage generally increases. Columns 2, 3, and 4 analyze communication in more detail. As the scope of the communication increases, concessions are larger. In fact, an additional talking point increases concessions by 0.5 percentage points (Column 2). Seller's concessions, as expected, are affected by buyers' communication, but not the seller's (Column 3). Specifically, buyers that mention a tight budget and having previously purchased from that seller obtain higher concessions (Column 4). Interestingly, mentioning being from the same hometown is not associated with higher concessions. Column 5 includes additional buyer characteristics, which turn out to be insignificant.

The variable capturing female activity in negotiation has a positive coefficient in all specifications, but this association does not reach statistical significance.

LASSO/LARS analyses strongly support the regression results. The process variable of communication (by the buyer) is shown to be the most relevant predictor (Table 2, Column SC), and the same specific communication variables (budget and previous purchase) that are significant in OLS regressions are also among the variables selected, while other communication variables that are not significant are not selected. Similarly, mediation is selected second, consistently with its significance in all regression specifications. Seller distance, again, is consistently selected by LASSO/LARS.

In Table 7, we analyze buyer concessions. In our first specification (Column 1), we observe a positive relationship between the presence of a mediator and buyers' concession percentage, as in the case of sellers. This result remains in all specifications. With fewer days towards the Festival, the buyer concedes more, as in the case of the seller. Buyer parties that include a woman seem to concede less, while women's active participation does not have an additional effect. Columns 2, 3 and 4 study the effects of communication in more detail. We do not find significant effects of communication or of any specific type of communication points mentioned by the seller. However, regressions and machine learning analyses partly diverge here–LASSO selects only two variables, and these are mediation (consistently with the regression), as well as communication scope.

In either method, we do not observe any significant effects of buyer characteristics (age, experience, identifiably wealthy buyer) on the percentage conceded by the buyer. Overall, Tables 6 and 7 show the following main results: Mediation leads both buyers and sellers to concede more. Communication coming from the buyer side, and establishing a positive association with the seller affects seller's concession positively. These two findings shed more light on the association of communication and mediation with a higher probability of sale. Generally, as the Festival gets closer, both buyers and sellers face pressure to concede more.

In both approaches, few tests give statistically significant results for buyer concessions. This could potentially be due to the nature of the market setting: buyers have multiple options to choose from, and are not subject to the time pressure borne by sellers to the same extent. In such a setting buyers could prefer to exercise their option values of waiting and observing market movements rather than buying quickly. This leads to many bargains in which buyers make smaller concessions than they otherwise would, making it difficult to link to underlying characteristics and process variables to concessions.

Table 6
Explaining seller's concession.

	(1)	(2)	(3)	(4)	(5)
Initial offer	0.003 (0.132)	0.003 (0.163)	0.003 (0.136)	0.003 (0.124)	0.006* (0.042)
Days remaining	−0.274* (0.028)	−0.286* (0.018)	−0.300** (0.008)	−0.273* (0.020)	−0.275 (0.102)
Mediation	3.122** (0.002)	2.998** (0.002)	3.125** (0.002)	3.285** (0.002)	2.959** (0.002)
Non-price communication	1.533** (0.002)				
Communication scope		0.546** (0.002)			
Communication by buyer			2.129** (0.002)		
Communication by seller			−0.339 (0.453)		
Communication -Buyer's budget				1.970** (0.002)	2.392** (0.002)
Communication -Prev. Purchase				3.538** (0.004)	3.006* (0.030)
Communication -Sheep. Char.				−0.409 (0.289)	−0.451 (0.383)
Communication -Same hometown				0.374 (0.461)	0.423 (0.505)
Communication -Seller's cost				0.486 (0.327)	0.280 (0.699)
Seller distance greater than 500 km	1.726** (0.006)	1.768** (0.006)	1.781** (0.002)	1.759** (0.002)	2.439** (0.004)
Seller is feeder	−0.446 (0.275)	−0.441 (0.275)	−0.488 (0.194)	−0.501 (0.210)	−0.742 (0.146)
Seller's remaining stock	−0.015 (0.081)	−0.014 (0.106)	−0.010 (0.202)	−0.011 (0.164)	−0.018 (0.100)
Buyer group size	0.146 (0.501)	0.190 (0.399)	0.114 (0.617)	0.205 (0.389)	0.235 (0.527)
Female presence in group	−0.106 (0.814)	−0.087 (0.842)	−0.058 (0.888)	−0.132 (0.778)	0.294 (0.603)
Female active in bargain	0.775 (0.144)	0.736 (0.166)	0.702 (0.180)	0.743 (0.168)	0.784 (0.287)
Buyer identifiably rich					−0.633 (0.447)
Buyer identifiably poor					−0.410 (0.545)
Buyer bargains for someone else					−0.143 (0.834)
Buyer age					0.034 (0.142)
Buyer experience					−0.615 (0.056)
Constant	0.838 (0.552)	1.206 (0.387)	1.303 (0.351)	1.103 (0.435)	−0.498 (0.823)
Observations	1026	1026	1026	1026	576
Adjusted R^2	0.063	0.062	0.078	0.076	0.103

The dependent variable is the percentage decrease in seller's price offers from their initial offer during the bargain. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted *p*-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Table 7
Explaining buyer's concession.

	(1)	(2)	(3)	(4)	(5)
Initial offer	0.001 (0.689)	0.001 (0.755)	0.001 (0.749)	0.001 (0.719)	0.001 (0.774)
Days remaining	−0.333* (0.028)	−0.330* (0.040)	−0.335* (0.026)	−0.367* (0.028)	−0.184 (0.435)
Mediation	2.647* (0.024)	2.582* (0.024)	2.613* (0.028)	2.652* (0.026)	3.597* (0.026)
Non-price communication	1.119 (0.108)				
Communication scope		0.348 (0.088)			
Communication by buyer			0.128 (0.820)		
Communication by seller			0.946 (0.142)		
Communication -Buyer's budget				−0.472 (0.369)	0.110 (0.886)
Communication -Prev. Purchase				−0.200 (0.876)	0.878 (0.521)
Communication -Sheep. Char.				0.623 (0.325)	0.474 (0.541)
Communication -Same hometown				0.567 (0.403)	0.835 (0.353)
Communication -Seller's cost				0.877 (0.148)	0.532 (0.517)
Seller distance greater than 500 km	1.211 (0.128)	1.250 (0.122)	1.240 (0.132)	1.300 (0.100)	1.097 (0.337)
Seller is feeder	0.399 (0.557)	0.431 (0.501)	0.457 (0.481)	0.428 (0.517)	1.310 (0.054)
Seller's remaining stock	−0.013 (0.218)	−0.013 (0.180)	−0.014 (0.162)	−0.014 (0.152)	−0.014 (0.281)
Buyer group size	−0.211 (0.429)	−0.183 (0.475)	−0.194 (0.431)	−0.249 (0.327)	−0.129 (0.709)
Female presence in group	−1.462* (0.036)	−1.452* (0.034)	−1.428* (0.028)	−1.373* (0.040)	−0.575 (0.467)
Female active in bargain	0.746 (0.236)	0.677 (0.293)	0.709 (0.238)	0.699 (0.265)	0.088 (0.904)
Buyer identifiably rich					0.053 (0.974)
Buyer identifiably poor					0.056 (0.952)
Buyer bargains for someone else					−1.008 (0.198)
Buyer age					−0.022 (0.529)
Buyer experience					0.015 (0.972)
Constant	3.324 (0.105)	3.678 (0.068)	3.537 (0.082)	3.778 (0.062)	2.771 (0.352)
Observations	555	555	555	555	331
Adjusted R^2	0.035	0.035	0.033	0.031	0.031

The dependent variable is the percentage increase in buyer's price offers from their initial offer during the bargain. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Interestingly, initial offers are uninformative about concessions, both for the buyer and the seller. One reason could be opposing potential effects of initial price on concessions. On the one hand, a lower initial offer necessitates less bargaining on the part of the buyer, and hence there may be less need for a concession. On the other hand, the seller could bargain harder if he starts with a lower price. This may be why there are no significant observed effects on average.

6.2.3. Bargaining duration and number of rounds

In all bargaining transactions, we record the total length of the negotiation in minutes (the time spent by the buyer at the tent until the transaction ends with a purchase or the buyer walking away), as well as the number of rounds of offers and counter-offers. While the duration variable is correlated with the number of offer rounds, it may also contain more information than the number of rounds because there can be silent spells or conversation.

For duration in minutes, machine learning algorithms select only two variables, both related to communication (Table 2, Column DUR). For the number of rounds, both mediation and communication variables are selected (Column NR). This highlights the fact that the main determinant of bargaining duration is communication between parties, as expected in the current setting. Note that bargains in our setting occur in real-time, and bargains take longer due to the presence of communication spells. The presence of a mediator elicits additional offers from both parties, as expected.

OLS regressions of duration and number of rounds (put in the Appendix for brevity, Tables A.2 and A.3) are consistent with the machine learning results: mediation and communication variables are associated with longer bargains and a higher number of rounds. A notable observation is that both duration and the number of rounds are primarily affected by communication that is of "cheap talk" in nature, i.e., claims regarding budget constraints or costs, rather than by communication points that establish association.[25] That is, the estimated benefit to the buyer of cheap talk in terms of higher concessions obtained from the seller (Table 6) requires additional costs in terms of time and effort. A bargain that involves cheap talk from both parties takes an average of 2.12 to 2.55 min (Table A.2, Columns 4 and 5) longer, which is significant in the current context where the average bargain is 2.84 min long.[26]

6.3. Valuations and prices

Having data, albeit noisy, on the WTP of buyers and WTA of sellers gives us a chance to study how elicited valuations track actual prices. We first look at the relationship of WTA and WTP with actual sales prices. Table 8 presents regressions of the final sale price on the experimentally-elicited WTA of the seller and the survey-elicited WTP of the buyer. Recall that we have two WTP values—the WTP for the specific negotiation that ended in a sale, and the overall WTP for a sheep for the Festival. Column 1 uses the former and Column 2 the latter WTP value, along with the daily WTA values that we collect (and linearly interpolate to days where we do not have these data). As expected, both variables have highly significant and positive effects: when WTA and WTP are higher, agreed-upon prices are higher. We also observe in Column 1 that the final sale price is more sensitive to WTA than to WTP, but this could be a reflection of the noisier nature of our WTP measure, rather than an indication of asymmetries in uncertainty between two sides of the market. Interestingly, we cannot reject the hypothesis that the sum of the coefficients of WTA and WTP equal one ($F_{1,16} = 0.00$, $p = 0.96$), suggesting that equal increases in both valuations, on average, lead to a commensurate, proportional response in the final selling price.

We also construct a measure of the total potential trade surplus ("pie size"), defined as the difference between buyer WTP and seller WTA in a given buyer–seller match, using the overall WTP measure that is elicited in all questionnaires regardless of whether a sale occurred. This variable has the expected positive relationship with the probability of a sale: a 100 TL increase in pie size (about 15% of the average sale price of a sheep in the market) is associated with a 6.2 percentage point increase in the probability of an agreement (from an unreported logit regression of the incidence of sale on pie size, clustering for buyer–seller pairs, $p < 0.001$).

We refrain from doing a surplus division analysis for bargains that end with a sale, as realized surplus values are negative for sellers or buyers or both in a significant number of successful transactions, and sample size is small. The negative values are in line with our observations in the buyer questionnaire, where many buyers stated that they had a lower WTP in fact but "forced themselves" to be able to pay extra required to buy the animal in question.[27] However, we still study the predictive power of our elicited WTPs and WTAs relative to other sets of variables in Section 6.4.

An analysis of seller surplus using the WTA variable and realized prices shows that as expected, conditional on a sale, seller surplus is higher when the initial offer is higher. Seller surplus is also higher for breeders, and higher for those who come from farther away (Table A.4 in Appendix A).[28] This latter result comes about because these sellers have lower WTA (due to a worse outside option) and the surplus they get in this market at the ongoing prices is higher. Buyer or process characteristics do not seem to have significant associations with seller surplus.

Finally, given that we use different methodologies and several different outcomes, we also present a summary table that reports, for each primary and intermediate outcome, the variables that are found to be consistently predictive across the two approaches of LASSO and standard multivariate regression, and the directions of the associations (please see Table 9).

[25] Note that claims establishing association are to some extent verifiable in the social (not legal) context due to their ties to common memory and space.

[26] For number of rounds, remaining stock of seller also turns out to be negatively significant. This variable in fact acts as a personalized timekeeper for the market deadline, and does so better than the number of days remaining. This is further supported by the fact that many sellers have sold out their stocks before the final day of the market.

[27] True WTP measurements through surveys are difficult and subjects themselves may not be aware of the price limit they can be pushed to. Due to the nature of our field setting, it was not possible to sell sheep to buyers and elicit an incentive-compatible WTP.

[28] This analysis is undertaken only for those observations where the measured seller surplus is non-negative.

Table 8
Final sale prices and valuations.

	(1)	(2)
WTA	0.547***	0.916***
	(0.0099)	(0.0099)
WTP (Purchase)	0.455***	
	(0.0099)	
WTP (Overall)		0.064*
		(0.0495)
Constant	−11.664	9.055
	(0.694)	(0.826)
Observations	180	168
Adjusted R^2	0.813	0.689

The dependent variable is the final agreed upon sale price for bargains ending with a sale. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted *p*-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Table 9
Summary of LASSO/LARS and regression results.

Variables	IO	PS	SC	BC	DUR	NR	FSP
Initial offer		(−)					(+)
Days remaining			(−)				(+)
Mediation		(+)	(+)	(+)		(+)	
Non-price communication		(+)	(+)			(+)	
Communication scope				(+)	(+)		
Communication by buyer			(+)		(+)	(+)	
Communication by seller							
Communication -Buyer's budget			(+)				
Communication -Seller's cost						(+)	
Communication -Prev. Purchase		(+)	(+)				
Communication -Sheep. Char.							
Communication -Same hometown		(+)					
Seller distance greater than 500 km.	(−)		(+)				(−)
Seller is feeder	(+)						
Seller's remaining stock	(+)						
Buyer group size							
Female presence in group							
Female active in bargain							
Buyer identifiably rich	(+)						
Buyer identifiably poor							
Buyer age							(−)
Buyer bargains for someone else							
Buyer income							
Buyer experience							(+)

The Table reports variables that are found to predict each outcome according to both LASSO and regression analysis. Abbreviations for dependent variables are; IO: Seller's Initial Offer, PS: Probability of Sale, SC: Seller's Concession, BC: Buyer's Concession, DUR: Bargaining Duration, NR: Number of Rounds, FSP: Final Sale Price.

6.4. The predictive power of groups of variables on bargaining outcomes

Although we collect data on many types of variables in the bargaining environment, it is difficult to draw directly causal conclusions on the effects of specific variables due to the lack of exogenous variation in our setting. However, one unique strength of our approach is that we collect a large set of naturally-occurring and experimentally elicited variables concurrently for the same bargains, allowing us to draw some inferences on which types or groups of variables better predict outcomes.

In this section, we put forward an analysis to establish the relevance and predictive power of different groups of variables for the primary bargaining outcomes of probability of sale and prices conditional on sale. For this purpose, we again use the classification of variables presented in Table 1. These are observable buyer characteristics, other buyer characteristics, seller characteristics, process variables (communication and mediation), situational variables (days left) and seller's opening strategy. We also consider the elicited WTP and WTA as a separate group that we call "valuations".

In Table 10, we first apply a Group LASSO algorithm to determine the priority of inclusion among different variable groups. This analysis shows which sets of bargaining variables are most relevant for predicting bargaining outcomes, establishing a hierarchy between groups of variables. We also report, for each bargaining outcome, the "standalone" predictive power of each variable set,

Table 10
Group LASSO analysis and the relative predictive power of variable groups for bargaining outcomes.

Group	Abbr.	Probability of sale		Final sale price	
		Group LASSO	Pseudo-R^2 (%)	Group LASSO	R^2 (%)
Opening strategy (Initial offer)	OS	2	0.30	1	81.3
Situational variable	St	5	0.00	2	4.14
Process variables	P	1	7.62	6	9.68
Seller characteristics	S	5	0.20	3	28.0
Observable buyer Char.	B1	3	0.76	5	3.67
Unobservable buyer Char.	B2	3	0.21	4	3.63
All			9.43		84.7
Valuations-Standalone	V		5.18		67.6
Valuations-Incremental on all	V		4.05		0.59

For each outcome, the first column gives the selection order by Group LASSO, and the second column reports the percentage of the variation in outcome explained, based on R^2 values (Pseudo-R^2 for logit regressions for PS) when the outcome is regressed on this variable group by itself. The row labeled "All" reports the overall variation collectively explained by the variable groups above it. The last two rows give the standalone and incremental explanatory power of valuations respectively, where the latter is the additional variance explained by Valuations conditional on that of all other variables.

by itself.[29] Finally, in the bottom panel, we consider the standalone as well as incremental contribution to R^2 of WTA and WTP valuations as a variable group (V), in order to gain some insight into the usefulness of gathering such data in the field when other variables are available, considering that valuations are normally unobservable in studies of bargaining that use naturally-occurring data.

Results reported in the top panel of Table 10 provide the following insights: For the probability of sale, the process variables of communication and mediation are picked first by the Group LASSO algorithm. Consistently with this, when considered by themselves, their standalone explanatory power (R^2) in a regression model is about 8%; higher than that of, for example, buyer and seller characteristics.[30] Seller characteristics capturing the cost structure and bargaining power of the seller, along with the opening strategy, on the other hand, turn out to be more important for explaining the variation in final prices than the process variables.

The bottom rows in Table 10 add additional findings regarding valuations, by studying the explanatory power of valuation measures by themselves as well as when conditioned on other covariates. The WTA and WTP we elicit have some predictive power by themselves for explaining the probability of sale (5.18 percent). This measure remains comparable when considering the incremental explanatory power of valuations, i.e., additional variance explained conditional on all other variable groups (4.05 percent). Valuations, when considered by themselves, also explain a large portion of the variation in the final price in successful bargains (67.6 percent). However, their incremental contribution turns out to be low for this outcome, when other variables are available. Overall, results suggest that WTA/WTP elicitation can be valuable over and above collecting seller/buyer characteristics in field contexts for predicting the probability of sale, but may not have much additional explanatory power for prices, provided that sufficient information on the characteristics of negotiation and the negotiating parties is available.

7. Discussion and concluding remarks

In this paper, we provide results from a unique data set on negotiations in the sheep market for the Festival of Sacrifice. Our data collection strategy attempts to approximate the observability that would be found in a lab experiment in the context of naturally-occurring negotiations, in the sense of collecting data on many factors that would be controlled (e.g., communication, time pressure) or induced (e.g., values, costs) in a lab setting with alternating-offer negotiation (as in, for example, Andersen et al. (2018)), thereby attempting to make them observable within the natural bargaining environment. Our setup goes beyond many observational datasets on negotiation in the sense of collecting not only sales and sale prices for realized transactions, but also concessions and several process variables in the course of both successful and unsuccessful negotiations. We use these data to shed some light on the broad research question of which individual covariates and groups of variables predict bargaining outcomes.

The first point to note is that our results put forward several expected empirical associations (e.g., concessions increasing and initial offers and prices decreasing as the Festival draws near, elicited WTP and WTA having expected effects on the probability of sale). This shows that bargaining behavior follows theoretical predictions and also gives us confidence in the collected and elicited data, despite the noise in the measurement of WTA, and WTP in particular.

[29] Note that LASSO/LARS based prioritization need not coincide with the relative explanatory power of variables or variable groups, in regression. This is because the explanatory power of a variable/group conditional on those that are previously selected by the procedure is not the same as the standalone explanatory power of the variable/group in linear regression, i.e., without conditioning on other features. For this reason, the order of selection is expected to correlate with the relative explanatory power of variables for earlier variables selected by LARS/LASSO, but may deviate from that at lower priority levels.

[30] We should note, however, that the relevance hierarchy of variables in an empirical study will always depend on how they are measured, and these results should be interpreted with the caveat that the buyer characteristics come from the buyer survey, and are self-reported.

Our results consistently show that process variables are important for bargaining outcomes. Non-price communication between bargaining parties emerges as an important variable here: negotiations where there is non-price-related communication between the buyer and seller are more likely to end with a sale, and the larger the scope of the conversation, the higher the probability of sale. This result is in line with Backus et al. (2020b), who show that the introduction of a text messaging system on an online platform to facilitate explicit communication improves the chances of reaching a successful trade on the platform. Having information on both buyer-side and seller-side communication, we observe that buyer-side communication is more conducive to sale. In particular, negotiation is more likely to end in a sale if the buyer uses conversation points that induce association (being from the same hometown) or signal a longer-term relationship (having made a previous purchase).

Most communication in strategic environments is considered to be "cheap-talk", as players in negotiation or in other types of strategic environments rarely have the ability or tools to verify their claims. However, this type of communication may indeed have an important role in negotiations (Crawford, 1990; Farrell & Gibbons, 1989). Contributing to this literature, our results show that one of the most effective communication points for buyers to obtain concessions from the seller is mentioning their budget constraint. This strategy is indeed used frequently by the buyers (in 25 percent of all bargaining transactions, and in 66 percent of buyer communication), suggesting that such "cheap talk" may have important effects. This result provides support from another market setting to Bhattacharya and Dugar (2023), who show that asking for a discount on the basis of affordability leads to higher surplus for buyers in a field experiment in fish markets, and to Lee and Ames (2017), who document a similar finding on the effectiveness of using limited resource rationales on the part of buyers in a laboratory study. Mentioning repeat purchases is associated with higher concessions from sellers as well. Overall, our results highlight that both partially verifiable messages that suggest association (same hometown, repeat purchase) as well as cheap-talk that suggests a lower ability to pay, can be associated with bargaining outcomes of interest. Results on the importance of mentioning previous purchases additionally underscore the importance of reputation building for sellers, even in a once-a-year market such as this one. This is reminiscent of local dealers displaying more positive reciprocity in trade in sportscard markets in List (2006).

We also find that the presence of a mediator facilitates a successful conclusion to negotiation: when a mediator is present, the probability of sale is higher, as mediation is associated with higher seller and buyer concessions. This result is in line with Larsen et al. (2021), who study the effects of (paid) mediators in alternating-offer, business-to-business negotiations in the used car market using observational data, and find large positive effects of mediators on the probability of a deal. The result also relates to a set of theoretical studies in economics and political science, showing that mediation can increase the efficiency of bargaining outcomes (e.g., Čopič & Ponsati, 2008). Experimental work in the lab has shown that mediation could also lead to higher impass, depending on the role and incentives of the mediator (e.g., Bazerman et al., 1992). Mediators being primarily altruistic facilitators in our setup may be one reason why their involvement is associated with a higher probability of sale.

We find that the opening price exhibits variation in that sellers tend to quote higher initial offers to rich-looking customers, providing some evidence for first-degree price discrimination in the market. In contrast to previous studies, we do not find that women (in our case, buyer parties including women) end up with worse bargaining outcomes.

There are several shortcomings of our study, the most notable of which arises from the observational nature of the data: due to the lack of exogenous variation, it is difficult to identify causal effects even though we control for many relevant variables. The second issue is the impossibility in this field setting to elicit buyer WTP via an incentive compatible mechanism, which forces us to use a survey measure that may not reflect true valuations, and makes it difficult to reliably study surplus division.

That said, our data can still be used to provide insights that can be relevant as the bargaining literature moves forward. Using naturally occurring data combined with elicited valuations, we can draw some inferences as to the relative importance of different variables and groups of variables. The robust results on the importance of process variables, in particular communication, for outcomes such as the probability of sale highlight the potential benefits of collecting information on these variables in studies of bargaining. While experimentally elicited valuations have strong predictive power for bargaining outcomes by themselves, their incremental contribution is not particularly large, if data on other, more easily observed bargaining variables are already available. Still, it should also be noted that the type of data in our study that uncovers valuations along with behavior could be valuable for structural estimation of alternative bargaining models as well.

Overall, our results provide a first peek into bargaining in a real market with alternating offer, free-form negotiations. Insights coming from rich correlational, naturally-occurring data provide a complement to laboratory and field studies that have exogenously manipulated specific, single variables to establish causal results. In addition to providing suggestions for enriching theoretical models based on aspects of real-life bargaining transactions most relevant for predicting outcomes, our exercise can also suggest which aspects (e.g., communication, mediation) to test further in experiments that can establish causality. This may then lead to policy insights on institutions that can potentially increase the efficiency of bargaining outcomes.

Data availability

The data used for the article is made publicly available.

Appendix A

Additional tables

Robustness: Missing observations and imputation

To understand the patterns of non-response in the buyer survey, we compare buyer characteristics that are directly observed (rather than solicited), as well as major bargaining outcomes between the samples with missing and non-missing questionnaire

Table A.1
Buyer's stated income and identifiable wealth.

	(1)	(2)
Buyer identifiably rich	2.716***	2.627***
	(0.725)	(0.747)
Buyer identifiably poor	−1.241**	−1.204**
	(0.397)	(0.425)
Helper dummies	NO	YES
Observations	632	632
Adjusted R^2	0.0780	0.0946

The dependent variable is buyer income, the categorical (1–4) income level of the buyer. Reported results are from Ordered Logit regressions with standard errors clustered at the buyer level. Standard errors are reported in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

responses. Table A.5 shows that many of the observed buyer characteristics and outcomes (size of the buyer group, presence and active negotiation of women, buyer identifiable wealth, initial offers, buyer and seller concessions) are similar between the two groups. However, the occurrence of a purchase is higher among those that respond to our questionnaire (14% vs. 24%, statistically significant at the 1% level), and consistently with this, number of rounds and duration are also higher in the group that answers the survey.

To test the robustness of our results to the missing observations issue, we run our regressions (using the full specification) with an imputed version of our data set.[31]

Table A.6 presents these robustness results. While interpreting this table, we focus on whether the results that OLS regressions and LASSO agree on (presented in Table 9), are robust in regressions with the imputed sample as well. As seen in Table A.6, our main results are replicated with the imputed samples.

Appendix B. Machine learning algorithms used

LASSO is a regularization method that adds a penalty term consisting of the L_1 norm of the parameter vector to the usual least squares objective function for a regression equation, which forces regression coefficients to shrink towards zero. The coefficient (weight) of the L_1 norm in the objective function, typically denoted by λ, is called the tuning parameter and controls the strength of the penalty applied, i.e., a larger tuning parameter will force a larger number of coefficients to shrink to zero. This gives LASSO very appealing variable selection properties (Hastie et al., 2017). The tuning parameter can be chosen via typical cross-validation. We follow the "one standard error" rule proposed by Hastie et al. (2017) and James et al. (2017) as our baseline selection method, which argues that the tuning parameter should be chosen to be one standard deviation above the value that minimizes the cross-validation error to select the most parsimonious model that also avoids overfitting.

LASSO usually provides unambiguous selection via cross-validation in cases where the cross-validation error is U-shaped in the tuning parameter. In some cases, however, the appropriate selection becomes less obvious due to relative flatness of cross-validation error around its minimum. The selection of the tuning parameter (hence the variable list surviving selection) is also subject to some uncertainty due to the stochastic nature of cross-validation, i.e., training and test sets being chosen randomly. To guide our variable selection in such cases, we additionally employ Least Angle Regression (LARS) (Efron et al., 2004) for a more complete analysis. LARS is a variant of forward stepwise regression that uses a priority selection method; it begins with the explanatory variable most correlated with the dependent variable, and makes updates to the model list one at a time by searching for the most optimal paths. The LARS algorithm is closely tied to LASSO, as it allows computing the entire LASSO path of all variables as the tuning parameter is varied in an efficient and intuitive way (Hastie et al., 2017), therefore observing the ordinal relevance of each covariate for the outcome to be studied. This allows us to observe a relevance hierarchy.

The LASSO variable selection procedure is performed using stacked imputations, which is known to give more efficient outcomes for variable selection and elimination problems in the presence of missing data (Du et al., 2022; Wood et al., 2008).[32] Five stacked imputations are used in all variable selection procedures. The first out of the five are also used in imputed regression analysis as described above. We included relevant dependent variables in the imputation process as well (Kontopantelis et al., 2017).[33][34]

[31] We use predictive mean matching for all imputations due to its versatility and robustness to misspecification (Van Buuren, 2018). Imputations are obtained using the mice package in R (Van Buuren & Groothuis-Oudshoorn, 2011). A separate imputation was required for bargains ending with a sale that uses this smaller sample alone, and another for surplus analysis that did not make use of extreme negative outliers, in order for these observations to not impact the quality of imputations.

[32] We also performed the LASSO procedure on complete cases whenever feasible, also experimenting with a smaller set of variables to retain acceptable sample sizes, and obtained similar outcomes.

[33] In order to examine the quality of our imputations, we check the correlations among different versions of variables with missing data. These correlations are in the range 0.92–0.96 for identifiably rich/poor dummies, 0.92–0.95 for seller's remaining stock, and 0.80–0.89 for buyer's reported age, experience and income.

[34] LASSO, LARS and Group LASSO analysis are performed using the glmnet (Friedman et al., 2010), lars (Efron et al., 2004), and grpreg (Breheny, 2015) packages in R, respectively.

Table A.2
Explaining bargaining duration (min).

	(1)	(2)	(3)	(4)	(5)
Initial offer	0.002*	0.002	0.002*	0.002*	0.003
	(0.034)	(0.056)	(0.034)	(0.030)	(0.074)
Days remaining	−0.060	−0.065	−0.069	−0.065	0.006
	(0.365)	(0.309)	(0.295)	(0.291)	(0.956)
Mediation	1.128**	0.848*	0.952*	0.998*	1.239*
	(0.012)	(0.038)	(0.022)	(0.016)	(0.020)
Non-price communication	1.526**				
	(0.002)				
Communication scope		0.667**			
		(0.002)			
Communication by buyer			1.434**		
			(0.002)		
Communication by seller			0.695**		
			(0.004)		
Communication -Buyer's budget				1.120**	1.406**
				(0.002)	(0.002)
Communication -Prev. Purchase				2.811	1.743
				(0.068)	(0.090)
Communication -Sheep. Char.				0.502*	0.532
				(0.028)	(0.151)
Communication -Same hometown				0.557	0.468
				(0.112)	(0.285)
Communication -Seller's cost				0.998**	1.146*
				(0.008)	(0.048)
Seller distance greater than 500 km.	0.359	0.380	0.381	0.365	0.266
	(0.268)	(0.260)	(0.248)	(0.254)	(0.551)
Seller is feeder	−0.010	0.020	0.020	0.024	0.218
	(0.972)	(0.934)	(0.958)	(0.910)	(0.507)
Seller's remaining stock	−0.007	−0.006	−0.004	−0.005	−0.008
	(0.178)	(0.228)	(0.393)	(0.343)	(0.264)
Buyer group size	0.016	0.081	0.021	0.064	−0.162
	(0.930)	(0.523)	(0.900)	(0.649)	(0.369)
Female presence in group	0.354	0.335	0.361	0.329	0.734
	(0.263)	(0.287)	(0.256)	(0.321)	(0.122)
Female active in bargain	−0.178	−0.236	−0.261	−0.254	−0.654
	(0.581)	(0.495)	(0.419)	(0.439)	(0.152)
Buyer identifiably rich					−0.396
					(0.513)
Buyer identifiably poor					−0.634
					(0.064)
Buyer bargains for someone else					−0.422
					(0.325)
Buyer age					−0.005
					(0.675)
Buyer experience					−0.128
					(0.451)
Constant	0.351	0.583	0.491	0.463	0.945
	(0.614)	(0.392)	(0.470)	(0.502)	(0.448)
Observations	986	986	986	986	557
Adjusted R^2	0.064	0.082	0.086	0.092	0.101

The dependent variable is the duration of the bargain in minutes. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Appendix C. Seller WTA elicitation and instructions

We told the sellers that we would buy three sheep from them, but that we would do this not through bargaining but via a specific method. They would be asked to name the minimum price they would sell a certain type of sheep for. But, the price they would actually get would be randomly determined. We knew the starting prices each seller offered for every type of sheep within a

Table A.3
Explaining total number of rounds in bargains.

	(1)	(2)	(3)	(4)	(5)
Initial offer	0.001* (0.016)	0.001* (0.028)	0.001* (0.022)	0.001* (0.020)	0.002** (0.006)
Days remaining	−0.071 (0.108)	−0.077 (0.094)	−0.079 (0.076)	−0.075 (0.078)	−0.039 (0.519)
Mediation	1.785** (0.002)	1.719** (0.002)	1.740** (0.002)	1.818** (0.002)	1.810** (0.002)
Non-price communication	0.873** (0.002)				
Communication scope		0.305** (0.002)			
Communication by buyer			0.705** (0.002)		
Communication by seller			0.349* (0.028)		
Communication -Buyer's budget				0.573** (0.006)	0.681* (0.020)
Communication -Prev. Purchase				1.601 (0.106)	0.878 (0.202)
Communication -Sheep. Char.				0.108 (0.443)	0.213 (0.371)
Communication -Same hometown				0.148 (0.479)	0.262 (0.405)
Communication -Seller's cost				0.743** (0.004)	0.580 (0.152)
Seller distance greater than 500 km.	0.219 (0.293)	0.250 (0.235)	0.243 (0.268)	0.229 (0.268)	0.319 (0.337)
Seller is feeder	0.240 (0.114)	0.238 (0.150)	0.248 (0.110)	0.246 (0.116)	0.161 (0.485)
Seller's remaining stock	−0.007** (0.006)	−0.007** (0.008)	−0.006* (0.030)	−0.006* (0.016)	−0.008* (0.024)
Buyer group size	0.003 (0.974)	0.030 (0.657)	0.002 (0.976)	0.023 (0.776)	−0.049 (0.663)
Female presence in group	−0.235 (0.198)	−0.226 (0.212)	−0.214 (0.244)	−0.214 (0.267)	0.117 (0.633)
Female active in bargain	0.223 (0.289)	0.202 (0.327)	0.187 (0.321)	0.179 (0.359)	−0.103 (0.725)
Buyer identifiably rich					−0.289 (0.535)
Buyer identifiably poor					−0.168 (0.487)
Buyer bargains for someone else					0.286 (0.397)
Buyer age					−0.003 (0.711)
Buyer experience					−0.162 (0.170)
Constant	1.212** (0.008)	1.404** (0.002)	1.332** (0.004)	1.340** (0.003)	1.331 (0.103)
Observations	1046	1046	1046	1046	589
Adjusted R^2	0.093	0.088	0.094	0.101	0.097

The dependent variable is the number of offer and counter-offer rounds in the bargain. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

standard bargaining process on a given day. Call this price p_{start}. Prices that increased in 10-TL increments were specified, within a range that started from 450 TL and continued up to $p_{start} + 50$ TL. The sellers were told that the actual price would be drawn from these set of prices, which were written on pieces of paper and placed into a bag, in their presence. For each type of sheep they own, the sellers were then asked to specify their minimum price (p_{min}), above which they would be willing to sell a sheep of that type, and below which they would not be. We explained to the sellers that the actual price for the sheep would be drawn randomly from

Table A.4
Explaining seller surplus.

	(1)	(2)	(3)	(4)
Initial offer	0.196*	0.205*	0.194*	0.202**
	(0.010)	(0.010)	(0.016)	(0.008)
Days remaining	−0.195	−1.654	−0.518	−1.109
	(0.946)	(0.591)	(0.860)	(0.741)
Mediation	13.318	18.862	15.153	16.493
	(0.158)	(0.068)	(0.120)	(0.096)
Communication	11.715			
	(0.112)			
Communication scope		−1.621		
		(0.539)		
Communication by buyer			3.812	
			(0.575)	
Communication by seller			4.253	
			(0.551)	
Communication -Buyer's budget				2.140
				(0.775)
Communication -Prev. Purchase				−9.418
				(0.385)
Communication -Sheep. Char.				0.455
				(0.962)
Communication -Same hometown				4.687
				(0.599)
Communication -Seller's cost				−0.860
				(0.940)
Seller distance greater than 500 km.	46.684*	49.531*	47.032**	48.231*
	(0.006)	(0.012)	(0.014)	(0.008)
Seller is feeder	−24.659*	−27.629**	−25.511*	−26.381*
	(0.016)	(0.006)	(0.020)	(0.036)
Seller's remaining stock	−0.164	−0.138	−0.159	−0.143
	(0.339)	(0.385)	(0.371)	(0.427)
Buyer group size	−1.796	−2.705	−1.553	−1.987
	(0.621)	(0.483)	(0.685)	(0.643)
Female presence in group	21.473	23.649	21.787	21.778
	(0.088)	(0.072)	(0.088)	(0.084)
Female active in bargain	−9.857	−9.111	−10.176	−8.302
	(0.363)	(0.412)	(0.349)	(0.475)
Buyer identifiably rich				
Buyer identifiably poor				
Buyer bargains for someone else				
Buyer age				
Buyer experience				
Constant	−119.396**	−110.607**	−113.404**	−114.955**
	(0.002)	(0.004)	(0.003)	(0.003)
Observations	129	129	129	129
Adjusted R^2	0.204	0.195	0.190	0.171

The dependent variable is Seller Surplus, the difference between the final sale price and experimentally elicited WTA measure. All columns report OLS regressions with standard errors clustered at the seller and buyer levels. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

Table A.5
Missing and non-missing questionnaire responses.

	Difference in means between samples with missing and non-missing questionnaire responses
Initial offer	1.22 (0.94)
Sale	0.1** (0.007)
Buyer concession (% of Initial offer)	0.11 (0.18)
Buyer group size	0.04 (0.76)
Buyer identifiably rich	0.045 (0.14)
Female presence in group	0.04 (0.54)
Female active in bargain	0.004 (0.95)
Conversation	0.07 (0.26)
Number of rounds in bargain	0.41* (0.03)
Duration of bargain (Min.)	0.67* (0.02)

Table displays the estimated difference in means between the sample answering and not answering the questionnaire, from regressions of the dependent variable on an indicator for taking the survey. Standard errors are clustered at the buyer level and p-values reported in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

the bag of prices (call this p_{draw}). A sale would occur if the price drawn exceeds the seller's minimum price, that is if $p_{draw} \geq p_{min}$, and the price actually paid to the seller would be p_{draw}. If the price drawn is lower than the seller's minimum price, then the sale would not take place, and the seller would keep his sheep. A number of questions were asked to the sellers to make sure that they understood the mechanism, and several examples were given. After having explained the mechanism to them, each seller was given a short verbal quiz on potential outcomes and their implications, in order to make sure that they understood the procedure. We are confident that the sellers understood the procedure well and that there was no incentive to misreport their actual minimum WTA.[35] The mechanism was concluded with the public draw of a seller, a type of sheep from that seller's flock, and the random price shortly into the morning, after which the actual purchase was made.[36] Specific instructions are given below.

QUESTIONNAIRE FOR THE PURCHASE OF SHEEP

Seller____________ Day____________

You will have a chance to potentially sell a sheep to us after answering the questions we will ask you. You mentioned that you had ____ types (kg.) of sheep in your flock. Let us consider a sheep of type ____ (kg.):

- We will ask you to tell us at which prices you will be willing to sell and which prices you will not be willing to sell this type of sheep to us.
- That is, your answer will be of the kind "I will sell if the price is above this level", and will not sell if below.
- We will then put papers in a bag with prices written on them between ____ - ____ in 10 TL increments.
- We will pull a price randomly from this bag in your presence.
- If you had answered that you would sell at this price, we will pay this price to you and will buy the sheep.
- If you had answered that you would not sell at this price, you will keep the sheep, there will be no exchange.
- That is, the sale price will be determined by a lottery.

[35] This information was obtained from each seller during the night, when there was no market activity. One concern here could be that the sellers may have wanted to help us by stating lower prices than they would actually accept. Notice, however, that such a strategy could only increase the chance that we buy, but not influence the price we actually pay. Still, we told them to treat this transaction as an actual marketplace sale.

[36] In two out of the three cases, the prices we randomly drew remained within 20–30 TLs of the minimum price chosen by the seller. The seller did not have the slightest objection to the transaction, which gave us additional confidence that the mechanism was understood well by the seller.

Table A.6
Regressions with imputed data.

	IO	PS	SC	BC	DUR	NR	FSP	SS
Initial offer		−0.0002	0.004*	0.001	0.002	0.001*	0.810**	0.120*
		(0.152)	(0.042)	(0.555)	(0.102)	(0.030)	(0.002)	(0.033)
Days remaining	−4.860	−0.0012	−0.153	−0.174	−0.008	−0.059	5.859	−1.383
	(0.068)	(0.910)	(0.178)	(0.291)	(0.920)	(0.230)	(0.090)	(0.667)
Mediation		0.278**	3.133**	4.006*	0.936*	1.881**	2.101	18.55
		(0.002)	(0.002)	(0.028)	(0.030)	(0.002)	(0.767)	(0.064)
Communication -Buyer's budget		0.016	1.970**	−0.537	1.012**	0.576*	−9.828	−0.891
		(0.643)	(0.002)	(0.289)	(0.004)	(0.020)	(0.174)	(0.906)
Communication -Seller's cost		0.046	0.299	1.275*	0.992**	0.641**	5.272	5.903
		(0.172)	(0.503)	(0.046)	(0.006)	(0.006)	(0.395)	(0.556)
Communication -Prev. Purchase		0.491**	3.707**	0.223	2.722*	1.545	−2.126	−17.88
		(0.002)	(0.002)	(0.806)	(0.038)	(0.106)	(0.796)	(0.777)
Communication -Sheep. Char.		−0.013	−0.418	0.083	0.485*	0.102	5.124	−10.820
		(0.663)	(0.279)	(0.872)	(0.048)	(0.465)	(0.483)	(0.415)
Communication -Same hometown		0.074*	0.571	0.641	0.608	0.227	−2.333	1.506
		(0.032)	(0.232)	(0.365)	(0.076)	(0.270)	(0.685)	(0.867)
Seller distance greater than 500 km.	−155.98**	0.021	2.311**	1.675*	0.425	0.269	−23.48*	40.41**
	(0.002)	(0.667)	(0.002)	(0.050)	(0.210)	(0.279)	(0.044)	(0.002)
Seller is feeder	64.31**	0.024	−0.733	−0.151	0.164	0.189	3.786	−24.90*
	(0.002)	(0.481)	(0.086)	(0.806)	(0.523)	(0.270)	(0.565)	(0.016)
Seller's remaining stock	2.541**	−0.0004	−0.034**	−0.019	−0.008	−0.007	0.103	0.0002
	(0.002)	(0.647)	(0.004)	(0.112)	(0.160)	(0.088)	(0.739)	(0.999)
Buyer group size	−3.673	−0.002	0.249	−0.263	0.062	0.005	−2.977	−0.784
	(0.291)	(0.876)	(0.277)	(0.162)	(0.643)	(0.958)	(0.497)	(0.861)
Female presence in group	−10.54	0.021	−0.129	−1.250	0.521	−0.224	−3.790	8.950
	(0.096)	(0.559)	(0.769)	(0.062)	(0.088)	(0.236)	(0.591)	(0.409)
Female active in bargain		0.010	0.801	0.526	−0.346	0.299	−7.810	2.289
		(0.796)	(0.152)	(0.285)	(0.287)	(0.138)	(0.353)	(0.836)
Buyer identifiably rich	34.5*	0.061	−0.125	0.354	0.374	0.016	14.026	12.19
	(0.040)	(0.281)	(0.866)	(0.671)	(0.393)	(0.974)	(0.126)	(0.264)
Buyer identifiably poor	−11.08	−0.041	−0.012	0.896	0.076	−0.016	−0.769	−1.567
	(0.132)	(0.128)	(0.968)	(0.138)	(0.747)	(0.920)	(0.908)	(0.853)
Buyer age	−0.074	−0.001	0.025	−0.030	0.002	−0.004	−0.615*	−0.440
	(0.780)	(0.615)	(0.068)	(0.182)	(0.854)	(0.485)	(0.040)	(0.140)
Buyer bargains for someone else		−0.003	−0.491	−0.508	−0.402	0.151	3.782	3.013
		(0.934)	(0.226)	(0.347)	(0.078)	(0.411)	(0.651)	(0.758)
Buyer experience		−0.009	−0.388*	0.294	0.013	−0.015	8.769*	5.364
		(0.517)	(0.024)	(0.236)	(0.910)	(0.856)	(0.016)	(0.153)
Constant	697.67***	−0.326	0.285	2.843	0.366	1.589**	77.90*	182.82**
	(0.000)	(0.628)	(0.855)	(0.133)	(0.674)	(0.003)	(0.020)	(0.002)
Observations	1015	1046	1046	555	1046	1046	241	143
Adjusted R^2	0.280		0.091	0.044	0.076	0.096	0.833	0.101

Abbreviations for dependent variables are; IO: Seller's Initial Offer, PS: Probability of Sale, SC: Seller's Concession, BC: Buyer's Concession, DUR: Bargaining Duration, NR: Number of Rounds, FSP: Final Sale Price, SS: Seller Surplus. All columns except (PS) report OLS (resp. logit) regressions with standard errors clustered at the seller and buyer levels. Coefficients reported in Column 2 (PS) are marginal effects at the mean. Romano–Wolf multiple testing adjusted p-values are in parentheses. Significance levels: * 0.05, ** 0.01, *** 0.001.

For example:

1. Suppose you have told us that you would not sell at any price below 700 TL.
   We draw a random price from the bag, and it is 680 TL. What will happen in this case? Since you answered that you would not sell, the exchange of sheep does not take place. You will keep the sheep.
   We draw a random price from the bag, and it is 800 TL. What will happen in this case? Since you answered that you would sell at this price, we will purchase the sheep from you. How much will we pay? 800 TL, because that is the price that came out of the bag.
2. Suppose you have told us that you would not sell at any price below 550 TL.
   We draw a random price, and it is 620 TL. What will happen in this case? (Seller will answer).
   We draw a random price, and it is 530 TL. What will happen in this case? (Seller will answer).

Think well before you choose the price that you say "I will not sell below this price". It is not correct to think that keeping this price as high as possible is good. This is not a bargain. The price you name to us will not affect for how much you will be selling the sheep. For instance, suppose that you would in fact make a profit if you sell it to us at 550 TL. However, suppose you have told us that you would not sell below 600. If we draw a price of 570, you will not be selling the sheep. But you told us that you would not sell below 600. You will not sell if price comes to be 570, but you were in fact ready to sell at 550. In this case you will not have made a sale that you in fact would be willing to, for no reason. There is no turning back. That is, the most logical thing for you to do is to tell us the lowest price that you would really be willing to sell.
At the end of the day, we will be selecting one of the sellers in the market by a lottery, in front of everyone. Then, we will choose the price by another lottery in the way we have told you. If the seller has told us that they would sell us at that price, the sale will take place. If the seller told us that they would not sell the sheep at that price, the sale will not take place.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.joep.2024.102707.

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