NORM ENFORCEMENT IN MARKETS
GROUP IDENTITY AND THE VOLUNTEERING OF FEEDBACK

Short title: Norm enforcement in markets

Gary E. Bolton, Johannes Mans, Axel Ockenfels†

January 2019

The provision of trader feedback is critical to the functioning of many markets. We examine the influence of group identity on the volunteering and informativeness of feedback. In a market experiment conducted simultaneously in Germany and the US, we manipulate the interaction of traders based on natural social and induced home market identities. Traders are more likely to provide feedback information on a trader with whom they share a common group identity, and the effect is more pronounced for social identity than for home market identity. Both kinds of group identity promote rewarding good performance and punishing bad performance.

Keywords: Social identity, reputation, electronic markets, trust, public good, experiment

JEL-Codes: C91; D4

---

† Corresponding author: Gary E. Bolton, Jindal School of Management, University of Texas at Dallas, 800 W. Campbell Rd 3.612, Richardson, Texas 75254, USA, gbolton@utdallas.edu. Financial support of the German Research Foundation (DFG) through the Research Unit "Design & Behavior (FOR 1371) and funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No 741409) is gratefully acknowledged. This paper reflects only the authors' view and the funding agencies are not responsible for any use that may be made of the information it contains. We thank Ben Greiner, Christoph Feldhaus, David Kusterer, Bettina Rockenbach, Anne Schielke and Peter Werner, as well as two referees and the editor for very helpful comments and suggestions.

I. INTRODUCTION

Traditionally, market reputations were spread by word-of-mouth. In the modern marketplace, reputation information, commonly referred to as feedback, is digitally collected from traders and disseminated to the market through institutionalized feedback systems. This innovation amplifies the reputation's role in enforcing norms of conduct in social and economic interaction. Indeed, digital social and economic platforms such as Airbnb, Amazon, eBay, Facebook, Uber and Yelp could not exist without the collection and dissemination of feedback on individuals' experiences.

Yet the success of these systems rests on a puzzle: Feedback information is given voluntarily. It is a public good, the cost incurred by the trader that takes the time to volunteer it, with the benefits accruing to the market at large. If people did not volunteer this information, then institutional feedback systems would collapse. So, what factors influence the provision of feedback information?

The main hypothesis we test here is that a trader is more likely to volunteer feedback on her trading partner when the two share a common group identity. Two observations suggest this hypothesis. First, in a data set of 640,854 trades taking place over 8 countries on the eBay marketplace, we observed that traders give feedback 70 percent of the time when the trade takes place within a country, but just 50 percent of the time when the trade takes place across countries, a 40 percent difference in feedback giving frequency.[1] So traders are more actively giving feedback, and in this sense more engaged in market norm enforcement, in their home markets than in away ones. There are of course other plausible explanations for this greater engagement other than group identity (see below; none of which are testable given the contents of our dataset). The second observation is better controlled albeit indirect evidence. It comes from recent studies of 2- and 3-person cooperation games. These find that the propensity for norm enforcement – punishing violations and rewarding conformity – is influenced by group identity (Bernhard et al. 2006, Chen and Li 2009, Götte et al. 2006, 2012, Mussweiler and Ockenfels 2013).[2] A good deal of this evidence suggests that norm enforcement is greater for interactions that take place within-group. As Götte et al. (2006) write,

> [Group] assignment does not lead to hostility, in the sense of vindictive punishment of outsiders, but does affect norm enforcement, enhancing willingness to enforce a norm of cooperation towards fellow platoon members. This suggests that the social aspect of organizations motivates efficient behavior even when ordinary incentives fail, and helps explain practices designed to foster social ties or group identification within an organization.

---

[1] See Appendix Table A1. The range of frequencies of feedback giving in Table A1 are typical to eBay; e.g., Resnick and Zeckhauser (2002), Dellarocas and Wood (2008), Jian, Mackie-Mason and Resnick (2010), and Bolton, Greiner and Ockenfels (2013).

[2] Early research in social psychology shows that social identity influences individual behavior in ways that favor in-social group members (Tajfel et al. 1971 and Tajfel and Turner 1979). Pechar and Kranton (2017) survey much of the experimental economics literature.

The hypothesis we test posits that the observed positive effect group identity has on norm enforcement in small group cooperative games extends to marketplaces. Of course, competitive markets and associated market feedback mechanisms differ substantially from small group cooperative games. There are reasons to suppose that group identity is less important in markets, or that competition in markets mitigate or wash out a group identity influence on norm enforcement. Enforcement through feedback is less direct and so might be less robust than what is observed in the simpler games; for instance, the person providing the information is different from the person who, in the future, provides the monetary reward or punishment through a change in trading behavior. Also, competitive environments might not only directly mitigate social influences such as identity concerns (as they are known to mitigate fairness concerns; Bolton and Ockenfels 2000, Fehr and Schmidt 1999); they might also indirectly mitigate group considerations as they present a substantially different set of strategic options and trade-offs, as well as competing sources of potential identities and heterogeneity of potential norms of conduct than found in the simpler games. Indeed, the difference in home and away market feedback frequency observed on eBay might simply be due to the practical obstacles to trading internationally, such as different quality standards, different delivery times, miscommunication due to language barriers, and self-selection into international trades.

The market game experiment we present here tests whether and how group identity affects norm enforcement in a market environment controlling for potential confounds, including the practical difficulties associated with away market trades. The experiment is also designed to untangle an ambiguity central to the hypothesis: Two distinct kinds of groups coincide with the *Home* and *Away* market designations, and either, both or none might influence trader feedback giving. One kind is the social group that a trader affiliates with. The vast majority of trades designated *Home* in the eBay data are between traders who reside in the same nation and so plausibly think of themselves as in the same *social* group. At the same time, most traders trade most of the time on the domestic market.[3] This might induce a 'home *market* identity', independent of any social similarity between traders yet also contributes to the norm enforcement differences. Moreover, an alternative hypothesis for seeing more feedback for trade in home markets in our observational data set is that a trader plausibly derives a greater benefit from contributing to norm enforcement in the home market than in the away market, just because future interaction is more likely on the home market. With observational data only, social and home market groups usually coincide in national transactions. Our experiment varies social identity and trading interaction patterns exogenously, allowing us to disentangle any effect each of these group identities might have.

[3] In our eBay dataset, even if we restrict ourselves to those traders who have a history to trade nationally *and* internationally, domestic trades account for nearly two thirds (64 percent) of all observed transactions.

An increased willingness to punish in-group members would be consistent with the 'black sheep effect', which supposes that deviant behavior by in-social group members is perceived as a potential threat to the group's identity and therefore judged more extremely than by out-social group subjects (Akerlof and Kranton 2000, Marques et al. 1988, Pinto et al. 2010). Overall, however, the experimental literature is mixed. While Shinada et al. (2004) and McLeish and Oxoby (2007), too, find that non-cooperative behavior is punished more severely by in-social group members than by out-social group members, Bernhard, et al. (2006b) and Chen and Li (2009) find the opposite. The latter argue that the observed increased leniency can be attributed to more altruism toward other in-group members' payoffs. In our competitive market setting, with only an indirect punishment channel via feedback production, altruism is arguably of lesser importance, so that under our main hypothesis, we should see evidence for the black sheep effect in our set-up.

Our experiment also deals with the accuracy of the feedback given. In our field data we see that, when feedback is given, it is somewhat more negative on average when the trader is giving the feedback on an away market (Appendix Table A2). As with the frequency of feedback giving, this might not only be attributable to group processes but also with the non-random interaction patterns and other considerations having to do with difficulties with international trade. Our experiment shows that common group identity encourages feedback frequency and that the feedback so given is an accurate indicator of a trader's record of norm observance.

While our focus will be group identity, there are often strategic and other psychosocial factors that may affect feedback giving, such as feedback retaliation, power in post-transaction conflict resolution, sorting into reviewing, and leniency when there is attributional uncertainty, which our study will abstract away from. See Ockenfels and Resnick (2012) for an overview, as well as the literature on various feedback distortions such as Avery et al. (1999), Miller et al. (2005), Dellarocas and Wood (2008), Bolton, Greiner and Ockenfels (2013 and forthcoming), Fradkin et al. (2018), Mayzlin et al. (2014), Nosko and Tadelis (2014), Bolton and Ockenfels (2014) and Bolton, Kusterer and Mans (forthcoming).

II. EXPERIMENTAL DESIGN

We investigate the effects of group identity in the context of a multi-period market game. The sellers and buyers in our experiment are drawn from the University of Cologne (UoC) and the University of Texas at Dallas (UTD), providing natural groups for the social identity manipulation. In addition, each trader is also assigned a market home identity, the place where they most frequently trade, either the Cologne (Type C) or Dallas (Type D) market.

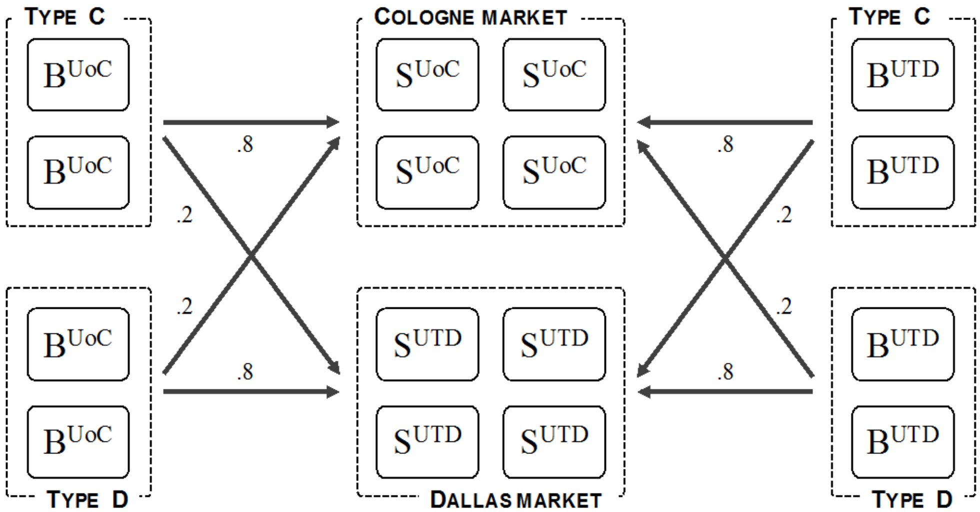


Figure 1: Home market identity assignment and trading partner matching for a matching group of 16 subjects.

Specifically, participants are divided into matching groups of 16 subjects each such that half are from UoC and half from UTD. Within each of these social identities (UoC or UTD), half are assigned the role of seller (S) and half the role of buyer (B). All sellers are assigned to the home market that agrees with their social identity. Half the buyers are assigned to the home market that agrees with their social identity; the other half are assigned to the home market opposite their social identity. The assigned roles were fixed throughout the experiment.

The market has 40 periods. For each period, buyers switch randomly between home and away markets such that they trade on their home market 80 percent of the time and on the away market the remaining 20 percent of the time. To ensure an equal number of sellers and buyers on each market, we draw a random number between 0 and 1. If the value of this number is less than or equal to 0.8 all buyers trade on their home market; otherwise all trade on the away market.

Figure 1 illustrates the resulting constellation of trading roles and identities within each matching group and in each period. An important feature of the procedure is that it allows us to separate social from market group effects. The design guarantees that each market has two in-social group buyers and two out-social group buyers. So, buyers from the in-social group and the out-social group access the provided feedback information an equal number of times. There is then no reason to provide more or better information to a particular market because there are more in-social group buyers trading there.

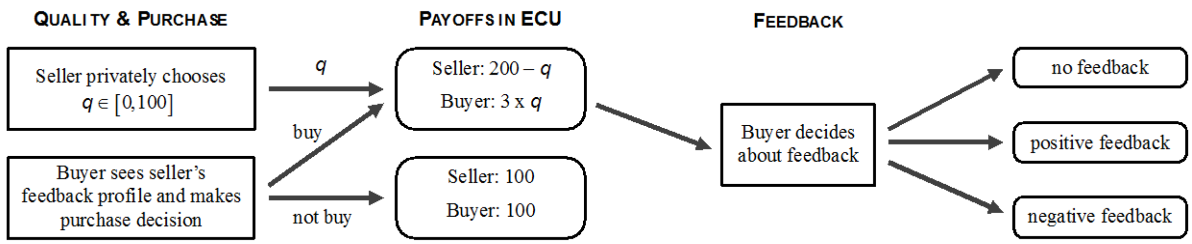


Figure 2: Market game with one-sided feedback option

The market game is illustrated in Figure 2. After traders are assigned to one of the two markets, they are randomly matched into seller-buyer pairs under the constraint that no pair is the same as in the previous period. Buyers are informed whether they are trading on their home market and so know whether the seller has the same social identity. Sellers, in contrast, know whether the matched buyer is from the UoC or UTD social identity but not the buyer's home market. At the beginning of each period, each trader receives an endowment of 100 ECU (= Experimental Currency Unit). The buyer then chooses whether to buy from the seller at a price equal to the endowment (100 ECU). In addition, we asked buyers which level of quality they believe to receive from sender. Simultaneously, the seller chooses a quality level q between 0 and 100 incurring costs equal to the quality choice if the product is sold. If the buyer chooses not to buy, payoffs are 100 ECU for each player. If the buyer chooses to buy, seller profit is given by his endowment plus price net of the costs for quality (= $200 - q$) and the buyer receives a profit of $3q$. Thus, the gains from trade increase with q and welfare is doubled when the seller ships full quality of 100.[4]

After the buyer is informed about the received quality, he has the option to leave the seller a "positive" or "negative" feedback rating at the cost of 1 ECU. Before a new period starts, the seller is informed about the feedback rating. Feedback given to the seller, in the form of the number of positive and the number of negative ratings, is presented to buyers paired with this seller at the beginning of each round.

All sessions took place in June 2014, simultaneously at the Cologne Laboratory for Economic Research (CLER, UoC) and the Laboratory for Behavioral Operations and Economics (LBOE, UTD) including ten matching groups with 160 subjects in total (80 from each university). Subjects in Cologne were recruited via ORSEE (Greiner 2004), for US participants a similar system called SONA (www.sona-systems.com) was used. Instructions were given to participants as handouts.[5] To make sure that the stage

[4] To adjust for currency differences between Germany and the US, we used two different exchange rates: 250 ECU = \$1 for participants at the University of Texas and 350 ECU = 1€ for participants at the University of Cologne. The ratio of these two conversion rates correspond approximately to the market exchange rate (\$1 = 0.74 €) at the time of the experiment (and subjects were informed of this). In addition to their period earnings from trading subjects received a show-up fee of \$5 (3€).

[5] In order to have identical instructions for participants at the University of Cologne and at the University of Texas at Dallas we first wrote a German version, which was then translated into English and proofread by a native speaker.

game and the matching procedure were well understood, subjects answered control questions prior to the start of the experiment. Control questions and the actual experiment were computer-based using SoPHIE (Hendriks 2012). At the end of the experiment, subjects answered a short questionnaire asking for some demographic characteristics, participants' affiliations with their own and the other university and how they made their decisions in the experiment. Sessions lasted approximately for 100 minutes and average earnings were 21€ for participants from UoC and $29 for UTD participants.

III. RESULTS

We examine feedback behavior and then move to trading behavior. As with other reputational feedback studies (e.g., Bolton et al. 2004), there is an endgame effect for feedback and market trading decisions and, as planned before the experiments were run, we do not include the final five periods in the analyses presented here. All reported results are similar if we run analyses including all periods. All statistical tests are two-tailed and based on means aggregated at the level of (fully independent) matching groups.

III.1 Feedback provision and content

The main focus of our study lies with the influence of group effects on buyer feedback provision – the frequency of feedback giving and feedback content. We begin with descriptive statistics that, while highly aggregated, provide a useful overview; later we derive inference results from regression models. Figure 3 exhibits feedback provision, aggregated across all trades, and conditional on quality received. The numbers (*N*) at the top of the graph indicate the number of trades in each bin. The u-shape of the histogram reflects the frequency of feedback giving, lowest at the midpoint of the quality scale and becoming more frequent the further one moves away from this quality level. This shows that, in our setting, norms are enforced by both rewarding trustworthy behavior and by punishing uncooperative behavior (see, for a related observation, Sutter et al. 2010).

This version was then translated back into German by a third person who is a native speaker in English and German. A comparison with the original German version showed only minor differences, which were then aligned. Both, the German and the English version of the instructions can be found in Appendix B. See screenshots in Appendix C.

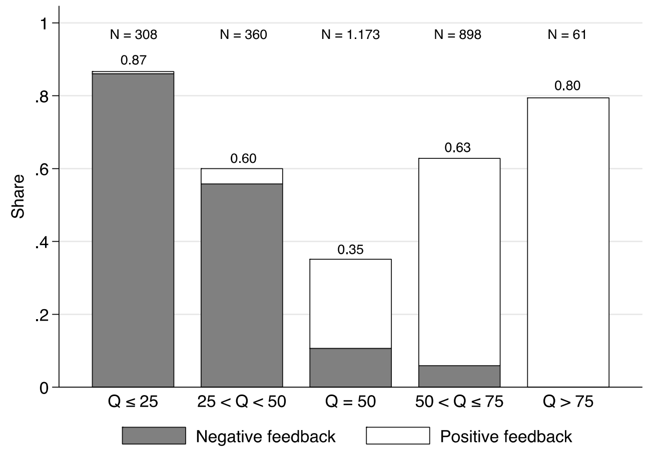


Figure 3: Buyers' provision of feedback broken out by received quality Q. Numbers at tops of bars are the frequencies of feedback giving associate with the quality level. Periods 1-35.

Also, from Figure 3 observe that, quality of 50 appears to function as a reference point for assessing seller performance in the sense that, when quality is below 50, 96 percent leave a negative feedback, and when quality exceeds 50, 91 percent leave a positive feedback. Only when quality is 50 is there much variance in ratings as 70 percent are positive. This particular quality might have become the reference point because it gives buyer and seller equal profit. Appendix A Table A3 breaks the descriptive statistics out by period.)

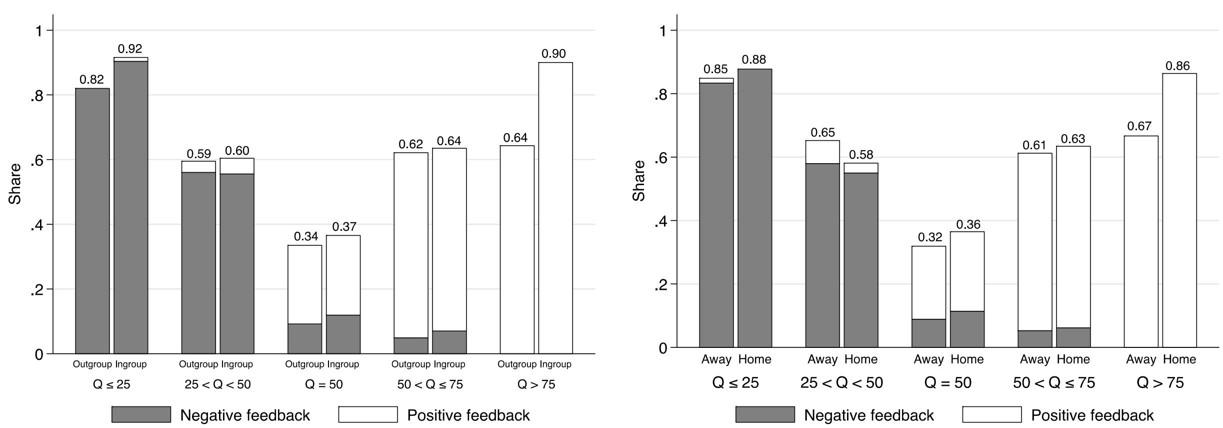


Figure 4: Buyer provision of feedback for in- and out-social group (left) and home and away (right) matches. Numbers at the tops of bars are the frequencies of feedback giving associated with the quality level. Periods 1-35.

Figure 4 breaks the feedback provision data out on the left by trading pair social group (in-group or out-group), and on the right by market identity (buyer is trading on home or away market). For all of these breakouts, we observe the same basic pattern with regard to feedback giving (u-shaped conditional on quality received) and feedback content (most feedback is positive above $Q = 50$ and negative below). That buyers are more likely to report extreme experiences is in line with field data by Dellarocas and Wood (2008) and Lafky (2014).

The most notable group differences in the figures are related to frequency of feedback giving. With regard to social group, for very low levels of quality, buyers' likelihood to leave a feedback rating on an in-group member increases by 10 percent and for very high levels of quality by 26 percent. For the market breakout, buyer likelihood to leave a feedback rating on home or away markets is very similar across all quality levels except for the highest category where feedback is given on home markets 86 percent and in away markets 67 percent of the time. Differences in the content of feedback given are less apparent in Figure 4.

Towards examining the significance of differences in the feedback frequencies we observed above, we first develop a regression model. Table 1 presents a series of probit regressions, all of which take whether the buyer gave feedback as the dependent variable. *In-social* and *Home* are indicator variables of whether the transaction takes place with the buyer's social group or on the buyer's home market, respectively. *Quality,* the actual quality the buyer received, and *Buyer Expected Quality,* the expectation stated by the buyer just prior to the transaction, are inserted separately. This formulation is sufficient to capture the effect the difference between actual and expected quality might have on feedback giving. It can also capture effects due to the individual variables per se. For example, actual quality might have an influence additional to any effect the difference with expected quality has. The formulation tests for this. If only the difference matters, then the estimated absolute value of the actual and expected quality coefficients should be similar (but we will see that in fact they differ).[6]

The u-shaped relationship between quality and the frequency of feedback giving is captured in Model 1 where quality has a negative effect but its quadratic term is significantly positive. Model 2 shows that the quadratic relationship is even stronger for in-social group trading pairs. Model 3 finds no analogous cross effect for trading pairs that share a home market, although it is significant in Model 4 which checks for an interaction effect for trading pairs that share the same social and market identity but finds none.[7]

---

[6] We also ran the models in Table 1 substituting the variable difference between received quality and expected quality for the received quality variable. The results, reported in Appendix Table A5, are similar to those in Table 1.

[7] As a further robustness check, we ran regressions with negative (for quality of 50 and below) and positive feedback (for quality of 50 and above) as dependent variable. We also ran regressions using a categorical quality variable. The results are similar to those reported here. See Appendix A Tables A6, and Figure A1 and Table A7 .

***Buyer gave feedback* (y/n)**	***Model 1***	***Model 2***	***Model 3***	***Model 4***
In-social (y/n)	0.075 (0.057)	1.151*** (0.333)	0.074 (0.057)	0.919** (0.455)
Home (y/n)	0.043 (0.062)	0.041 (0.063)	0.159 (0.284)	0.100 (0.356)
Quality $\in$ [0, 100]	-0.064*** (0.006)	-0.044*** (0.008)	-0.056*** (0.009)	-0.020* (0.012)
Quality^2	0.001*** (<0.001)	<0.001*** (<0.001)	0.001*** (<0.001)	<0.001 (<0.001)
In-social X Quality		-0.059*** (0.014)		-0.079*** (0.020)
In-social X Quality^2		0.001*** (<0.001)		0.001*** (0.000)
Home X Quality			-0.015 (0.012)	-0.036** (0.016)
Home X Quality^2			<0.001 (<0.000)	<0.001** (<0.001)
In-social X Home				0.624 (0.712)
In-social X Home X Quality				0.015 (0.031)
In-social X Home X Quality^2				<-0.000 (<0.000)
Buyer Expected Quality	0.004** (0.002)	0.004* (0.002)	0.004* (0.002)	0.003 (0.002)
UTD (y/n)	-0.104* (0.061)	-0.103* (0.061)	-0.102* (0.061)	-0.103* (0.062)
Seller percent positive feedback	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)
Period	-0.017*** (0.003)	-0.018*** (0.003)	-0.017*** (0.003)	-0.018*** (0.003)
Intercept	1.594*** (0.220)	1.240*** (0.245)	1.551*** (0.274)	1.239*** (0.329)
Log likelihood	-1326.4	-1316.9	-1325.0	-1287.9
N	2139	2139	2139	2139

Table 1: Random effects probit regression with buyer feedback election as dependent variable. Dummy variables for matching groups; periods 1-35; *t*-statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We will use the model in Table 1 to develop *p*-values for group effects at various levels of quality. But before leaving Table 1 we point out some other notable influences on feedback giving. The frequency of buyers leaving feedback decreases with period and also with an increase in the seller's feedback score.[8]

[8] We take the percentage of positive feedbacks (percent positive; *PP*) as a measure of sellers' trustworthiness. From the models in Appendix A Table A4 the percentage positive provides a higher model fit in terms of log likelihood than does the number of positive and negative feedback ratings included separately. Hence, percent positive appears the better predictor for seller trustworthiness.

Both these effects suggest that buyers consider the social benefit of the resulting feedback, in terms of both the number of future trading opportunities the feedback will be available for and the marginal value of their feedback for evaluating the seller, when deciding on whether to incur the cost of giving feedback. Also, buyers from UTD are weakly significantly less likely to provide feedback than buyers from UoC, evidence that social group identity *per se* can influence the frequency of feedback giving.

Turning back to the issue of the significance of group effects on feedback giving: Figure 5 displays probabilities of buyers' feedback giving at different levels of quality as predicted by marginal effects calculated based on Model 4 in Table 1. We first examine the left-side panel comparing in- and out-social group feedback giving. With the exception of medium levels of quality, reporting probabilities are greater for in-social than for out-social group matches. For example, an in-social group seller who ships zero quality receives feedback nearly always (98 percent), whereas his out-social group counterpart gets feedback in about four of five transactions (82 percent). And for high quality levels between 60 and 90 reporting probabilities are 14 to 37 percent larger in in-social group than in out-social group matches.

Overall there is more rewarding *and* more punishing if traders share a social identity. From Figure 5 (and also Figure 4), we see that social in- and out-group differences are not consistently large across all quality levels. They are significant and large exactly when it matters most. One might have thought that social identity is only a second-order concern, or a tie-breaker, kicking in when there is otherwise little reason to punish or reward performance and when indifference regarding feedback content is largest (namely for 'medium' quality). But, in fact, social identity affects behavior most when the effect is most valuable to the market, at very low and very high quality levels.

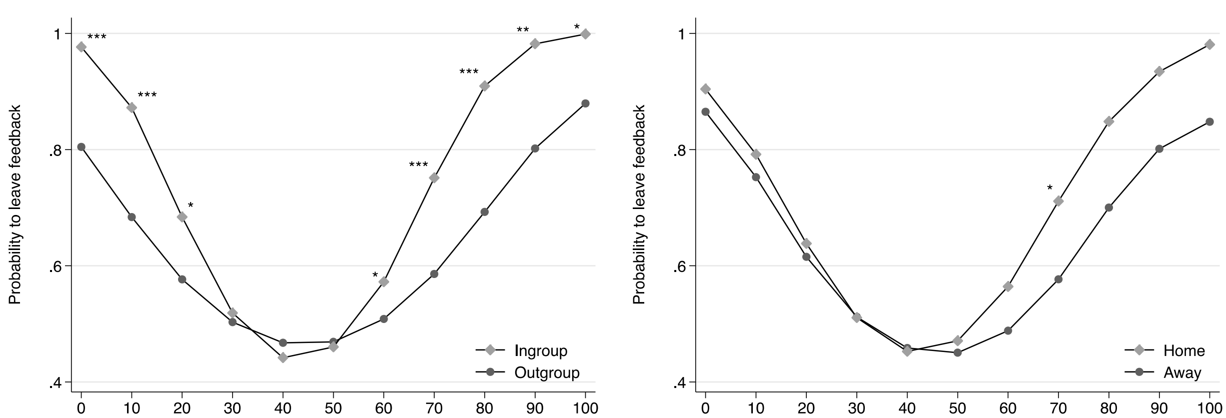


Figure 5: Predicted probabilities of buyer leaving feedback at the respective quality levels for in- and out-social group (left) and for away and home (right) matches, from Model 4, Table 1. Asterisks refer to tests comparing probabilities across curves at individual quality levels based on marginal effects (standard errors computed using delta method), $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The right-side panel of Figure 5 compares predicted probabilities of home and away market feedback giving. For quality of 50 and below the curves are almost identical. For quality above 50 buyers seem to be more willing to leave a rating when trading on their home market although the differences are largely insignificant.

Turning now to the content of feedback given, recall that Figures 3 and 4 showed little difference across in- and out-group in this regard. Table 2 takes a closer look, presenting a probit regression taking whether the buyer gave positive feedback as the dependent variable (here we restrict attention to those buyers that gave feedback). Variables are defined as for Table 1, with *High* (*Low*) *Quality* referring to actual quality the buyer received. *Quality* and *Expected Buyer Quality* are entered as separate variables (on the same rational given for doing so in Table 1). Consistent with what we observed in Figures 3 and 4, the model finds little social or home market group effect in feedback given, all other things equal. Receiving high or low quality has the expected effect on what feedback is given (q = 50 is the baseline case). Additional analyses, extending the model to include further cross effects, showed no consistent differences in feedback content with regard to group identity.

***Buyer gave positive feedback* (y/n)**	
In-social (y/n)	-0.033 (0.118)
Home (y/n)	-0.200 (0.131)
Low Quality $\in$ [0, 49]	-2.510*** (0.181)
High Quality $\in$ [51, 100]	1.247*** (0.139)
Buyer expected Quality	-0.038*** (0.004)
UTD (y/n)	0.306** (0.131)
Seller percent positive feedb.	0.005** (0.002)
Period	-0.009 (0.006)
Intercept	2.997*** (0.373)
Log likelihood	-305.0
N	1094

Table 2: Random effects probit regression conditional on feedback given (buyer positive feedback = 1). Dummy variables for matching groups included in all models. Periods 1-35; *t* statistics in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Summarizing the results in this section: We observe a significant and substantial increase in feedback giving when buyer and seller are from the same social group. This is evidenced by the consistent difference in the quadratic relationship between quality and feedback giving for in-social groups on display in Table 1, as well as the consistent and significant increases in feedback giving when quality deviates from the norm displayed for in-social trading pairs in Figure 5. Data for home market trading pairs show the same trends, although the significance of the differences is less consistent in Table 1 as well as Figure 5. Importantly, the increase in feedback frequency associated with both kinds of group identity promote rewarding good performance and punishing bad performance via the reputation channel: there is no leniency effect associated with in-group (out-group) ratings as evidenced by Table 2.

III.2 Trading behavior

How is trading behavior affected by group identity? We have seen that buyer norm enforcement is generally stronger within groups. Ceteris paribus, this should lead to more efficient trade, more trust and more trustworthiness, in our market. However, a few studies suggest that competition can mitigate concerns for the social environment (such as Falk and Szech 2013), although other studies cast doubt on the robustness of such findings (e.g., Sutter et al. 2016, Bartling et al. 2018). Other studies find that group identity does not affect cooperation if subjects are threatened to be rewarded or punished subsequently (such as Mussweiler and Ockenfels 2013). In our set-up, trader decisions are shaped by various strategic aspects, such as competitive pressure; this is particularly so for sellers in our set-up as they face potential punishment or reward in the buyer feedback stage. Moreover, sellers do not observe the market identity of buyers, and so can only respond to social identity information. The regressions in Table 3 test for trader favoritism with a series of regressions that examine buyer willingness to purchase, seller quality sent, trader profits and total market efficiency.

Dependent	Purchase (y/n)	Quality Shipped	Buyer Profit	Seller Profit	Market Efficiency
In-social (y/n)	0.226* (2.092)	0.283 (0.676)	1.388 (2.842)	5.516*** (2.105)	2.281* (2.311)
Home (y/n)	0.239* (2.542)		2.732 (2.446)	4.634** (1.815)	2.570** (3.025)
In-social X Home	-0.148 (-1.114)		-0.180 (3.441)	-3.851 (2.543)	-2.054 (-1.729)
Seller percent pos. feedb.	0.024*** (20.493)	0.085*** (0.012)	0.403*** (0.027)	0.351*** (0.021)	
UTD market (y/n)	0.276*** (4.340)	-1.045 (0.684)	2.106 (1.602)	-4.452*** (1.195)	2.023*** (3.680)
Period	-0.016*** (-4.560)	-0.299*** (0.035)	-0.475*** (0.084)	0.056 (0.062)	-0.152*** (-5.482)
Log likelihood	-1009.7	-10904.1	-13422.4	-10447.0	-9428.6
N	2677	2677	2677	2677	2800

Table 3: Random effects tobit regression (probit for Purchase model). Dummy variables for matching groups included in all models. Periods 1-35; *t* statistics in parentheses; * 0.1, ** *p* < 0.05, *** *p* < 0.01. Observations in first four models lower (N=2677) restricted to observations where seller has received at least 1 feedback; *Seller percent positive feedback* is otherwise not well defined. Quality Shipped regression does not include *Home* variable because sellers did not observe buyer home market, only buyer social identity.

Regarding buyer behavior, observe from the Purchase regression in Table 3 that social group and home market group matchings exhibit a weakly significant increased rate of purchase, which contributes to a statistically significant increase in seller profits, holding seller feedback scores fixed. We do not find corresponding and statistically significant effects for seller behavior, and thus buyer profits remain unchanged. That is, buyers tend to be more responsive to identity information than sellers in the trading phase, so that in-group sellers' profits increase, while buyers do not benefit from a shared identity. Overall, a shared identity increases market efficiency, although only weakly so for in-social identity.

IV. DISCUSSION AND CONCLUSION

Without norm enforcement via feedback systems, many economic and social Internet platforms could not exist. Motivated by observational data from eBay on feedback given in cross-national trading and by previous research on norm enforcement and group identity in non-market contexts, we experimentally investigate whether and how a shared social and market identity of traders affect feedback in a multinational market. We find that shared identities strongly affect feedback giving. Using university affiliations as natural social identity, we observe that both positive (rewarding good quality with a positive rating) and negative reciprocity (punishing inferior quality with a negative rating) are much more likely in in-social group matches. The probability of reciprocally giving feedback for high and low levels of quality increase by 14 to up to 37 percent. Moreover, while one might have initially thought that social identity is only a second-order concern, kicking in when there is otherwise little reason to punish or reward performance and when indifference regarding feedback content is largest (namely for 'medium' quality), social identity effects are in fact strongest when the they are most valuable to the market, at very low and very high quality levels.

Our study suggests a number of interesting paths for further research. Given the crucial importance of feedback for the functioning of many digital platforms, our findings may help explaining why platforms such as such as Airbnb and eBay often emphasize the social "community" character of the interaction. However, more research is needed on whether trust in markets can be effectively promoted by shaping one's perception of shared social identity among traders.

In both Cologne and Dallas markets, it was clear that the quality that leads to a 50-50 split of profits between buyer and seller acted as the market norm for satisfactory seller delivery. The 50-50 rule is likely special to our laboratory set-up. That said, many markets supposedly develop norms for satisfactory goods and service, and we would conjecture that our results, permutated to the new norm, would continue to hold. A different question is the impact of social identity on norm-enforcement in contexts in which there is uncertainty about, or heterogeneity with respect to, the relevant market norm. One hypothesis is that, as long a clear social norm is lacking, the traders' willingness to punish or reward others is mitigated. Then, the role of social identity is not so much norm-enforcement but facilitating norm development.

Our experiment design allows us to observe that social identity is more important for norm-enforcement than market identity; our buyers are willing to leave a rating and contribute to the feedback public good even on less frequently visited markets if they share their social identity with the trading partner. This holds despite the fact that there was no reason, from a purely rational perspective, to care about social identity, yet strategic traders should care more about norm-enforcement in one's home market than in the away market. This way, social identity not only substantially affects non-strategic market behavior, but also, by the same token, shapes critical strategic aspects of the market environment. That said, there is an interesting variation that might produce a larger market identity effect than we observe here: If the home market develops a different norm than the away market, we would expect stronger norm enforcement when both partners share a common market identity (and know this), a lack of common market identity being an acceptable excuse for failure to coordinate on a market norm. This hypothesis, too, must be left to future research.

Affiliations: Gary Bolton (University of Texas at Dallas, USA), Johannes Mans (University of Cologne, Germany), Axel Ockenfels (University of Cologne, Germany)

REFERENCES

Akerlof, George A. and Rachel E. Kranton. 2000. “Economics and Identity.” *Quarterly Journal of Economics* 115 (3): 715–753.

Anderson, E. W. 1998. “Customer Satisfaction and Word of Mouth.” *Journal of Service Research* 1 (1) (August 1): 5–17.

Ba, Sulin and Paul A. Pavlou. 2002. “Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior.” *MIS Quarterly* 26 (3): 243–268.

Bajari, Patrick and Ali Hortacsu. 2003. “The Winner’s Curse, Reserve Prices, and Endogenous Entry: Empirical Insights from eBay Auctions.” *The RAND Journal of Economics* 34 (2): 329–355.Bartling, Björn, Ernst Fehr and Yagiz Özdemir. 2018. "Do Markets Undermine Morality?" Presented in Bonn in June 2018.

Beenen, Gerard, Kimberly Ling, Xiaoqing Wang, Klarissa Chang, Dan Frankowski, Paul Resnick and Robert E. Kraut. 2004. “Using Social Psychology to Motivate Contributions to Online Communities.” In *Proceedings of 2004 ACM Conference on Computer Supported Cooperative Work*, 212–221. New York.

Bernhard, Helen, Urs Fischbacher and Ernst Fehr. 2006a. “Group Affiliation and Altruistic Norm Enforcement.” *American Economic Review* 96 (2): 217–221.

———. 2006b. “Parochial Altruism in Humans.” *Nature* 442 (August 24): 912–915.

Bolton, Gary E, Ben Greiner and Axel Ockenfels. 2013. “Engineering Trust - Reciprocity in the Production of Reputation Information.” *Management Science* 59 (2): 265–285.

Bolton, Gary E., Ben Greiner, and Axel Ockenfels. Forthcoming. “Dispute Resolution or Escalation? The Strategic Gaming of Feedback Withdrawal Options in Online Markets.” *Management Science*.

Bolton, Gary E., Elena Katok and Axel Ockenfels. 2004. “How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation.” *Management Science* 50 (11) (November): 1587–1602.

Bolton G. E., and A. Ockenfels (2000). ERC: A theory of equity, reciprocity, and competition. *American Economic Review* 90, 166 – 193.

Bolton, Gary E., and Axel Ockenfels. 2014. “Does Laboratory Mirror Behavior in Real World Markets? Fair Bargaining and Competitive Bidding on eBay.” *Journal of Economic Behavior and Organization*, 97, 143– 154.

Bolton, Gary E., David J. Kusterer and Johannes Mans. 2014. “Leniency in Feedback Giving.” *Management Science,* forthcoming.

Chen, Yan, F Maxwell Harper, Joseph Konstan and Sherry Xin Li. 2010. “Social Comparisons and Contributions to Online Communities: A Field Experiment on MovieLens.” *American Economic Review* 100 (4): 1358–1398.

Chen, Yan, and Sherry Xin Li. 2009. “Group Identity and Social Preferences.” *The American Economic Review* 99 (1): 431–457.

Chevalier, Judith A. and Dina Mayzlin. 2006. “The Effect of Word of Mouth on Sales: Online Book Reviews.” *Journal of Marketing Research* 43 (3): 345–354.

Dellarocas, Chrysanthos. 2003. “The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms.” *Management Science* 49 (10): 1407–1424.

———. 2005. “Reputation Mechanism Design in Online Trading Environments with Pure Moral Hazard.” *Information Systems Research* 16 (2) (June): 209–230.

Dellarocas, Chrysanthos and Charles A Wood. 2008. “The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias.” *Management Science* 54 (3) (March): 460–476.

Dholakia, Utpal M., Richard P. Bagozzi and Lisa Klein Pearo. 2004. “A Social Influence Model of Consumer Participation in Network- and Small-Group-Based Virtual Communities.” *International Journal of Research in Marketing* 21 (3) (September): 241–263.

eBay Enterprise. 2014. “Cross-Border Ecommerce: Catching the Trade Winds.” *Last Accessed: 19.08.2014*. http://www.ebayenterprise.com/commersations/blog/cross-border_ecommerce_catching_the_trade_winds.

EMOTA. 2014. “E-Commerce in Europe.” *Last Accessed: 19.08.2014*. http://media.wix.com/ugd/b18286_390bb25f5c1340fbbc9df4945b56ad16.pdf.

European Commission. 2013. “Digital Agenda Scoreboard 2013.”

Falk, Armin, Nora Szech. 2013. Morals and markets. *Science* 340 707–711.

Fehr, Ernst, and Simon Gächter. 2002. “Altruistic Punishment in Humans.” *Nature* 415 (10): 137–140.

Fehr E., and K. M.Schmidt (1999).A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics* 114, 817 – 868.

Fershtman, Chaim and Uri Gneezy. 2001. “Discrimination in a Segmented Society: An Experimental Approach.” *The Quarterly Journal of Economics* 116 (1): 351–377.

Fischbacher, Urs, Simeon Schudy, and Sabrina Teyssier. 2014. “Heterogeneous Reactions to Heterogeneity in Returns from Public Goods.” *Social Choice and Welfare* 43 (1) (August 15): 195–217.

Fisher, Joseph, R. Mark Isaac, Jeffrey W. Schatzberg and James M. Walker. 1995. "Heterogenous Demand for Public Goods: Behavior in the Voluntary Contributions Mechanism." *Public Choice* 85 (3-4) (December): 249–266.

Andrey Fradkin, Andrey, Elena Grewal, and David Holtz. 2018. " The Determinants of Online Review Informativeness: Evidence from Field Experiments on Airbnb." Working paper.

Freund, Caroline L. and Diana Weinhold. 2002. "The Internet and International Trade in Services." *American Economic Review* 92 (2): 236–240.

———. 2004. "The Effect of the Internet on International Trade." *Journal of International Economics* 62 (1) (January): 171–189.

Godes, David and Dina Mayzlin. 2004. "Using Online Conversations to Study Word-of-Mouth Communication." *Marketing Science* 23 (4) (November): 545–560.

Greiner, Ben. 2004. "The Online Recruitment System ORSEE 2.0 - A Guide for the Organization of Experiments in Economics." Working Paper.

Haile, Daniel, Abdolkarim Sadrieh and Harrie a a Verbon. 2008. "Cross-Racial Envy and Underinvestment in South African Partnerships." *Cambridge Journal of Economics* 32 (2001): 703–724.

Heap, Shaun P Hargreaves and Daniel John Zizzo. 2009. "The Value of Groups." *The American Economic Review* 99 (1): 295–323.

Hendriks, Achim. 2012. "SoPHIE - Software Platform for Human Interaction Experiments." *Working Paper*. Working Paper.

Hortaçsu, Ali, F Asís Martínez-Jerez and Jason Douglas. 2009. "The Geography of Trade in Online Transactions: Evidence from eBay and MercadoLibre." *American Economic Journal: Microeconomics* 1 (1): 53–74.

Houser, Daniel and John Wooders. 2006. "Reputation in Auctions: Theory, and Evidence from eBay." *Journal of Economics & Management Strategy* 15 (2): 353–369.

Hu, Nan, Paul A Pavlou and Jennifer Zhang. 2006. "Can Online Reviews Reveal a Product's True Quality? Empirical Findings and Analytical Modeling of Online Word-of-Mouth Communication." In *Proceedings of the 7th ACM Conference on Electronic Commerce*, edited by D.Pennock J. Feigenbaum J.Chuang, 324–330. New York: ACM Press.

Hu, Nan, Paul A Pavlou and Jie Zhang. 2009. "Overcoming the J-Shaped Distribution of Product Reviews." *Communications of the ACM* 52 (10): 144–147.

Isaac, R. Mark, Kenneth F. McCue and Charles R. Plott. 1985. "Publi Goods Provision in an Experimental Environment." *Journal of Public Economics* 26: 51–74.

Isaac, R. Mark and James M. Walker. 1988. "Group Size Effects in Public Goods Provision: The Voluntary Contributions Mechanism." *The Quarterly Journal of Economics* 103 (1): 179–199.

Jian, Lian, Jeffrey K Mackie-Mason and Paul Resnick. 2010. “I Scratched Yours : The Prevalence of Reciprocation in Feedback Provision on eBay.” *The B . E . Journal of Economic Analysis & Policy* 10 (1): 1–38.

Lafky, Jonathan. 2014. “Why Do People Rate? Theory and Evidence on Online Ratings.” *Games and Economic Behavior* (March).

Lendle, Andreas, Marcelo Olarreaga, Simon Schropp and Pierre-Louis Vézina. 2012. “There Goes Gravity: How eBay Reduces Trade Costs.” Working Paper.

Li, Sherry Xin, Kutsal Dogan and Ernan Haruvy. 2011. “Group Identity in Markets.” *International Journal of Industrial Organization* 29 (1): 104–115.

Li, Xinxin and Lorin M. Hitt. 2008. “Self-Selection and Information Role of Online Product Reviews.” *Information Systems Research* 19 (4) (December): 456–474.

Livingston, Jeffrey A. 2005. “How Valuable Is a Good Reputation? A Sample Selection Model of Internet Auctions” 87 (3): 453–465.

Luca, Michael. 2011. “Reviews, Reputation, and Revenue: The Case of Yelp.com.” Working Paper.

Ludford, Pamela J., Dan Cosley, Dan Frankowski and Loren Terveen. 2004. “Think Different: Increasing Online Community Participation Using Uniqueness and Group Dissimilarity.” In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 6:631–638. New York.

Marques, José, Dominic Abrams and Rui G Serôdio. 2001. “Being Better by Being Right: Subjective Group Dynamics and Derogation of in-social group Deviants When Generic Norms Are Undermined.” *Journal of Personality and Social Psychology* 81 (3): 436–447.

Marques, Jose M. and Vincent Y Yzerbyt. 1988. “Short Note The Black Sheep Effect : Judgmental Extremity towards In-social group Members in Inter- and Intra-Group Situations.” *European Journal of Social Psychology* 18: 287–292.

Marques, Jose M. Vincent Y Yzerbyt and Jacques-philippe Leyens. 1988. “The ‘Black Sheep Effect’: Extremity of Judgments towards In-social group Members as a Function of Group Identification.” *European Journal of Social Psychology* 18: 1–16.

McDonald, Cynthia G. and V. Carlos Slawson. 2002. “Reputation in an Internet Auction Market.” *Economic Inquiry* 40 (3): 633–650.

McLeish, Kendra N. and Robert J. Oxoby. 2007. “Identity, Cooperation and Punishment.” Working Paper.

Melnik, Mikhail I. and James Alm. 2003. “Does a Seller’s eCommerce Reputation Matter? Evidence from eBay Auctions.” *The Journal of Industrial Economics* 50 (3) (March 27): 337–349.

Mussweiler, Thomas and Axel Ockenfels. 2013. “Similarity Increases Altruistic Punishment in Humans.” *Proceedings of the National Academy of Sciences of the United States of America* 110 (48) (November 26): 19318–23.

Ockenfels, Axel. 2003. “Reputationsmechanismen auf Internet-Marktplattformen: Theorie und Empirie:” *Zeitschrift für Betriebswirtschaft,* 73(3): 295-315.

Ockenfels, Axel, and Paul Resnick. 2012. “Negotiating reputations.” In: Gary Bolton, and Rachel Croson (eds), *The Oxford Handbook of Economic Conflict Resolution,* Oxford University Press, 223-237.

Paypal. 2013. “Modern Spice Routes: The Cultural Impact and Economic Opportunity of Cross-Border Shopping.” *Last Accessed: 19.08.2014*. https://www.paypal-media.com/assets/pdf/fact_sheet/PayPal_ModernSpiceRoutes_Report_Final.pdf.

Pechar, Emily, and Rachel Kranton. 2017. “Moderators of Intergroup Discrimination in the Minimal Group Paradigm: A Meta- Analysis.”, Working paper.

Pinto, Isabel R, José M Marques, John M Levine and Dominic Abrams. 2010. “Membership Status and Subjective Group Dynamics: Who Triggers the Black Sheep Effect?” *Journal of Personality and Social Psychology* 99 (1) (July): 107–19.

Resnick, Paul and Richard Zeckhauser. 2002. “Trust among Strangers in Internet Transactions: Empirical Analysis of eBay’s Reputation System.” *Advances in Applied Microeconomics* 11: 127–157.

Resnick, Paul, Richard Zeckhauser, John Swanson and Kate Lockwood. 2006. “The Value of Reputation on eBay: A Controlled Experiment.” *Experimental Economics* 9 (2): 79–101.

Reuben, E. and A. Riedl. 2009. “Public Goods Provision and Sanctioning in Privileged Groups.” *Journal of Conflict Resolution* 53 (1) (November 12): 72–93.

Shinada, Mizuho, Toshio Yamagishi and Yu Ohmura. 2004. “False Friends Are Worse than Bitter Enemies.” *Evolution and Human Behavior* 25 (6) (November): 379–393.

Sutter, Matthias, Stefan Haigner and Martin Kocher (2010). "Choosing the Carrot or the Stick? Endogenous Institutional Choice in Social Dilemma Situations." *The Review of Economic Studies* 77(4), 1540-1566.

Sutter, Matthias, Jürgen Huber, Michael Kirchler and Matthias Sutter (2016). "Where to Look for the Morals in Markets?" IZA Discussion Paper 10105.

Tajfel, Henri, M. G. Billig, R. P. Bundy and C. Flament. 1971. “Social Categorization and Intergroup Behavior.” *European Journal of Social Psychology* 1 (2): 149–178.

Tajfel, Henri and John Turner. 1979. “An Integrative Theory of Intergroup Conflict.” In *The Social Psychology of Intergroup Relations*, edited by Stephen Worchel and William Austin, 33–47. Monterey, CA: Brooks/Cole.

Tan, Fangfang. 2008. “Punishment in a Linear Public Good Game with Productivity Heterogeneity.” *De Economist* 156 (3) (September 23): 269–293.

Tsutsui, Kei and Daniel John Zizzo. 2014. “Group Status, Minorities and Trust.” *Experimental Economics* 17 (2) (May 11): 215–244.

Wang, Zhongmin. 2010. “Anonymity, Social Image, and the Competition for Volunteers: A Case Study of the Online Market for Reviews.” *The B.E. Journal of Economic Analysis & Policy* 10 (1) (January 21): 1–34.

Xiao, Erte and Daniel Houser. 2005. “Emotion Expression in Human Punishment Behavior.” *Proceedings of the National Academy of Sciences of the United States of America* 102 (20): 7398–7401.

Zhu, Feng and Xiaoquan Zhang. 2010. “Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics.” *Journal of Marketing* 74 (2): 133–148.

APPENDIX A – SUPPLEMENTARY TABLES AND FIGURES

		Feedback provision					
		Overall		Buyers		Sellers	
	# Transactions	Home	Away	Home	Away	Home	Away
Overall	N = 640,845	71.65%	49.83%	71.49%	49.55%	71.80%	50.10%
US	N = 268,369	65.73%	57.34%	65.42%	58.00%	66.04%	56.68%
Germany	N = 170,010	77.85%	52.36%	78.22%	52.17%	77.47%	52.54%
UK	N = 124,357	75.00%	46.73%	74.76%	44.91%	75.23%	48.55%
France	N = 35,723	75.26%	40.42%	74.94%	42.98%	75.57%	37.85%
Australia	N = 28,356	75.54%	36.10%	74.85%	33.74%	76.22%	38.46%
Belgium	N = 10,876	78.11%	67.37%	76.85%	66.33%	79.36%	68.41%
India	N = 2,344	13.13%	17.43%	9.93%	14.68%	16.33%	20.18%
Poland	N = 810	48.66%	66.35%	48.44%	66.35%	48.87%	66.35%

Table A1: Empirical data on feedback provision collected on eBay in November/December 2006. 640,845 successful transactions from eight different domains and six different categories (cellphones, fragrances, antiques, cartridges, money, and amazon vouchers).

	Share of positive feedback ratings								
		Overall			Buyers			Sellers	
	# Ratings	Home	Away	# Ratings	Home	Away	# Ratings	Home	Away
Overall	906,544	97.93%	96.04%	452,270	97.62%	97.56%	454,274	98.23%	94.53%
US	351,643	97.70%	97.73%	175,050	97.31%	98.23%	176,593	98.09%	97.23%
Germany	263,031	98.46%	96.28%	132,136	97.95%	97.39%	130,895	98.98%	95.16%
UK	181,869	97.94%	94.19%	90,511	97.97%	97.24%	91,358	97.91%	91.16%
France	50,788	96.77%	95.84%	25,404	96.60%	96.62%	25,384	96.94%	95.05%
Australia	41,216	98.14%	94.54%	20,379	98.00%	98.41%	20,837	98.28%	90.76%
Belgium	16,547	97.53%	97.44%	8,141	97.40%	97.51%	8,406	97.66%	97.38%
India	625	78.59%	94.37%	238	92.34%	100.00%	387	70.14%	90.91%
Poland	825	97.38%	97.10%	411	97.66%	97.10%	414	97.10%	97.10%

Table A2: Empirical data on content of feedback ratings collected on eBay in November/December 2006. 640,845 successful transactions from eight different domains and six different categories (cellphones, fragrances, antiques, cartridges, money, and amazon vouchers).

		Periods			
		All	**1 – 12**	**13 – 24**	**25 – 35**
Quality	$N = 2800$	46.38	48.35	47.89	42.58
Equal split	$N = 2800$	41.89%	49.27%	43.85%	31.70%
Sold products	$N = 2800$	80.39%	82.81%	80.83%	77.27%
Efficiency	$N = 2800$	69.12%	70.11%	69.58%	67.54%
Feedback given	$N = 2251$	52.15%	58.60%	51.29%	45.59%
Positive feedback	$N = 1174$	62.01%	63.52%	63.07%	58.39%
Negative feedback	$N = 1174$	37.99%	36.48%	36.93%	41.61%
Percent positive	$N = 2677$	60.92%	60.97%	60.85%	60.95%

Table A3: Descriptive statistics for experimental data.

Quality	***Model 1***	***Model 2***
In-social group	0.283	0.193
	(0.676)	(0.658)
Percent positive	0.085^{***}	
	(0.012)	
# positive feedbacks		0.300^{*}
		(0.121)
# negative feedbacks		-1.294^{***}
		(0.180)
UTD	-1.045	-0.649
	(0.684)	(0.666)
Period	-0.299^{***}	-0.152^{*}
	(0.035)	(0.059)
Intercept	43.266^{***}	46.604^{***}
	(1.550)	(1.296)
Log likelihood	-10904.1	-11404.2
N	2677	2800

Table A4: Random effects tobit regression with quality as dependent variable (lower limit = 0; upper limit = 100). Dummy variables for matching groups included in all models. Periods 1-35; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Model 1	Model 2	Model 3	Model 4
In-social	0.075 (0.057)	1.151^{***} (0.333)	0.074 (0.057)	0.919^{**} (0.455)
Home	0.043 (0.062)	0.041 (0.063)	0.159 (0.284)	0.100 (0.356)
Quality	-0.060^{***} (0.006)	-0.041^{***} (0.008)	-0.052^{***} (0.009)	-0.017 (0.012)
Quality2	0.001^{***} (0.000)	0.000^{***} (0.000)	0.001^{***} (0.000)	0.000 (0.000)
In-social X quality		-0.059^{***} (0.014)		-0.079^{***} (0.020)
In-social X quality2		0.001^{***} (0.000)		0.001^{***} (0.000)
Home X quality			-0.015 (0.012)	-0.036^{**} (0.016)
Home X quality2			0.000 (0.000)	0.000^{**} (0.000)
In-social X home				0.624 (0.712)
In-social X home X quality				0.015 (0.031)
In-social X home X quality^2				-0.000 (0.000)
Expected - actual quality	0.004^{**} (0.002)	0.004^{*} (0.002)	0.004^{*} (0.002)	0.003 (0.002)
UTD	-0.104^{*} (0.061)	-0.103^{*} (0.061)	-0.102^{*} (0.061)	-0.103^{*} (0.062)
Seller percent positive feedback	-0.003^{***} (0.001)	-0.003^{***} (0.001)	-0.003^{***} (0.001)	-0.004^{***} (0.001)
Period	-0.017^{***} (0.003)	-0.018^{***} (0.003)	-0.017^{***} (0.003)	-0.018^{***} (0.003)
Intercept	1.594^{***} (0.220)	1.240^{***} (0.245)	1.551^{***} (0.274)	1.239^{***} (0.329)
Log likelihood	-1326.4	-1316.9	-1325.0	-1287.9
N	2139	2139	2139	2139

Table A5: Random effects probit regression with buyer feedback election as dependent variable. Dummy variables for matching groups; periods 1-35; *t*-statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Dependent variable	***Buyer gave negative feedback*** *Q ≤ 50*	***Buyer gave positive feedback*** *Q ≥ 50*
In-social group	0.372^{*}	-1.247^{**}
	(1.981)	(-2.873)
Home	0.159^{+}	0.020
	(1.817)	(0.307)
Quality	-0.039^{***}	0.025^{***}
	(-11.641)	(4.835)
In-social group X Quality	-0.005	0.023^{**}
	(-1.076)	(2.890)
Exp. Quality	0.030^{***}	0.006^{***}
	(13.212)	(3.489)
UTD	-0.315^{***}	-0.085
	(-3.571)	(-1.347)
Percent positive	-0.003^{*}	0.006^{***}
	(-2.037)	(5.070)
Period	-0.014^{***}	-0.012^{***}
	(-3.337)	(-3.772)
Log likelihood	-630.6	-1196.7
N	1740	2040

Table A6: Random effects probit regression with negative/positive feedback as dependent variable. Dummy variables for matching groups included in all models. Periods 1-35; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

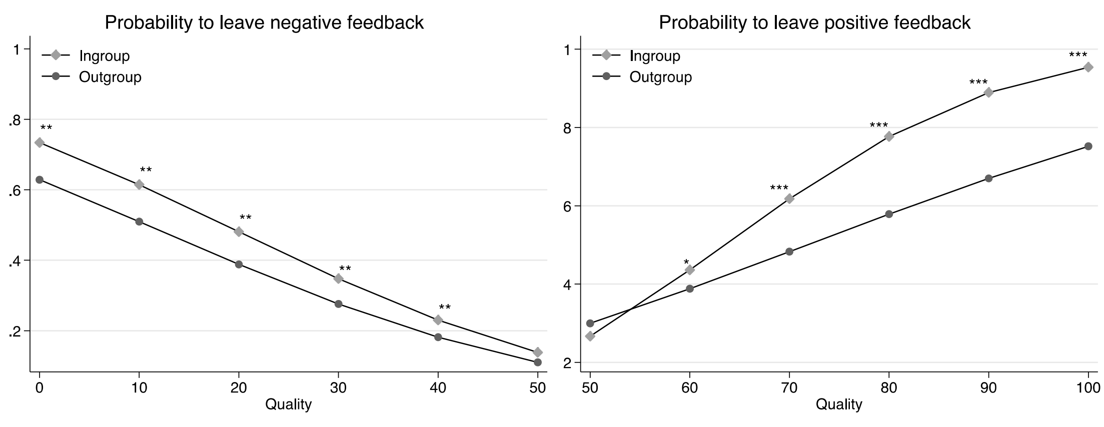


Figure A1: Probability to leave negative or positive feedback. Left panel based on Model 1 in Table A6. Right panel based on Model 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Buyer gave feedback (y/n)	Model 1	Model 2	Model 3
In-social group	0.104*	0.113	0.104*
	(1.777)	(1.290)	(1.766)
Home	0.025	0.023	0.091
	(0.394)	(0.358)	(0.947)
Quality 0-25	1.802***	1.544***	1.783***
	(12.203)	(8.353)	(8.138)
Quality 26-49	0.769***	0.822***	0.976***
	(7.388)	(5.521)	(5.215)
Quality 51-75	0.819***	0.877***	0.901***
	(11.989)	(9.251)	(7.464)
Quality 76-100	1.031***	0.186	0.755*
	(3.735)	(0.422)	(1.854)
Exp. Quality	0.003	0.003	0.003
	(1.398)	(1.315)	(1.317)
UTD	-0.092	-0.090	-0.093
	(-1.472)	(-1.415)	(-1.486)
Percent positive	-0.002*	-0.002**	-0.002**
	(-1.951)	(-2.034)	(-2.026)
Period	-0.024***	-0.025***	-0.024***
	(-7.464)	(-7.676)	(-7.507)
In-social group X Quality 0-25		0.717**	
		(2.275)	
In-social group X Quality 26-49		-0.099	
		(-0.505)	
In-social group X Quality 51-75		-0.114	
		(-0.880)	
In-social group X Quality 76-100		1.480**	
		(2.423)	
Home X Quality 0-25			0.052
			(0.180)
Home X Quality 26-49			-0.293
			(-1.350)
Home X Quality 51-75			-0.118
			(-0.833)
Home X Quality 76-100			0.523
			(0.934)
Intercept	0.087	0.092	0.058
	(0.475)	(0.490)	(0.304)
N	2139	2139	2139
Log likelihood	-1253.3	-1246.2	-1251.6

Table A7: Random effects probit regressions on feedback provision. Group dummies included. Periods 1-35; *t* statistics in parentheses; * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01.

APPENDIX B – INSTRUCTIONS

INSTRUCTIONS

Welcome and thank you for participating in this experiment. Please use the Login Code to log into the experiment. Please keep this Login Code until the end of the experiment. We need this Login Code to pay you your earnings.

You can earn money in this experiment. The specific amount depends on your decisions and the decisions of other participants. Take the time to read the instructions carefully and please make sure that you understand everything. If you have questions, please raise your hand and one of the supervisors will come to help you. From now on until the end of the experiment, please do not communicate with other participants. For the experiment to run smoothly, it is important that all participants focus solely on the experiment. For this reason, please put away your cellphones, magazines, and study materials. If you do not comply with these rules we may have to exclude you from the experiment and all payments.

This experiment will be conducted here and in a laboratory at the University of Cologne (Germany). This means that subjects from the ***University of Texas at Dallas*** *and from the* ***University of Cologne*** *participate in this experiment at the same time. During the experiment you interact with subjects from the University of Texas at Dallas (participants from Dallas) as well as with subjects from the University of Cologne (participants from Cologne). Whether you interact with a participant from Dallas or Cologne will be shown on your screen. All participants receive the same information. All decisions that you take are anonymous.*

In the experiment we use ECU (Experimental Currency Unit) as the monetary unit. At the end of the experiment your payoffs will be converted from ECUs into US Dollars (250 ECU = 1 US Dollar) and paid out in cash plus a show-up-fee of $5. The conversion rate for the participants at the University of Cologne is adjusted to the current exchange rate between US Dollars and Euro.

In this experiment there are **buyers** and **sellers**. Your role will be randomly determined at the beginning of the experiment and remains the same for the entire experiment. There are as many buyers as there are sellers. All participants have the same probability to be in the role of the buyer and seller, respectively. Before the first period starts, you will be informed whether you are in the role of a buyer or seller. In total, the experiment lasts for **40** periods.

MARKETS AND BUYER TYPES

In this experiment there are two markets: a **Dallas market** and a **Cologne market**. Sellers always stay on their home market: **Sellers from Dallas** always trade on the **Dallas market** and **sellers from Cologne** always trade on the **Cologne market**.

Buyers do not stay on the same market, but switch between the two markets. There are two different types of buyers: **type D** buyers are more likely to trade in Dallas and **type C** buyers are more likely to trade in Cologne. Specifically:

- Buyers of **type D** in each round have a probability of 80% to trade on the Dallas market and a probability of 20% to trade on the Cologne market.
- Buyers of **type C** in each round have a probability of 20% to trade on the Dallas market and a probability of 80% to trade on the Cologne market.

There are as many buyers of type D as of type C. Each buyer, regardless of whether he/she is a participant from Dallas or Cologne, has the same probability to be chosen a type D or type C buyer. At the beginning of the experiment, each buyer will be randomly assigned a type (type D or type C), which remains the same for the entire experiment.

At the beginning of each round, each buyer is assigned to trade on the Dallas market or the Cologne market. The assignment is done according to the probabilities laid out above. The market chosen will be shown on the buyer's screen. Each buyer is then matched randomly to a seller on this market. It is guaranteed, that buyers are not matched to the same seller in two consecutive rounds. The buyer gets to know how many positive and negative feedbacks the matched seller received so far. The seller gets to know whether the matched buyer is a participant from Dallas or Cologne.

TRADE

At the beginning of each round, sellers and buyers receive an endowment of 100 ECU. In each round the seller offers a good to the buyer and the buyer decides whether he/she wants to buy the good at a price of 100 ECU. If the buyer decides not to buy the good both, seller and buyer, keep their endowment of 100 ECU and the round ends. If the buyer decides to buy the good, he/she pays a price of 100 ECU to the seller. At the same time the seller chooses the quality of the good he/she wants to send to the buyer in case he/she buys the good. Quality ranges between 0 and 100. Each quality point costs the seller 1 ECU and increases the good's value to the buyer by 3 ECU, for example:

- If the quality is 0, the seller has costs of 0 ECU and the buyer receives a good with a value of 0 ECU.
- If the quality is 50, the seller has costs of 50 ECU and the buyer receives a good with a value of 150 ECU.
- If the quality is 100, the seller has costs of 100 ECU and the buyer receives a good with a value of 300 ECU.

Overview of period payoffs for sellers and buyers:

	Seller	**Buyer**
Buyer does not buy:	100 ECU	100 ECU
Buyer buys:	200 ECU – Quality	3 x Quality

FEEDBACK

The buyer then gets to know the quality that the seller has chosen. Afterwards, the buyer may leave a feedback rating for the seller. Leaving a feedback rating costs 1 ECU. The feedback can either be "positive" or "negative". In the following rounds buyers get to know how many positive and how many negative feedbacks the matched seller has received so far. The seller gets to know whether and what kind of feedback he/she received from the matched buyer and a new round starts.

If you have any further questions, please raise your hand and one of the supervisors will come to help you.

INSTRUCTIONS – GERMAN VERSION

Herzlich willkommen und vielen Dank für Ihre Teilnahme an diesem Experiment. Bitte loggen Sie sich mit dem Login Code in das Experiment ein. Bewahren Sie den Login Code bis zum Ende des Experiments auf. Wir benötigen den Login Code um Ihnen Ihren Verdienst auszuzahlen.

In diesem Experiment können Sie Geld verdienen. Wie viel hängt sowohl von Ihren eigenen als auch den Entscheidungen der anderen Teilnehmer ab. Bitte lesen Sie sich die Instruktionen sorgfältig durch und stellen Sie sicher, dass Sie alles verstanden haben. Wenn Sie Fragen haben, heben Sie bitte kurz Ihre Hand und einer der Experimentleiter wird zu Ihnen kommen, um Ihnen zu helfen. Bitte kommunizieren Sie ab jetzt nicht mehr mit anderen Experimentteilnehmern. Damit das Experiment ohne Verzögerungen durchgeführt werden kann ist es wichtig, dass sich alle Teilnehmer ausschließlich auf das Experiment konzentrieren. Bitte legen Sie deswegen Handys, Zeitschriften, Lernunterlagen etc. zur Seite. Sollten Sie sich nicht an diese Regeln halten, müssen wir Sie vom Experiment und jeglichen Auszahlungen ausschließen.

Dieses Experiment wird gleichzeitig hier und in einem Labor an der University of Texas at Dallas (USA) durchgeführt. Das bedeutet, dass an diesem Experiment gleichzeitig Teilnehmer der ***Universität zu Köln*** *und der* ***University of Texas at Dallas*** *teilnehmen. Sie interagieren also sowohl mit Teilnehmern des Labors an der Universität zu Köln (Teilnehmer aus Köln) als auch mit Teilnehmern des Labors an der University of Texas at Dallas (Teilnehmer aus Dallas). Ob Sie in einer Runde mit einem Teilnehmer aus Köln oder Dallas interagieren, wird Ihnen auf dem Bildschirm angezeigt. Alle Teilnehmer erhalten die gleichen Informationen. Alle Entscheidungen, die Sie treffen, sind anonym.*

In diesem Experiment verwenden wir die Währung ECU (Experimental Currency Unit). Am Ende des Experiments werden Ihre Verdienste in Euro umgerechnet (350 ECU = 1 €) und Ihnen, zuzüglich der Prämie für Ihr Erscheinen von 3 Euro, in bar ausbezahlt. Der Umrechnungskurs für die Teilnehmer an der University of Texas at Dallas richtet sich nach dem aktuellen Wechselkurs zwischen Euro und US Dollar.

In diesem Experiment gibt es **Käufer** und **Verkäufer**. Ihre Rolle wird am Anfang des Experiments zufällig bestimmt und bleibt während des gesamten Experiments gleich. Es gibt genauso viele Käufer wie Verkäufer. Alle Teilnehmer haben die gleichen Wahrscheinlichkeiten die Rolle des Käufers bzw. Verkäufers zugewiesen zu bekommen. Vor der ersten Runde werden Sie darüber informiert, ob Sie Käufer oder Verkäufer sind. Insgesamt dauert das Experiment **40** Runden.

MÄRKTE UND KÄUFER-TYPEN

In diesem Experiment gibt es zwei Märkte: einen **Köln Markt** und einen **Dallas Markt**. Die Verkäufer bleiben immer auf ihrem Heimatmarkt: **Verkäufer aus Köln** handeln immer auf dem **Köln Markt** und **Verkäufer aus Dallas** handeln immer auf dem **Dallas Markt**.

Die Käufer bleiben nicht immer auf dem gleichen Markt, sondern wechseln zwischen den beiden Märkten. Es gibt zwei unterschiedliche Käufer-Typen, Käufer vom **Typ K** handeln eher auf dem Köln Markt und Käufer vom **Typ D** handeln eher auf dem Dallas Markt:

- Käufer vom **Typ K** handeln in jeder Runde mit einer Wahrscheinlichkeit von 80% auf dem Köln Markt und mit einer Wahrscheinlichkeit von 20% auf dem Dallas Markt.
- Käufer vom **Typ D** handeln in jeder Runde mit einer Wahrscheinlichkeit von 20% auf dem Köln Markt und mit einer Wahrscheinlichkeit von 80% auf dem Dallas Markt.

Es gibt genauso viele Käufer vom Typ K wie vom Typ D. Jeder Käufer, egal ob er ein Teilnehmer aus Köln oder Dallas ist, hat die gleiche Wahrscheinlichkeit ein Typ K oder Typ D Käufer zu sein. Zu Beginn des

Experiments wird jedem Käufer zufällig ein Typ zugewiesen (Typ K oder Typ D), der dann für das gesamte Experiment gleich bleibt.

Zu Beginn jeder Runde wird für jeden Käufer anhand der obengenannten Wahrscheinlichkeiten bestimmt, ob er auf dem Köln Markt oder auf dem Dallas Markt handelt. Auf dem Bildschirm wird dem Käufer angezeigt auf welchem Markt er in dieser Runde handelt. Jeder Käufer wird dann zufällig einem der Verkäufer auf diesem Markt zugeteilt. Hierbei ist sichergestellt, dass ein Käufer in aufeinanderfolgenden Runden nicht mit dem gleichen Verkäufer handelt. Der Käufer erfährt wie viele positive und wie viele negative Bewertungen der ihm zugeteilte Verkäufer bereits erhalten hat. Der Verkäufer erfährt ob der ihm zugeteilte Käufer ein Teilnehmer aus Köln oder Dallas ist.

HANDELN

Zu Beginn jeder Runde erhalten Verkäufer und Käufer eine Rundenausstattung von 100 ECU. Der Verkäufer bietet in jeder Runde dem Käufer ein Gut an und der Käufer entscheidet, ob er das Gut zum Preis von 100 ECU kaufen möchte. Wenn der Käufer sich entscheidet das Gut nicht zu kaufen, behalten beide, Verkäufer und Käufer, ihre Rundenausstattung von 100 ECU und die Runde ist beendet. Wenn der Käufer sich entscheidet das Gut zu kaufen, zahlt er dem Verkäufer den Preis von 100 ECU. Gleichzeitig wählt der Verkäufer die Qualität des Gutes, die er an den Käufer senden möchte falls dieser das Gut kauft. Die Qualität liegt zwischen 0 und 100. Jeder Punkt Qualität kostet den Verkäufer 1 ECU und erhöht den Wert des Gutes für den Käufer um 3 ECU, zum Beispiel:

- Wenn die Qualität 0 ist, hat der Verkäufer Kosten in Höhe von 0 ECU und der Käufer erhält ein Gut mit einem Wert von 0 ECU.
- Wenn die Qualität 50 ist, hat der Verkäufer Kosten in Höhe von 50 ECU und der Käufer erhält ein Gut mit einem Wert von 150 ECU.
- Wenn die Qualität 100 ist, hat der Verkäufer Kosten in Höhe von 100 ECU und der Käufer erhält ein Gut mit einem Wert von 300 ECU.

Die Rundenverdienste des Verkäufers und Käufers im Überblick:

	Verkäufer	**Käufer**
Käufer kauft nicht:	100 ECU	100 ECU
Käufer kauft:	200 ECU – Qualität	3 x Qualität

BEWERTUNG

Der Käufer erfährt dann die Qualität, die der Verkäufer gewählt hat. Danach kann der Käufer eine Bewertung über den Verkäufer hinterlassen. Die Abgabe einer Bewertung kostet den Käufer 1 ECU. Die Bewertung kann entweder „positiv“ oder „negativ“ sein. In den folgenden Runden erfahren die Käufer wie viele positive und wie viele negative Bewertungen ein Verkäufer bereits erhalten hat. Nachdem der Verkäufer erfahren hat, ob und welche Bewertung er erhalten hat beginnt eine neue Runde.

Wenn Sie Fragen haben, heben Sie bitte Ihre Hand und einer der Experimentleiter wird dann zu Ihnen kommen, um Ihnen zu helfen.

APPENDIX C – SCREENSHOTS

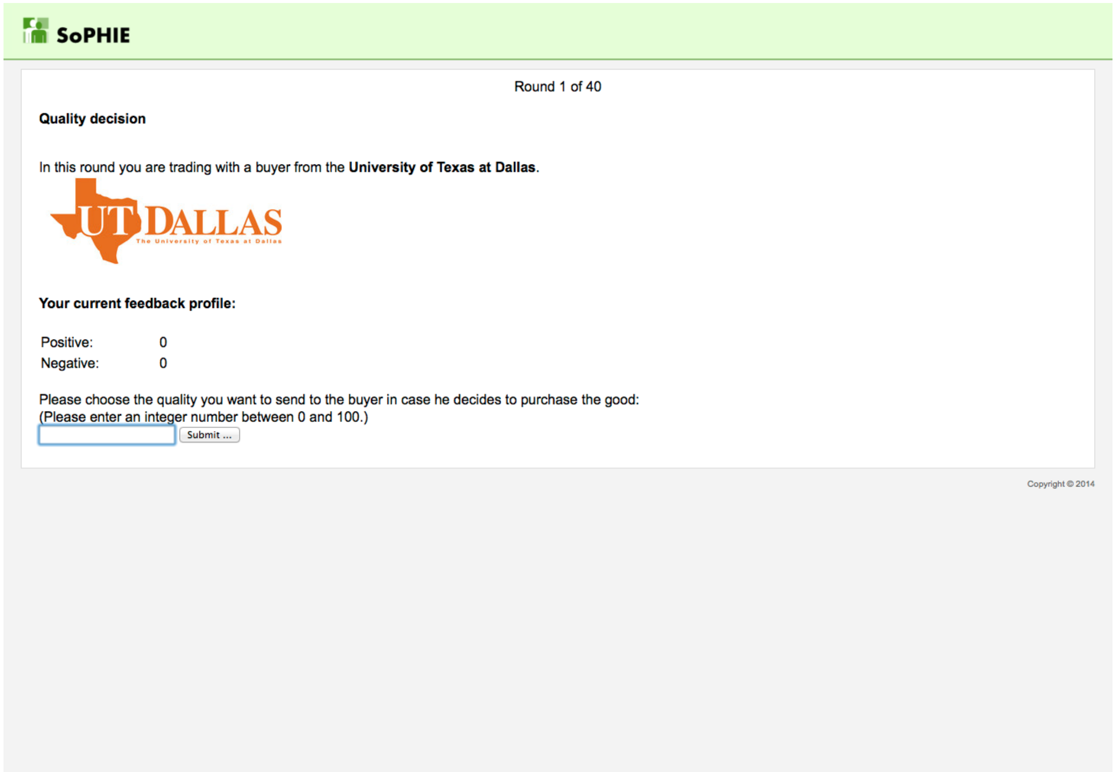


Figure C1: Quality decision

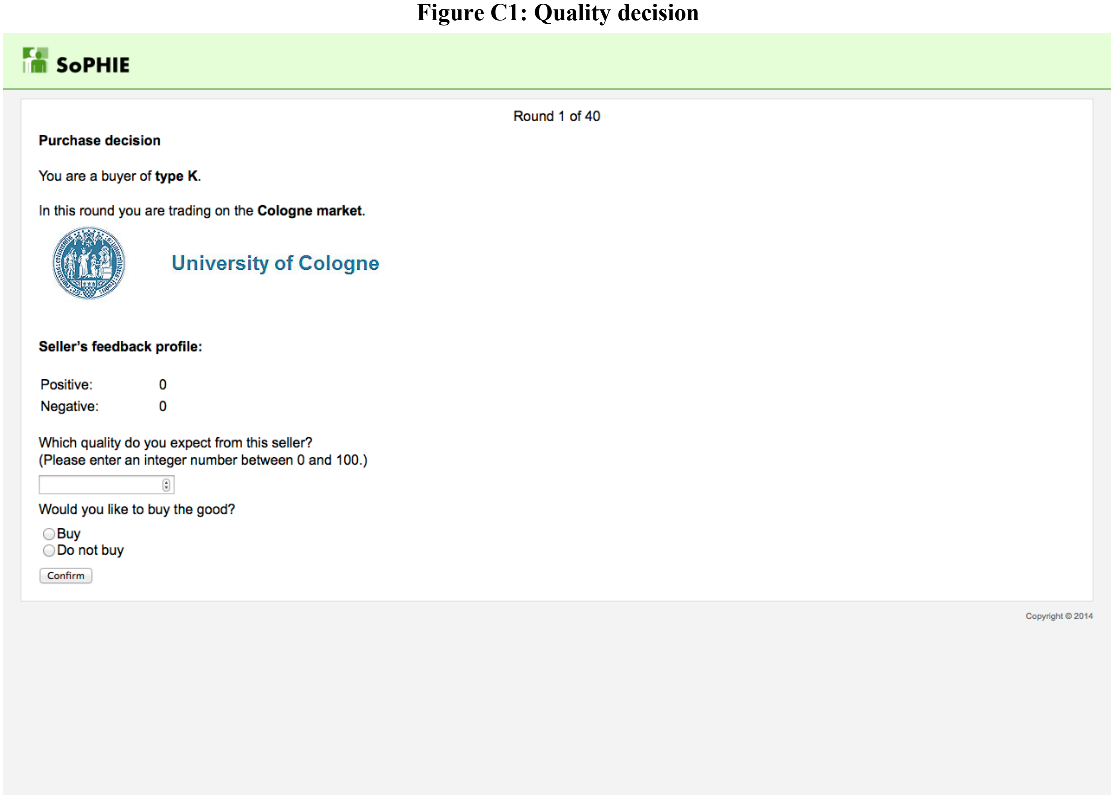


Figure C2: Purchase decision

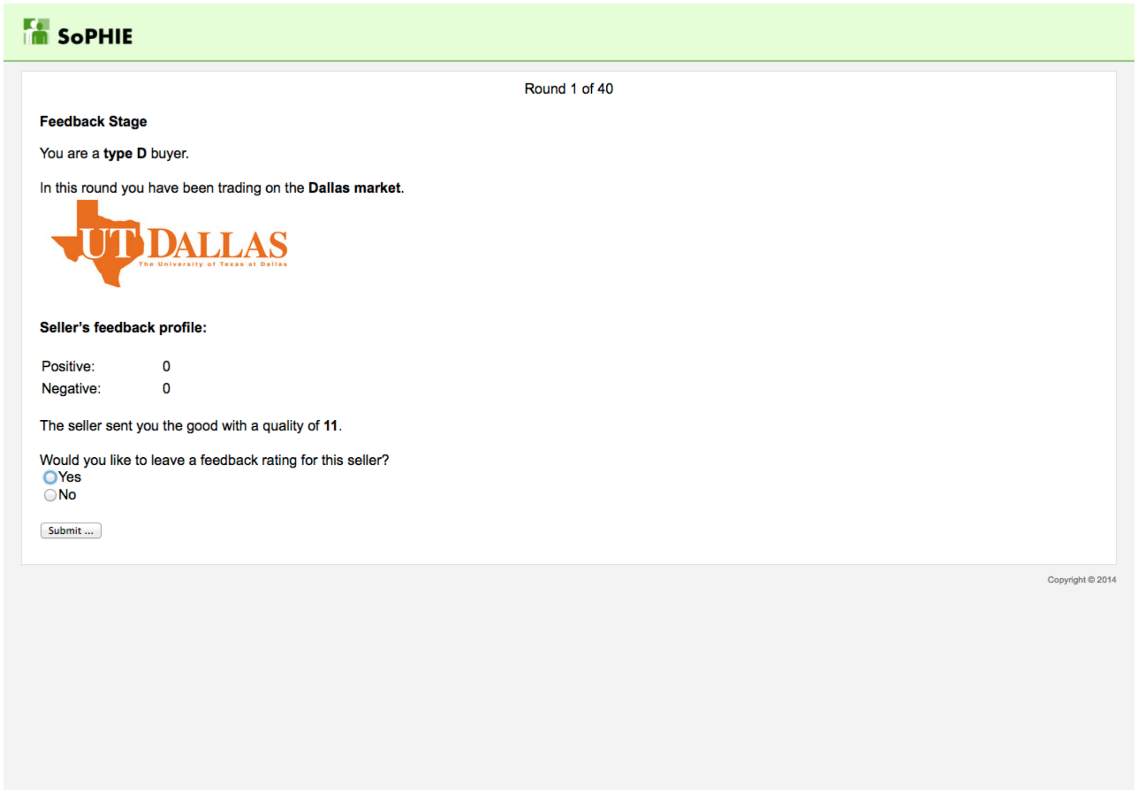


Figure C3: Feedback decision

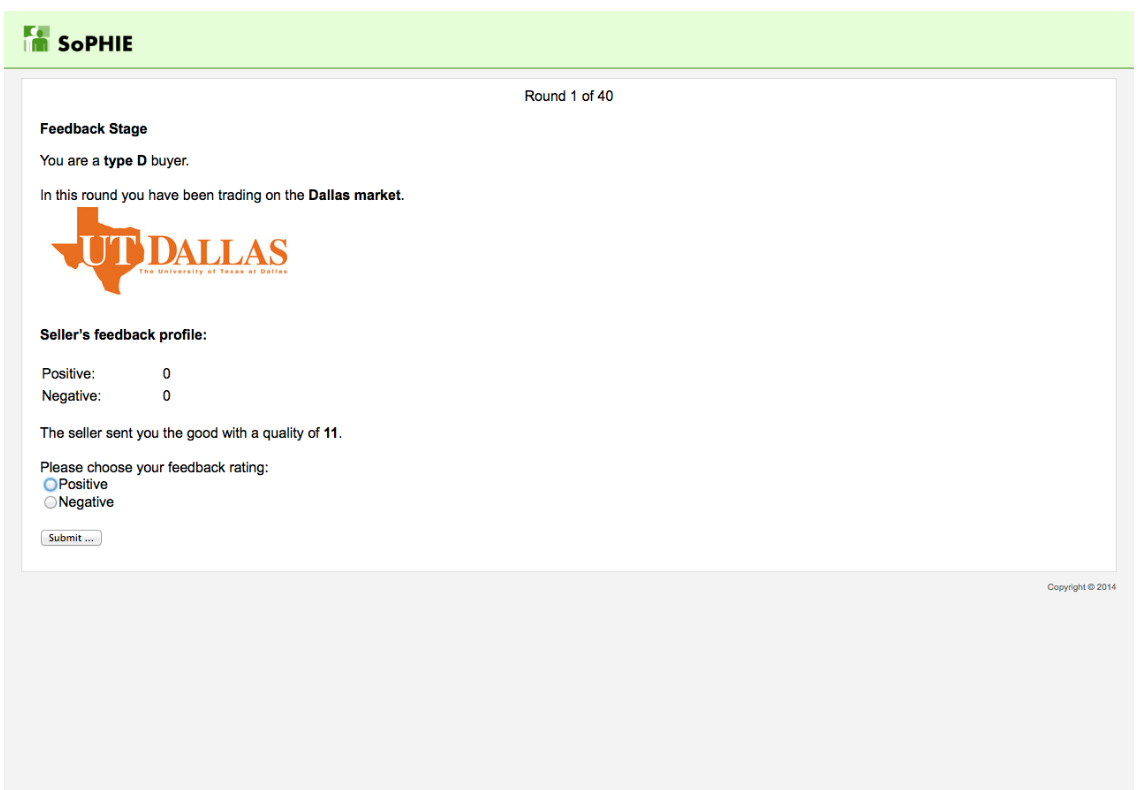


Figure C4: Feedback rating

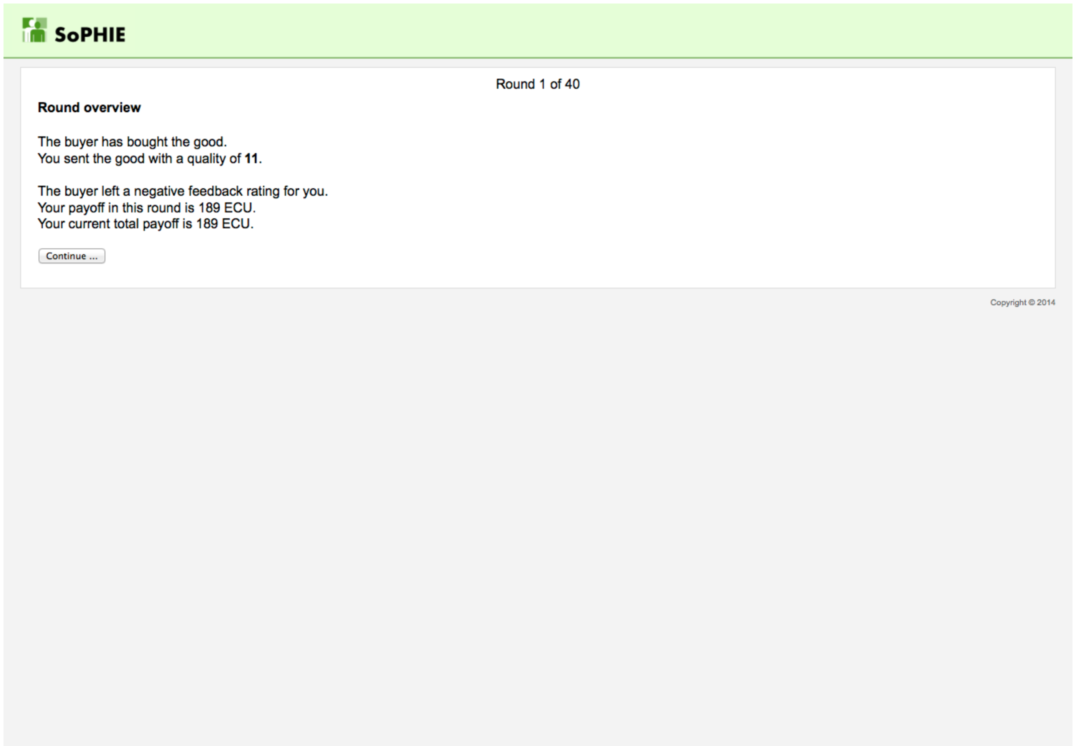


Figure C5: Period summary seller

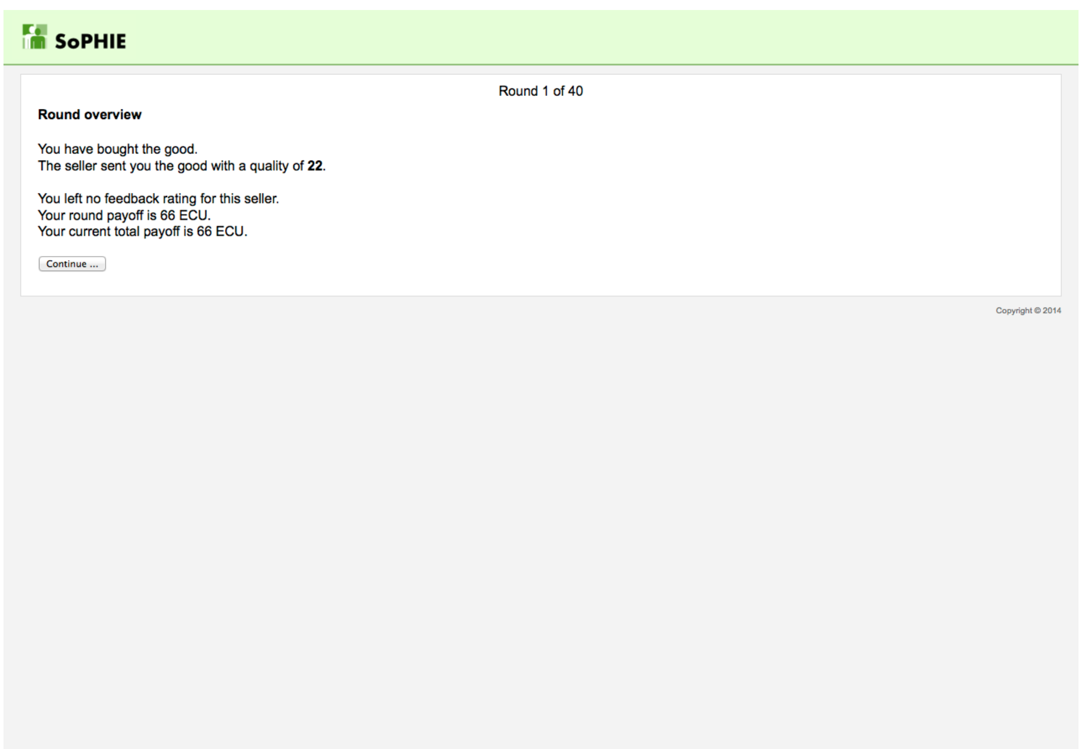
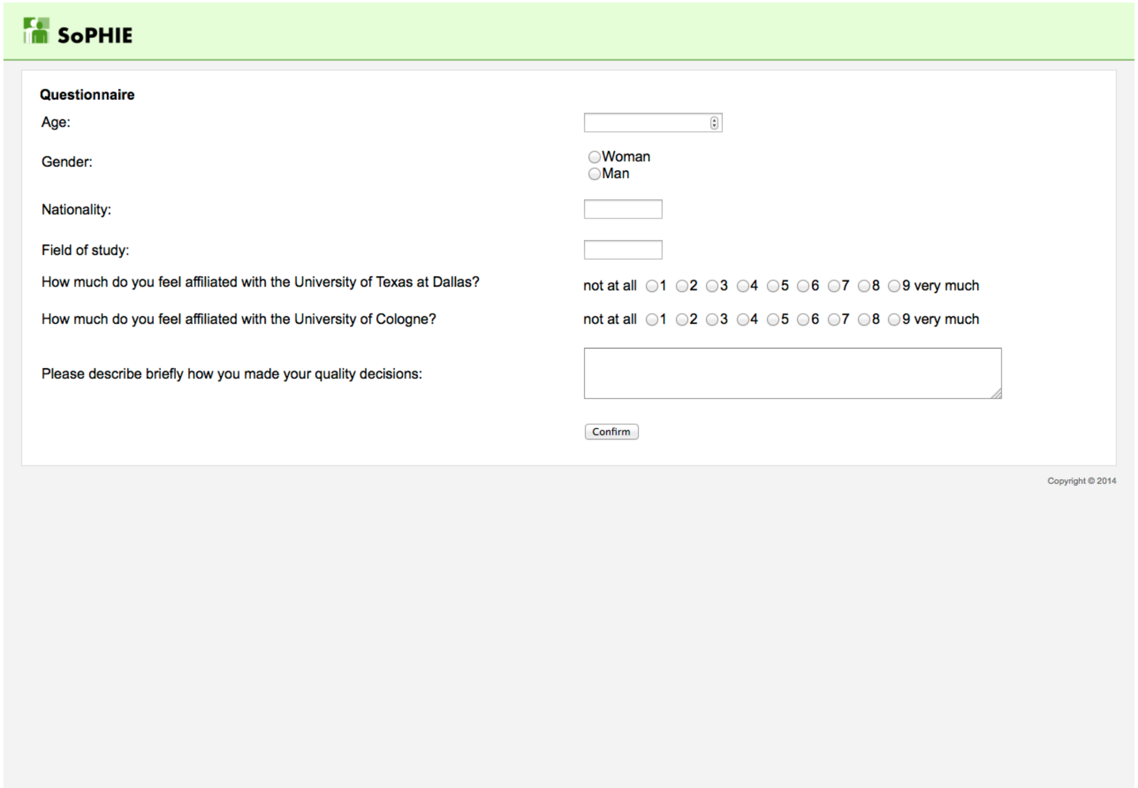


Figure C6: Period summary buyer


SoPHIE

Questionnaire

Age:

Gender: Woman / Man

Nationality:

Field of study:

How much do you feel affiliated with the University of Texas at Dallas? not at all 1 2 3 4 5 6 7 8 9 very much

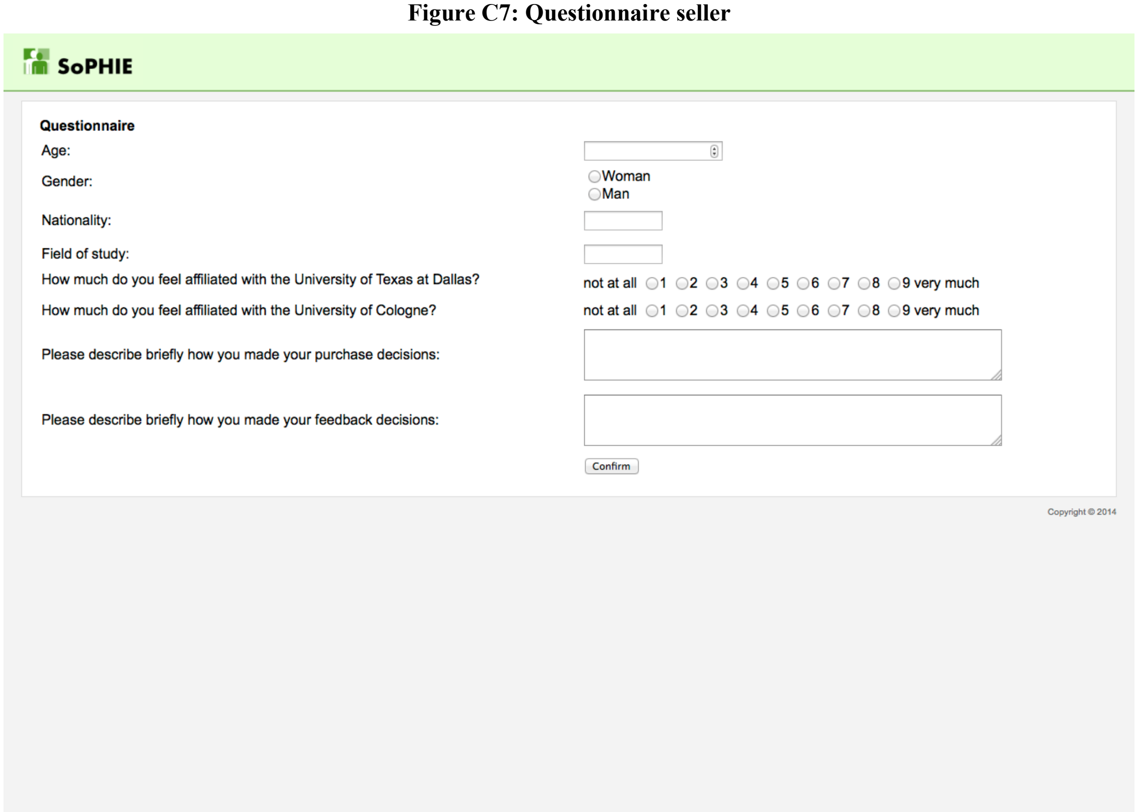
How much do you feel affiliated with the University of Cologne? not at all 1 2 3 4 5 6 7 8 9 very much

Please describe briefly how you made your quality decisions:

Confirm

Copyright © 2014

Figure C7: Questionnaire seller


SoPHIE

Questionnaire

Age:

Gender: Woman / Man

Nationality:

Field of study:

How much do you feel affiliated with the University of Texas at Dallas? not at all 1 2 3 4 5 6 7 8 9 very much

How much do you feel affiliated with the University of Cologne? not at all 1 2 3 4 5 6 7 8 9 very much

Please describe briefly how you made your purchase decisions:

Please describe briefly how you made your feedback decisions:

Confirm

Copyright © 2014

Figure C8: Questionnaire buyer