Selling "Money" on eBay: A Field Study of Surplus Division *

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Abstract

We study the division of trade surplus in a natural field experiment on German eBay. Acting as a seller, we offer Amazon gift cards with face values of up to 500 Euro. A random selection of buyers, the subjects of our experiment, make price offers according to the rules of eBay. Using a novel decomposition method, we infer the trade surplus from the data and find that on average the buyers offer one quarter of the surplus to the seller. Additionally, we document: (i) insignificant effects of stake size; (ii) poor use of strategically relevant public information; and (iii) differences between East and West German subjects.

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JEL codes: *C72, C93, C57.*

1 Introduction

Bilateral trade is at the core of economics. Trade occurs if it generates some surplus, that is, if a buyer is willing to pay more than what a seller is willing to accept. When the buyer and the seller bargain about the price, they bargain about the division of trade surplus.

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Bargaining over the surplus division has been extensively studied in the literature, both empirically and theoretically. Theoretical studies of bargaining follow two approaches. The first is the *axiomatic* approach, which was put forth by John Nash (1950) and which looks at bargaining outcomes that satisfy a set of desirable axioms.[1] The second is the *strategic* approach, which focusses on equilibrium outcomes of bargaining games. The simplest game of bargaining, the Ultimatum Game, involves two players and a single take-it-or-leave-it offer from one player to the other (Güth et al., 1982).[2] In the unique subgame-perfect equilibrium of this game the proposer offers to himself the entire surplus and nothing to the responder. The responder accepts such offer. In a more complex game, players can exchange offers over several rounds, including the extreme case of an infinite-horizon bargaining game (Rubinstein, 1982). Shifting from a one-round bargaining game to an infinite-horizon model leads to a drastic increase in the first mover's offer to the second player (Selten, 1965).[3]

On the empirical side, several studies have tested the Ultimatum Game. The main surprising result is that most opening offers in the lab deviate from the above mentioned unique subgame-perfect equilibrium of the ultimatum game, where the first mover obtains the entire surplus. Instead, the proposed division of surplus observed in the lab is more consistent with both the outcome of an infinitely repeated bargaining game and the axiomatic solutions, where both parties get a positive share. Whether the specific bargaining protocol that is behind the Ultimatum Game plays any role in this result is still an open question. However, given the common critique of laboratory studies (see, e.g., Levitt and List, 2007), the more primary question is whether the non-trivial division of surplus observed in the lab also occurs in real life

[1]The central axiomatic notions are the Nash bargaining solution, the Kalai-Smorodinski solution and the Egalitarian solution (e.g., Thomson, 1994). When two parties bargain over money and their utilities are linear, all three solutions imply the same outcome: the equal division of surplus.

[2]The first mover (proposer) makes takes-it-or-leave offer to split a sum between him and the responder (the second mover). If the responder accepts this offer the split is implemented, otherwise both players' payoff is zero.

[3]See also Binmore et al. (2007) and references therein.

bargaining.

The goal of our paper is to study bargaining outcomes in a natural field setting. In particular, we are interested in the share of surplus that a proposer gives to a receiver during the first stage of a bargaining game that can have at most three rounds. Such bargaining over surplus division happens on a daily basis at the online trading platform of eBay. That is why, to conduct our experiment, we used the existing bargaining mechanism known as the "Buy-it-now or Best offer" selling format of eBay.de. Mimicking the typical eBay sellers of gift cards, we collect price offers for Amazon gift cards of different nominal values. In this format the seller initially fixes a starting price and buyers either buy the product at this starting price or make offers below it.[4] The buyers make their price offers to the seller privately: they cannot observe the offers of other buyers. The sellers are responders and can either accept the offer, reject it, make a counter-offer or not react at all, according to the platform's rules. If a buyer's offer is accepted, he receives the card from the seller and then he can credit the card's nominal value to his Amazon account to use it for purchasing anything available on Amazon. In our experiment, by choosing the face values of Amazon gift cards, we control the variable which is typically unobserved, namely, the buyer's valuation.

From the viewpoint of any buyer, trade surplus is the difference between his valuation and the seller's opportunity cost. The seller's opportunity cost is defined by the possibility to trade with other buyers or to use the card eventually on his own.[5] All those are unknown to the buyer and he forms an estimate of the seller's opportunity cost. When the buyer offers to the seller strictly more than his estimate of the seller's outside option, he offers a non-zero share of trade surplus.

If the buyers' subjective estimates of the seller's outside option were observable to us, solving for the share of surplus that each buyer offers to the seller would be

[4]This trading format should not to be confused with eBay's second-price ascending auction, where the seller set the starting price and bidders bid over a pre-defined by the seller period of time.

[5]Obviously, for the market of gift cards to exist, sellers' own valuation of the card must be less than the nominal value of the card.

a trivial task. However, the natural field setting precludes us from observing these estimates. As result, to identify the share of surplus that a given buyer offers to the seller we have to infer the buyer's belief about the seller's opportunity cost.

We develop a novel statistical method that allows to infer the subjects' beliefs from our data. In the model underlying our statistical analysis the beliefs can be any: we require neither a consistency with the public data, nor rational belief formation, nor a common prior. In fact, the heterogeneity of offers observed during the experiment is incompatible with any such restriction. We view an offer as a sum of two components: a reimbursement of the perceived seller's outside option and a proposed share of surplus. Clearly, it is not possible to estimate both parts of the offer at the level of *individual* observation. However, we can implement an *aggregate* decomposition program, i.e., infer the unobserved distributions of both components of the offer: the estimates of the seller's opportunity cost and the proposed surplus shares.

To decompose the observed distribution of normalized offers in two underlying unobserved distributions we must solve an integral equation with two unknown functions. This problem is infinite-dimensional and computationally hard. To obtain a feasible program, we reduce the dimensionality. In line with the standard approximation theory, we restrict the set of possible distributions to a family of finite polynomials. Our search for the fitting distribution starts with the uniform law as a candidate solution for both functions. We consecutively raise the polynomial degree until the optimal solution passes a pre-specified goodness-of-fit test.[6]

Our main decomposition findings are presented in Figure 5. The distribution of proposed shares of trade surplus is U-shaped with modes at 0 and 50%; the average proposed share is close to 24%. By the very nature of our estimation method, this distribution of shares is free from any effects of competition among buyers or any other origins of buyers' beliefs about the seller's outside option. Hence, it can

[6] To check the robustness of the main method's findings, we also apply two further estimation methods, including a non-parametric one.

be compared to the findings from experiments on a one-short bilateral bargaining model, such as the Ultimatum Game.

Our results imply that even in a large anonymous market like eBay, equal splitting of the trade surplus is quite common. Whether the equal split is due to social preferences, cultural norms, its salience, simplicity, or the axiomatic properties of the egalitarian solution, our results imply that it occurs not only in the lab, but also in the field. The average share offered in the field is at the bottom of the range of estimates obtained in the lab experiments of the Ultimatum Game (e.g., Oosterbeek et al., 2004). About 40% of all subjects behave in line with the maximization of individual monetary payoffs, offering no more than 10 % of the trade surplus.

Our estimation technique rests on three assumptions. First, the card is worth its nominal value to any buyer who makes a valid offer in the experiment. The money on the Amazon account, can indeed be split, stored, combined with other payment methods and used for purchasing goods from both Amazon and third-party sellers that operate on the platform. To an Amazon customer, since (almost) all goods can be purchased through Amazon, a voucher is almost as universal as money.[7] If, however, the cards are worth less than their nominal value to some buyers then our results imply that the sharing is even more generous than our estimates suggest. More precisely, the estimated distribution is first-order stochastically dominated by the true one. In that sense, we have obtained a lower bound on the sharing intentions (see also Section 5.1).

Second, we assume buyers' risk-neutrality. In the lab studies of bargaining, this assumption is standard. Moreover, our data suggests that the subjects are risk-neutral within the relevant range of payoffs. This is shown by contradiction. If the subjects were risk-averse in this range, we would have observed that the distribution of offers changed as we increased the stake. This, however, is not the case in our

[7] On the other hand, the gift cards are *not* worth their face value to those selling them, or generally non-customers of Amazon. EBay customer protection service is very efficient in Germany and it guarantees that the buyer gets all goods *as described*; seller fraud is therefore not a determinant of the card's value.

data (see Section 5.2).

The third assumption postulates that subjects' beliefs and sharing intentions are statistically independent. This follows from the conventional economic approach to rationality, which implies maximization of utility subject to one's beliefs. Fundamentally, utility formalizes preferences over allocations while the belief function reflects the knowledge about the game. We similarly regard sharing intentions as an expression of subjects' preferences while their beliefs are formed through their information and individual experiences of bargaining.

To complement the estimates obtained from the aggregate decomposition of offers we obtain a number of further interesting results from the regression analysis. First, as noted above, we find that the observed distributions of normalized offers[8] do not vary with the amount of money at stake. Second, we find that the observed buyer behaviour is insensitive to public information about the degree of competition, as well as to the public history of sellers' responses to price offers. Third, we use data on buyers' postal codes to classify the subjects in two regions, East and West Germany. While both groups of offers tend to cluster at 50% of the card's value, the "naïve equal split" is more prevalent among subjects in East Germany.[9] Thereby, West German subjects are more likely to make winning high offers, that is, to be consistent with the theoretical prediction of a model with multiple buyers competing for a unit of Amazon gift card.

The next section describes the experiment and its data. The decomposition strategy and its results are presented in Section 3; robustness checks are described in Appendix A.4. Section 4 reports on the regression analysis. Section 5 discusses the assumptions and the related literature. Section 6 concludes.

[8]A normalized offer is a price offer divided by the card's face value. For example, the value of a normalized offer that corresponds to 40 Euro for a 50-Euro gift card is 0.8.

[9]A 50% offer can be viewed as an equal split of trade surplus only under a "naïve" assumption that the seller's outside option is 0.

2 Experiment

2.1 Amazon Gift Cards

We set up a controlled environment within an existing secondary market for Amazon gift cards on the German site of eBay (www.ebay.de). Amazon gift cards are used primarily as presents.[10] Typically, the gift giver would go to the Amazon website, pay V Euro to get a sixteen-digit code, and transmit the code to the gift receiver. Subsequently, the receiver logs in to his Amazon account, enters the code and gets V Euro credited to his account. The account credit can be used for purchasing any goods offered on the Amazon website,[11] it can be split, combined with other payment methods and stored for up to three years.

If the gift card owner does not intend to use the code, he puts it up for sale in a secondary market. Upon purchase, the code is transmitted in a secure message. In Germany, reselling Amazon gift cards on eBay is very common. For instance, 87 gift cards were on sale at 7 p.m. on June 13, 2014, and 1962 sales in total were posted within 114 days prior to that date. Nominal values of gift cards ranged from 5 to 2500 Euro.[12] The quarterly market turnover is estimated at 70 000 Euro.[13]

2.2 The "Buy-it-now or Best Offer" format on Ebay

In the experiment, we employ the *Buy-it-Now or Best Offer* (BINBO) format of eBay, *Sofortverkauf oder Preisvorschlag* in German. The BINBO sales format is an alternative

[10]Other uses include: reward for participation in internet surveys, including lottery prices, payment for consumer-to-consumer online purchases, bonus to third-party promotions.

[11]The goods can be bought from Amazon.com, Inc. / Amazon EU S.a.r.l. as well as any other seller, private or institutional, that uses Amazon as platform.

[12]One may wonder that such expensive goods could be sold anonymously over the Internet. This is due, to a large extent, to efficient consumer protection services offered by eBay, as well as the importance of reputation, see Resnick et al. (2006). Note also that Germany ranks high on the level of trust between strangers, see Fukuyama (1995). On the relation between culture and e-commerce diffusion see Gibbs et al. (2003).

[13]Own estimate, based on Q4 2015.

to the better-known eBay auction, which is an English auction where the bidders openly compete with each other.

The rules of BINBO are as follows. Initially, the seller posts an ask price and invites the buyers to either pay the ask price or make their own price offer. When a buyer makes an offer, the seller has forty-eight hours (or less, if the listing expires earlier) to accept, reject, or make a counter-offer. When a price offer is accepted, the card is sold and the game ends. A listing becomes inactive if it expires or if the card is sold to a buyer. EBay users can browse the history of inactive listings.

The BINBO game is illustrated in Figure 1. The card value is normalized to 1. The buyer's offer is denoted b_i, where i refers to a buyer-seller pair. When b_i is below the ask price, the seller accepts or rejects; no reply is strategically equivalent to a rejection. If the seller accepts he gets b_i, if he rejects he saves the opportunity cost of trade c_i. The seller's cost of trade c_i is due to the opportunity to trade with other buyers and the card's usage value to the seller. The buyer gets $1 - b_i$ in case of acceptance and zero in case of rejection. If the buyer accepts the seller's ask price, b_i equals the ask price and the seller is contractually bound to accept and transfer the card code. When an offer b_i is accepted, the surplus $1 - c_i$ is effectively split between the buyer who gets $1 - b_i$ and the seller who "gets" $b_i - c_i$. Note that Figure 1 omits the possibility of counter-offers; their role is discussed in Section 5.4.

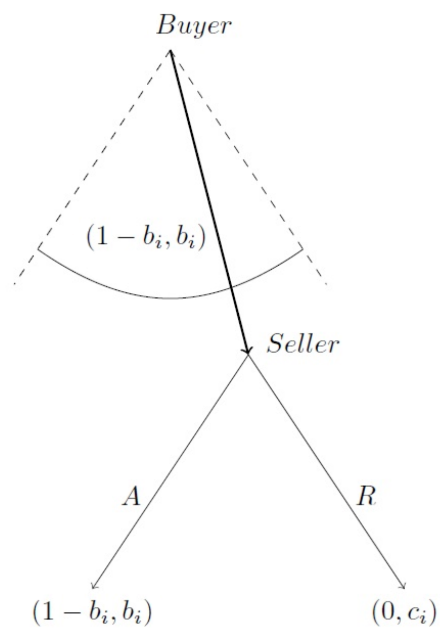


Figure 1: BINBO.

When an eBay user makes a price offer he becomes a subject of our study. The subject (buyer) observes the posted price and the following information. First, he can observe the total number of offers received by the seller: 0, 1, 2, etc., the timing and the status of each offer: pending, rejected, counter-offer received. Second, the buyer observes the number of minutes left before the listing expires, the seller's feedback score, and the other items the seller currently offers for sale. The buyers can also observe the history of previously offered items of this seller. The part of information about the seller's history that is most easy to access is the list of all feedback entries (positive, negative, neutral) that are left to the seller for the items that he has sold.

Importantly, only the seller can see how much money is being offered. The buyers can only observe how many, if at all, competitors are present.[14] Naturally, no-one observes the total number of competing buyers to arrive before the expiry of the listing, as part of that information pertains to the future.

2.3 Listings

We offered Amazon gift cards with a range of face values: 5, 10, 20, 50, 100, 200, and 500 Euro, i.e., in total seven treatments. In two waves of the experiment, March to July 2014 and March 2015, we posted over 200 listings. Each listing had a duration of three days, the lowest possible duration on eBay. Short duration has been chosen to approximate as closely as possible a one-short bargaining game. We used five different seller accounts with feedback scores ranging from no feedback and no tenure to 430 stars and 10 years tenure. The seller accounts were real eBay accounts with real feedback. Each seller account listed one or two gift cards at a time, and the nominal values of the gift cards rotated between seller accounts over the entire duration of the experiment.

We drafted the listings in a way that mimics the common practice of the gift card sales via the BINBO format. Relying on the history of similar posts, we used typical wording and set the initial ask prices above the nominal value of the gift card

[14]Similarly, in Camerer (2003) and Roth et al. (1991), the proposers do not observe their competitors' offers.

(it is standard for all sellers of the Amazon cards to post them on Ebay at 120% of the card's face value).[15] On top of replicating the common practice, the excessive ask price allowed us to limit the number of actually executed transactions: rational buyers should not accept to pay more than the card's nominal value. To our surprise, the excessive ask price was accepted on a few occasions.[16] As those bids are hard to interpret in a sure manner, in this paper, we concentrate on offers that do not imply a loss for the buyer. Finally, to unify the sellers' response to offers, we let all offers to expire without any our response.[17]

2.4 An Illustration

As an illustration, consider one round of the experiment. We list a gift card with the nominal value of 100 Euro on June 1 at 1:08 p.m. We receive the first offer of 90 Euro from the buyer having the user name *"lu..er"* and who has 6 eBay feedbacks as of June 3 10:16 a.m. and the second offer of 80 Euro from the buyer *"xx...30"* with 60 feedbacks at 1:23 p.m.

At the moment *"lu..er"* placed his offer, he could observe that there were no offers outstanding (and 'lu..er" was aware as well that he has no competitors so far). In contrast, the second buyer *"xx...30"* was able to see that he was facing competition from one other buyer.

We let both offers expire on June 4 at 1:08 p.m. This generated two observations. The data collected per observation include the offered amount, the exact timing and order of the offer, the buyer characteristics (eBay alias, feedback score and registered postal code), as well as the seller's information and the exact time the listing was posted. We also keep track of the announcements that did not receive any offers.

[15] E.g., we set the ask price of a 100 Euro gift card equal to 119 Euro.

[16] Malmendier and Lee (2011) offers a plausible explanation of overbidding.

[17] The text of the announcement and the video illustration URL are given in Appendix A.1.

2.5 Data

72 percent of the listings receive at least one offer within the three-day period. The number of offers per listing ranges from 0 to 15, with 1.6 offers made on average. One offer per listing is both the median and the most frequent number of offers, and corresponds to the situation of bilateral trade.

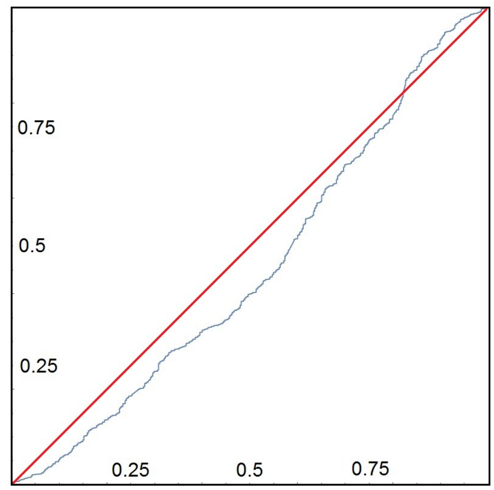


Figure 2: Cumulative distribution functions of the observed (blue), and uniform (red) arrival times, normalized to one.

The subjects come from across the country, 15 percent of the offers originate in East Germany (former German Democratic Republic).[18] The most experienced buyer in the sample was registered on eBay 16 years prior to our experiment. On average, buyers had 8.5 years of eBay experience.

The distribution of the arrival times of price offers within the duration of sale is plotted in Figure 2. The diagonal corresponds to the uniform distribution. The times are normalized to one according to the formula $\frac{t_{\text{offer}} - t_{\text{listing}}}{3 \times 24 \times 60}$, where t is expressed in minutes. Contrary to the case of eBay's ascending auction, where the bidding frequencies spike at the end of sale (see, e.g., Roth and Ockenfels, 2002), we do not observe any such patterns in the arrival rates in the BINBO format we use in the experiment. Indeed there is no benefit to a strategic delay of entry in BINBO.

The offers in our sample range from 1 Euro, the lowest admissible offer on eBay, to the entire nominal value of the gift card. To make the data comparable across treatments, we normalize the offers by dividing each offer by the nominal value of the gift card. The pooled data display clustering: the normalized offers concentrate

[18] Five offers from Austria were not included in either East- or West-German group.

Voucher Value	All	5 €	10 €	20 €	50 €	100 €	200 €	500 €
No. of Listings	221	46	25	19	22	36	43	30
No. of Offers	358	42	45	38	57	60	74	43
Average Bid	0.73	0.71	0.77	0.73	0.77	0.70	0.72	0.71
Std. Err.	0.04	0.11	0.11	0.12	0.10	0.09	0.08	0.11
Std. Dev.	0.23	0.23	0.18	0.17	0.17	0.27	0.23	0.29
Median	0.80	0.80	0.80	0.75	0.80	0.80	0.79	0.82

Table 1: Descriptive statistics of normalized offers $b_i = B_i / V_i$, "Offer / Nominal Value".

around 0, 50, 80, and 90 percent of the gift card value (see Figure 4).

The descriptive statistics, broken down with respect to nominal value treatments, are reported in Table 1. Overall, the distribution of offers is right-skewed: every second offer exceeds 80 percent of the nominal value. The average offer in our sample ranges from 71 to 77 percent of the nominal value and does not display monotonicity with respect to the gift card's nominal value. The same is true of median values that range from 75 to 82 percent of the nominal value.

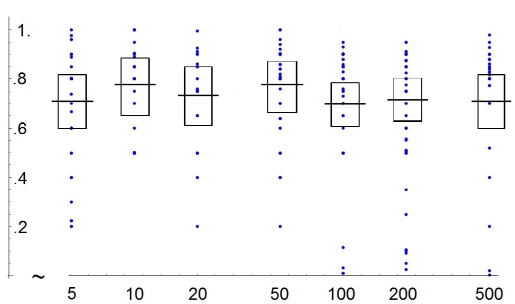


Figure 3: Gift card nominal values along the horizontal axis in log scale. Normalized offers, mean, standard error band along the vertical axis.

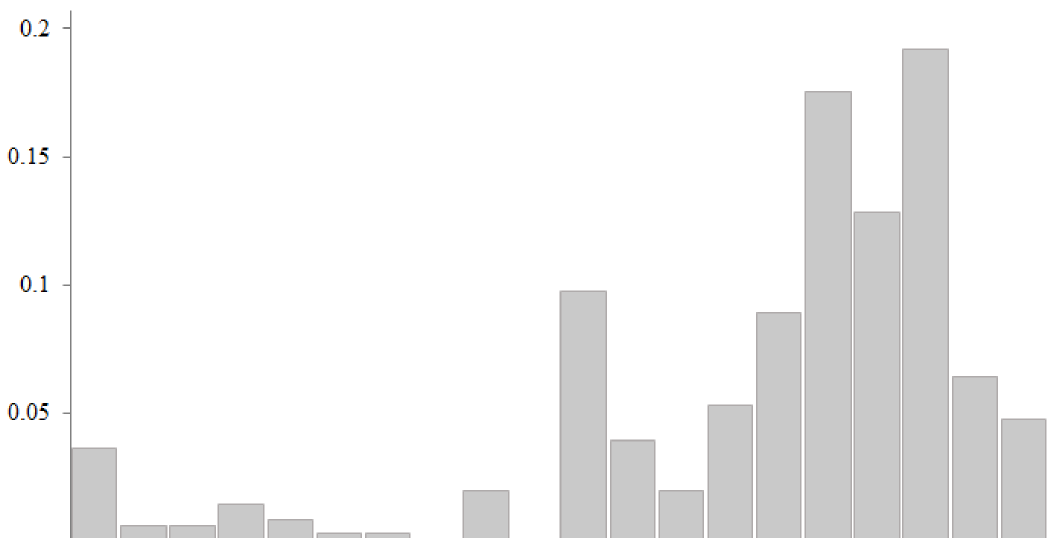
Figure 3 presents the data, where the logarithm of the nominal card value is plotted against the horizontal axis and the normalized offer is the dependent variable on the vertical axis. We use the one-way ANOVA to test whether the empirical averages vary across the nominal value treatments. We find the null hypothesis of equal means is not rejected,[19] implying the normalized offers' invariance in scale. Pairwise linear and log-linear regressions yield a similar finding: the nominal value does not have a statistically significant effect on the normalized price offers (see Table 4). Overall, our analysis indicates that stake size does not affect the normalized offers in the

[19] ANOVA *P-value* $= 0.50$.

population of eBay buyers. Similar findings were obtained in the lab settings by Cameron (1999), Munier and Zaharia (2002), Hoffman et al. (1996), Slonim and Roth (1998).[20]

3 Decomposition of Offers

In this section we study the sharing intentions behind the subjects' offers in the experiment. Figure 4 is a histogram that presents the data pooled across value treatments.



b_i	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95
$h(b_i)$	0.04	0.01	0.01	0.01	0.01	0	0	0	0.02	0	0.1	0.04	0.02	0.05	0.09	0.18	0.13	0.19	0.06	0.05

Figure 4: Empirical frequency $h(b_i)$ of normalized offers $b_i = B_i/V_i$. The relative offers b_i are grouped into five-percent bins and plotted against the horizontal axis. The bins include the upper bound of the interval, for instance, the last bin corresponds to $b_i \in (0.95, 1]$.

The experimental data displays substantial heterogeneity and irregular clustering: in particular, we observe clusters at around 0, 50 and between 80-90 percent of

[20] A meta-study by Oosterbeek et al. (2004) documents a small negative effect of increasing stake size. Slonim and Roth (1998) and Roth and Erev (1995) find a positive effect when the game is played in the first round or only played once.

the card's nominal value.[21] We make some preliminary observations by inspecting the data. Firstly, making near-zero offers is only worthwhile if the subject believes that the seller's outside option (cost) was zero. Under the same belief, an offer of 50%, where we observe a spike in frequency, would correspond to an equal splitting of surplus. In reality the seller's cost of trade is different from zero; this appears to be the belief of the majority, but not all of the subjects.

The comparison of the observed eBay offers to the results of Roth et al. (1991) is key to understanding our approach to data analysis. Roth et al. (1991) conduct parallel laboratory experiments in a bilateral (ultimatum game) and competitive settings, and observe subjects interacting repeatedly over ten rounds. In the competitive setting, nine or seven buyers simultaneously make offers to the seller, which is similar to our setting with the exception that the number of players is known. The paper reports the distribution of offers across all rounds in the bilateral setting (there is no need to distinguish between the rounds since behaviour does not change significantly) and the distribution of offers in the competitive setting in the first and in the final, tenth round. While the play in the bilateral case is persistent and incompatible with the subgame-perfect equilibrium, the competitive case displays fast convergence to the equilibrium prediction. Juxtaposing their experimental results with ours suggests that the eBay subjects do not perceive the game in the same way. Part of the subjects appear to play a bilateral game while the other part behaves competitively. Moreover, the competitive fraction's behaviour resembles that of the first rounds of competitive play Roth et al. (1991).

Fundamentally, our field experiment features the setting where the degree of competition is uncertain, the total number of competitors is not known in advance and their offers are not observed publicly. Hence, it is not surprising that the resulting behaviour differs from the case where the number of players is fixed and commonly known, as it happens in Roth et al. (1991) and Bolton and Ockenfels (2014).

[21] Bolton and Ockenfels (2014) also observe the spike at 50 percent in a framed eBay experiment and point out that it is consistent with subjects' social preferences.

Therefore, the observed stark heterogeneity of eBay offers is due to not only to the subjects' sharing intentions, but also to their perceptions of the game, or the "aggregate uncertainty". Our goal is to disentangle the effects of both sources of heterogeneity. Thereby we remain intentionally agnostic as to what the buyers believe to be their competition. In other words, we do not impose any structure on the subjects' beliefs about the game and hence the seller's outside option. The beliefs are inferred from the data through the decomposition of offers.

3.1 The Decomposition Problem

The aggregate decomposition is a novel method of statistical inference. The underlying model allows for heterogeneity across two dimensions: the perceptions of the seller's outside option (seller's cost) and the sharing motives. The perception of the seller's cost c is subject to uncertainty of the number of competing bids and of their sizes, as well as the seller's own usage value of the card, if any. In our model, the buyer's perceptions of c are captured by a distribution function $\Phi_i(c)$ that we refer to as the buyer i's belief over c.[22] The buyers' beliefs are thus the *first source* of offers heterogeneity.

The second source of the observed subject heterogeneity is the sharing motive, or the fraction of surplus that a subject offers in excess of the seller's cost. Consider first a *fixed* seller cost c. The surplus from trade is given by $1 - c$, the difference between the buyer's value and the seller's cost. In the game of bargaining over the surplus $1 - c$ the buyer's price offer implies how the surplus is split. Buyer i's price offer b_i leaves the seller with a share s_i of surplus: $s_i = \frac{b_i - c}{1-c}$, where c is the seller's true cost. For a fixed c, the price offer $b_i(c)$ is therefore given by

$$b_i(c) = c + s_i(1-c). \tag{1}$$

[22]Formally, $c = \max\{u_s, \max\{b_j : j \in J\}\}$ where u_s is the seller's own usage value, and J is the set of competitors, b_j is the bid of competitor j.

However, since c is uncertain, the offer is given by

$$\begin{aligned} b_i &= \int b_i(c) d\Phi_i(c) = \int \left[c + s_i (1 - c)\right] d\Phi_i(c) \\ &= c_i + s_i (1 - c_i), \end{aligned} \tag{2}$$

where $c_i \equiv \int c d\Phi_i(c)$. The observed offer b_i is a solution to the bargaining problem, given buyer i's *subjective* expectation over the seller's cost c. Note that (2) implies that the first moment c_i of $\Phi_i(c)$ is sufficient information to calculate the buyer's offer when s_i is known.

Equation (2) summarizes two sources of variation in offers that we observe. First, the subjects vary in the normalized shares s_i they are willing to offer to the seller. Second, they differ in their expectations c_i of the seller's opportunity cost c. To understand the prevalence of sharing rules in the data, we have to extract s_i from the observed normalized offers b_i.

Clearly c_i and s_i cannot be identified from an observed offer b_i. Since the observed offer is a function of two unknowns, decomposing b_i is not feasible at the level of individual observations. However, one can implement an *aggregate* decomposition of the observed distribution of normalized offers into a distribution of shares s_i and a distribution of the first moments of the belief functions c_i. The aggregate decomposition implies splitting of the observed distribution of offers into a distribution of shares s_i and a distribution of subjective expectations (first moments of the belief functions) c_i. We drop the subscript i in what follows.

To formally specify the decomposition problem, we let $f(s)$ and $g(c)$ denote, respectively, the unobserved distributions of the shares s and of the cost expectations (belief first moments) c. Let $h(b)$ be the observed distribution of offers. Capitals F, G, and H denote the corresponding cumulative distribution functions. For simplicity we think of all three distributions as having continuous supports. We assume that the $supp(g) = [0,1], supp(f) = [0,0.5]$, where the 0.5 bound follows from the standard other-regarding preference theories.[23] Note that "selfish" offers (maximizing individual payoffs given subjective beliefs) correspond to $s_i = 0$ for all i and are therefore allowed in this specification.

Assuming that offered shares and expectations of the seller's outside option are distributed independently in the population, the distributions are related through the following equations:

$$\begin{aligned} H(b) &= \Pr(c + s(1-c) < b) = \Pr\left(c < b, s < \frac{b-c}{1-c}\right) \\ &= \int_0^b \left[\int_0^{\frac{b-c}{1-c}} f(s)\,ds\right] g(c)\,dc = \int_0^b F\left(\frac{b-c}{1-c}\right) g(c)\,dc. \end{aligned} \tag{3}$$

The cumulative distribution function H on the left-hand side is given by the observations in our experiment. The right-hand side integrates over all c and s that generate an offer less or equal to b, according to (2). The essence of the decomposition problem is to find $f(s)$ and $g(c)$ that best fit equation (3) given $H(b)$ constructed from the experimental data.

3.2 Computational Issues and Uniqueness

Decomposing the observed distribution of normalized offers into two underlying unobserved distributions is equivalent to solving an integral equation with two unknown functions. As $f(.)$ and $g(.)$ belong to infinite-dimensional spaces, the decomposition problem (3) is infinite-dimensional and, therefore, computationally hard. Finding a solution calls for a reduction in the problem's dimensionality to a point where optimization becomes computationally feasible. What complicates the analysis further is that while the solution to (3) exists it may not be unique unless the space of functions $f(.)$ and $g(.)$ is restricted.[24]

[23] See, e.g., Fehr and Schmidt (1999) [Proposition 1], Ockenfels and Bolton (2000) [Statement 3].

[24] There always exists a trivial corner solution, where $h \equiv g$ and f is a Dirac delta function with the entire probability mass concentrated at zero. Sadovnichy (1986) shows that, for a given kernel

Our approach to solving the decomposition problem (3) addresses both the dimensionality reduction and the uniqueness issue. The baseline program is reported in the next section 3.3. It relies on the standard approximation theory and searches for a solution in the space of polynomials. Additionally, we present alternative solution methods in the appendix. Appendix A.4.1 reports on a non-parametric solution where the dimensionality is reduced by discretizing the supports of f and g. In the Appendix A.4.2 we restrict f and g to the class of beta functions, which permits a global search for four parameter estimates (two for each distribution).

3.3 Polynomial Approximation

Our baseline program achieves the reduction of dimensionality by restricting the solution to a set of continuous functions, namely, to a space of parametric functions. Following the standard approximation theory, the space of finite polynomials is the best choice within a parametric class.[25] Hence, our goal is to identify a polynomial approximation of H (3). Consequently, we treat both f and g as linear combinations of Chebyshev polynomials:

$$f_n(s;\gamma) = \sum_{k=0}^{n} \gamma_k T_k(s), \quad 0 \leq s \leq 0.5, \tag{4}$$

$$g_m(c;\delta) = \sum_{i=0}^{m} \delta_k T_k(c), \quad 0 \leq c \leq 1, \tag{5}$$

where $T_k(x)$ is a k-degree Chebyshev polynomial of the first kind.

The iterative procedure starts at $n = m = 0$. That is, the initial candidate solution is a pair of zero-degree polynomials, corresponding to two uniform distributions.

function $F(b,c)$, a Volterra integral equation such as (3) is a contraction mapping and hence has a unique solution g^*. Since both f and g are restricted to the class of probability measures, Sadovnichy's result does *not* imply that one can generate multiple solutions by simply varying the kernel function.

[25]By the Stone-Weierstrass theorem, the subset of polynomials is dense in $\mathcal{C}[a,b]$ which means that any continuous function on a bounded interval can be approximated arbitrarily well by a sufficiently large degree polynomial.

Subsequently, we start to raise the polynomial degree of each function separately. At each iteration we search for the vector of parameters (γ,δ) that minimizes the Kolmogorov-Smirnov distance between $\hat{H}(.)$ and $H(.)$

$$(\gamma_n^*,\delta_m^*) = \underset{(\gamma,\delta)}{\arg\min}\, d_{KS}\left(\hat{H}(\cdot;\gamma,\delta),H(\cdot)\right) \tag{6}$$

subject to $\int_{-\infty}^{0} f_n(s;\gamma)\,ds = 0,\quad \int_{0.5}^{+\infty} f_n(s;\gamma) = 0,\quad f_n(s;\gamma) \geq 0;$ and $\int_{-\infty}^{0} g_n(c;\delta)\,dc = 0,\quad \int_{1}^{+\infty} g_n(c;\delta)\,dc = 0,\quad g_n(c;\delta) \geq 0$. The Kolmogorov-Smirnov distance is defined by

$$d_{KS}\left(\hat{H}(\cdot),H(\cdot)\right) = \sup_{b\in[0,1]}\left|\hat{H}(b) - H(b)\right|, \tag{7}$$

where $\hat{H}(.)$ is the following composition of f_n and g_m

$$\hat{H}(b;\gamma,\delta) = \int_0^b \int_0^{\frac{b-c}{1-c}} f_n(s;\gamma)\, g_m(c;\delta)\, ds dc. \tag{8}$$

Once we find the best approximations $(f_n(\cdot;\gamma_n^*),g_m(\cdot;\delta_m^*))$ for fixed polynomial degrees n and m, we compute the respective composition $\hat{H}(\cdot;\gamma_n^*,\delta_n^*)$, and compare it to the observed cumulative distribution $H(\cdot)$. We dismiss the solution if the respective Kolmogorov-Smirnov distance between $\hat{H}(\cdot;\gamma,\delta)$ and $H(\cdot)$ exceeds the bootstrapped critical value and proceed to the next iteration allowing for an extra polynomial term.[26] If the solution passes the test, it is accepted and the iterative procedure stops. The rationale behind the iterative procedure is to obtain a solution that is compatible with the observed data on the one hand and avoids overfitting on the other.

Applying the iterative procedure to the experimental dataset we find the solution $f(\cdot;\gamma_3^*)$, $g(\cdot;\delta_4^*)$ reported in Table 2 and plotted in Figure 5.[27] The corresponding

[26]Bootstrap critical values corresponding to 358 observations are 0.049 for significance at 10%, 0.057 for significance at 5%, and 0.071 for significance at 1%.

[27]We used Mathematica's differential evolution fitting method, allowing for 500 iterations at each round of search. The advantage of the differential evolution method is that it is consistent at finding the global solution. The search procedure requires that a continuous version of H is generated. To

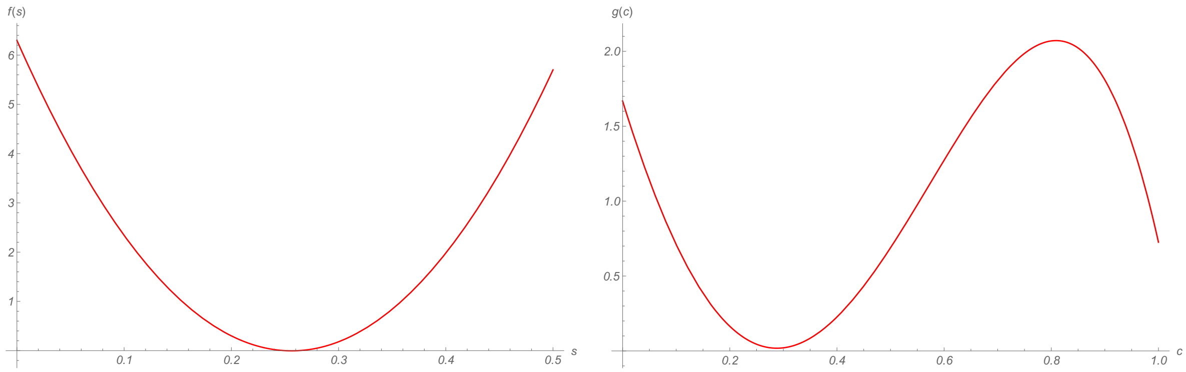


Figure 5: Estimated densities $f(s;\gamma_3^*)$ (left) and $g(c;\delta_4^*)$ (right)

Chebyshev coefficient estimates are given in the Appendix, Table 10. The solution is achieved at $n = 3$, $m = 4$; other distance-minimizing solutions achieved with the same total number of parameters do not pass the test. We conclude that $f(\cdot;\gamma_3^*)$, $g(\cdot;\delta_4^*)$ is the uniquely optimal polynomial approximation.

3.4 Results of Polynomial Decomposition

The estimate of the distribution of sharing rules f implies that 36.8% of the subjects offer 40 to 50% of the trade surplus to the seller. About 41% of all our subjects make "greedy" offers and propose no more than 10 % of the trade surplus to the seller. The remaining subjects make offers between 10 and 40%. The average offer to the seller amounts to 23.8% of the respective trade surplus.

s:	0-10%	10-20%	20-30%	30-40%	40-50%
$\hat{f}^p(s)$:	41.6	11.6	0.8	9.2	36.8

c:	0-10%	10-50%	50-60%	60-70%	70-80%	80-90%	90-100%
$\hat{g}^p(c)$:	11.5	10	9.7	15.5	19.7	19.9	13.4

Table 2: Estimated distributions of sharing rules $\hat{f}^p(s)$ and cost expectations $\hat{g}^p(c)$ in the population of eBay buyers (in percentage points). $d_{KS} = 0.03561$.

that end, we derive a non-parametric kernel density function from the data, setting the Gaussian bandwidth.

The estimated $g(.)$ implies that two belief types prevail in the population of bidders. There is a fraction of "naïve" subjects, who make their offers under the assumption that the seller's outside option is null. The first moments of the beliefs of the remaining "sophisticated" majority of the subjects are described by a bell curve centered nearly the observed average offer of 75%. This suggests a certain "crowd wisdom" manifests itself in the eBay market of Amazon gift cards – the expectations of seller's cost are correct, on average, in the "sophisticated" group of subjects, even though there is noise around the value.

4 Regression Analysis

By design of the experiment, we know exactly what information was available to any given buyer at the time he made the offer, as well as the buyer's geographic location and eBay experience. We perform simple regression analysis to investigate whether the normalized offers b_i, before decomposition, can be explained by these observable characteristics. The answer is largely negative, as documented in the next four subsections. All regression results are reported in Appendix A.2.1.

4.1 Competition Marks

We start by looking at the effects of information about the number of competitors for a gift card. In BINBO, the buyers observe two signals informative of competition intensity. The first signal is the amount of time remaining before the listing expires: the more time is left, the more buyers are expected to arrive by the end of sale, and the higher is the degree of competition. The second signal is the number of offers already outstanding by the time a given buyer makes his offer; naturally this signal conveys the information in a more direct way. Both indicators are displayed next to the ask price and barely involve any search effort (see the screen-cast URL p. 32). Both indicators should make buyers update their beliefs about the seller's outside option. This, in turn, should have an effect on the buyers' normalized offers. However the regression results demonstrate that both signals have insignificant effects on the subjects' normalized offers (see Table 4 in the Appendix).

We take a further step to verify whether the simplest binary indicator of competition produces an effect. Specifically, we split the offers in two groups: those arriving *first* on a listing and those arriving when at least one other has been already made. The respective empirical distributions are presented in Figure 7 in the Appendix. Again, we find no significant difference in both groups' mean offers.[28]

Beside the obvious explanation that any updating, however simple, is inhibited by cognitive costs, we offer two alternative reasons why the competition marks fail to produce any significant effects in the experiment. First, the subjects may use a rule of thumb when making offers, drawing on their past experience of gift card sales. Such approach is aimed at a longer-term market performance and substantiated by a large bulk of psychological literature, e.g., Tversky and Kahneman (1974), Newell et al. (1972), Gigerenzer (2007). Second, the buyers may (rationally) expect that if the gift cards remain unsold by the deadline they go on sale again in the future. Therefore, the expected stream of future offers may outweigh any present competition, making the latter effect statistically insignificant.

This result justify the "agnostic" decomposition approach to understanding the heterogeneity of offers.

4.2 Subjects' Learning

Next, we test whether the normalized offers change over the course of our experiment, which may occur due to subjects learning about the environment. The subjects get information about the seller's response strategy from two sources. First, the history of sales was available through eBay's search engine at the time we conducted

[28] ANOVA *P-value* $= 0.13$.

the experiment. For all five accounts used in the experiment, browsing the history of the account revealed that a number of gift cards were listed exclusively in BINBO format and remained unsold.[29] While this information could have stopped some buyers from making an offer, the regression analysis suggests that the *size* of normalized offers was unaffected by history (see Tables 5 and 6 in the Appendix). To proxy the opportunity of learning from history, we use calendar time: subjects participating at the start of the experiment have less evidence on our response behaviour than those arriving toward the end of the experiment. The insignificance of the respective coefficient implies that the subjects did not browse sale histories or did not take the information into account.

Second, buyers can learn from their own experiences of making an offer to a particular seller. To study the possible effect, we look at the sub-sample of the recurrent buyers. In total, 56 out of 277 buyers in our experiment made offers on multiple listings. We track how those buyers' offers change over time. Specifically, we calculate the increment of each subsequent offer relative to the previous offer that buyer made. This variable captures the subject's learning dynamics due to his or her experience with one of the seller accounts we use. Student's test finds no statistically significant change in offers between two consecutive rounds of a subject's participation.[30]

4.3 Effects of Experience

Buyers' eBay experience, proxied by their feedback score, has a mild positive effect on normalized offer sizes (significance at 10%; see Tables 5, 6, 7 and 8 in the Appendix).[31] Even if the effect is statistically non-zero, its size is extremely small. For instance, a completely inexperienced buyer offers 1 percentage point less than an average buyer with 450 feedback entries. Recall that in Roth et al. (1991) competition

[29] Apart from a few cases when we received offers to pay the posted price that exceeds the card's value.

[30] *P-value* $= 0.32$.

[31] Note this is an imperfect measure of experience, due to the voluntary nature of ratings. In particular, sellers' incentives to leave feedback are limited, since they can only leave positive feedback.

among bidders increases from one round to the next as the game is repeated. The effect we observe could hence be a consequence of the fact that inexperienced buyers underestimate the degree of competition.

A similarly sized effect, also statistically significant, is produced by the increase of the seller's feedback score. However, while the effect of buyer experience is linear, the marginal effect of the seller's experience decreases. Specifically, the effect on the normalized offer of extra feedback that the seller receives decreases drastically after just 12 feedback entries.[32] Here, we may be observing the buyers' self-enforcing belief that more experienced sellers receive more, or higher, offers. The positive effect of seller's experience on BINBO prices is also documented in Backus et al. (2018).

The effects of buyer and seller experience do not display complementarity, i.e., there is no evidence that more experienced buyers make significantly higher or lower offers to more experienced sellers.

4.4 East and West Germany

Using data about buyers' registered postal codes, we identify the impact of each subject's location on the size of the offer. Our sample contains about 15% of offers originating from the former GDR territory.[33] Our main observation here is that when subjects are grouped by region, there are important differences in the distribution of offers between East and West Germany. In the latter group, we observe a larger number of offers that are close to the competitive prediction – near 95 percent of the gift card value. By contrast, the buyers from East Germany make more offers in a close neighbourhood of 50 percent of the total value. (See Fig. 6 in the Appendix).

[32]There is a statistically significant effect of seller experience when we use the feedback score from 5 accounts jointly (*P-value* is equal to 1.9×10^{-4}). Splitting the sample into two groups, for sellers with zero feedback and at least 12 feedback entries results in *P-value* of 0.79 and 0.68, respectively.

[33]Postal codes are only indicative of current residency, not the subject's origin.

Can this variety in offers be attributed to the remaining cultural differences between East and West Germany? From the previous analysis we know that a buyer's experience affects the average size of his offer to the seller: more experienced buyers tend to make slightly higher offers. Since West German buyers in our sample have more experience with eBay, the regional difference we observe may be due to the difference in experience. In order to correct for the possible bias, we extract a subsample of buyers from West Germany that has the same the distribution of feedback scores as the East German sample. After the correction, the distributions of normalized offers remain virtually unchanged and the same difference patterns emerge. The equal split of the "naïve surplus" is a significantly more important focal point for East German subjects, while the competitive offers are more common among the West German subjects.

The differences documented here are supported by some of the previous literature. In a large scale empirical study Alesina and Fuchs-Schuendeln (2005) found that East Germans displayed higher preference for equality and redistribution – something that could reinforce the prevalence of equal splits. In two waves of a public good experiment, Ockenfels and Weimann (1999) and Brosig-Koch et al. (2011) find important differences in East and West German behaviour, which persisted two decades past the reunification. Focusing on children and adolescents aged 10 to 18, John and Thomsen (2013) find more support for other-regarding preferences in East than in West Germany.

5 Discussion

5.1 Subjects' valuations

Suppose that the subjects do not always value the cards at their full nominal value. In that case the distribution of bids is given by:

$$H(b) = \int_0^b \left[\int_b^1 F\left(\frac{b-c}{v-c}\right) dW(v|v>b) \right] g(c)\, dc, \tag{9}$$

where $dW(v|v>b)$ is the conditional distribution of the subject's true valuation v. The valuation of a rational subject cannot be lower than his bid b, but it cannot exceed 1 since the gift card can be bought at price 1 on the Amazon website. Comparing the original problem with (9) we observe that our reported estimate $\hat{F}$ is in this case is equivalent to the expectation of F over the values v:

$$\hat{F}\left(\frac{b-c}{1-c}\right) \equiv \int_b^1 F\left(\frac{b-c}{v-c}\right) dW(v|v>b). \tag{10}$$

Since function F is a c.d.f. and increasing, we obtain the inequality:

$$\begin{aligned} \hat{F}\left(\frac{b-c}{1-c}\right) &= \int_b^1 F\left(\frac{b-c}{v-c}\right) dW(v|v>b) \\ &\geq \int_b^1 F\left(\frac{b-c}{1-c}\right) dW(v|v>b) = F\left(\frac{b-c}{1-c}\right). \end{aligned} \tag{11}$$

Inequality (11) implies that our estimate $\hat{F}$ is first-order stochastically dominated by F. Therefore, if the subjects' valuations are less that the card's value then our estimate of sharing rules provides a lower bound on the actual sharing.

5.2 Risk-neutrality assumption

We have assumed that the buyers are risk-neutral. This assumption is supported by our own data from the various nominal value treatments. It is also confirmed by the existent literature. In particular, given the empirical evidence for an increased risk aversion at higher monetary stakes (see, e.g., Holt and Laury (2002) and references therein), if buyers were risk-averse we would observe a trend in relative offers as nominal values change from 5 to 500 Euro.[34] The regression results do not support this hypothesis (see Tables 4-9 in Appendix). Similarly, Fehr-Duda et al. (2010) demonstrate that the risk aversion is not identifiable in the data when the stakes are comparable to ours.

5.3 Competition with other sellers

As sellers of gift cards, we face competition from other sellers present on eBay throughout the entire duration of the experiment. However, such competition is irrelevant for our analysis, since a gift card bought at a discount gives to an Amazon customer an equivalent amount of Amazon cash. As long as preferences for Amazon cash are insatiable, at least locally, the demand for transaction does not depend on the presence of other sellers offering similar cards.

5.4 The first stage of a multi-stage bargaining game

Figure 1 does not reflect the possibility of the seller's counteroffer as a third possible action. If the seller makes a counter-offer we are back to the top node where the buyer moves and the game is repeated once (and only once) again.[35] The game

[34]In 2014, the median disposable net income per capita in Germany amounted to 1644 Euro per month (European Commission data: `http://ec.europa.eu/eurostat/web/gdp-and-beyond/quality-of-life/median-income`)

[35]EBay rules allow at most three exchanges of offers between a buyer and a seller. In practice, the sellers barely ever respond with a counter-offer, thus the buyers should rationally expect to have only one chance to call a price.

depicted in Figure 1 would be repeated at once again and then terminate.

Our data do not support the hypothesis that subjects intend to play a multi-stage game. If this intention were present, then (*i*) offers would arrive on the first day of the listing (as the buyers would expect that they are starting a dialogue with the seller), and (*ii*) low offers would be made more frequently than higher offers within the first hours. Figure 2 in Section 2.5 suggests that there is no systematic difference in the timing of arrival across 3 days of listing, therefore (*i*) does not hold. Table 4, and more generally the results reported in Section 4.1, imply that (*ii*) is not true either.

Furthermore, even if our analysis failed to capture the fact that the subjects are actually expecting to reach the stage where the seller makes a counter-offer, it is the subjects' first offers that are the most indicative of their true sharing intentions, i.e., the minimum surplus that they would like to give to the seller.

5.5 Related Literature

According to Card et al. (2011), laboratory experiments constitute about three quarters of all experimental economics. Following the agenda of Levitt and List (2009), List (2011), and Galizzi and Navarro Martinez (2015) who emphasize the importance of the field experiments, we study surplus sharing in the field and obtain estimates that can be compared with laboratory findings. In the lab, our setup is closest to the Ultimatum Game, which has been studied extensively – see, for example, Güth and Kocher (2013), van Damme et al. (2014), as well as Camerer (2003) and Bearden (2001). Comparing our findings, we conclude that subjects tend to be less generous in the field than in the lab. Similarly, in the case of gift exchanges, List (2006) finds less evidence for social preferences in the field as compared to the lab in otherwise equivalent settings.

The prominence of the equal splitting of trade surplus that we document can be explained by a theory of social preferences. One strand of this literature includes consequentialist theories, where agents have preferences over the distribution of final payoffs: Fehr and Schmidt (1999) and Ockenfels and Bolton (2000). An opposing view is that subjects' behaviour is motivated by reciprocity in response to actions and intentions of opponents, for instance: Rabin (1993), Falk and Fischbacher (2006), Dufwenberg and Kirchsteiger (2004), Charness and Rabin (2002). Taking a dynamic approach, Alger and Weibull (2013) rationalize social preferences as a stable evolutionary outcome. Alternatively, the egalitarian division of surplus is central to the theories of Boehm et al. (1993) and Henrich et al. (2006).

By the nature of data it studies, our paper contributes to the growing economic literature on eBay users' behaviour. This literature focuses predominantly on the effects of users' reputation on transaction prices (e.g., Resnick et al. (2006), Cabral and Hortascu (2010), Nosko and Tadelis (2015)) or the benefits from gaming the mechanism, such as snipe bidding (e.g., Roth and Ockenfels (2002), Ely and Hossain (2009)). Notable exceptions are Bolton and Ockenfels (2014) and Backus et al. (2018), who also use eBay to study bargaining. Bolton and Ockenfels (2014) design a framed experiment matching student subjects through the eBay platform. Backus et al. (2018) study the bargaining process using a large dataset with real eBay interactions. Our approach combines elements of both. We differ from the former in conducting a natural field experiment. We differ from the latter in focusing specifically on Amazon gift cards, which allows us to control the buyers' valuations. Most importantly, we develop a novel decomposition technique that permits us to document the sharing of surplus in the field.

6 Conclusion

In this paper we present a natural field experiment on the amount of surplus offered by the proposer during the first stage of a three-round bargaining game. The main goal of our experiment is to document the distribution of surplus sharing rules prevalent in an online market place like eBay. We have established that the equal split of surplus is less prevalent in the field than in the lab. Yet, the prevalence of equal splitting allows us to conclude that surplus sharing is an important price determinant in the field.

The key feature of our setup that makes it distinct from a typical lab experiment of the Ultimatum Game is the uncertainty of the buyer about the overall number of competitors.[36] Arguably, this feature is inherent to many real world markets. As a result, compared to the settings with a publicly-observed degree of competition, we do not observe buyers rallying up their offers to the whole nominal value of the card. Instead, there is a significant dispersion in the observed offers. This implies that there is some non-zero surplus from a match of a given buyer and a seller (remember that the surplus in our setting is defined *relative to the highest competing offer*). In turn, the presence of a non-zero surplus allows buyers to express their sharing intentions more saliently.

The natural downside of conducting a field experiment is that one cannot perfectly control for players' unobservable characteristics that define their behaviour. In particular, because of the uncertainty concerning the degree of competition, the beliefs of our subjects are less predictable than in the lab. We tackle this problem with a new method to decompose the observed distribution of offers into a distribution of unobserved expected values of the seller's opportunity cost and a distribution of unobserved shares of surplus proposed by buyers.

Our main findings suggest that even in large one-shot interaction markets like eBay, participants offer to equally split the surplus very frequently. In particular, we find that about 37% of players offer to the seller nearly a half of the total trade surplus, while selfish players (offering 0-10% of surplus) constitute a roughly equal subject pool (41%). The average amount of surplus offered by the buyer to the seller amounts to about 24%. Similarly to the lab findings, this result appears inflated; it

[36] In contrast, Roth et al. (1991), Fischbacher et al. (2009) look at the behaviour within the ultimatum game where the number of competing proposers is commonly known.

is counter-intuitive that anyone would give up a quarter of trade surplus to a one-shot counter-party. Since markets are never thought of as appealing to any form of altruism, it is hard to reconcile them with surplus sharing. However our analysis shows that the observed behaviour is inconsistent with the hypothesis that no buyer offers to share the surplus from trade with the seller. Furthermore, the estimated frequencies of offered shares of surplus are within the range of estimates emerging in the lab studies. This implies that despite all the discrepancies between the lab and the field, lab experiments on surplus division provide a valid insight into the field behaviour – not just qualitatively, but also quantitatively.

To conclude, the eBay platform, featuring the stochastic arrival of buyers, could be considered as a fair representation of a generic market place found all over the world. Most of those markets are dynamic and uncertain – the population of traders evolves over time, some participants quit the market, while new participants enter at random. Traders do not possess perfect and commonly shared information, instead they learn about prices and the fierceness of competition via their own private experiences of bargaining with different sellers or through the observations of market clearing; all in the same way as what happens on eBay. Our analysis suggests that because of such uncertain and evolving degrees of competition, and hence the sellers' outside option, even a large market offers a scope to share the surplus non-trivially. Our paper offers a new result to improve our understanding of how competition and strategic uncertainty interact with the individual preferences for fairness.

A Appendix

A.1 Experiment

An example text used in the description box of a listing (German):

> ```
> "Biete hier einen Amazon-Gutschein im Wert von 50 Euro
> an, gültig bis zum xx.xx.20xx. Der Gutscheincode wird
> nach Zahlungseingang auf meinem Konto am gleichen Tag
> via eBay Mitteilung versendet. Es handelt sich um echte
> Geschenkgutscheine (keine Aktionsgutscheine!), d.h. sie
> haben keinen Mindestbestellwert, es können mehrere Gutscheine
> kombiniert werden, und eventuelles Restguthaben verbleibt auf
> dem Amazon-Kundenkonto."
> ```

English translation:

> ```
> "I offer here an Amazon gift card worth 50 Euro, valid until
> xx.xx.20xx. The card code is sent to you via eBay message
> on the same day I receive payment. These are actual gift
> certificates (not promotion coupons!), that is, there is
> no minimal purchase requirement, multiple coupons can be
> combined, and any residual credit would remain on the Amazon
> account."
> ```

Watch a video illustration at:[37]

https://www.youtube.com/watch?v=dKCsOhItstw.

[37] ATTENTION Anonymous Referee: YouTube tracks viewers' information, please take the necessary precautions to protect your anonymity.

A.2 Tables

A.2.1 Regression Analysis

Variable	Description	Range
normalized offer	Offer divided by the card's nominal value	0.02 .. 1
nominal	Gift card's nominal in Euro	5 .. 500
time to deadline	Time left to listing expiry when offer is made divided by listing duration	0.0007 .. 0.9988
order	1, if the offer arrives first on the listing, 2, if second etc.	1 ..15
trend	Time elapsed since the arrival of the first offer, in days	0 .. 359.20
buyer_exp	Number of buyer's eBay stars when he makes offer	1.. 8847
seller_exp	Number of seller's eBay stars when he receives offer	1 .. 511

Table 3: Regression variables.

Dep.: normalized offer	Model 1	Model 2	Model 3	Model 4	Model 5
constant	0.736***	0.751***	0.737***	0.741***	0.762***
nominal	$-6.5 \cdot 10^{-5}$		$-6.5 \cdot 10^{-5}$	$-6.8 \cdot 10^{-5}$	$-6.4 \cdot 10^{-5}$
log(nominal)		$-5.8 \cdot 10^{-3}$			
time to deadline			$-1.8 \cdot 10^{-3}$	$2.1 \cdot 10^{-3}$	$4.6 \cdot 10^{-3}$
order				$-2.1 \cdot 10^{-3}$	$-4.1 \cdot 10^{-3}$
trend					$-1.2 \cdot 10^{-4}$
N obs	358	358	358	358	358
R sq.	0.001	0.001	0.002	0.002	0.006

Table 4: Regression models 1-5.

Dep.: normalized offer	Model 6	Model 7	Model 8	Model 9	Model 10
constant	0.733***	0.747***	0.751***	0.763***	0.753***
buyer_exp	$2.9 \cdot 10^{-5}$*	$3.0 \cdot 10^{-5}$**	$2.8 \cdot 10^{-5}$ *	$2.9 \cdot 10^{-5}$*	$2.8 \cdot 10^{-5}$ *
trend	$-1.24 \cdot 10^{-4}$	$-1.1 \cdot 10^{-4}$	$-1.4 \cdot 10^{-4}$	$-1.5 \cdot 10^{-4}$	$-1.1 \cdot 10^{-4}$
order		$-5.0 \cdot 10^{-3}$	$-5.8 \cdot 10^{-3}$	$-5.2 \cdot 10^{-3}$	$-5.9 \cdot 10^{-3}$
time to deadline			$8.9 \cdot 10^{-3}$	$8.9 \cdot 10^{-3}$	$11 \cdot 10^{-3}$
nominal			$-4.8 \cdot 10^{-5}$		$-5.0 \cdot 10^{-5}$
log(nominal)				$-4.55 \cdot 10^{-3}$	
offer number					$-2.0 \cdot 10^{-5}$
N obs	358	358	358	358	358
R sq.	0.01	0.01	0.01	0.02	0.02

Table 5: Regression models 6-10.

Dep.: normalized offer	Model 11	Model 12	Model 13	Model 14	Model 15
constant	0.684***	0.695***	0.69***	0.701***	0.716***
log(buyer_exp)	$1.2 \cdot 10^{-2}$*	$1.2 \cdot 10^{-2}$*	$1.2 \cdot 10^{-2}$ *	$1.21 \cdot 10^{-2}$ *	$1.2 \cdot 10^{-2}$*
trend	$-1.18 \cdot 10^{-4}$	$-1.3 \cdot 10^{-4}$	$-1.4 \cdot 10^{-4}$	$-1.3 \cdot 10^{-4}$	$-1.43 \cdot 10^{-4}$
order		$-4.2 \cdot 10^{-3}$	$-4.7 \cdot 10^{-3}$	$-4.9 \cdot 10^{-3}$	$-4.5 \cdot 10^{-3}$
time to deadline			$11.6 \cdot 10^{-3}$	$10.3 \cdot 10^{-3}$	$10.3 \cdot 10^{-3}$
nominal				$-5.8 \cdot 10^{-5}$	
log(nominal)					$-6.16 \cdot 10^{-3}$
N obs	358	358	358	358	358
R sq.	0.01	0.012	0.012	0.014	0.014

Table 6: Regression models 11-15.

Dep.: normalized offer	Model 16	Model 17	Model 18	Model 19	Model 20
constant	0.703***	0.736***	0.742***	0.714***	0.723***
buyer_exp	$2.41 \cdot 10^{-5}$	$2.68 \cdot 10^{-5}$*	$2.55 \cdot 10^{-5}$	$2.43 \cdot 10^{-5}$*	$2.53 \cdot 10^{-5}$*
seller_exp	$9.9 \cdot 10^{-5}$*	$1.09 \cdot 10^{-4}$ *	$1.17 \cdot 10^{-4}$ *		
log(seller_exp)				$1.60 \cdot 10^{-2}$***	$1.52 \cdot 10^{-2}$***
trend		$-1.2 \cdot 10^{-4}$	$-1.2 \cdot 10^{-4}$	$-1.37 \cdot 10^{-4}$	$-1.43 \cdot 10^{-4}$
order		$-7.5 \cdot 10^{-3}$	$-8.55 \cdot 10^{-3}$	$-10.9 \cdot 10^{-3}$	$-10.2 \cdot 10^{-3}$
time to deadline			$1.11 \cdot 10^{-2}$	$1.75 \cdot 10^{-2}$	$1.76 \cdot 10^{-2}$
nominal			$-7.04 \cdot 10^{-5}$	$-8.01 \cdot 10^{-5}$	
log(nominal)					$-4.68 \cdot 10^{-3}$
N obs	358	358	358	358	358
R sq.	0.016	0.022	0.025	0.036	0.034

Table 7: Regression models 16-20.

Dep.: normalized offer	Model 21	Model 22	Model 23	Model 24
constant	0.636***	0.666***	0.669***	0.669***
log (buyer_exp)	$0.98 \cdot 10^{-2}$	$1.07 \cdot 10^{-2}$	$1.05 \cdot 10^{-2}$	$1.1 \cdot 10^{-2}$
log (seller_exp)	$1.32 \cdot 10^{-2}$ **	$1.51 \cdot 10^{-2}$ ***	$1.61 \cdot 10^{-2}$ ***	$1.52 \cdot 10^{-2}$ ***
trend		$-1.41 \cdot 10^{-4}$	$-1.39 \cdot 10^{-4}$	$-1.47 \cdot 10^{-4}$
order		$-8.7 \cdot 10^{-3}$	$-1.04 \cdot 10^{-2}$	$-9.66 \cdot 10^{-3}$
time to deadline			$2.11 \cdot 10^{-2}$	$2.13 \cdot 10^{-2}$
nominal			$-8.4 \cdot 10^{-5}$	
log(nominal)				$-5.55 \cdot 10^{-3}$
N obs	358	358	358	358
R sq.	0.023	0.032	0.036	0.034

Table 8: Regression models 21-24.

Dep.: normalized offer	NL Model 1	NL Model 2	NL Model 3	NL Model 4
constant	0.63***	0.66***	0.703***	0.67***
log(seller_exp)	$1.32 \cdot 10^{-2}$**	$5.8 \cdot 10^{-3}$		
log(buyer_exp)	$9.83 \cdot 10^{-3}$	$5.1 \cdot 10^{-3}$		
*log(buyer_exp) * log(seller_exp)*		$1.4 \cdot 10^{-3}$		
seller_exp			$9.76 \cdot 10^{-5}$	$1.16 \cdot 10^{-3}$*
buyer_exp			$2.34 \cdot 10^{-5}$	$5.75 \cdot 10^{-5}$*
*seller_exp*buyer_exp*			$2.78 \cdot 10^{-9}$	
seller_exp²				$-2.25 \cdot 10^{-6}$
buyer_exp²				$-6.54 \cdot 10^{-9}$
N obs	358	358	358	358
R sq.	0.023	0.024	0.016	0.026

Table 9: Regression models 25-28.

A.2.2 Decomposition

Coefficient	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	
Estimate	-12.3	30.3	-12.3	8.0	
Coefficient	$\hat{\delta}_0$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	$\hat{\delta}_4$
Estimate	4.9	-5.3	1.1	2.1	-2.1

Table 10: Chebyshev polynomial coefficients.

s:	0-10%	10-20%	20-30%	30-40%	40-50%
$\hat{f}^{np}(s)$:	25.9	7.4	3.7	18.5	44.4

c:	0-10%	10-50%	50-60%	60-70%	70-80%	80-90%	90-100%
$\hat{g}^{np}(c)$:	14.3	7.1	5.4	17.9	23.2	21.4	10.7

Table 11: Non-parametric estimate of the distributions of sharing rules ($\hat{f}$) and beliefs ($\hat{g}$).

s:	0-10%	10-20%	20-30%	30-40%	40-50%
$\hat{f}^{\beta}(s)$:	23.5%	12.9%	12.0%	15.2%	36.4%

c:	0-10%	10-50%	50-60%	60-70%	70-80%	80-90%	90-100%
$\hat{g}^{\beta}(c)$:	0.4%	22.1%	11.9%	14.4%	16.6%	17.9%	16.7%

Table 12: Parametric estimates when f and g are restricted to the class of β distributions. $\alpha^f = 0.230$, $\beta^f = 0.031$; $\alpha^g = 2.470$, $\beta^g = 1.121$, Kolmogorov-Smirnov distance = 0.066 (rejected).

Iteration	0	1	2	3	4	5	6	7	8	9	10	11	12	13	...	50
$f(b_1)$	20%	14.3%	11.1%	9.1%	14.3%	20.0%	22.2%	26.3%	28.6%	27.3%	26.1%	28.0%	26.9%	25.9%		25.9%
$f(b_2)$	20%	14.3%	11.1%	18.2%	14.3%	13.3%	11.1%	10.5%	9.5%	9.1%	8.7%	8.0%	7.7%	7.4%		7.4%
$f(b_3)$	20%	14.3%	11.1%	9.1%	7.1%	6.7%	5.6%	5.3%	4.8%	4.5%	4.3%	4.0%	3.8%	3.7%		3.7%
$f(b_4)$	20%	28.6%	33.3%	27.3%	28.6%	26.7%	27.8%	26.3%	23.8%	22.7%	21.7%	20.0%	19.2%	18.5%		18.5%
$f(b_5)$	20%	28.6%	33.3%	36.4%	35.7%	33.3%	33.3%	31.6%	33.3%	36.4%	39.1%	40.0%	42.3%	44.4%		44.4%
$g(b_1)$	10%	7.1%	5.6%	4.8%	8.3%	7.7%	10.0%	9.4%	10.5%	11.4%	12.5%	12.5%	13.5%	14.3%		14.3%
$g(b_2)$	10%	7.1%	5.6%	4.8%	4.2%	3.8%	3.3%	3.1%	2.6%	2.3%	2.1%	2.1%	1.9%	1.8%		1.8%
$g(b_3)$	10%	7.1%	5.6%	4.8%	4.2%	3.8%	3.3%	3.1%	2.6%	2.3%	2.1%	2.1%	1.9%	1.8%		1.8%
$g(b_4)$	10%	7.1%	5.6%	4.8%	4.2%	3.8%	3.3%	3.1%	2.6%	2.3%	2.1%	2.1%	1.9%	1.8%		1.8%
$g(b_5)$	10%	7.1%	5.6%	4.8%	4.2%	3.8%	3.3%	3.1%	2.6%	2.3%	2.1%	2.1%	1.9%	1.8%		1.8%
$g(b_6)$	10%	7.1%	5.6%	4.8%	4.2%	3.8%	3.3%	3.1%	5.3%	6.8%	6.3%	6.3%	5.8%	5.4%		5.4%
$g(b_7)$	10%	14.3%	16.7%	19.0%	16.7%	15.4%	16.7%	15.6%	15.8%	15.9%	16.7%	16.7%	17.3%	17.9%		17.9%
$g(b_8)$	10%	14.3%	16.7%	19.0%	20.8%	23.1%	23.3%	25.0%	23.7%	22.7%	22.9%	22.9%	23.1%	23.2%		23.2%
$g(b_9)$	10%	14.3%	16.7%	19.0%	20.8%	23.1%	23.3%	25.0%	23.7%	22.7%	22.9%	22.9%	23.1%	21.4%		21.4%
$g(b_{10})$	10%	14.3%	16.7%	14.3%	12.5%	11.5%	10.0%	9.4%	10.5%	11.4%	10.4%	10.4%	9.6%	10.7%		10.7%
KS-stat	0.1364	0.1658	0.0667	0.0398	0.0327	0.0264	0.0196	0.0171	0.0143	0.0127	0.0106	0.0089	0.0081	0.0077		0.0077

Table 13: The consecutive iterations of the binary search procedure.

Iteration	0	1	2	3	4	5	6	7	8	9	10	11	12	...	24	...	50
$f(b_1)$	16.7%	12.5%	9.1%	8.3%	8.3%	13.3%	16.7%	19.0%	21.7%	22.2%	19.4%	21.2%	22.9%		23.7%		23.7%
$f(b_2)$	16.7%	12.5%	9.1%	8.3%	8.3%	6.7%	5.6%	4.8%	4.3%	3.7%	6.5%	6.1%	5.7%		8.5%		8.5%
$f(b_3)$	16.7%	12.5%	9.1%	8.3%	8.3%	6.7%	5.6%	4.8%	4.3%	3.7%	3.2%	3.0%	2.9%		1.7%		1.7%
$f(b_4)$	16.7%	12.5%	18.2%	16.7%	16.7%	20.0%	22.2%	19.0%	17.4%	18.5%	19.4%	21.2%	22.9%		16.9%		16.9%
$f(b_5)$	16.7%	25.0%	27.3%	33.3%	33.3%	33.3%	33.3%	33.3%	34.8%	33.3%	32.3%	30.3%	28.6%		37.3%		37.3%
$f(b_6)$	16.7%	25.0%	27.3%	25.0%	25.0%	20.0%	16.7%	19.0%	17.4%	18.5%	19.4%	18.2%	17.1%		11.9%		11.9%
$g(b_1)$	10.0%	7.1%	5.6%	4.5%	7.7%	7.4%	9.4%	11.1%	10.8%	12.2%	13.3%	13.0%	13.7%		15.6%		15.6%
$g(b_2)$	10.0%	7.1%	5.6%	9.1%	7.7%	7.4%	6.3%	5.6%	5.4%	4.9%	4.4%	4.3%	3.9%		2.6%		2.6%
$g(b_3)$	10.0%	7.1%	5.6%	4.5%	3.8%	3.7%	3.1%	2.8%	2.7%	2.4%	2.2%	2.2%	2.0%		1.3%		1.3%
$g(b_4)$	10.0%	7.1%	5.6%	4.5%	3.8%	3.7%	3.1%	2.8%	2.7%	2.4%	2.2%	2.2%	2.0%		1.3%		1.3%
$g(b_5)$	10.0%	7.1%	5.6%	4.5%	3.8%	3.7%	3.1%	2.8%	2.7%	2.4%	2.2%	2.2%	2.0%		2.6%		2.6%
$g(b_6)$	10.0%	7.1%	11.1%	9.1%	7.7%	7.4%	6.3%	5.6%	5.4%	4.9%	4.4%	4.3%	3.9%		2.6%		2.6%
$g(b_7)$	10.0%	14.3%	16.7%	18.2%	19.2%	18.5%	18.8%	19.4%	18.9%	19.5%	20.0%	19.6%	19.6%		19.5%		19.5%
$g(b_8)$	10.0%	14.3%	16.7%	18.2%	19.2%	18.5%	18.8%	19.4%	21.6%	22.0%	22.2%	23.9%	23.5%		27.3%		27.3%
$g(b_9)$	10.0%	14.3%	16.7%	18.2%	19.2%	22.2%	21.9%	22.2%	21.6%	22.0%	22.2%	21.7%	21.6%		19.5%		19.5%
$g(b_{10})$	10.0%	14.3%	11.1%	9.1%	7.7%	7.4%	9.4%	8.3%	8.1%	7.3%	6.7%	6.5%	7.8%		7.8%		7.8%
KS		0.1250	0.0550	0.0411	0.0361	0.0322	0.0271	0.0231	0.0190	0.0171	0.0161	0.0151	0.0129		0.0066		0.0066

Table 14: The consecutive iterations of the binary search procedure, with restriction 0.6.

A.3 Figures

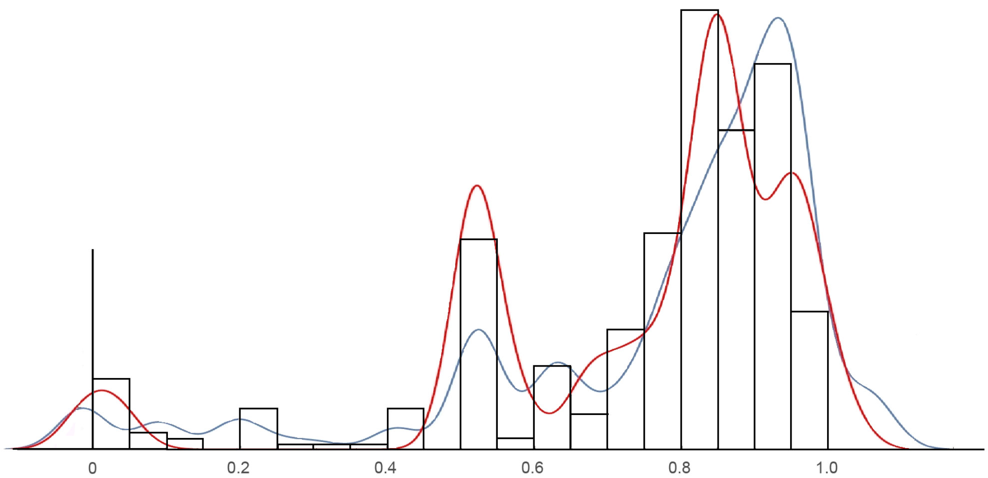


Figure 6: Smooth kernel histograms for the offers made by the East (red) and the West German participants (blue).

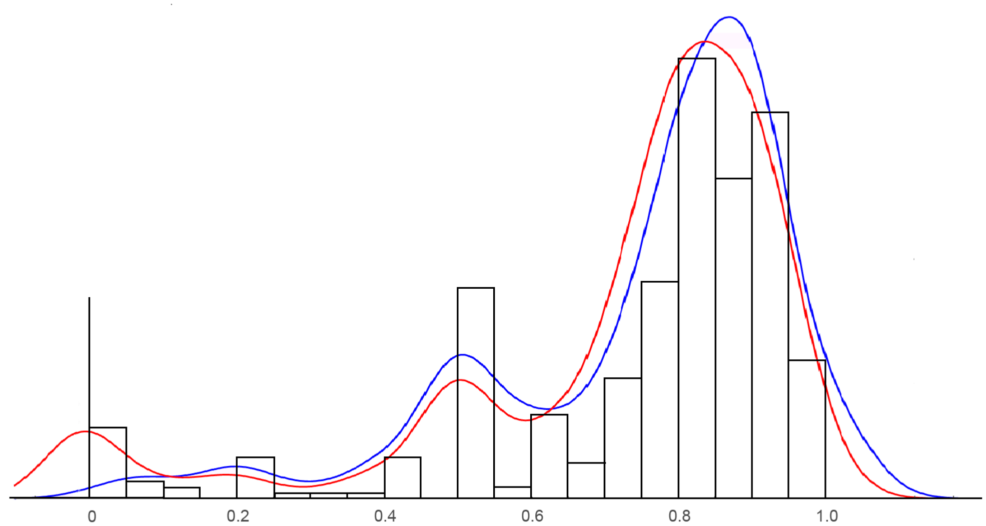


Figure 7: The histogram of the normalized offers (grey bars) and smooth kernel histograms for the offers made first (blue) and all the higher-order offers (red).

A.4 Robustness Checks

A.4.1 Non-parametric Decomposition

As an alternative way to solve for f and g, we discretize the support of distributions in (3) and we search for finite solution approximations using a non-parametric approach. In an iterative procedure with the initial state where both f and g are uniform, we gradually increase precision until the solution cannot be improved. The estimates of f and g are chosen to minimize the Kolmogorov-Smirnov distance as a goodness-of-fit criterion, adapted to the discrete case:

$$d_{KS}\left(\hat{H}, H\right) \equiv \sup_{\{b_k\}_{k=1,..,10}} \left|\hat{H}\left(b_k\right) - H\left(b_k\right)\right|, \tag{12}$$

where both $\hat{H}$ and H are defined on a set of bins $(b_1, b_2, .., b_{10}) = (0.1, 0.2, .., 1)$. In the discrete problem, we look for $\hat{f}$ and $\hat{g}$ that minimize (12), subject to $\hat{f}\left(b_k\right) = 0$ for $k = 6, 7, .., 10$, and $\sum_k \hat{f}\left(b_k\right) = \sum_k \hat{g}\left(b_k\right) = 1$. (Recall that $\hat{f}$ and $\hat{g}$ define $\hat{H}$ according to (8)).

We estimate discretized versions of f and g simultaneously at each iteration. As a starting point of recurrence, we consider uniform f and g that correspond to the maximal entropy in both c and s (See Table 13 in the Appendix). That is, we assign equal mass to each of the 5 bins of f and 10 bins of g at the first iteration. The candidate solution can be represented as a vector of ones: $v_1 = (1, 1, .., 1)$; it corresponds to the distribution of probability mass across bins before normalization. v_1 is the unique candidate solution at the first iteration, thus we set $v_1^* = v_1$ At the second iteration, we consider all elements $e_{2,k}$ of the set $\{0, 1\}^{15}$ and the respective $v_{2,k} = v_1 + e_{2,k}$. This gives $2^{15} = 32768$ candidate solutions (f, g) and we choose the one that minimizes the Kolmogorov-Smirnov distance (after the appropriate normalization) – v_2^*. Generally, in iteration t, we go through all possible constellations of adding one unit or not changing the mass in the bins of distributions defined by v_{t-1}^* selected at iteration $t-1$. Among the pairs of f and gn we select the one that minimizes the Kolmogorov-Smirnov distance and take it to iteration $t+1$. The process is repeated until the result at a subsequent iteration stays unchanged. Note that as the depth of the binary search tree increases, the estimates become increasingly precise. The results of the non-parametric approach are presented in Table 11. Table 14 presents the results of decomposition when the upper bound of the support for f is changed to 0.6.

Define $\hat{H}^{np}$ as in (8) by substituting in $\hat{f} = \hat{f}^{np}$ and $\hat{g} = \hat{g}^{np}$ from Table 11. $\hat{H}^{*}$ is an extremely good fit for H: the Kolmogorov-Smirnov distance is 7.7×10^{-3}, meaning that the maximal divergence between $\hat{H}^{np}$ and H across bins is less than 1 percentage point. The corresponding bootstrap test does not distinguish between H and $\hat{H}^{np}$ at the conventional significance levels,[38] implying that H and $\hat{H}^{*bp}$ can be regarded as equivalent.

As a further robustness check, we relax the restriction on the support of f allowing six bins; similar results are obtained (see Table 14).

A.4.2 Parametric Decomposition with Beta Distributions

As a further robustness check, we look for estimates $\hat{f}^{\beta}$ and $\hat{g}^{\beta}$ within the class of the beta distributions. The beta class is chosen due to its support on [0, 1], small number of parameters and flexibility, as Beta distributions can have one or two modes.[39] Since each of the distributions f and g is pinned down by two parameters, the problem to find the suitable $\hat{H}(.)$ in (7) is now (only) four-dimensional. We estimate the parameters by random grid search. More precisely, we fix a grid size for each of four parameters and randomly choose the grid position. For every intersection of the grid (a combination of four parameter values), we compute the discretized versions of f and g, estimate the integral (8), then we calculate the Kolmogorov-Smirnov distance and reiterate to find the best-performing combination of parameters. By performing the procedure multiple times, we refine the search and narrow down the parameters ranges. A random grid search permits us to trace out local minima and find the global solution. We report the parametric estimates of distributions $\hat{f}^{\beta}$ and $\hat{g}^{\beta}$ Table 12. The parametric Beta estimates $\hat{f}^{\beta}$ and $\hat{g}^{\beta}$ are dominated by both the parametric and the non-parametric solutions reported in the main text of the paper (Kolmogorov-Smirnov distance $= 0.066$). The distributions have a shape similar to the non-parametric estimates $\hat{f}^{*}$ and $\hat{g}^{*}$, with the exception of the lowest bin in the distribution of cost estimates $\hat{g}$.

[38]Bootstrap critical values corresponding to 358 observations are 0.049 for significance at 10%, 0.057 for significance at 5%, and 0.071 for significance at 1%.

[39]Excluding the uniform distribution.

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