Journal of Behavioral and Experimental Economics 72 (2018) 17–27

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

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

Markets, trust and cultural biases: evidence from eBay☆

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ARTICLE INFO

Keywords:
Market
Trust
Culture

JEL classification:
D63
D80
L86
Z10

ABSTRACT

A body of research argues that cultural biases in trust may be responsible for economic backwardness. This paper studies the role of cultural biases in a real-world market, eBay, with well-designed features intended to facilitate cooperation. We analyze the buyer's decision to leave negative feedback as an act of mistrust towards the seller. To identify the effects of buyer characteristics on feedback choices, we exploit an identification strategy that leverages high-volume data from millions of transactions. We find that negative feedback decreases as buyers gain experience on the market. Also, we show that measures of pro-social beliefs and behavior do not explain feedback choices. Our favorite interpretation is that cultural biases in trust may have limited importance in markets with effective reputation-building mechanisms.

1. Introduction

Economists have long acknowledged that trust is key to economic development. Arrow (1972) famously stated that much of the economic backwardness in the world can be explained by a lack of mutual confidence. Various measures of trust have been shown to be correlated to economic choices (Knack and Keefer, 1997; Guiso et al., 2004, 2010; Algan and Cahuc, 2010). Furthermore, a body of research argues that many differences in trust can be attributed to cultural biases (Putnam, 2000; Tabellini, 2010; Algan and Cahuc, 2010; Nunn and Wantchekon, 2011). In other words, individuals from different cultures differ in key beliefs and preferences that result in different propensities to trust others.[1]

Assuming that such cultural biases exist,[2] it remains unclear how these biases interact with formal institutions, such as markets. Some argue that trust is complementary to institutions, because it can facilitate the jobs of government officials and support proper functioning of markets (Putnam, 2000). Others argue that institutions and trust are substitutes for each other, because formal institutions are most needed in low-trust environments (Knack and Keefer, 1997). This paper contributes to this debate by studying the role of cultural biases in trust in the context of a real-world market, eBay, with well-designed features that are intended to facilitate cooperation.

As the most popular online auction site in the United States, eBay reported a commerce volume of nearly $150 billion in 2011 (eBay's Annual Report, 2011). Its success is commonly attributed to its feedback mechanism, which facilitates cooperation through reputation building (Klein et al., 2009). Shortly after buying a product, a buyer can choose to leave positive or nonpositive feedback about the seller. In this paper, we study trust by analyzing the feedback choices made by eBay buyers.

We provide a simple model of negative feedback based on two key principles from behavioral economics: betrayal aversion and spite (Berg et al., 1995; Fehr, 2009; Bohnet et al., 2008; Sapienza et al., 2013). If the buyer feels that the seller has cheated in the transaction, for instance by sending a defective product, the buyer incurs a psychological cost from betrayal. The buyer can reduce this psychological cost by retaliating against the seller with nonpositive feedback, which imposes a pecuniary cost on the seller (Cabral and Hortaçsu, 2010). The decision to leave negative feedback thus depends on the buyer's willingness to trust the seller.

To study the buyer characteristics that are associated with the buyers' feedback choices, we collected data on feedback left by buyers for more than 20 million eBay transactions from 2009–2012. When comparing feedback across buyers, however, there is an identification challenge. In addition to different buyer characteristics, buyers also may leave different feedback because they acquire different products, at different prices, and from different sellers. To address this challenge, we introduce an identification strategy that leverages high-volume data from millions of transactions. We compare feedback choices across pairs of buyers who made purchases under the exact same circumstances (i.e., they bought the same

☆ This Draft: November 2017. First Draft: July 2012. I am thankful to Alberto Alesina, Nicolas Bottan, Seth Stephens-Davidowitz and Martin Tetaz for their valuable comments. The usual disclaimer applies.

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[1] For example, these cultural biases may arise because of decision making heuristics (Nunn, 2012).

[2] It is still unclear whether the differences in trust attributed to cultural biases are actually a byproduct of institutional factors (Fehr, 2009).

https://doi.org/10.1016/j.socec.2017.11.004
Received 13 January 2017; Received in revised form 8 November 2017; Accepted 14 November 2017
Available online 21 November 2017
2214-8043/

product, from the same seller, at the same price). Observing the same information ensures that any differences in feedback choices can be plausibly attributed to differences in buyer characteristics.

We find that feedback choices are significantly associated with several buyer characteristics and with the expected sign. For example, buyers are more likely to leave nonpositive feedback if they live further away from rather than closer to the seller, most likely because the probability of shipping problems increases with distance. We also find that more educated buyers are more likely than less educated buyers to leave nonpositive feedback, which is consistent with the evidence that educated individuals are more likely to detect if the seller cheats (Jin and Kato, 2006).

First, we investigate the role of market experience in buyers' trusting behavior. As discussed in Guiso et al. (2008), buyers may become more confident about the seller's trustworthiness as they gain experience in the market. We test this prediction by using two measures of the buyer's experience on eBay: the time elapsed since the buyer joined eBay and the buyer's own feedback score. We find that these two measures of buyer experience have large negative effects on the likelihood of nonpositive feedback. Our favorite interpretation is that, as buyers gain experience on eBay, they become more confident about the trustworthiness of sellers.

Second, we investigate the role of cultural biases in trust. Given that eBay offers detailed information about the past behavior of the seller, usually for thousands of previous transactions, it is possible that buyers use this information to form a belief about the trustworthiness of the seller and therefore are unaffected by their cultural biases regarding trust when deciding to leave negative or positive feedback. If buyers' beliefs about trust are affected by cultural biases, then their feedback decisions will be affected by these cultural biases.

We proxy for buyers' cultural biases in trust using measures of pro-social beliefs and pro-social behavior in the buyers' locations. According to the literature on social capital, these measures reflect cultural biases in trust (Algan and Cahuc, 2010; Nunn, 2012). For example, one widely used measure of pro-social beliefs corresponds to the following question from the General Social Survey: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" If cultural biases were important, we would expect individuals scoring higher in this survey measure to be less likely to choose nonpositive feedback. On the contrary, we find correlations that are close to zero and precisely estimated. If anything, the evidence suggests that individuals from more pro-social areas are slightly more likely to leave nonpositive feedback.

Moreover, we show that the buyer's county of residence explains only a small fraction of the variation in nonpositive feedback. This finding suggests that spatial differences in formal and informal institutions, including but not limited to cultural biases, may not be important factors in feedback behavior on eBay. One interpretation for this evidence is that, even if cultural biases in trust are important for other economic transactions, they have limited importance in presence-of-good institutions such as electronic markets with effective reputation-building mechanisms. For instance, Minnesota residents tend to score higher than residents from Louisiana in measures of social capital. If two individuals were offered to buy a given product on the street, it is possible that the individual from Minnesota would be more willing to buy this product than an individual from Louisiana. However, if the same product was offered on eBay, both individuals would have access to the same detailed information about the seller's past behavior[3] and thus would be equally confident about the trustworthiness of the seller, regardless of their cultural biases. This interpretation suggests that market institutions and trust are substitutes. From a policy perspective, these findings imply that technological innovations aimed at encouraging cooperation (e.g., reputation-building mechanisms) may be effective in overcoming cultural barriers to economic development.

This paper relates to various strands of literature. First, it is related to a literature that studies the relationship between cultural biases in trust and market behavior. Guiso et al. (2010) provide unique evidence using data on bilateral trust between European countries. They find that low bilateral trust between countries leads to decreased trade, portfolio investment, and direct investment, even after controlling for various country characteristics. Our findings are not inconsistent with their evidence, as arguably most of the transactions that they study do not benefit from the same quality of reputation-building mechanisms available to eBay users. Also, our findings support the model proposed by Guiso et al. (2008), according to which individuals become more trusting when they participate in markets.

Second, this paper is related to a literature that studies the validity of survey measures of trust by comparing the responses to these questions with behavior in laboratory experiments. These papers find a weak relationship between survey measures of trust and behavior in the lab (e.g., Glaeser et al., 2000; Fehr et al., 2003; Ermisch et al., 2009). However, there are concerns about the external validity of laboratory experiments, especially regarding social preferences (Levitt and List, 2007). This paper contributes to this literature by showing that these same survey measures of trust do not correlate with behavior in a naturally occurring market either.

The paper proceeds as follows. Section 2 introduces a stylized model of the buyer's decision to leave feedback about the seller. Section 3 presents the econometric model. Section 4 presents the data. Section 5 discusses the results. The final section concludes.

2. A model Of trust and negative feedback

This section presents a model to explain why buyers leave negative feedback on eBay and how that decision depends on beliefs about trustworthiness. This model proposes that buyers use negative feedback to punish sellers whom they think have cheated them in the transaction.

2.1. Motivation

Our model of negative feedback is based on two key principles from behavioral economics: betrayal aversion and spite. The trust game (Berg et al., 1995) provides a unique test of betrayal aversion. In this game, a sender chooses how much money to send to a receiver, and the receiver can send some of that amount back to the sender. For each dollar sent back by the receiver, the sender gets a multiple of that amount (greater than one). Several factors influence the decisions of both senders and receivers. Some researchers have tried to isolate these factors by using variants of the trust game. Whether the sender sends money depends crucially on whether the sender thinks that the receiver will send some money back (Chaudhuri and Gangadharan, 2007).

Part of the reason why the sender cares about the amount sent back by the receiver is material. The other part is due to betrayal-aversion: the sender may not send money because of the anticipated disutility from being betrayed by another human being. Bohnet et al. (2008) conducted an experiment that illustrates this principle. Senders in their game faced two equivalent scenarios in terms of expected payoffs for both players. In one scenario, the outcome was determined by the choice of a human receiver. In the alternative scenario, the outcome was determined by a random number generator that behaved exactly like the human receivers. Bohnet et al. (2008) showed that senders are less willing to send money to the receiver when the receiver is another human being. They interpreted this finding as evidence that, in addition to any material payoffs, individuals face a psychological cost when

[3] Next to the seller's name, eBay shows the feedback score (roughly equal to the difference between the number of positive and negative feedback ratings) and the percentage of positive feedback. Clicking on the seller's name directs the user to the seller's page, which contains more information about the seller (e.g., the date when the seller became member). Clicking on the seller's feedback score directs the user to the complete record of the feedback received by the seller, starting with the most recent ones, along with a summary of the most recent feedback received.

feeling betrayed by another human being.

The ultimatum game is a popular framework for the study of social preferences that can be used to identify spite. In the ultimatum game, a proposer suggests how to divide money between herself or himself (the proposer) and another player (the responder). Then, the responder must decide whether to accept the offer, in which case the proposed split is implemented, or reject the offer, in which case neither player receives any money. Blount (1995) developed a variant of this game to show that individuals show spite (i.e., they get utility from punishing individuals who betray them). Blount (1995) also compares the standard version of the ultimatum game with an alternative version, in which the proposal is not set by the proposer but by a random number generator, and shows that a given offer is more likely to be rejected if it comes from the proposer than if it comes from a random number generator. This finding indicates that individuals are willing to forgo consumption in exchange for punishing individuals who act unfairly towards them. In the next section, we apply these two principles from behavioral economics, betrayal aversion and spite, to a model of negative feedback on eBay.

2.2. Setup

Our model has two types of agents: a continuum of consumers indexed by subscript i and a single seller. The seller decides only whether to "cheat" in the sale (e.g., send a defective product). Because we are interested in analyzing the decisions of the consumer only, we take the seller's decision as exogenous.[4] The consumers must decide whether to buy the product ($B_i = 1$) or not buy the product ($B_i = 0$). Conditional on buying the product, the consumer must choose whether to leave negative feedback about the seller ($N_i = 1$) or not ($N_i = 0$).

If the seller cheats, then the probability of the product breaking is $b_c \in (0, 1)$. If the seller does not cheat, then the probability of the product breaking is $b_n \in (0, 1)$, with $b_c > b_n$. Because b_c and b_n are bounded away from 1 and 0, an item may break even if the seller did not cheat and an item may not break even if the seller did cheat. We interpret cheating broadly to include failure to test the unit, mailing non-working or low-quality units, mailing units with missing or non-original parts, and failure to ship on time. According to the eBay data described in Section 4.1, these are among the most common reasons for leaving negative feedback.

Conditional on buying the product, the consumer does not observe directly whether the seller cheated but only whether the product breaks. After observing whether the product breaks, the consumer must decide whether to leave negative feedback.[5] In contrast with other online commerce platforms, an eBay buyer can leave feedback about the seller only and not about the product.[6] Negative feedback hurts sellers by damaging their reputations and thus reducing future sales (for evidence, see Cabral and Hortaçsu, 2010). Thus, if a buyer thinks that the seller cheated, then the buyer can leave negative feedback as punishment at no cost (since 2008, eBay sellers cannot leave negative feedback about buyers as retaliation).

We denote $q_i \in (0, 1)$ as consumer i's prior probability that the seller cheated at the time of deciding whether to buy the product. This parameter is heterogeneous to represent that, although all consumers observe the same information about the seller, consumers may differ in their beliefs about the seller. They may start out with different prior beliefs about the trustworthiness of others, or they may interpret the information differently.

If the consumer buys the product, she or he must pay a fixed price, $p > 0$, regardless of whether the product breaks. If the product does not break, then the buyer gets utility from using the product whose monetary equivalent is $v > p$. If the product breaks, the buyer gets no utility from using the product[7] and suffers a psychological cost from feeling betrayed by the seller. If the buyer thinks that there is x probability that the seller cheated, then the buyer incurs a psychological cost, $x \cdot \delta$, where the parameter $\delta > 0$ represents the maximum cost of betrayal. The buyer can reduce the psychological burden of feeling betrayed by punishing the seller with a negative review. If the buyer thinks that there is x probability that the seller cheated, then the buyer gains $x \cdot s^I \cdot \delta$ from the thought of punishing a seller who cheated but loses $(1 - x) \cdot s^{II} \cdot \delta$ from the thought of punishing a seller who did not cheat. The parameters $s^I \in (0, 1)$ and $s^{II} \in (0, 1)$ represent the degrees of vindictiveness and remorsefulness, expressed as shares of the psychological cost from betrayal.[8]

2.3. Main hypothesis

If the product does not break, then the buyer never leaves negative feedback. Conditional on breaking, whether the buyer leaves feedback depends on whether she or he is sufficiently confident that the seller cheated. Given the prior belief q_i, we can use Bayes' rule to determine the belief that the seller cheated, conditional on the product breaking:

$$P(Cheated|Broke) = \frac{Pr(Broke|Cheated)Pr(Cheated)}{Pr(Broke)} = \frac{b_c q_i}{(1 - q_i)b_n + q_i b_c}$$

With this posterior belief, we can write $N(q_i)$, the net utility from leaving negative feedback (relative to not leaving negative feedback):

$$N(q_i) \equiv \frac{q_i b_c}{(1 - q_i)b_n + q_i b_c} \cdot \delta \cdot s^I + \left(1 - \frac{q_i b_c}{(1 - q_i)b_n + q_i b_c}\right) \cdot \delta \cdot (-s^{II}) \qquad (1)$$

The first term is the expected benefit from punishing a seller who cheated, and the second term is the expected cost from punishing a seller who did not cheat. The buyer leaves negative feedback only if $N(q_i) > 0$. The following Proposition 1 provides the key comparative static:

Proposition 1. *An individual's negative feedback is increasing in that individual's level of mistrust.*

Proof. From (1), it follows that the buyer leaves negative feedback only if $q_i > \hat{q}_N \equiv \frac{s^{II} b_n}{b_c s^I + s^{II} b_n}$. Thus, for an individual with $q_i < \hat{q}_N$, a sufficiently large increase in q_i takes q_i above $\hat{q}_N$ and thus the individual goes from not leaving negative feedback to leaving negative feedback. The intuition is straightforward. Individuals who have negative beliefs about the trustworthiness of the seller at the time of buying the product would have even more negative beliefs if the product breaks. Because of these negative beliefs, they have more to gain by leaving negative feedback (through vindictiveness) and less to lose (through remorsefulness). Thus, leaving negative feedback is more attractive to less trusting individuals. □

In the empirical section, we study two buyer characteristics that are believed to explain variation in q_i: the buyer's experience in the platform, which is hypothesized to reduce q_i (Guiso et al., 2008), and the cultural biases in trust, as proxied by pro-social beliefs and behavior, which also are hypothesized to reduce q_i (e.g., Nunn, 2012; Chaudhuri and Gangadharan, 2007).

[4] We are implicitly assuming that the seller expects to derive some gains from cheating, otherwise no consumer would ever expect a seller to cheat.

[5] eBay buyers have up to 60 days after a transaction is completed for leaving feedback to the seller.

[6] On amazon.com, for example, a buyer can leave feedback both to a given product (which can be sold by hundreds of different sellers) and to the seller from which the buyer bought the product.

[7] This is just a simplifying assumption. In practice, it is not uncommon for the sellers to replace products, although the costs of shipping back the product are usually faced by the buyer.

[8] In this model, we allowed cultural biases in trust to be represented by heterogeneity in beliefs, q_i. In an alternative specification, cultural biases in trust could be allowed to arise due to differences in preferences: i.e., through heterogeneity in s^I, s^{II} or δ.

2.4. Extension: Aggregate outcomes

In the case of cultural biases in trust, we lack individual-level measures. We therefore cannot test Proposition 1 directly and instead rely on aggregate data. In this section, we translate Proposition 1 into its equivalent with group-level data. The concern with aggregate data is selection bias. If we increase trust in a specific area and artificially hold constant the decision to buy the product, then it would follow from Proposition 1 that negative feedback should decrease. However, increasing trust in the area also affects the decision to buy the product. Specifically, some infra-marginal individuals may switch from not buying the product to buying the product. This switch introduces a selection bias that goes in the opposite direction of Proposition 1, because these infra-marginal individuals are likely to leave negative feedback. If the selection bias is severe enough, it could revert the sign of the relationship between trust and negative feedback.

To conduct comparative statics at the aggregate level, we introduce the decision to buy the product. Let $B(q_i)$ be the expected utility from buying the product (relative to not buying the product):

$$B(q_i) \equiv [1 - q_i b_c - (1 - q_i) b_n] v - p - q_i b_c \delta \left[1 - I_{N(q_i)>0} \cdot \left(s^I - s^{II} \frac{1 - q_i}{q_i} \frac{b_n}{b_c} \right) \right] \quad (2)$$

The first term represents the expected intrinsic utility from the consumption of the product, the second term is the price, and the third term represents the expected non-pecuniary utility from feelings of betrayal-aversion, vindictiveness and remorse. The consumer buys the product only if $B(q_i) > 0$.

We also introduce a few parameter restrictions. We focus on the cases $[1 - b_n]v - p > 0$ and $v(1 - b_c) - p - b_c\delta(1 - s^I) < 0$, which guarantee that $B(0) > 0$ and $B(1) < 0$. We assume that the distribution of q_i has full support over the range [0,1]. These conditions rule out two extreme scenarios where everyone buys the product and nobody buys the product. Second, we assume that $s^{II} > \frac{b_c - b_n}{b_n}\frac{v}{\delta} + \frac{b_c}{b_n}(1 - s^I)$. This assumption guarantees that $\frac{\partial B(q_i)}{\partial q_i} < 0$, thus excluding the extreme situation where individuals can get so much utility from vindictiveness that they are likely to buy the product if they think the seller is likely to cheat.[9]

The conditions $\frac{\partial B(q_i)}{\partial q_i} < 0$, $B(0) > 0$ and $B(1) < 0$ imply, through the mean value theorem, that there is a unique $\hat{q}_B \in (0, 1)$, such as $B(\hat{q}_B) = 0$:

$$\hat{q}_B = \frac{v(b_n - 1) + p + b_n s^{II} \delta}{\delta(s^I b_c + b_n s^{II}) - (b_c - b_n)v - b_c \delta}$$

A consumer buys the product only if $q_i \leq \hat{q}_B$. Note that there is a set of parameters where $\hat{q}_N \geq \hat{q}_B$, in which case nobody leaves negative feedback. We assume that the parameters do not fall in this range, otherwise there would be no negative feedback to be studied.

Assume there are J groups, denoted by subscript j, each with a continuum of consumers of mass 1. Within each group j, the values of q follow the distribution $Beta\left(\frac{\bar{q}_j}{1-\bar{q}_j}, 1\right)$, where $\bar{q}_j$ corresponds to the mean of q in group j. The following Proposition 2 states the relationship between the average level of trust and the share of negative feedback:

Proposition 2. *The share of negative feedback in an area is increasing in the average mistrust in that area.*

Proof. Let S_j denote the share of individuals leaving negative feedback (conditional on buying the product and the product breaking). To prove this proposition, we need to prove that $\frac{\partial S_j}{\partial \bar{q}_j} > 0$. Using the utility-maximizing thresholds for the consumers, it follows that: $S_j = \frac{F_j(\hat{q}_B) - F_j(\hat{q}_N)}{F_j(\hat{q}_B)}$, where $F_j(q)$ is the cumulative distribution of q in area j. This results in $S_j = 1 - \left(\frac{\hat{q}_N}{\hat{q}_B}\right)^{\frac{\bar{q}_j}{1-\bar{q}_j}}$. Taking the derivative with respect to $\bar{q}_j$, we obtain: $\frac{\partial S_j}{\partial \bar{q}_j} = -\left(\frac{\hat{q}_N}{\hat{q}_B}\right)^{\frac{\bar{q}_j}{1-\bar{q}_j}} \ln\left(\frac{\hat{q}_N}{\hat{q}_B}\right)(1 - \bar{q}_j)^{-2}$. Using the assumption that $\hat{q}_N < \hat{q}_B$, it follows that $\ln\left(\frac{\hat{q}_N}{\hat{q}_B}\right) < 0$ and thus $\frac{\partial S_j}{\partial \bar{q}_j} > 0$. □

This proposition shows that, under a set of reasonable functional form assumptions, the prediction from Proposition 1 applies in the aggregate-level analysis. This does not imply that there is no selection bias, however, as Proposition 2 shows only that the magnitude of selection bias is not severe enough to reverse the sign of the relationship given by Proposition 1. Moreover, as discussed in Appendix A, this sign reversal is theoretically possible under extreme functional form assumptions.

3. Econometric model

In terms of the model from Section 2, we determine whether certain buyer characteristics (e.g., pro-social beliefs) makes that buyer more or less likely to mistrust the seller and leave negative feedback. The identification challenge in comparing feedback across buyers is that buyer characteristics may be correlated to other transaction characteristics, such as product and seller characteristics. For example, educated buyers may be more likely to buy high-quality products from trustworthy sellers. These products may be less likely to break and thus less likely to receive negative feedback. To disentangle the effect of buyer characteristics from the other transaction characteristics, we compare feedback choices across buyers who bought the same product from the same seller at the same price and observed the same information.[10]

Consider the following linear probability model of the choice to leave nonpositive feedback:

$$N_{ij} = \alpha Z_i + \eta_j + \epsilon_{ij}$$

Subscript i indexes buyers, and subscript j indexes items. An item is defined as a group of transactions involving the same product, from the same seller, sold at the same price around the same time.[11] The dependent variable N_{ij} equals 100 if buyer i left nonpositive feedback about the seller regarding item j and 0 otherwise. In practice, we observe three possible outcomes: positive, neutral, or negative feedback. In terms of consequences for the seller, neutral feedback is perceived by users to be much closer to negative than positive feedback (Cabral and Hortaçsu, 2010). For simplicity, we analyze the probability of leaving nonpositive (neutral and negative) feedback. The results are robust

[9] Individuals with lower belief in trustworthiness (higher q_i) find buying the product less attractive through two channels: they expect to obtain v with a lower probability; and they expect to pay the psychological cost δ with a higher probability. But there is one channel through which a higher q_i increases the attractiveness of buying the product. When the product breaks the individual has the opportunity to recover part of the psychological cost through the negative feedback, but the possibility of punishing a seller that did not cheat limits the value of this psychological insurance. A higher q_i implies a lower probability of punishing a seller that did not cheat, and thus increases the expected value of buying the product through the term $-(1 - q_i)b_n N_i s^{II}\delta$. Under special circumstances – e.g., when the psychological cost of betrayal is extremely large relative to the value of the product – this latter effect can dominate.

[10] Once the listing has sold one unit, sellers face lots of restrictions to modify it (see http://pages.ebay.com/help/sell/revising_restrictions.html). Seller can change the Buy-It-Now price at any time, but that is not a problem because the price at which the product was sold is always observable to us.

[11] We do not observe the time of the purchase, but we do observe the time of the feedback. A given item only includes feedback left during the same quarter of the year. For a vast majority of items all the feedback was received within the same 30-days window. Since buyers have up to 60 days to leave seller feedback, it is likely that all those transactions took place within a few days.

even if we use alternative specifications.[12]

Importantly, η_j denotes item fixed effects. The inclusion of these effects implies that we compare feedback choices only across buyers who bought the same product, with the same description, from the same seller, and at the same price.[13] Last, Z_i is a vector of buyer characteristics. The two key buyer characteristics included in Z_i correspond to the two hypotheses to be tested: the experience of the buyer on the platform and cultural biases in trust, as proxied by the pro-social beliefs and behavior in the buyer's location.

4. Data

4.1. Ebay data

To compare feedback across buyers who bought the same product from the same seller, we collect data on products that were sold in multiple units by the same seller.[14] Multi-unit products are most commonly sold by medium and large eBay sellers, so we construct a list of 94 such sellers, including many of the most popular sellers on the platform. For the sellers in our sample, the average number of feedback responses received since they became members is 250,000, with a minimum of 4300 and a maximum of more than 3,000,000. All statistics reported in this section are computed with the final sample, which is used for the regression analysis. For each seller in the sample, we use web scraping to collect data on all feedback left by buyers during 2009–2012. These data include more than 20 million feedback decisions, such as the type of feedback (negative, neutral, or positive), the date when the feedback was left, product details (e.g., price, auction type), and public information about the seller and buyer.[15] The products cover most product categories on eBay (e.g., fashion, electronics, home, garden). The most typical products sold by the sellers in the sample are electronic products like laptops, tablets, mp3 players, home appliances, and cellphones. The average price in the sample is \$15, with a median of \$6, a minimum of \$0.01, and a maximum of \$5999.

One of the most important buyer characteristics that we measure is the buyer's experience on eBay. We construct two measures of experience using information that is directly observable from the buyer profile: the buyer's feedback score, which is based on seller feedback, and the buyer's eBay seniority, which is the time elapsed since the buyer first joined eBay and the date of the feedback response.

The other key buyer characteristic that we measure is the cultural bias in trust, as proxied by the average pro-social beliefs and behavior in the buyer's location. To construct these proxies, we identify the location of the buyers. The eBay user profiles include only the user's country, which is not detailed enough for our analysis. We thus collect data on the shipping location of the products sold by the buyer in the previous 90 days (the period during which the shipping information is publicly available) and of currently offered products. In most cases, the shipping location is the same for all items sold by a given buyer. For non-matching locations, we use the most frequent location. A limitation of identifying the buyer location in this way is that we are limited to the buyers that either sold a product in the past 90 days or are currently offering a product. Thus, we can identify the buyer location for only 17% of the observations.[16] As they do not contribute to the identification of the parameters of interest, we drop observations for which the information on buyer location is missing.[17] We collect data on millions of transactions, so this rate of missing data does not present a major problem in terms of the statistical precision of our estimates. However, it does affect the external validity of the results, because the eBay buyers who also act as sellers may differ from the average eBay user in some characteristics.

Given that some nonpositive feedback relates to problems with shipping, it is useful to control for the geographic distance between the buyer and seller. The seller location is easily obtained from looking at the shipping location of the products that the seller sold in the past 90 days and of the products currently offered by the seller.[18] Most sellers are located in the United States, spanning 16 U.S. states, followed by Hong Kong. We create a variable equal to the distance between the buyer and the seller (geodesic distance) using the population-weighted centroid of the county as a proxy for the user's geolocation.[19]

Because of the inclusion of item fixed effects, items for which either all feedback is positive (a significant share of items) or nonpositive (very rare) do not contribute to the identification of any of the parameters of the model. Thus, we drop these observations from the sample.[20] The final sample contains 241,547 observations on 7112 items. The average nonpositive feedback in the sample is 4.12%,[21] with roughly equal contributions of negative and neutral feedback.[22] The low level of nonpositive feedback speaks highly about the success of eBay as a platform in sustaining good behavior among sellers.

When a buyer leaves feedback for a seller, the buyer must describe the reason for the feedback. To provide a qualitative description of such feedback data, we randomly sample 500 nonpositive feedback descriptions and use them to assign the following categories. For 57% of the nonpositive feedback, the buyer indicates a problem with the product, such as an item that is broken or malfunctioning upon arrival or broken after use, a wrong item, an item missing parts or with non-original parts, and an item not as described or with disappointing quality. Another 26% of the nonpositive feedback can be categorized as shipping problems, typically because the product never arrived but also because the product arrived later than expected. About 4% of the nonpositive feedback corresponds to communication issues, such as the seller taking too long to respond to a question or not responding at all. The remaining 13% of the nonpositive feedback descriptions do not have enough information to assign a category. Most of these reasons for

[12] For example, the results are similar if we define the dependent variable as 100 if the feedback is negative and 0 if the feedback is positive or neutral.

[13] We also include a small set of variables controlling for the time when the feedback was left: the number of days elapsed between the listing was opened and the feedback was left, dummies for day-of-the week and dummies for months of the year. The inclusion of these control variables has little effect on the results.

[14] On eBay, multi-unit auctions have all winning bidders pay the same price, equal to the lowest successful bid. If the items are sold through the Buy-it-Now method, then the posted price can change over time, but because of the item fixed effect we will only compare feedback across products sold at the exact same price. For a given feedback we identified whether the auction type was "best offer" and we dropped those cases – they are an insignificant share of the total.

[15] If the product was refunded or returned, the sellers can ask the buyers to withdraw the negative/neutral feedback, and even request a revision to eBay (5 revision requests are allowed for every 1000 feedback ratings given to the seller). Unfortunately, our data does not include information on replacements, refunds or feedback revisions.

[16] Missing values are mostly due to the fact that the buyer currently has not any items on sale and has not sold any items during the last 90 days, but in some cases missing values are due to invalid or imprecise information on shipping location (e.g., denoting "United States" for shipping location).

[17] Unsurprisingly, results are similar if instead we allow observations with missing location information to contribute to the identification of the coefficients on the variables with non-missing data.

[18] In a few cases a seller had more than one shipping location, in which case we used the most frequent location.

[19] This distance variable takes the value zero for purchases from non-U.S. sellers and we always add a dummy variable indicating the seller is international. The results are robust if we exclude purchases from international sellers. Additionally, we include a dummy for whether the seller and the buyer are from the same state, to control for any differential treatment regarding shipping, taxes or laws.

[20] It would be misleading to include these observations in the count of observations corresponding to the regression analysis. Similarly, it would be misleading to compute summary statistics (e.g., the baseline rate of nonpositive feedback) using these observations.

[21] The average feedback in the initial sample is much lower than this, around 1.5%. The difference is mainly due to the fact that we dropped items for which 0% of the feedback was nonpositive (because they do not offer within-item variation in the outcome of interest).

[22] The seller in the sample with the worst reputation has 5.67% of nonpositive feedback, while the seller with the best reputation received only 0.38% of nonpositive feedback.

leaving negative feedback are consistent with the model in Section 2, where the buyer observes a problem (e.g., the product stopped working) and must decide whether the seller is to be blamed.

4.2. Complementary data

We used complementary datasets to proxy for buyer characteristics that are not directly observable from the eBay data. We use geographic averages in the buyer location (state level, county level, or both), depending on data availability.

The main measure of pro-social belief is LSS Honest, which is based on data collected by the DDB Life Style Survey. This variable corresponds to the geographic average of the responses to the survey question, "Are most people honest?" Answers range from "Definitely disagree (1)" to "Definitely agree (6)." The database has a large sample size and includes county identifiers, so we compute the average responses at the state and county levels. The second measure of pro-social belief is GSS Trust, which corresponds to the state-level average response to the following question from the General Social Survey: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people? Can't be too careful (0); Depends (1); Most people can be trusted (2)."

We construct two of the most widely used measures of pro-social behavior: rates of volunteering in charitable organizations and rates of voting turnout. The variable LSS Volunteering measures the frequency of volunteering using survey responses from the LSS. Voting turnout is measured using the rate of turnout during the 2008 presidential election. We also collect data on two indexes of social capital that are constructed with a combination of various measures of pro-social behavior: the Putnam's Social Capital Index (available at the state level) and the Civic Life Index (available at the county level).

Although pro-social beliefs are positively correlated to pro-social behavior, the two are not identical (Alesina and La Ferrara, 2002). Table 3 shows the correlation matrix for some state-level measures of pro-social beliefs and behavior in our data. The correlation coefficients are usually high between pairs of belief measures, between pairs of behavior measures, and between pairs of beliefs and behavior. However, there is plenty of orthogonal variation: the pairwise correlation coefficients range from a minimum of 0.393 (between LSS Volunteering and Voting Turnout) to a maximum of 0.876 (between Putnam Index and LSS Honest).

We construct measures of socio-economic characteristics in the buyer's place of residence to have a benchmark against which we can compare the effects of pro-social beliefs and behavior. We collect data from the American Community Survey on characteristics such as age, education (the share of individuals older than 25 with a College degree), mean household income, and population density. Additionally, we collect data on crime rates from the 2008 Uniform Crime Report and on rates of Internet fraud complaints from the Internet Fraud Complaint Center. See Table 1 for all data definitions and Table 2 for their descriptive statistics.

5. Results

5.1. The effect of buyer experience on feedback choices

The first hypothesis to test is whether experience with eBay reduces non-positive feedback. Table 4 presents the main set of regression results. Each column corresponds to a separate OLS regression of non-positive feedback on the variables listed (in addition to the item fixed effects and the additional control variables, whose coefficients are not reported). Column (1) includes the two measures of buyer's experience on eBay as main regressors. The results indicate that nonpositive feedback is decreasing in the two measures of buyer experience on eBay. These two coefficients are statistically highly significant. Doubling the buyer's eBay seniority (i.e., a log-increase of 0.69) decreases the likelihood of nonpositive feedback by 0.32 percentage points, equivalent to 7.8% of the mean rate of nonpositive feedback. Doubling the buyer's feedback score decreases the likelihood of nonpositive feedback by 0.64 percentage points, equivalent to 15.5% of the mean rate of nonpositive feedback.

To assess how economically significant these effects are, column (1) includes an additional regressor as benchmark: the distance between the buyer and seller. The results indicate that increased distance from the seller is associated with a higher likelihood of nonpositive feedback. This finding is consistent with the fact that a significant share of nonpositive feedback relates to shipping and that long distances may increase shipping problems. In terms of magnitude, doubling the distance from the seller increases the likelihood of nonpositive feedback by around 0.1 percentage points, which is equivalent to 2.3% of the mean rate of nonpositive feedback. The effects of the measures of buyer experience are roughly 2.4 and 5.7 times larger in magnitude than the effect of distance.

One possible interpretation for the effects of buyer's seniority and feedback score is that as buyers gain experience on eBay, they become more confident about the trustworthiness of the sellers (i.e., lower q_i). This interpretation is consistent with the model from Guiso et al. (2008), where individuals who start with a belief about trustworthiness of others that is systematically low correct that belief as they gain experience with market transactions. However, an alternative explanation could be that buyers learn over time how to deal with seller problems, thereby increasing the likelihood of a positive experience with the seller.

As a robustness check, column (2) of Table 4 includes some additional regressors: basic socio-economic characteristics, as proxied by county-level averages. To facilitate the comparison across several different independent variables, we report standardized coefficients for all the county-level and state-level variables (i.e., the coefficients correspond to the marginal effect of a standard-deviation-increase in the corresponding independent variable).[23] By comparing columns (1) and (2), we observe that the coefficients on buyer's experience do not change after controlling for socio-economic characteristics.

5.2. The effect of pro-social attitudes on feedback choices

The second hypothesis to test is whether strong pro-social beliefs and behavior reduce non-positive feedback.

5.2.1. Geographic differences

We start with a semi-parametric analysis of geographic differences in feedback. Previous literature argues that a substantial variation in trust exists across the U.S. territory (Alesina and La Ferrara, 2002) and that such variation seems to respond to cultural biases (Algan and Cahuc, 2010). If this is true, then we can test the importance of cultural biases by measuring whether substantial variation in the rates of nonpositive feedback occurs across the U.S. territory. To explore this hypothesis, we estimate the linear probability model for nonpositive feedback in which the main buyer characteristic corresponds to a set of state dummies. Fig. 1 reports the coefficients on those dummies. Because Missouri is the omitted category, each coefficient represents the difference in the rate of nonpositive feedback with respect to Missouri. Under the null hypothesis of no state effects, the class dummies should not be jointly significant, which we can test with an F-test. We reject the null hypothesis of no state effects ($p - value < .01$).

To quantify the magnitude of the state effects, we estimated a random effects specification that assumes that the state-specific effects are normally distributed with mean zero and variance σ_{FE}. The estimate for the state level σ_{FE} is 0.20 (0.06). This estimate means that moving to

[23] To assess the economic magnitude of these standard deviations, summary statistics for the raw data are reported in Table 2.

Table 1
Data definitions.

Variable Name	Definition
Nonpositive Feedback	100 if the feedback is negative or neutral, 0 if it is positive. Source: eBay data.
Distance from Seller	Distance (in thousand miles) between the city-centroids of buyer and seller, as the crow flies. Source: eBay data.
Buyer's eBay Seniority	Days elapsed since the buyer joined eBay until the feedback was left. Source: eBay data.
Buyer's Feedback Score	The feedback score gives +1 point for each positive rating, no points for each neutral rating and −1 point for each negative rating, no matter whether the rating is received as a buyer or as a seller. Source: eBay data.
LSS Honest	Average response to the question "Are most people honest? Definitely disagree (1); Generally disagree (2); Moderately disagree (3); Moderately agree (4); Generally agree (5); Definitely agree (6)." Source: DDB Life Style Survey, 1975–1998.
GSS Trust	Average response to the question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people? Can't be too careful (0); Depends (1); Most people can be trusted (2)." Source: General Social Survey, 1972–2008.
Putnam's Social Capital Index	Comprehensive Social Capital Index, based on 14 indicators about community organizational life, engagement in public affairs, community volunteerism, sociability and trust. Source: Putnam (2000).
Civic Life Index	Index based on density of civic and non-profit organizations, voting turnout and census completion rates. Source: Rupasingha, A.; Goetz, S. and Freshwater, D. (2006), "The Production of Social Capital in US Counties," Journal of Socio-Economics, Vol. 35, pp. 83–101.
LSS Volunteering	Average response to the question "With what frequency did you do volunteer work in the last 12 months? None (1); 5–8 times (2); 9–11 times (3); 12–24 times (5); 25–51 times (6); 52+ times (7)." Source: DDB Life Style Survey, 1975–1998.
Voting Turnout Rate	Number of votes for all presidential candidates in the 2008 election divided by the adult population. Source: own calculations with 2008 Electoral College Results and U.S. Census population data.
Median Age	Source: American Community Survey 5-Year Estimates, 2006–2010.
Share with College	Share of population 25 years and over with a college degree or higher. Source: American Community Survey 5-Year Estimates, 2006–2010.
Mean Income	Mean household income in 2010 dollars. Source: American Community Survey 5-Year Estimates, 2006–2010.
Population Density	Number of inhabitants per square mile. Source: American Community Survey 5-Year Estimates, 2006–2010.
Internet Complaints rate	Number of complaints of internet fraud per 100,000 population over the years 2008-10. Source: Internet Fraud Complaint Center.
Crime rate	Number of reported crimes in 2008 per 1000 inhabitants. Source: Uniform Crime Report.

Table 2
Descriptive statistics.

	Mean	Sd	Min	Max
Nonpositive feedback	4.12	19.87	0.00	100.00
Distance from seller	1.13	0.82	0.00	5.02
Buyer's eBay seniority	2233.82	1364.94	5.00	5869.00
Buyer's feedback score	778.72	3318.09	−1.00	1,016,136.00
LSS honest (county)	3.75	0.30	1.00	6.00
LSS honest (state)	3.79	0.10	3.52	4.06
GSS trust (state)	0.80	0.13	0.38	1.24
LSS volunteering (county)	2.32	0.41	1.00	7.00
Voting turnout rate (county)	0.54	0.12	0.02	7.18
Putnam's soc. cap. index (state)	−0.23	0.51	−1.43	1.71
Civic life index (county)	−0.74	1.05	−3.80	10.79
Median age (county)	36.91	3.88	21.70	61.40
Mean income (county)	72,827.50	18,555.92	28,594.00	137,810.00
Share with college (county)	0.29	0.10	0.04	0.71
Pop. density (county)	2686.79	8374.11	0.09	69,357.68
Internet complaints rate (state)	85.32	22.94	46.59	463.36
Crime rate (county)	0.05	0.03	0.00	0.36

Notes: 241,547 observations on 7112 items. See Table 1 for data definitions.

Table 3
Correlation matrix for measures of pro-social beliefs and pro-social behavior.

	LSS honest	GSS trust	LSS volunteering	Voting turnout
GSS trust	0.773			
LSS volunteering	0.630	0.571		
Voting turnout	0.520	0.525	0.393	
Putnam index	0.876	0.829	0.744	0.519

Notes: $N = 50$ (i.e., one observation per U.S. state). See Table 1 for data definitions and Table 2 for descriptive statistics.

Table 4
Regression analysis of nonpositive feedback.

	Dep. Var.: Nonpositive feedback			
	(1)	(2)	(3)	(4)
Log(Buyer's eBay seniority)	−0.4629***	−0.4662***	−0.4669***	−0.4683***
	(0.0498)	(0.0498)	(0.0498)	(0.0499)
Log(Buyer's feedback score)	−0.9203***	−0.9159***	−0.9161***	−0.9162***
	(0.0431)	(0.0431)	(0.0431)	(0.0431)
Log(Distance from seller)	0.1357**	0.1392**	0.1347**	0.1409**
	(0.0546)	(0.0553)	(0.0555)	(0.0553)
LSS Honest (county)			0.0551	
			(0.0425)	
Civic life index (county)				0.0834
				(0.0533)
Median age (county)		−0.0632	−0.0693	−0.1023**
		(0.0452)	(0.0457)	(0.0515)
Share with college (county)		0.1883**	0.1820**	0.1256
		(0.0775)	(0.0784)	(0.0868)
Mean income (county)		−0.0631	−0.0669	−0.0167
		(0.0764)	(0.0766)	(0.0820)

Notes: 241,547 observations on 7112 items. All the coefficients except those of the variables in logs correspond to standardized coefficients (i.e., the marginal effect of a one-standard-deviation increase in the corresponding independent variable). Each column corresponds to a separate OLS regression of nonpositive feedback on the variables listed and a set of controls: item fixed effects, distance between buyer and seller, dummy for whether buyer and seller are from the same state, the number of days elapsed between the listing was opened and the feedback was left, dummies for day-of-the week and dummies for months of the year. The independent variables take the value 0 if missing and the regression always includes a dummy variable indicating whether the information for that observation is missing. By definition of item, all transactions within a given item correspond to the same product listing, from the same seller, at the same price and for the same 90-days window. The terms in brackets "(state)" and "(county)" indicate that the variable corresponds to state- and county-averages, respectively. Heteroscedasticity-robust standard errors are clustered at the item level. See Table 1 for data definitions and Table 2 for descriptive statistics.

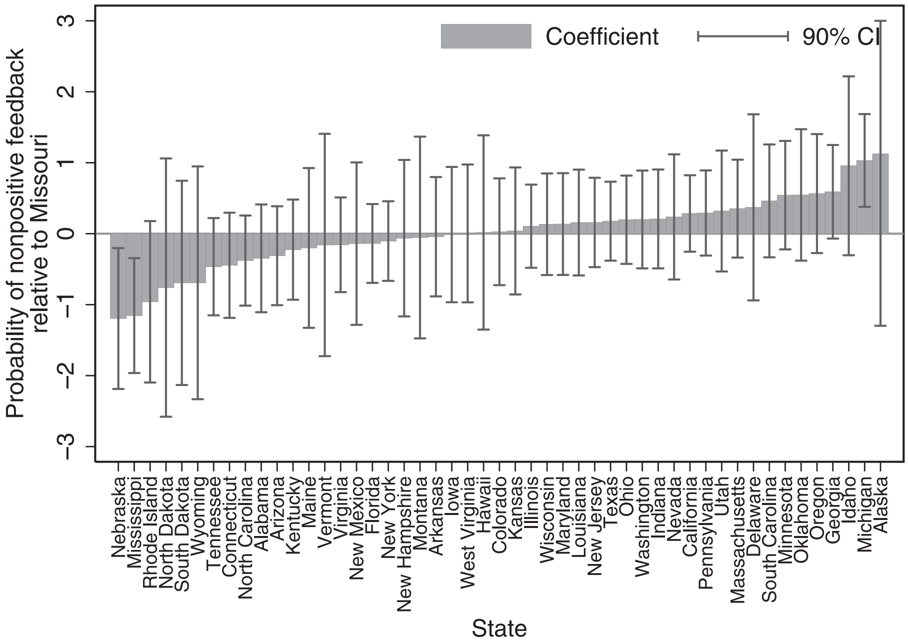

Fig. 1. Differences in rates of nonpositive feedback across states. *Notes:* 241,547 observations on 7112 items. Each bar corresponds to one of 29 coefficients on a set of state dummies in a regression of nonpositive feedback that includes a set of controls: item fixed effects, distance between buyer and seller, dummy for whether buyer and seller are from the same state, the number of days elapsed between the listing was opened and the feedback was left, dummies for day-of-the week and dummies for months of the year. The omitted state is Missouri. By definition of item, all transactions within a given item correspond to the same product listing, from the same seller, at the same price and for the same 90-days window. The confidence intervals were computed using heteroscedasticity-robust standard errors clustered at the item level. See Table 1 for data definitions and Table 2 for descriptive statistics.

a state that is one standard deviation more trusting decreases nonpositive feedback by only 0.2 percentage points, which is slightly less than 5% of the mean nonpositive feedback. Thus, state-level differences in feedback choices are statistically significant but economically small. Reproducing the analysis at the county level yields similar results.[24] The small variation in nonpositive feedback across areas suggests that spatial variation in formal and informal institutions, including but not limited to cultural biases, may not play an important role in feedback choices.

In addition to quantifying the size of the state effects, it is also useful to visualize the geographic distribution of nonpositive feedback. Fig. 2(a) shows a map of the state fixed effects reported in Fig. 1. A darker shade represents a higher propensity of nonpositive feedback (i.e., higher mistrust towards the seller). In turn, Fig. 2(b) shows the geographic distribution of mistrust based on the widely used measure GSS Trust, for which it is possible to take state averages. Consistent with Alesina and La Ferrara (2002), Fig. 2(b) indicates that higher mistrust is common in the southern and southeastern United States. However, the geographic distribution of nonpositive feedback (Fig. 2(a)) does not seem to coincide with the geographic distribution of cultural biases in trust (Fig. 2(b)).

5.2.2. Correlation to pro-social beliefs and behavior

We can use a more parametric approach to test the hypothesis that strong pro-social beliefs and behavior are associated with low nonpositive feedback. Column (3) in Table 4 corresponds to a regression of nonpositive feedback on a measure of pro-social beliefs (LSS Honest), and column (4) uses a measure of pro-social behavior (Civic Life Index). In both columns, we control for the same set of socio-economic characteristics introduced in column (2).

The coefficient on LSS Honest from column (3), 0.0551, is positive, close to zero, statistically insignificant, and precisely estimated. Contrary to our hypothesis, if anything, strong pro-social beliefs are associated with higher nonpositive feedback. However, this positive effect is statistically and economically insignificant: an increase of one standard deviation in LSS Honest increases non-positive feedback by a mere 0.0551 percentage points (or 1.3% of the mean of the dependent variable). Due to high statistical precision, we can rule out even tiny negative effects (e.g., the 95% confidence interval rules out coefficients of −0.028 or below).

One possibility is that survey measures of pro-social beliefs fail to show the expected correlation to nonpositive feedback not because cultural biases matter, but because these survey questions may not be valid measures of beliefs about trustworthiness (e.g., Glaeser et al. (2000). To address this potential problem, column (4) adds the main measure or pro-social behavior, Civic Life Index. The coefficient on Civic Life Index from column (4) yields results that are similar to the results from LSS Honest: the coefficient (0.0834) is positive, close to zero, statistically insignificant, precisely estimated, and the 95% confidence interval rules out coefficients of −0.021 or below.

We can use the effects of other buyer characteristics as benchmarks for the effects of pro-social beliefs and behavior. In column (3), for example, education has a statistically significant association with feedback choices, but age and income have statistically insignificant effects. An increase of one standard deviation in the share of college graduates in the county increases the probability of nonpositive feedback by 0.19 percentage points, equivalent to 4.6% of the mean rate of nonpositive feedback. This effect is certainly greater in magnitude than the effects of pro-social beliefs and behavior. One interpretation for this coefficient is that educated buyers are likely to detect when a seller tries to trick them. This interpretation is consistent with the finding from Jin and Kato (2006) that even reputable sellers offer products meant to take advantage of unsophisticated buyers.

As a robustness check, Table 5 presents regression results using alternative measures of buyer characteristics. Each coefficients from this table comes from a separate OLS regression of nonpositive feedback on the corresponding independent variable, along with the standard set of controls. The first group of coefficients from Table 5 indicates that, consistent with the above findings, all measures of pro-social beliefs are positively correlated to nonpositive feedback. Such correlation is positive and economically small: 0.0644 for county-level LSS Honest, 0.0565 for state-level LSS Honest, and 0.1081 for state-level GSS Trust. The coefficient is statistically different from zero for state-level GSS Trust but insignificant for the state- and county-level measures of LSS Honest. However, given the precision of the estimates, we cannot reject the null hypothesis that these three coefficients are equal. Moreover, the coefficients are precisely estimated, so we can exclude the possibility of moderate negative effects for standard confidence levels.

[24] The county level estimate of σ_{FE} is 0.37 (0.084). That is, moving to a county that is one standard deviation higher in the distribution of county effects results in a increase of nonpositive feedback of around 9% of the average nonpositive feedback rate.

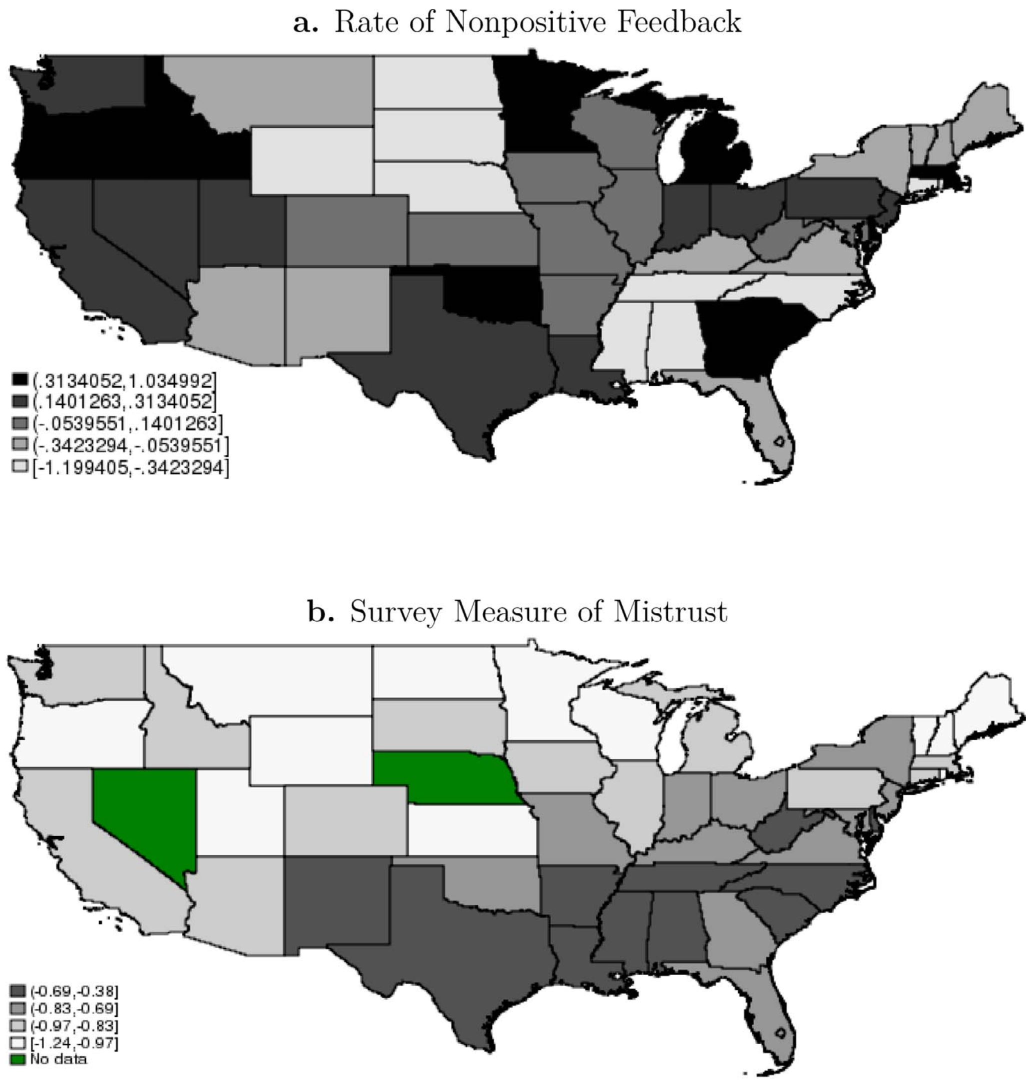

Fig. 2. Differences in rates of nonpositive feedback versus differences in survey measures of trust. *Notes:* (a) This maps shows the same coefficients depicted in Fig. 1. Higher values (i.e., darker shade) imply higher higher probability of nonpositive feedback. See note to Fig. 1 for details on how the state effects were estimated. The range of the color scales correspond to the five quintiles of the outcome. (b) Average responses by state from the following survey question of the General Social Survey, 1972–2008: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" Higher values (i.e., darker shade) imply higher mistrust. The range of the color scales correspond to the five quintiles of the outcome.

The second group of coefficients from Table 5 studies the association between nonpositive feedback and the various measures of pro-social behavior: the rate of volunteering, the rate of voting turnout, the Putnam Index, and the Civic Life Index. All variables have a positive, small, precisely estimated, and statistically insignificant association to nonpositive feedback. Again, using measures of pro-social behavior instead of pro-social beliefs seems to provide a consistent picture.

The third group of coefficients from Table 5 show the correlation between nonpositive feedback and various socio-economic variables. Age, income, and education have statistically significant correlations to nonpositive feedback: buyers from young, rich, and educated areas are likely to leave nonpositive feedback. Although the standardized coefficients are small, in absolute value, they are larger than the coefficients corresponding to pro-social beliefs and behavior. In other words, some basic socio-economic variables are better predictors of actual trusting behavior on eBay than the measures of pro-social beliefs and behavior. Other characteristics, such as population density and crime rates, are not significantly correlated to nonpositive feedback.

5.3. Discussion

Some limitations with the data and the identification strategy are worth mentioning. First, we do not observe information for users who bought the product but chose not to leave feedback.[25] If we had such data, we would study the probability of leaving negative feedback conditional on buying the product. Instead, we analyze the probability of leaving nonpositive feedback conditional on buying the product and leaving some feedback. However, we do not see any obvious reason why this data limitation would introduce a systematic bias in the estimates.

Second, many buyer characteristics must be proxied using average characteristics in the area where the buyer is located. Those same characteristics also may affect the decision to buy the product, creating potential for selection bias. For instance, as discussed in Section 2.4, this bias may lead to an underestimation of the effect of trust on nonpositive feedback. This selection bias may explain, either partially of completely, why pro-social beliefs and behavior do not explain feedback choices.

Third, given that we are not exploiting experimental or quasi-experimental data, the estimates are subject to potential omitted-variable bias. For instance, it is possible that the measures of pro-social beliefs

[25] There are ways to imperfectly infer non-feedback such as looking at feedback left from sellers to buyers (for an econometric analysis of the probability of leaving feedback see Cabral and Hortaçsu, 2010). However, that was not feasible in our case due to limitations on the data collection method.

Table 5
Correlation between nonpositive feedback and average characteristics at the buyer's location.

	Dep.: Nonpositive feedback	
	Std. Coeff.	Std. Error.
Pro-social beliefs:		
LSS honest (county)	0.0644	(0.0416)
LSS honest (state)	0.0565	(0.0418)
GSS trust (state)	0.1081***	(0.0414)
Pro-social behavior:		
Civic life index (county)	0.0222	(0.0444)
LSS volunteering (county)	0.0566	(0.0451)
Voting turnout rate (county)	0.0126	(0.0420)
Putnam's soc. cap. index (state)	0.0431	(0.0418)
Socio-Economic characteristics:		
Median age (county)	−0.1399***	(0.0440)
Mean income (county)	0.1033**	(0.0444)
Share with college (county)	0.1588***	(0.0445)
Pop. density (county)	−0.0078	(0.0478)
Internet complaints rate (state)	0.0283	(0.0459)
Crime rate (county)	0.0187	(0.0434)

Notes: 241,547 observations on 7112 items. Standardized coefficients stand for the marginal effects of a one-standard-deviation increase in the independent variables. Each row corresponds to a separate OLS regression of nonpositive feedback on the variable listed and a set of controls: item fixed effects, distance between buyer and seller, dummy for whether buyer and seller are from the same state, the number of days elapsed between the listing was opened and the feedback was left, dummies for day-of-the week and dummies for months of the year. The independent variables take the value 0 if missing and the regression always includes a dummy variable indicating whether the information for that observation is missing. By definition of item, all transactions within a given item correspond to the same product listing, from the same seller, at the same price and for the same 90-days window. The terms in brackets "(state)" and "(county)" indicate that the variable corresponds to state- and county-averages, respectively. Heteroscedasticity-robust standard errors are clustered at the item level. See Table 1 for data definitions and Table 2 for descriptive statistics.

and behavior are positively correlated to some unobserved characteristics that have a positive effect on nonpositive feedback. This would bias the coefficient on pro-social beliefs and behavior upwards, which could explain why we fail to find a negative effect of pro-social beliefs and behavior on nonpositive feedback.

6. Conclusions

We study buyers decisions to leave nonpositive feedback on eBay, which are driven by buyers' beliefs about sellers' trustworthiness. To isolate differences in feedback choices that can be attributed to buyer characteristics, we compare feedback from pairs of individuals who bought the same product from the same seller at the same price and who observed the same information. First, we find that nonpositive feedback is strongly decreasing in the buyer's experience on eBay. This finding is consistent with the view that agents learn about trustworthiness through market transactions, such that individuals eventually attain unbiased beliefs about trustworthiness if they can access markets. Second, we find that feedback choices are not significantly associated with measures of pro-social beliefs and behavior. Our favorite interpretation for this finding is that, although cultural biases in trust may be important determinants of economic exchange in other contexts, they seem to have limited importance in the presence of good institutions, such as an electronic market with effective reputation-building mechanisms.

To better understand these findings, future research should study trusting behavior by looking at other choices besides feedback. For instance, it would be interesting to explore data on winning and non-winning bids to test whether bidders in less trusting areas are willing to bid less for a given item and whether that relationship is stronger among items that we suspect to be more trust-intensive.

Appendix A. Selection bias: Further discussion

In Proposition 1 we show that, when using aggregate data, the selection bias does not revert the sign of the relationship between trust and negative feedback under reasonable functional form assumptions. In this Appendix, we provide a simple proof that this relationship could be reversed under extreme functional form assumptions.

Assume a general cumulative distribution function $F_j(q)$ for group j, and solve for S_j:

$$S_j = \frac{F_j(\hat{q}_B) - F_j(\hat{q}_N)}{F_j(\hat{q}_B)}$$

Now, let's compare these shares across two groups, j_1 and j_2. Ideally, we would like that if $F_{j_1}(q)$ first-order stochastically dominates $F_{j_2}(q)$, then $S_{j_1} < S_{j_2}$. However, if $F_{j_1}(q)$ first-order stochastically dominates $F_{j_2}(q)$, then that does not guarantee that $\frac{F_{j1}(\hat{q}_B) - F_{j1}(\hat{q}_N)}{F_{j_1}(\hat{q}_B)} < \frac{F_{j2}(\hat{q}_B) - F_{j2}(\hat{q}_N)}{F_{j_2}(\hat{q}_B)}$. Fig. A.1 provides two examples. The solid lines indicate the cumulative distribution functions for q in each group (high- and low-trust). For a given group j, the pair of brackets indicate the values of $F_j(\hat{q}_B) - F_j(\hat{q}_N)$ and $F_j(\hat{q}_B)$. Thus, the ratio between the top and bottom brackets equals S_j. Fig. A.1(a) shows a case where $F_j(q)$ first-order stochastically dominates $F_k(q)$ and we do observe $S_j < S_k$. This is the case that arises with traditional functional form assumptions. On the other hand, Fig. A.1(b) shows a counter-examples, relying on an extreme functional form, where $S_j > S_k$.

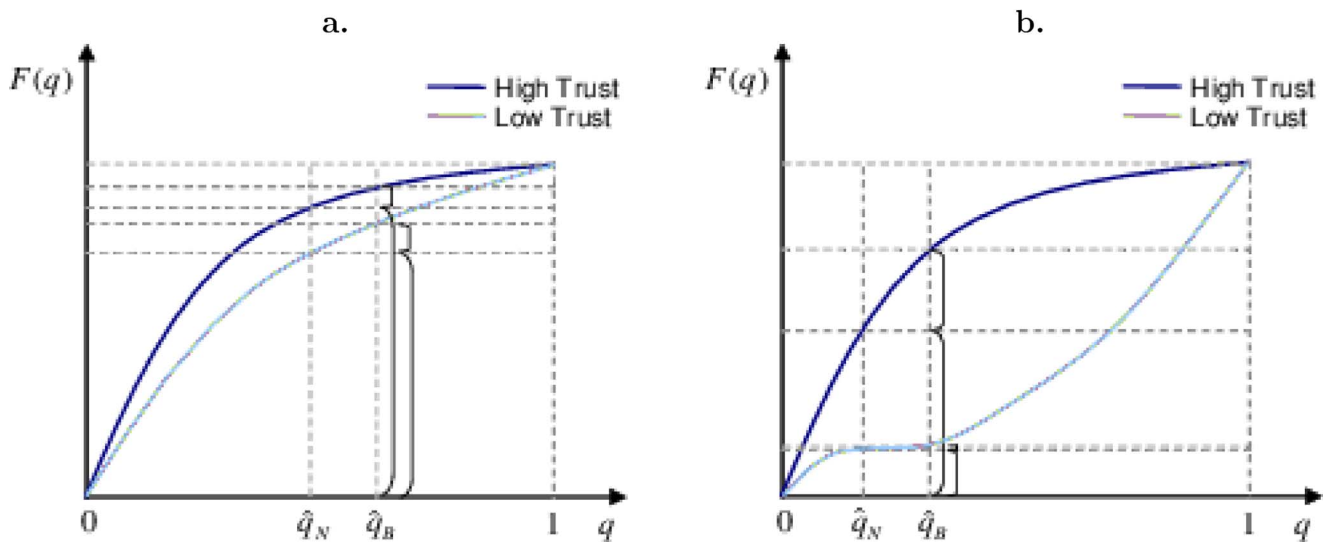

Fig. A.1. Relationship between the distribution of q in an area and the probability of negative feedback. *Notes:* Each curve corresponds to a cumulative distribution function, $F(q)$. For a given group j, the pair of brackets indicate the values of $F_j(\hat{q}_B) - F_j(\hat{q}_N)$ and $F_j(\hat{q}_B)$. Thus, the ratio between the top and bottom brackets equals P_j.

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