13. Testing sociological theories with digital trace data from online markets

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1 INTRODUCTION

Sociologists have researched the causes and consequences of collective action, trust building, reputation formation, social preferences, discrimination, and social inequality since long before the advent of the internet (Coleman, 1990; Hedström & Bearman, 2009; Bowles & Gintis, 2011). In the last two and a half decades, digital trace data of online market transactions has been used to research these topics. At the turn of the century, such datasets were mostly collected by 'hand'; researchers browsed through a selection of items offered by sellers in online market platforms, stored the HTML pages on their computers, extracted the relevant information from these HTML pages, and stored it in spreadsheets for later analyses (Diekmann et al., 2009). However, very soon researchers started scraping transaction data from online markets automatically using bots and regular expressions (Przepiorka, 2013; Diekmann et al., 2014). This approach, although not without risk, allowed collecting large sets of digital trace data from online markets. These datasets are still valuable and used today to test new hypotheses, as test beds for statistical modelling exercises and to teach computational and quantitative research methods to sociology students (Keuschnigg et al., 2018).

One reason for why online market data from the first decade of this century is still valuable for research and teaching purposes is that, at that time, most online market platforms did not employ so-called matching algorithms. Matching algorithms, as the one introduced by eBay in Spring 2008 (Netzloff, 2008; see also Nash, 2008), score sellers based on the information these sellers provide on their profile pages and the offers they post. Sellers with higher scores appear higher up in buyers' search results. Moreover, matching algorithms also take into account information about potential buyers (e.g., language, geographical location) that is available through these buyers' web browsers to provide them with suitable search results (Graham & Henman, 2019). Hence, scraping data from market platforms that employ matching algorithms will not allow one to recreate the decision situations that potential buyers and sellers faced on these platforms. What is more, many online market platforms introduced restrictions on web scraping and employed means to prevent excess and unwelcome bot activity on their servers (Przepiorka, 2011).[1]

These and other developments have restricted university researchers in collecting digital trace data from online markets for scientific purposes. On the one hand, restrictions on data collection are necessary to protect market participants' rights of controlling their personal data (European Parliament and Council, 2016). On the other hand, these restrictions bring about an unequal distribution of the means of knowledge production. By incorporating large research facilities in their proprietary realm, online market platforms not only outcompete public universities in their quest for knowledge on human behaviour, but also confine the effective use of this knowledge for the public good. This is even more problematic in the light of the growing influence online markets and other platforms have on people's lives, their preferences, beliefs, and activities. However, an independent evaluation of the workings of online market platforms is crucial for informing the design and implementation of public digital infrastructures through which citizens, consumers, and organizations can interact in pursuit of their goals and benefit from the digital revolution.

This chapter aims at contributing to this idea by giving a selected review of research conducted to learn more about (1) the trust-building capabilities of reputation systems employed in online markets, (2) online traders' motives for contributing to reputation systems by leaving feedback after completed transactions, and (3) the susceptibility of reputation-based online markets to social influence and discrimination.

2 A THEORETICAL MODEL OF ONLINE MARKET EXCHANGE

In Chapter 5 of his seminal book *Foundations of Social Theory*, James Coleman describes the trust problem that can arise between agents in social and economic exchange as a social dilemma: Two agents can both gain from voluntarily exchanging resources (e.g., money, commodities, services), but refrain from the exchange, if the agent transferring their resources first (the truster) cannot expect the other agent (the trustee) to live up to their part of the agreement. However, if the trustee is trustworthy with a certain probability (p), depending on the gains (G) and losses (L) that can result from the exchange, the truster might still make an advance (i.e., transfer their resources first). Coleman formalizes the trust problem in a threshold model in which a rational and self-regarding truster makes an advance, if the odds of the trustee being trustworthy are larger than the ratio of losses and gains, that is, if $p/(1-p) > L/G$ (Coleman, 1990). In terms of the probability that the trustee is trustworthy, it must hold that

$$p > \frac{L}{G+L} \tag{13.1}$$

Coleman's threshold model can be derived from the trust game with incomplete information (TGI) commonly employed in game theory to model the trust problem (e.g., Dasgupta, 1988; Voss, 1998; Raub, 2004; Przepiorka, 2021).[2] The TGI is depicted as a game tree in Figure 13.1, where, for the sake of exposition, the truster is labelled as buyer, who can decide whether or not to buy, and the trustee is labelled as seller, who, upon receipt of the buyer's money, can decide whether or not to ship the merchandise the buyer paid for (think buyers and sellers on eBay). The letters below each terminal node of the game tree denote buyer payoffs (first row) and seller payoffs (second row). The ordering of buyer payoffs is $R > P > S$ in both subtrees of the TGI. The ordering of seller payoffs is $T > R > P$ in the right subtree, and it is $R + b > T - c$ and $R + b > P$ in the left subtree. In other words, in the right subtree, the seller is untrustworthy because their payoff from shipping is *lower* than their payoff from not shipping ($R < T$). In the left subtree, the seller is trustworthy, because their payoff from shipping is *higher* than their payoff from not shipping ($R + b > T - c$); this results from the additional benefit b and/or cost c that the seller respectively obtains from shipping or incurs from not shipping the merchandise the buyer paid for.[3]

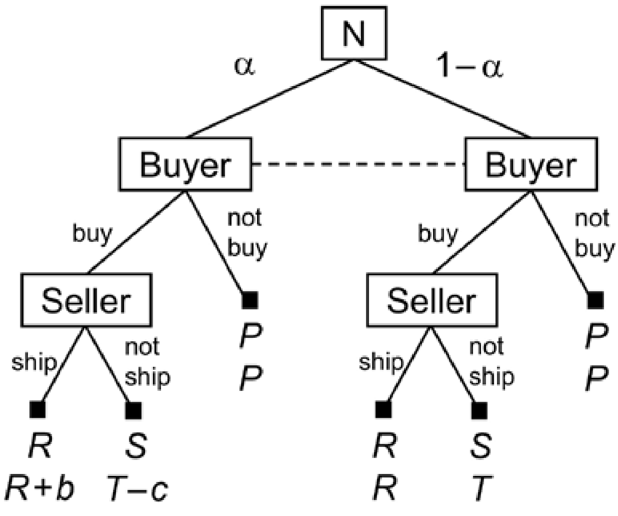


Figure 13.1 Trust game with incomplete information

In the TGI, the buyer's uncertainty about the seller's trustworthiness is modelled with the buyer's information set. The buyer's information set comprises the two decision nodes and the dashed line denoting that the buyer does not know at which node they are. However, the buyer knows the probability α by which chance (i.e., 'Nature') decides whether they are at the left decision node. With probability $1 - \alpha$ they are at the right decision node.

If the buyer decides to buy and the seller turns out to be untrustworthy, the seller keeps the buyer's money without sending anything back, and the buyer's and seller's payoffs are S and T, respectively. If the buyer decides to buy and the seller turns out to be trustworthy, the seller ships the merchandise upon receipt of the buyer's money, and the buyer's and seller's payoffs are R and $R + b$, respectively. If the buyer refrains from buying, both the buyer and seller (irrespective of the seller's trustworthiness) receive payoff P. Based on the payoff orderings, the buyer prefers to buy from a trustworthy seller ($R > P$) but not from an untrustworthy seller ($P > S$), and both a trustworthy and an untrustworthy seller prefer that the buyer buys ($R + b > P$ and $T > P$, respectively).

As mentioned above, the buyer only knows the probability α with which the seller is trustworthy. Since, as in Coleman's model, the buyer is assumed to be rational and self-regarding, the buyer decides to buy, if the expected payoff from doing so is larger than P, that is, if $\alpha R + (1 - \alpha)S > P$. In terms of the probability that the seller is trustworthy, it must hold that

$$\alpha > \frac{P - S}{R - S} \tag{13.2}$$

Equations 13.1 and 13.2 are equivalent. In Coleman's threshold model, p corresponds to α in the TGI, L is the loss the buyer suffers from trusting an untrustworthy seller ($L = P - S$), and G the buyer's gain from trusting a trustworthy seller ($G = R - P$). Finally, the sum of G and L in the denominator on the right-hand side of Equation 13.1 corresponds the denominator on the right-hand side of Equation 13.2 ($G + L = R - P + P - S = R - S$).

The TGI is often used to model the interaction between buyers and sellers in anonymous online markets such as eBay (Güth & Ockenfels, 2003; Przepiorka, 2013; Jiao et al., 2021). In these markets strangers trade with each other across large geographical distances and often follow the convention that the buyer sends the money before the seller ships the merchandise (Diekmann et al., 2009). The increasing popularity of anonymous online markets for social and economic exchange is in need of explanation, because it challenges the widespread view that traders' embeddedness in social networks of ongoing relations and a functioning legal environment are necessary preconditions for cooperative market exchange to emerge (Granovetter, 1985; Przepiorka et al., 2017).

Most online market exchanges are governed by reputation systems (Kollock, 1999; Resnick et al., 2000), which allow traders to comment on another's behaviour, attributes, products, and services with ratings and text messages. These ratings constitute traders' reputations, which can be conceived of as signals of these traders' trustworthiness (Przepiorka & Berger, 2017). Since building a good reputation from positive ratings and reviews takes time and requires cooperative behaviour, only trustworthy sellers will bother to invest in building one. Hence, buyers can infer sellers' trustworthiness from their good reputations (Shapiro, 1983; Przepiorka, 2013). How would a buyer who faces two sellers, one with an established and one with no reputation, decide?

Coleman (1990) further describes how the extent of the trust problem in social and economic exchange can vary depending on the information the truster has about the potential gains and losses and the trustee's trustworthiness. According to Coleman's threshold model (and the TGI), a buyer decides to exchange with the seller from which they expect the highest gain. From a seller with an established reputation, the buyer expects to gain G with certainty (R in the TGI). From a seller with no reputation, the buyer expects to gain $pG - (1 - p)L$ or, correspondingly in the TGI, $aR + (1 - \alpha)S$.

This argument seemingly suggests that a buyer would always choose the seller with an established reputation, and sellers with no record of past transactions would not be able to establish their business in the market (Frey & van de Rijt, 2016; Lukac & Grow, 2021). However, sellers without a good reputation can invest in building one by offering discounts (d) that make buyers indifferent between their offers and the offers of established sellers (Shapiro, 1983; Przepiorka, 2013). For a buyer to be indifferent between exchanging with a seller with an established reputation and a newcomer or even to prefer to exchange with the newcomer, it must hold that $pG - (1 - p)L + d \geq G$. Hence, the discount d that newcomers must offer to build their reputation is

$$d \geq (1-p)(G+L) \tag{13.3}$$

From this argument it follows that seller reputations and these sellers' business success will be correlated. Two hypotheses that result from this theoretical argument have been tested with transaction data from peer-to-peer online markets.

H1: The better a seller's reputation, the higher will be the probability the seller's items will be sold.

H2: The better a seller's reputation, the higher is the price the seller can obtain for their items.[4]

The next section reproduces an empirical analysis testing the two hypotheses based on a dataset collected on a large peer-to-peer online market.

3 TRUST, REPUTATION, AND ONLINE MARKET EXCHANGE

In peer-to-peer online markets, information about potential gains and losses is readily available via the item pages on which a seller's products and services are advertised and can be ordered by buyers. The big unknown, however, remains sellers' trustworthiness. Clearly, information about sellers' reputations will affect buyers' beliefs about sellers' trustworthiness. However, transaction data from online markets do not usually reveal much about buyers' (and sellers') beliefs. At the same time, such data provide an excellent source of behavioural information that allows for indirect tests of hypotheses involving psychological mechanisms. This section reproduces an analysis testing the two aforementioned hypotheses based on a dataset of almost 90,000 auctions of memory cards for electronic devices (Przepiorka & Aksoy, 2021). The dataset was collected on eBay.de in November and December 2006 (Przepiorka, 2013).

A typical approach to testing hypotheses H1 and H2 is to use a binary dependent variable indicating whether an item was sold and the selling price of sold items, respectively, and regress these variables on the number of positive and negative seller ratings.[5] However, hypotheses H1 and H2 imply a causal relation between seller reputations and these sellers' business success. Therefore, many other seller, item, and market characteristics must be controlled for in multiple regression models to identify the reputation effect (Morgan & Winship, 2015). This identification strategy is defendable as long as most information a buyer could have considered about the seller, item, and market context is accounted for in the statistical analysis (Przepiorka & Aksoy, 2021). Conducive to this identification strategy is, moreover, if the data sample comprises a homogeneous item (e.g., a particular memory card). A homogeneous item not only reduces the number of potential covariates to be considered but also the likelihood of omitting an important covariate in one's subsequent analyses (Diekmann et al., 2014).

The reputation of an online market seller is typically operationalized by the log-transformed number of positive ratings (plus one as the logarithm of zero is undefined) and the log-transformed number of negative ratings (plus one). The log transformation accounts for the assumption that the absolute effect of the number of ratings on a seller's business success is increasing at a decreasing rate. For example, a seller with 100 positive ratings will be perceived more favourably by buyers than a seller with 50 positive ratings, whereas a seller with 1100 and a seller with 1050 positive ratings will not make the same level of difference in buyers' perceptions. Next to the seller reputation variables, many other (mostly dummy) variables are included in such an analysis. These other variables include, for example, payment methods and shipping conditions offered by the seller, the number of similar items offered for sale at the same time, whether an offer ends on a weekend, the hour of day at which an offer ends, attributes of the item (e.g., memory capacity), a seller's country of origin, etc.

Table 13.1 shows the main results of the regression model estimations. Model M1 is a logistic regression with the probability of item sale as the dependent variable. Model M2 is an ordinary least squares (OLS) regression with the selling price (in euros) of sold items as the dependent variable. Both models account for the fact that many sellers offer items repeatedly by estimating cluster-robust standard errors at the seller level. The four explanatory variables

Table 13.1 *Regression models of probability of sale and selling price testing hypotheses H1 and H2*

	M1 Probability of sale (logit regression)		**M2 Selling price (log) (OLS regression)**	
	Coef.	**SE**	**Coef.**	**SE**
Const.	10.405***	1.434	3.322***	0.364
Main explanatory variables				
log(# pos. ratings + 1)	0.333***	0.075	0.093***	0.020
log(# neg. ratings + 1)	−0.213*	0.092	−0.084***	0.019
log(initial price in €)	−1.005***	0.125	0.058***	0.015
log (∅ shipping costs in €)	−2.158***	0.262	−0.731***	0.071
Control variables included	Yes		Yes	
N_1	88452		61744	
N_2	3248		3051	
Pseudo R^2	0.44			
adj. R^2			0.68	

Note: The table lists coefficient estimates and cluster-robust standard errors (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logit and OLS regression models. The binary outcome variable of model M1 is one if the auction received at least one bid and is zero otherwise. The outcome variable of model M2 is the log-transformed selling price (in euros) of auctions that received at least one bid and thus were sold. N_1 denotes the number of cases (auctions) and N_2 denotes the number of clusters (sellers). The full table is available in the online appendix of Przepiorka and Aksoy (2021).

included in Table 13.1 are the number of positive seller ratings, the number of negative seller ratings, the initial item price set by the seller, and the average cost of the shipping options offered by the seller for a particular item. All four variables are log transformed.

The average shipping costs are a proxy for the actual shipping cost, which are unobserved. Both average shipping costs and initial item price exhibit negative effects on the probability of sale. However, if an item is sold, unlike average shipping costs, initial item price has a positive effect on final item price (i.e., winning bid). These results are in line with how item prices drive behaviour in online auction markets (Przepiorka, 2013). Most importantly, the number of positive ratings and the number of negative ratings exhibit, respectively, a positive and negative effect on both sales and prices. These results support hypotheses H1 and H2. But how substantial are these reputation effects?

Based on model M1 in Table 13.1, the effect of the log number of positive ratings on the probability of sale can be calculated as follows: If the number of positive ratings increases by the factor 2.7 (which corresponds to a one-unit increase on a natural log scale), the odds of a successful sale increase by 29.5% = 100 × [exp(0.333) − 1]. Taking the unconditional selling probability of .7 obtained from the same dataset, this increase corresponds to .04 (i.e., four percentage points). Correspondingly, based on model M2 in Table 13.1, if the number of positive ratings increases by the factor 2.7, the item price increases by 9.7% = 100 × [exp(0.093) − 1]. Taking the average selling price of €15 obtained from the same data, this increase corresponds to €1.46. The same exercise can be performed with the coefficients for the number of negative ratings.

Although these effects are substantial, one may object that they are calculated based on an almost threefold increase of the explanatory variables. It is therefore important to put this effect calculation into context. Unlike most variables frequently encountered in the social sciences (e.g., five-point items used in surveys), sellers' numbers of positive and negative ratings can have a considerable range. In the example discussed above, the number of positive and negative ratings have a range of, respectively, 275,000 and 1890 between the 5th and 95th percentiles. Hence, threefold increases in reputations across sellers are not uncommon.

These results corroborate that a good reputation can have a substantial effect on an online seller's business success. In fact, these hypotheses have been tested many times by means of digital trace data from online markets collected by hand, automatically scraped, or obtained from the administrators of an online market platform. A recent meta-analysis, synthesizing evidence from 125 papers, corroborates the existence of such a reputation effect, albeit with considerable variation in effect sizes due to differences in operationalizations of seller reputation and seller business success, market contexts, product features, and research designs (Jiao et al., 2022). However, for the reputation mechanism to be effective in promoting cooperative market exchange, market participants must share truthful information about their past transactions in the form of quantitative ratings and text comments. The next section discusses research investigating online traders' motives for leaving such feedback.

4 SOCIAL VALUE ORIENTATION, RECIPROCITY, AND REPUTATION FORMATION

Reputation systems employed in peer-to-peer online markets benefit all market participants. However, individual traders' contributions to these reputation systems with feedback information are voluntary and costly in terms of time and effort. Hence, reputation systems are collective goods that are subject to a free-rider problem (Bolton et al., 2004). A reputation system can also be regarded as a peer sanctioning system through which cooperative behaviour can be rewarded and uncooperative behaviour can be punished with positive and negative feedback, respectively (Resnick et al., 2000; Simpson & Willer, 2015). In this sense, reputation systems in online markets can be conceived as second-order collective goods (Yamagishi, 1986; Heckathorn, 1989; Kollock, 1999). Second-order cooperation at the feedback stage creates the reputational incentives that promote first-order cooperation at the transaction stage (Diekmann et al., 2014). But what motivates traders to contribute to the collective good of a reputation system by leaving feedback after finished transactions? Based on assumptions of rational and purely self-regarding actors, no feedback should be left, and reputation-based online markets should not exist. How then can the growing popularity of reputation-based online markets be explained?

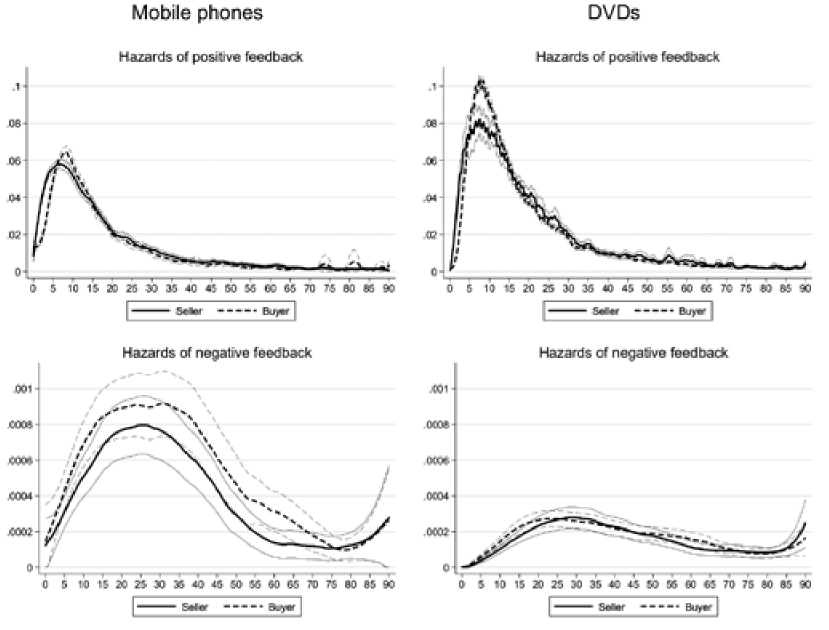
Research in marketing and human–computer interaction has shown that people differ in their motives for leaving feedback (Hennig-Thurau et al., 2004; Picazo-Vela et al., 2010; Cheung & Lee, 2012). People want to 'let off steam', express their satisfaction, reward or punish the seller for respectively a good or bad service, inform future consumers about a product or a seller, and leave feedback because others do. Also, people can be deliberately more or less accurate about their experiences in their feedback. In more abstract terms, this research identifies concerns for oneself (i.e., self-regarding preferences), social value orientation (i.e., other-regarding preferences), reciprocity, and conformity as main drivers of traders leaving feedback after completed online market transactions (Macanovic & Przepiorka, 2022). However, this research is based mostly on small-scale, non-representative surveys, measuring respondents' intentions and attitudes with respect to leaving feedback. Although these findings establish the set of motives online traders may have for leaving feedback, they are limited in what one can learn about the relative importance of these motives in actual online markets.

There are a few studies that use digital trace data from online markets to learn something about traders' motives for leaving feedback. Most of these studies are based on the analysis of timed feedback events produced by traders after completed transactions on eBay. At the time these datasets were collected, traders could leave feedback up to 90 days after a transaction. Moreover, eBay employed a reciprocal rating system, which allowed buyers to rate sellers and, in the same way, sellers to rate buyers. All but one of the half a dozen studies that report feedback rates from eBay markets report numbers above 50 per cent (see Bolton et al., 2013; Diekmann et al., 2014). Although these rates are indicative of traders' cooperation at the feedback stage, they do not reveal *why* these traders leave feedback.

To address this question, Jian et al. (2010) developed a model to estimate the proportion of traders' different feedback strategies based on feedback data obtained from eBay. The authors assumed three strategies that individual traders can employ – (1) do not give feedback, (2) give feedback unconditionally, and (3) reciprocate feedback (i.e., give feedback only after receiving feedback) – and estimated buyers' and sellers' probabilities of choosing one of the strategies in a statistical model. They found that the reciprocal feedback strategy was chosen by buyers and sellers in, respectively, 23 per cent and 20 per cent of the cases, whereas the unconditional feedback strategy was chosen in, respectively, 38 per cent and 47 per cent of the cases. Their findings indicate that both reciprocity and other-regarding preferences play an important role in motivating traders to leave feedback (see also Dellarocas & Wood, 2008).

In a similar vein, Diekmann et al. (2014) analysed hundreds of thousands of feedback events that occurred after transactions of mobile phones and DVDs on eBay. The results of their event history analysis corroborated that reciprocity, other-regarding preferences, and strategic motives play an important role in traders leaving feedback. First, reciprocal motives are consistent with their finding that traders' propensities to leave feedback increased significantly after they received a rating from a trading partner. Second, other-regarding motives are consistent with their finding that traders were more likely to give a positive rating and they were less likely to give a negative rating to a trading partner with fewer ratings. In other words, traders anticipated the impact their feedback could have on the business success of trading partners that were still building their reputation. Finally, they found evidence for strategic motives. Some traders postponed leaving negative feedback to the very end of the rating period of 90 days, likely because they feared receiving negative feedback in return.

Figure 13.2 shows non-parametric estimation results for the hazard rates of positive feedback (top panels) and negative feedback (bottom panels) in the mobile phone and DVD markets examined by Diekmann et al. (2014). Hazard rates are, roughly speaking, the probabilities that feedback is left at a specific time given that no feedback was left before. The figure shows that positive feedback is left much more frequently and earlier than negative feedback. While the probability of positive feedback occurring peaks between day 5 and 12 after completed transactions, the probability of negative feedback occurring peaks between days 20 and 35. This late arrival of negative feedback is likely due to delays in payment or shipping and lasting disputes between buyers and sellers, which also cause either party to leave a negative feedback eventually. Another noteworthy difference between the hazard rates of positive and negative feedback is the second peak in the hazard rates of negative feedback that occurs towards the end of the rating period of 90 days. Again, this second peak is indicative of traders trying to avoid retaliatory negative feedback by leaving feedback just before the end of the feedback period.



Note: Hazard rates with 95 per cent confidence bands (thin lines).
Source: Adapted with permission from Diekmann et al. (2014).

Figure 13.2 *Hazard rates of sellers' and buyers' rating decisions*

These studies confirm that the motives for leaving feedback identified in survey-based research form the basis of reputation systems in real online market contexts. However, using digital trace data of feedback events to study online traders' motives for leaving feedback also has limitations. First, the evidence for reciprocity and strategic motives is tied to these studies' use of feedback data from eBay's two-sided rating system. It is an open question as to how far traders leave feedback to reciprocate the experience they had at the transaction stage and how important strategic considerations for leaving feedback are if reciprocating feedback is not possible. Second, traders' motives for leaving feedback can only be inferred indirectly from these traders' feedback behaviour. Behavioural evidence that is consistent with predictions derived from a psychological mechanism cannot rule out alternative explanations. Relatedly, the lack of behavioural evidence for a particular motive does not rule out the motive's relevance for traders' feedback behaviour. Different motives can counteract each other, which also makes it difficult to establish the relative importance of motives at both the aggregate and individual levels. Experimental research (Abraham et al., 2021; Hoffmann et al., 2021) and the automatic analysis of feedback texts (Macanovic & Przepiorka, 2023) could offer new insights into the dynamic interplay of traders' motives for leaving feedback and the organizational features of reputation-based online markets.

Leaving feedback after completed online market transactions constitutes a simple social situation opening little possibility for self-presentation. It is therefore plausible to assume that feedback texts are reflective of the direct motives the authors had for leaving feedback rather than just being socially accepted, post hoc justifications of their actions. Starting from this premise and a thorough theoretical framework of motives for leaving feedback, Macanovic and Przepiorka (2023) combine manual and automatic text-mining methods to investigate the motivational landscape of reputation-based online markets. Their approach allows them to tie motives for leaving feedback (e.g., other-regarding preferences, reciprocity) and motive co-occurrences to actual online traders and transactions. This, in turn, enables them to investigate the relative importance of these motives in promoting cooperative market exchange and the stability of reputation-based online markets.

5 SOCIAL INFLUENCE, DISCRIMINATION, AND THE VIABILITY OF ONLINE MARKETS

Reputation systems establish barriers to market entry because market entrants must invest in building a good reputation by offering their products at lower prices and behaving cooperatively over an extended period. Once these traders acquire a good reputation, they are compensated for their initial investments by trading partners willing to pay for a good reputation (Shapiro, 1983). At the same time, sellers that do not intend to stay in the market long enough to be compensated for their initial investment in a good reputation will refrain from entering the market. Hence, at least in theory, the interplay of the reputation and the price mechanisms deters untrustworthy sellers without precluding trustworthy sellers from entering the market (Przepiorka & Aksoy, 2021). However, it has been argued and shown that the reputation mechanism can instigate success-breeds-success dynamics by which actors that are preferentially chosen gain in reputation more quickly and outcompete other actors in spite of these actors' comparable, initial ability levels (DiPrete & Eirich, 2006; van de Rijt et al., 2014). The same holds for products and services (Salganik & Watts, 2009; Keuschnigg, 2015). The reputation mechanism can thus produce a hierarchization of actors, products, and services that is not reflective of these actors', products', and services' underlying qualities (although see Przepiorka et al., 2020).

To explore this possibility, Frey and van de Rijt (2016) conducted a behavioural laboratory experiment in which they emulated the interaction dynamics of buyers and sellers in an anonymous online market. In their experiment, they randomly assigned participants to several experimental conditions that differed in the extent of information provided to buyers about sellers' reputations (see also Kollock, 1994; Brown et al., 2004). The experiment lasted over several rounds in which each of the buyers had to choose one from among several sellers to interact with. After every interaction between a buyer and a seller, which was implemented as a trust game (see Figure 13.1), seller reputation information was generated automatically. Trustworthy sellers gained in reputation, untrustworthy sellers lost in reputation, and sellers that were not chosen neither gained nor lost in reputation. Their results showed that if sellers could acquire a reputation, (1) sellers were chosen by buyers based on their reputation and (2) sellers chosen in the first rounds were chosen preferentially in future rounds. That is, although sellers did not differ in any observable traits at the start of the experiment, the ones that were chosen first gained in reputation earlier and were chosen again in future rounds to the detriment of the sellers that were not chosen from the start. Based on these findings, the authors concluded that the reputation mechanism commonly implemented in anonymous online markets can lead to arbitrary inequality among sellers due to a success-breeds-success dynamic (see also van de Rijt & Frey, 2020).

However, in their experiment, Frey and van de Rijt (2016) induced an oversupply of sellers and the trust game payoffs were constant throughout the experiment; sellers could not use the price mechanism to compete for buyers. If similar sellers enter a new market selling a product for which there is less demand than supply, arbitrary inequality will emerge naturally as a result of market forces. Once supply and demand are balanced, the sellers that are still in the market can, *ceteris paribus*, expect to be chosen to similar extents by buyers. In equilibrium even new sellers should be able to enter the market and build a good reputation for being trustworthy and reliable by initially lowering their prices (see above).

Results from analyses of digital trace data from reputation-based online markets corroborate the idea that buyers indeed trade off sellers' reputations against the prices these sellers set for their products and services (Snijders & Weesie, 2009; Przepiorka, 2013). Moreover, even though buyers in online markets follow other buyers in their decisions of which sellers to buy from, they might not follow others at any price. Przepiorka and Aksoy (2021) test this conjecture based on the analysis of a large set of online auction data. They demonstrate that online buyers herd on offers that received bids from up to two previous buyers and that herding declines once an auction reaches three bidders and a certain price level. Przepiorka and Aksoy (2021) show moreover that herding buyers do not neglect the reputation of the sellers whose offers they herd on; buyers that join an auction at a later stage do not seem to blindly trust previous buyers to have fully scrutinized the seller's offer (although see Simonsohn & Ariely, 2008).

In many online markets buyers and sellers can interact exclusively online without having to reveal much personal information *ex ante* because payment is via bank transfer or credit card and the merchandise is shipped by mail or the service provided online. In these online markets the trust-building capacity of reputation systems will be effective with not much more than seller reputations and item prices as information inputs (Przepiorka et al., 2017). However, many online market platforms facilitate the initiation of transactions between two or more parties that eventually have to meet in person. For example, bed-and-breakfast platforms match hosts and guests that often share the same apartment or even room for a short period of time; lift platforms match drivers and passengers that share the same car for the duration of an often long ride; tutoring platforms match tutors and students that spend time together for the duration of mostly several lessons; dating platforms match people that want to be intimate with each other for one night or longer (see Coyle & Alexopoulos, Chapter 11 and Skopek, Chapter 12 in this volume); etc. The trust-building capacity of reputation systems may not suffice in these cases because people have to meet in person to complete the exchanges; other means such as verified identities, phone numbers, headshots, copies of passports, or collaterals are needed to overcome potential trust problems. While clearly necessary, such additional information gives rise to discrimination of all sorts.

The possibility of discrimination being at play in online markets has been tested via quasi-experimental research designs. Doleac and Stein (2013) conducted a field experiment in which they sold portable media players via Craigslist (an online, peer-to-peer flea market) in different states in the United States. In their experiment, they systematically varied the skin colour of the hand holding the item in a picture posted with the ad. They plausibly assumed that potential buyers would infer the race of the seller from the item picture. Their results showed that allegedly black sellers received fewer messages and offers, lower final price offers, and were trusted less by potential buyers than allegedly white sellers. The latter finding manifested itself in buyers being reluctant to include their real names in email correspondence or to agree on mail delivery and long-distance payment when dealing with seemingly black sellers. Similar results were obtained in studies using non-experimental digital trace data from a car-pooling platform (Tjaden et al., 2018) and a peer-to-peer motorcycle rental platform (Kas et al., 2021).

Tjaden et al. (2018) used ride data from a German car-pooling platform and estimated the price penalty that drivers with non-German sounding names had to pay to be 32 per cent. That is, on average, drivers with Arab, Turkish, or Persian sounding names had to offer their rides at a 32 per cent lower rate to obtain the same number of clicks on their offers than drivers with German-sounding names. The authors also found that additional information such as a better reputation score could reduce the gap in the outcome variable. The latter finding suggests that reputation systems may help to overcome the adverse effects of discrimination in online markets. However, Kas et al. (2021) object this conjecture by arguing that minority group members, when entering a market, will have a harder time building their reputation because of discrimination. Moreover, due to the success-breeds-success dynamics described above, these minority members will be further disadvantaged in the market. Kas et al. (2021) corroborate their argument through the analysis of timed interaction data from a Dutch peer-to-peer motorcycle rental platform. Their results thus suggest that minority members that are subject to discrimination by majority group members may not simply compensate their worse market outcomes by building a good reputation.

Although it is clear from these and other studies that minority group members are discriminated against in online and other markets (see also, e.g., Auspurg et al., 2019; Hangartner et al., 2021), many studies also provide evidence that discrimination is sensitive to prices and competition. For example, Doleac and Stein (2013) show that competition among buyers reduces the outcome differences between seemingly black and white sellers of portable media players on Craigslist. In a market in which demand exceeds supply, buyers are more willing to take risks by posting higher bids on items offered by sellers with a lower reputation or sellers they trust less for other reasons (e.g., because they belong to a minority group) (see also Przepiorka, 2011). Of course, if buyers can be selective because there is an oversupply of a particular item or service, outcome differences between sellers due to discrimination must be addressed actively. This can be done via the price mechanism and signals of trustworthiness such as verified identities (Przepiorka, 2011) or charitable giving (Elfenbein et al., 2012). Obviously, these measures do not eradicate differences in market outcomes between sellers from minority and majority groups. However, when applied at time of market entry, they can help to minimize outcome differences by stalling processes of cumulative disadvantage. Lower prices, reliable identity information, and generosity have been shown to be substitutes for reputation and therefore could establish viable, additional trust-building mechanisms in reputation-based online markets.

6 CONCLUSIONS

Throughout history, the effectiveness of mechanisms promoting cooperative market exchanges commonly depended on actors' social embeddedness (Granovetter, 1985; Diekmann & Przepiorka, 2019). In the last two and a half decades, peer-to-peer online markets have fundamentally transformed the ways in which people engage in social and economic exchange. Modern information and communication technology has substituted informal institutional elements rooted in actors' social relations with semi-formal institutional elements such as reputation systems and escrow services. As a consequence, cooperative market exchanges today also depend on the quality of the institutional set-up of online market platforms and thus on the expert judgements of market designers, business consultants, and software engineers. Yet, online market platforms are vulnerable to attempts of exploitation of institutional and technical loopholes, but also to the unintended negative consequences of market participants' purposive actions.

The ongoing shift in the socio-structural foundations of market action has created new challenges but also opened new opportunities for researchers to study the mechanisms underlying (among others) collective action, social cohesion, inequality, norms, and trust. These topics have been at the core of sociological scholarship not only since Coleman's seminal book *Foundations of Social Theory*.

In this chapter I have shown how Coleman's threshold model of trust in social and economic exchange can be applied to derive hypotheses about traders' behaviour in reputation-based online markets. The model, which is closely related to the trust game with asymmetric and incomplete information known from game theory (Raub, 1992; Raub & Weesie, 2000), allows to make predictions about the conditions under which buyers in anonymous online markets are more likely to trust sellers with their money. Research shows that especially the additional information about sellers' reputations provided via reputation systems commonly implemented in online markets positively affects buyers' trust in sellers (Jiao et al., 2021, 2022).

Although Coleman's model is silent about where reliable information about seller reputations comes from, sociological theories of collective action and cooperation in social dilemmas have contributed to our understanding of why online traders leave feedback after completed transactions (Heckathorn, 1989; Simpson & Willer, 2015). Despite the fact that reputation systems are collective goods and therefore subject to the free-rider problem (Bolton et al., 2004), research shows that online traders leave feedback on their trading partners at high rates. Other-regarding preferences, reciprocity, but also self-regarding and strategic considerations have been shown to drive online traders' feedback behaviour (Diekmann et al., 2014).

Online market contexts have also provided a test bed for theories about social influence and discrimination. Both mechanisms have been shown to spur social inequalities in general and among sellers in online markets in particular (Kas et al., 2021). It has been argued and shown that reputation formation can be subject to a success-breeds-success dynamic because sellers with a better reputation attract more buyers (Frey & van de Rijt, 2016). However, the boundary conditions under which the reputation mechanism produces inequitable outcomes because it prevents new traders from entering the market have not yet been established (Przepiorka & Aksoy, 2021).

Further research is necessary to obtain a better understanding of the dynamic interplay of feedback giving, reputation formation, and cooperation in reputation-based online markets. Apart from mapping the boundary conditions of the reputation mechanism to promote cooperation in humans, it could be fruitful to investigate the relation between generalized and particularized trust by showing how generalized trust interacts with people's motivations to participate in reputation-based online markets (Uslaner, 2018; Schilke et al., 2021). To what extent does the effectiveness of reputation systems in promoting cooperative market exchange depend on people's generalized trust? Could online markets that employ reputation systems nurture generalized trust in people who have little trust in strangers? Addressing these questions could unveil online markets' potential to create the economic interdependencies that foster cooperation and integration in heterogeneous, modern societies (Baldassarri & Abascal, 2020).

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NOTES

1. *The Robots Exclusion Protocol* was introduced in the 1990s to give website owners a means to informally regulate bot activity on their websites (see www.robotstxt.org/).
2. This was first pointed out by Raub (1992). Moreover, Raub and Weesie (2000) point out that Coleman's threshold model neglects the strategic nature of the trust dilemma where also the trustee decides whether or not to honour trust.
3. A seller's additional benefits (b) and costs (c) from shipping or not shipping, respectively, can be divided in to extrinsic (i.e., contextual) and intrinsic (i.e., psychological) benefits and costs. A seller's extrinsic benefits and costs result from the seller's social and institutional embeddedness that incentivizes the seller to act in the buyer's interest. A seller's intrinsic benefits and costs result from the seller's other-regarding preferences and internalized norms of reciprocity and fairness (Riegelsberger et al., 2005; Przepiorka & Berger, 2017).
4. In equilibrium, if demand and supply are balanced, H1 may not obtain. See Section 5 for a discussion on how the reputation effect may depend on the relation between demand and supply.
5. Note that these hypotheses apply to different types of transactions implemented in online markets. Some market platforms implement auction mechanisms through which buyers determine the prices of items (i.e., products or services), other platforms only allow fixed-price formats where prices are set by the sellers who offer these items online, and yet other platforms allow both formats (see, e.g., Przepiorka, 2013).

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