NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Elina Ishmukhametova, Marina Sandomirskaia

THE PROBLEM OF REPUTATION RELIABILITY IN ONLINE FREELANCE MARKETS

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: ECONOMICS
WP BRP 260/EC/2023

HSE University

The Problem of Reputation Reliability in Online Freelance Markets

Elina Ishmukhametova[1,2], Marina Sandomirskaia[1]

[1] HSE University, Moscow, Russian Federation

[2] University of Lille, Lille, Hauts-de-France, France

Abstract

This paper explains how the problem of reputation credibility may arise in online freelance markets, as clients often complain about the quality of the completed work irrespective of the price and the rating of the worker. We develop a dynamic signaling model of falsified reputation purchase by low-skilled freelancers, focusing on a semi-separating equilibrium in every period. The main result states that when the costs of purchasing reputation are high, only the maximum rating is bought. This is due to low-skilled freelancers wanting to be chosen by clients in order to recoup their losses. When the costs are low, a variety of reputations are observed, but the reputation mechanism is not credible and adds little new information to prices.

Keywords: reputation, freelance, marketplace.

JEL: C73, D82

1 Introduction

Online freelance marketplaces are websites and online platforms which match self-employed sellers of services which can be delivered electronically to buyers (clients). The most popular professions on freelance markets are programming, copywriting, design, web design, translating and tutoring, and music and video processing (Chechulina, 2016). The demand for freelancers increased by 17.2% in 2019, and there was a 12.1% increase in wages (Inc., 2019). About 40% of Russians want to change their jobs and most of them lean toward such professions as editors, entrepreneurs, or data scientists. An important criterion is the possibility to work online (TASS, 2020). These trends can be explained by two factors apart from technological advances. First, freelance markets offer services at lower prices on average (Ba, Pavlou, 2000). Second, it is a low-cost way to trade with geographically distant economic agents (Yoganarasimhan, 2013).

However, despite the growth of online freelancing, it faces challenges, and the main one is information asymmetry. For clients it is difficult to distinguish whether sellers provide high- or low-quality service. Sellers use this informational opportunity to act opportunistically (Akerlof, 1970). Therefore, in the absence of information, sellers may provide low-quality services, escape with advanced payments, delay the job, not complete it, or steal intellectual property that was given to them and sell it or use it for their own interests (Yoganarasimhan, 2013). In order to prevent such violations, online platforms established reputation mechanisms: ratings and written reviews. These mechanisms help to eliminate dishonest behavior and allow anonymous geographically dispersed players to make deals without face-to-face interaction (Dellarocas, 2003). Reputation can be of different forms, but feedback usually includes a rating out of 5 and a non-obligatory written review about the work completed. Online reputation mediators are responsible for feedback processing and changing reputation histories on summary statistics (Dellarocas, 2005). Only with information from past interactions, the trade between strangers become possible.

Despite the benefits of reputation, it may fail in some cases. For example, imperfect monitoring, unverified and voluntary feedback, retaliation, and Sybil attacks may influence the true image of sellers (Yoganarasimhan, 2013). Hence, the question of reputation credibility arises concerning online freelance marketplaces. It has been argued that no matter how many diverse freelance platforms there are, clients often complain that the quality of the service is low no matter how much they pay or what the rating of the freelancer is. Such results can be due to reputation inflation from the buyer side when peer-to-peer interaction makes clients feel uncomfortable giving negative feedback (Filippas et al., 2019). They can also be caused by reputation manipulation by low-skilled freelancers. In this case, reputation may not work and may lead new clients to sellers with low-quality service.

This paper investigates what happens when feedback can be adjusted at some cost by low-skilled freelancers. Would the rating system be credible or non-credible? Can clients trust it while making their choice? Another important issue concerns the reasonable dynamics of this effect on freelance markets for people who would like to enter the market.

We construct a dynamic signaling model based on trade names (Tadelis, 1999) and reputation effects (Fudenberg and Tirole, 1991). The model represents a simplified freelance market and client choice conditional on reputation and pricing. Reputation is a signal for a buyer about the quality of the service and therefore low-skilled freelancers want to imitate high-skilled ones. We introduce the mechanism of truthful reputation accumulation and the purchase of false reputation score from external service, which allows falsifying the reputation signal.

The main result of our analysis is that when the costs of purchasing a false reputation are high, only the maximum rating is bought. The model can be assumed as a near-dynamic model as the decisions of both parties in each period do not depend on previous periods, but reputation purchase binds all the periods (see Fudenberg and Tirole (1991)). We show that reputation can be misleading and does not allow freelancers to be separated, since when a freelance market exists long enough all accounts will have a reputation (true or false) which is close to the highest possible reputation level.

The structure of this paper is as follows. Section 2 considers reputation analysis in the literature, with a focus on online platform interaction. Section 3 describes the ingredients and the main assumptions of the theoretical model. Section 4 presents the model solution and section 5 highlights the results. Section 6 offers some concluding remarks and directions for future research.

2 Literature Review

The first strand of the literature concerns reputation on online *freelance* platforms. Yoganarasimhan (2013) explores how much attention buyers pay to sellers' reputation. The author finds that clients pick winners of the auction not only by price but also by taking into account sellers' reputation, bid prices, other bid attributes, and the costs of waiting and canceling. Despite the possibility of reputation underestimation in freelance platforms because of system failures (Kauffman, Wood, 2000), Yoganarasimhan (2013) shows that, in reality, buyers value reputation in decision making. The author provides a dynamic structural framework for modeling and predicting the winning probability under changing parameters (numbers of ratings, average ratings, and maximum bids). This major finding suggests that reputation is a signal for clients, which is used in the following research. However, this paper examines the market only from the buyers' perspective. Our research uses reputation as a signal for clients, and also focuses on the sellers.

Price and reputation are the key quality signals to clients about the expected outcome (Gu, Zhu, 2021; Ba, Pavlou, 2002), and freelancer earnings positively correlate with reputation scores (Gandini et al., 2016).

The problem of reputation inflation is that reputation tends to be biased over time and does not reveal the true level of quality. Clients misreport if they have a bad experience, giving high scores even if they do not like the result of the work (Filippas et al., 2019). Raters are afraid of retribution from sellers and negative feedback can be costly. Even if there is no possibility for ”tit-for-tat” rating behavior, employers still give inflated reviews as transactions are more personal in an online labor market. Whereas, there is no inflation effect at impersonal platforms with product assessment, such as film reviews.

Generally, positive reviews correlate more weakly with the price premium than negative ones. The latter strongly correlate with low prices and unsuccessful results of an interaction (Brown, Morgan, 2006). Negative feedback affects the prices of collectible coins much more than positive feedback (Lucking-Reiley et al., 2007). In the market of Paul Reed Smith guitars on eBay, negative feedback has an adverse impact on the likelihood of a sale (Eaton, 2002). These results support the idea for our model that negative feedback has a larger impact than positive and may destroy the reputation of a freelancer. Some clients write detailed reviews without rating the worker, however, text is hard for quick analysis and is usually ignored (Ma et al., 2021). Even though these papers challenge reputation sustainability, they do not consider the possible problem of reputation purchase which could be also inhibit feedback effectiveness.

The second strand of literature concentrates on the broader meaning of reputation mechanisms, without focusing on the platform framework. The use of reputation as a social control system has been studied for a long time (Greif, 1993; Milgrom et al., 1990). Tadelis (1999) presents a model about name trade in terms of reputation. A firm is the bearer of reputation, and its name is an intangible asset that can be sold. The author considers two-period and three-period models with an extension to an infinite time horizon. The idea of name purchase by the bad type agents reveals the fact that the good history of the name creates expectations of good future performance. If a new agent can secretly buy a name with a decent history, they will earn more revenue than they would with a new name. The same could happen in the freelance marketplace. Accounts with good ratings and feedback can be bought by low-skilled freelancers. The purchase of Instagram accounts with a specific number of followers may also represent the same idea.

Tadelis (2016) describes the role of reputation and how it works in an online marketplace. He highlights problems of bias in feedback and reputation system because of retaliation concerns, which confirms that reputation may fail.

The model design for the current research is drawn from Fudenberg and Tirole's chapter (1991) about reputation effects. The Chain-Store Game represents the situation when reputation is built by a weak (strategic) incumbent, which has a choice between fighting or accommodating a new entrant to the market. The following model considers a low-skilled freelancer who has a choice between setting high (or low) prices and thus creating an image for the client as a high (or low) skilled freelancer.

The third strand refers to rating systems and the possibility of rating purchase and manipulation. There is much evidence that people are influenced by opinions and feedback before deciding to purchase (Thompson, 2003; Chevalier, Mayzlin, 2006). One review may influence all sellers, as buyers update their beliefs using this small piece of information. Buyers may decide to remain silent and leave the market after an unsuccessful deal without any feedback. This situation may incur a positive bias in sellers' reputations, which makes the reputation mechanism itself less efficient (Nosko, Tadelis, 2015). However, not only the buyer may influence on the efficiency of reputation. There are also many manipulation strategies in online platforms by sellers, which makes it difficult for clients to infer the true quality of the product (Dellarocas, 2006). Dini and Spagnolo (2009) identified the problem of buying reputation on eBay. They showed how the reputation system can be manipulated by purchasing cheap positive feedback and that this may influence the trust of buyers. Brown and Morgan (2006) also discussed the market for feedback and if someone decides to search for "positive feedback" in the eBay search engine, there are many results with low prices for e-books, digital photographs, etc.

Extremely positive feedback is not always the best way to maximize profits. Strategic consumers who are fully aware of the seller's censorship capabilities may treat any bad review as good news about product quality. The model of Smirnov and Starkov (2022) reveals that having no bad reviews is perceived as a bad sign for strategic consumers because any new piece of information improves their beliefs about the product. However, an improvement in reviews also may lead to an increase in sales (Chevalier, Mayzlin, 2006). Thus, the problem of purchasing feedback and ratings is common and complicates the buyer's choice. Once firms using feedback manipulation, they may be locked into a race, which will cause a decrease rather than increase in profits (Dellarocas, 2006). In this case, it is important to study the possible effect of feedback manipulation in online freelance platforms as previous studies were not focused on different types of sellers.

3 Market participants

Consider a dynamic model, where in each period a client (buyer) employs a freelancer (seller). There are two types of freelancers, depending on their service quality: high and low skilled. They have different levels of productivity θ_H and θ_L, respectively, where $\theta_H > \theta_L$. Levels of productivity do not depend on the effort of freelancers and reflect the utility of a client from working with a particular freelancer. The share of high-skilled freelancers is $p_0 \in [0, 1]$, while the share of low-skilled freelancers is $1 - p_0$. The distribution of agent types is constant over time.

Assume that high-skilled freelancers set only a high price π_H, as setting a low price π_L is the worst strategy for them[1] ($\pi_H \geq \pi_L > 0$). Low-skilled freelancers may choose to post either a low price or a high price. When a low-skilled freelancer sets a high price, they compete with high-skilled freelancers for the same consumer, who cannot distinguish them. In the long term, when reputations are established, low-skilled freelancers must care also about the similarity of reputation with high-skilled ones to be indistinguishable. When a low-skilled freelancer sets a low price, they reveal their type and attracts only the category of clients who avoid any risk and prefer not to pay more for the phantom chance of high quality.

When the game starts, at $t = 1$, freelancers can only post prices. No reputations exist at this period. Observing the distribution of prices and comparing this with a prior distribution of types, a mass of clients, normalized to 1, chooses with which probability to hire the freelancer with a low or high price. After this period, a high-skilled freelancer gets one positive feedback for free, such that their reputation becomes equal to the probability to be chosen. A low-skilled freelancer receives negative feedback, which destroys the possibility of operating effectively on the platform using their current account in the future. In the next period, they start from the scratch and create a new account. This account could either be with no reputation (an empty account), or with a corresponding level of fake reputation if the low-skilled freelancer decides to act opportunistically and buy reputation.

[1]We take this assumption from Tadelis (1999). This can be extended to different prices for high-skilled freelancers, which makes further analysis more complicated technically, but keeps the same qualitative conclusions.

The latter could be done if they want to compete with high-skilled and high-rated workers, but this is costly.

At every next period, a new client observes the actual distributions of prices and reputations, and they are familiar with the average platform quality, represented by p_0. In this case, a client can update the posterior distribution to find a high-skilled freelancer among those with high prices and the highest reputation, but they have no real experience of being able to choose a known and guaranteed high-skilled freelancer. The reputation of a truly high-skilled freelancer is just the expected accumulated reputation from being chosen in every previous period. The falsified reputation of a low-skilled freelancer can be the same or lower. Accumulating a high reputation is free of charge for a high-skilled freelancer, but it is costly for a low-skilled one, since they have to pay for an extra level. Thus, the latter should calculate whether a higher rating attracts a sufficient number of new clients to compensate expenditures for purchasing a fake reputation.

Let us solve the model for different periods starting from the point of reputation absence.

4 Dynamic model

4.1 $t = 1$: no reputation

When the platform is established, a set of freelancers enters the market. The prior belief of a client is that they meet a high-skilled freelancer with probability p_0. First, a low-skilled freelancer sets price π_H with probability λ_1 and π_L with probability $1 - \lambda_1$. A high-skilled worker posts π_H with probability 1 as she is not a strategic agent in the model. The posted price is a signal to a client about the expected quality of service. The client's utility includes the productivity of a worker determined by their true type minus the paid price. The client observes the price strategies and updates their beliefs about the distribution of types using the Bayesian rule:

$$p_1 := Prob(\theta_H|\pi_H) = \frac{p_0}{p_0 + (1-p_0)\lambda_1},$$
$$Prob(\theta_H|\pi_L) = 0.$$

Taking this update into account, we can construct the expected utilities of a client from choosing a cheap or an expensive freelancer:
$EU_c(\pi_H) = p_1\theta_H + (1-p_1)\theta_L - \pi_H,$
$EU_c(\pi_L) = \theta_L - \pi_L.$

Since we are motivated by a situation when clients have different experiences on the platform and choose workers with different prices, we equalize the two expected utilities. This implies

$$p_1 = \frac{\pi_H - \pi_L}{\theta_H - \theta_L} \leq 1 \iff \pi_H - \pi_L \leq \theta_H - \theta_L.$$

This condition implies that a situation when all freelancers can gain a positive demand in equilibrium is possible only if the difference in quality is greater than the difference in prices. In order to generate such a posterior belief, a low-skilled freelancer should randomize with probability

$$\lambda_1 = \frac{p_0(\frac{\theta_H - \theta_L}{\pi_H - \pi_L} - 1)}{1 - p_0}$$

The reverse logic holds for freelancers: a low-skilled worker considers mixing only if they are indifferent between the two available prices. This is reached when a client chooses workers with different prices with some positive probabilities. Assume that the probability of a client ordering services from a freelancer with the price π_L is $\alpha_1^1 \in [0,1]$. Then the probability of choosing a low-skilled freelancer with the price π_H is $(1-\alpha_1^1)(1-p_1)$. The expected utility of a low-skilled

worker from different pricing strategies is given by
$EU_s^L(\pi_H) = (1-p_1)(1-\alpha_1^1)\pi_H,$
$EU_s^L(\pi_L) = \alpha_1^1\pi_L.$

This allows us to describe an equilibrium choice of a client at the first stage:

$$1-\alpha_1^1 = \frac{\pi_L}{(1-p_1)\pi_H + \pi_L}.$$

Comparing the shares of clients preferring high or low prices and accounting for the formula for p_1, we deduce the following proposition.

Proposition 1. *Under the absence of reputation, the majority of clients decide to order services at the low price iff the difference in productivity is higher than π_H.*

In this case, the posterior belief that the expensive freelancer is high-skilled is too low, which motivates clients to avoid risk.

The equilibrium is generally semi-separating, which means that a low-skilled freelancer uses both prices as signals with positive probabilities. However, when the difference in prices grows to the difference in productivity, the equilibrium tends to be separating.

Proposition 2. *Under the absence of reputation, when the difference in prices equals the difference in productivity, prices reveal the quality of service and low-skilled freelancers set only low prices.*

Proof. If $\pi_H - \pi_L \to \theta_H - \theta_L$ then $\lambda_1 = \frac{p_0(\frac{\theta_H-\theta_L}{\pi_H-\pi_L}-1)}{1-p_0} \to 0$. This means that the semi-separating equilibrium tends to the separating one, and the share of low-skilled freelancers competing in price with high-skilled shrinks to 0. □

Since this proposition is obtained under the assumption that clients must choose both categories of offers, we may claim that this happens only if all low-skilled freelancers choose the low price. Even a small deviation to the high price shifts the posterior probability down and enforce clients to avoid the high price offer.

After clients make their choice and the interaction occurs, a high-skilled freelancer will get a unit of positive feedback (rating) for free, and their expected reputation after period 1 will equal $R^1_{\text{max}} = (1 - \alpha^1_1)p_1$. A low-skilled freelancer will get negative feedback, which makes their further operation on the platform with the current account unprofitable.

4.2 $t = 2$: first possibility to buy a fake reputation

At $t = 2$, a low-skilled freelancer has to create a new account on the platform. If they prefer to operate as a new worker, it will be obvious for a potential client that an empty account without reputation belongs to a low-skilled freelancer, regardless of the posted price of service. In order to imitate a high-skilled freelancer, now the low-skilled freelancer should be indistinguishable in both price and rating. Therefore, they should make a purchase of R^1_{max} fake reputation points to mimic effectively. Let one unit of fake reputation cost c in some external complemented market of fake accounts. Assume that a low-skilled freelancer decides to buy R^1_{max} reputation with probability γ_2 and not to buy any reputation and compete with an empty account with probability $1 - \gamma_2$. If R^1_{max} points are bought, then they set the high price with probability λ_2. If a low-skilled freelancer does not buy maximum reputation, then the low price is always set, since no client will choose a freelancer with a high price and lower than R^1_{max} reputation. The choices of a freelancer are presented in the Fig. 1.

After the reputation-price decision of freelancers, a client observes the prices and the reputations on the platform. They also remember the prior distribution p_0. The client understands that only a freelancer with the high price and maximum

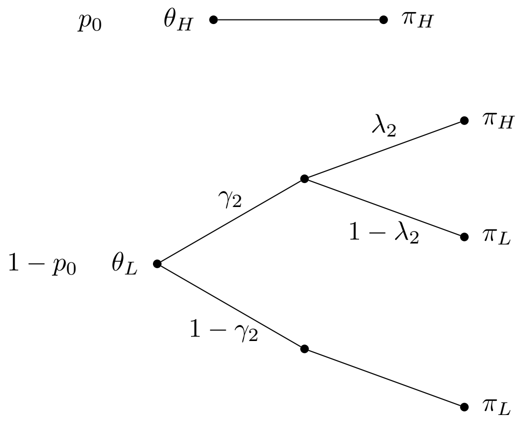

Figure 1: $t=2$, $R^1_{\text{max}}=(1-\alpha^1_1)p_1$

reputation can be high-skilled. The posterior belief of this situation is calculated as:

$$p_2 = Pr(\theta_H|\pi_H, R^1_{\text{max}}) = \frac{p_0}{p_0+(1-p_0)\gamma_2\lambda_2}.$$

Clients build their expectations about the benefits from choosing different combinations of prices and reputation.

$EU_c(\pi_H, R^1_{\text{max}}) = p_2\theta_H + (1-p_2)\theta_L - \pi_H$

$EU_c(\pi_L, R^1_{\text{max}}) = \theta_L - \pi_L$

$EU_c(\pi_L, 0) = \theta_L - \pi_L$

It is clear now that the client will never choose a freelancer with a high price and zero reputation, that is why we have already excluded this strategy for a low-skilled freelancer as dominated. In order to motivate a freelancer to choose any other kind of strategy and produce variety on the platform, we claim that all kinds of freelancers are chosen in equilibrium by some share of clients. Hence, we put the indifference condition for a client between all the utilities above. This yields $p_2 = \frac{\pi_H-\pi_L}{\theta_H-\theta_L}$ and, thus, $p_2 = p_1$. Probability λ_2 of posting a high price if the maximum reputation is bought is also calculated as

$$\lambda_2 = \frac{p_0(\frac{\theta_H-\theta_L}{\pi_H-\pi_L}-1)}{(1-p_0)\gamma_2} = \frac{\lambda_1}{\gamma_2},$$

so the total probability of imitating a high-skilled freelancer remains the same.

Similar to $t = 1$, we claim a low-skilled freelancer is indifferent to choosing any of the three strategies (except for $(\pi_H, 0)$). Let $\alpha_1^2 \in [0, 1]$ be the probability of a client ordering services from a freelancer with the price π_L and zero reputation, $\alpha_2^2 \in [0, 1]$ be the probability of a client ordering services with the price π_L and R^1_{max}. Therefore, a service with the price π_H and the reputation R^1_{max} is ordered with probability $1 - \alpha_1^2 - \alpha_2^2 \in [0, 1]$. Then the expected utilities for low-skilled freelancers with different reputation levels and prices are

$$EU_s^L(\pi_H, R^1_{\text{max}}) = (1 - p_2)(1 - \alpha_1^2 - \alpha_2^2)\pi_H - R^1_{\text{max}}c$$
$$EU_s^L(\pi_L, R^1_{\text{max}}) = \alpha_2^2\pi_L - R^1_{\text{max}}c$$
$$EU_s^L(\pi_L, 0) = \alpha_1^2\pi_L.$$

Equating the given expected utilities pairwise and noting that $p_1 = p_2$, we get expressions for α_1^2, α_2^2, $1 - \alpha_1^2 - \alpha_2^2$.

$$\alpha_1^2 = \frac{(1 - p_1)\pi_H(1 - \frac{R^1_{\text{max}}c}{\pi_L}) - R^1_{\text{max}}c}{2(1 - p_1)\pi_H + \pi_L}$$

$$\alpha_2^2 = \frac{(1 - p_1)\pi_H(1 + \frac{R^1_{\text{max}}c}{\pi_L})}{2(1 - p_1)\pi_H + \pi_L}$$

$$1 - \alpha_1^2 - \alpha_2^2 = \frac{\pi_L + R^1_{\text{max}}c}{2(1 - p_1)\pi_H + \pi_L}$$

.

The first immediate implication is that $\alpha_1^2 < \alpha_2^2$. In other words, even if clients understand that a low price means low quality, they are ready to choose a freelancer with a reputation more often than without it.

It is clear that $\alpha_1^2 < 1$, $\alpha_2^2 > 0$, $1 - \alpha_1^2 - \alpha_2^2 > 0$. Other restrictions on the probabilities provide the following conditions for the cost c:

$$\begin{array}{rcl}
\alpha_1^2 > 0 & \Rightarrow & c < c_1^2 = \frac{(1-p_1)\pi_H\pi_L}{R^1_{max}(\pi_L+(1-p_1)\pi_H)} \\
\alpha_2^2 \leq 1 & \Rightarrow & c \leq c_2^2 = \frac{\pi_L((1-p_1)\pi_H+\pi_l)}{R^1_{\max}(1-p_1)\pi_H} \\
1 - \alpha_1^2 - \alpha_2^2 \leq 1 & \Rightarrow & c \leq c^2 = \frac{2(1-p_1)\pi_H}{R^1_{\max}}.
\end{array}$$

Proposition 3. *When the costs of buying reputation are high, there are no freelancers who do not buy reputation at $t = 2$.*

Proof. When $\alpha_1^2 > 0$, there are freelancers who do not buy reputation. Comparing the threshold values of c, one obtains $c_1^2 < c_2^2$ and $c_1^2 < c^2$ (since $c_1^2 = c^2(1-\alpha_1^1)/2$). Therefore, c_1^2 is the lowest threshold and with the growth of c the very first category of freelancers that cease to exist are those without reputations. If $c \geq c_1^2$, then only freelancers with a reputation $R^1_{\max}$ operate on the platform. □

This can be explained by the fact that if the cost of buying reputation is too low, then agents understand that consumers will know this fact. Reputation can be easily purchased in this case and it becomes a weak signal. Workers with different reputation levels will provide only low quality for clients, which makes their experience on the platform unsatisfactory. However, when reputation costs are higher than c_1^2, reputation starts to be a better signal. If $c \geq c_1^2$ then freelancers with zero reputation do not exist, and a client chooses between freelancers with high reputation and a low price versus high reputation and a high price. This means that a low-skilled freelancer has to buy $R^1_{\max}$ rating. It is equivalent to using the condition $\alpha_1^2 = 0$ in their utilities. However, in this case we come across the exact situation solved at $t = 1$, and the clients select in the same proportion as at $t = 1$. Therefore, propositions 1 and 2 hold for this case.

4.3 Arbitrary $t > 2$: variety of reputation

Until period t, a high-skilled freelancer has accumulated reputation R_{max}^{t-1} for free. This is just the sum of probabilities of being chosen in all previous periods; we define the formula below, after introducing the system of notation.

A low-skilled freelancer has to create a new account. When they decide what level of fake reputation to buy, it becomes obvious that any level lower than R_{max}^{t-1} immediately reveals the low quality of their services. A freelancer with a lower than maximum reputation will never set a high price, since a client never chooses them in this case. Assume that a low-skilled freelancer decides to buy the maximum reputation R_{max}^{t-1} with probability γ_t, and after this they post the high price with probability λ_t. The posterior belief of a client that a freelancer with the high price and reputation is high-skilled is given by

$$p_t = Pr(\theta_H | \pi_H, R_{\text{max}}^{t-1}) = \frac{p_0}{p_0 + (1 - p_0)\gamma_t \lambda_t}.$$

Assume that a low-skilled freelancer can buy any rating from the finite grade $R_0^t < R_1^t < R_2^t < \ldots < R_{k-2}^t < R_{k-1}^t$, where $R_0^t = 0$ and $R_{k-1}^t = R_{\text{max}}^{t-1}$. This is reasonable only if a client may choose a freelancer with any given level of reputation, so a client must be indifferent among all offers (π_H, R_{k-1}^t), (π_L, R_{k-1}^t), (π_L, R_{k-2}^t), ..., (π_L, R_0^t). Similar to $t = 2$, this provides the condition for posterior beliefs $p_k = p_1$ and the probability of imitating a high-skilled freelancer $\lambda_t \cdot \gamma_t = \lambda_1$. Thus, it is clear that in every period, the equilibrium strategy of a low-skilled freelancer equalizes the client's expected utilities of any experience on the platform. This implies the same expected share of a high quality service at every moment.

Since a client is indifferent between offers, let them choose a freelancer with a low price and R_i^t, $i = 0, ..., k-1$, rating with probability α_{i+1}^t, and a freelancer with the high price and R_{max}^{t-1} rating with probability $1 - \sum_{i=1}^{k} \alpha_i^t$. There are freelancers who buy all these different ratings only if clients are indifferent among the corresponding utilities:

$$EU_s^L(\pi_H, R_{\text{max}}^{t-1}) = (1-p_t)(1-\textstyle\sum_{i=1}^k \alpha_i^t)\pi_H - R_{\text{max}}^{t-1}c$$
$$EU_s^L(\pi_L, R_i^t) = \alpha_{i+1}^t \pi_L - R_i^t c, \quad i = 0, \dots, k-1$$

We can represent any probability $\alpha_\cdot^t$ in terms of α_1^t:

$$\alpha_{i+1}^t = \alpha_1^t + \frac{R_i^t c}{\pi_L}.$$

Equalizing $EU_s^L(\pi_H, R_{\text{max}}^{t-1}) = EU_s^L(\pi_L, R_0^{t-1}) = \alpha_1^t \pi_L$, we obtain

$$\alpha_1^t = \frac{(1-p_1)\pi_H(1-\frac{c}{\pi_L}\sum_{i=1}^{k-1} R_i^t) - R_{\text{max}}^{t-1}c}{k(1-p_1)\pi_H + \pi_L},$$

$$\alpha_k^t = \frac{(1-p_1)\frac{\pi_H}{\pi_L}(\pi_L + c(kR_{\text{max}}^{t-1} - \sum_{i=1}^{k-1} R_i^t))}{k(1-p_1)\pi_H + \pi_L},$$

$$1 - \sum_{i=1}^{k} \alpha_i^t = \frac{c(kR_{\text{max}}^{t-1} - \sum_{i=1}^{k-1} R_i^t) + \pi_L}{k(1-p_1)\pi_H + \pi_L}.$$

For any t, evidently, $\alpha_1^t < 1$, $\alpha_k^t > 0$, and $1 - \sum_{i=1}^k \alpha_i^t > 0$. Moreover, $\alpha_{i+1}^t > \alpha_i^t$. This means that clients always value reputation and choose freelancers with a higher rating more frequently, even if they understand that they can be low-sklled. This effect compensates for the larger expenditures of a low-skilled freelancer on the purchase of a higher reputation. The reverse restrictions on probabilities generate the conditions on c:

$$\alpha_1^t > 0 \quad \Rightarrow \quad c < c_1^t = \frac{(1-p_1)\pi_H\pi_L}{\pi_L R_{\text{max}}^{t-1} + (1-p_1)\pi_H \sum_{i=1}^{k-1} R_i^t}$$

$$1 - \sum_{i=1}^{k} \alpha_i^t \le 1 \quad \Rightarrow \quad c \le c^t = \frac{k(1-p_1)\pi_H}{kR_{\text{max}}^{t-1} - \sum_{i=1}^{k-1} R_i^t}.$$

The notation for intermediate thresholds c_i^t is:

$$\alpha_i^t > 0 \quad \iff \quad c < c_i^t.$$

5 Results

From the equations above, it follows that $\alpha_1^t < \alpha_2^t < \ldots < \alpha_i^t < \alpha_{i+1}^t < \ldots < \alpha_k^t$. Then the thresholds are also ordered: $c_1^t < c_2^t < \ldots < c_i^t < c_{i+1}^t < \ldots < c_k^t$. This means that with the growth of cost c, freelancers with the lowest reputation disappear from the platform one by one. If the grades of possible reputation are not too dense, meaning $k \leq t$, the following proposition holds.

Proposition 4. *Under the infinite growth of t, the higher the costs of purchasing reputation, the higher reputation levels present on the freelance platform. In other words, a wide range of (fake) reputation is observed in the freelance platform only if the cost of reputation falsification tends to 0.*

Remark. A natural special case of the reputation grade corresponds to the situation when the possible ratings coincide with the maximum ratings from all previous periods, $R_{k-i}^t = R_{\max}^{t-i}$. In this case $k = t$, and

$$R_{\max}^{t-1} = \sum_{j=1}^{t-1} p_j \left(1 - \sum_{i=1}^{j} \alpha_i^j\right).$$

This result shows that under different cost levels, different reputation configurations arise. When $t \to \infty$ and $c \to 0$ then freelancers with all possible reputation levels are present in the market. However, in this situation, *reputation is a weak signal* as everyone can afford to buy almost free reputation to reach the maximum level. The only mechanism that will work in this case is the mechanism of price setting, and reputation adds a little to clients' choice.

On the other hand, when fake reputation costs c are high, most freelancers prefer to buy the maximum reputation points, and again the reputation provides little new information to clients. Therefore, it doesn't allow distinguishing the types of worker effectively.

An interesting property, which extends proposition 1, can be obtained by a comparison of the equilibrium shares of clients α_k^t and $1 - \sum_{i=1}^{k} \alpha_i^t$, who prefer the freelancer with the highest reputation, but at low or high prices respectively.

Proposition 5. *Under an arbitrary distribution of reputation levels, the greater share of clients decide to order services at the low price and maximum reputation than at the high price and maximum reputation iff the difference in productivity is higher than* π_H.

This proposition is correct not only in the case where all reputation levels are present on the platform, but also for greater c, when the lowest reputation levels disappear sequentially.

6 Concluding remarks

This paper sheds some light on the problem of reputation credibility of high- and low-skilled freelancers in online freelance markets. Reputation does not work perfectly as there are ways to manipulate it. The main challenge of the current research is to understand what happens when low-skilled freelancers falsify their reputation. We show that reputation can be an unreliable signal, though clients used it (Yoganarasimhan, 2013), (Filippas et al. 2019). We sharpen this idea in order to demonstrate how reputation on an online platform may fail in the long-run.

The model introduces the mechanism of reputation manipulation by the purchase of fake reputation point/reviews from an external market. The main result states that when the costs of purchasing are high, then only maximum ratings are bought. In this case, the reputation mechanism is compromised, since if the freelance market exists long enough, all accounts will have reputation which is close to the highest possible reputation level. Hence, reputation can be misleading, and one should not blindly trust in it. The observation of different cost thresholds help us to specify which reputation levels are bought by low-skilled freelancers. Using the information on the diversity of reputation levels, it may be helpful for a quality prediction on a new platform. If the reputation across freelancers does not vary much and is relatively high, then the costs of reputation falsification may be assumed to be above average. Otherwise, the more the rating levels diverge, the lower the cost of reputation purchase for low-skilled freelancers.

Another result is that when costs are low, the reputation mechanism can be regarded as a weak signal and clients have to make a choice based on prices only. In this case, there are low-skilled freelancers with different ratings in the market and all of them can buy some reputation, but the client in fact immediately predicts their low quality. However, a higher rating here is associated with a greater probability of being chosen. If any of the low-skilled freelancers set the high price, then they need to buy the maximum rating in order to be chosen.

There are several possibilities for the future research. First, the range of prices and productivities can be extended to more than two element sets, and high-skilled freelancers can act strategically too. Second, the costs of exerting effort by freelancers may be implemented. It could be assumed that both types of freelancers may do their job well, however, low-skilled workers need to make more efforts for this. This may add more validity to the results of the given framework and, by analogy with Spense's job market signaling model, may even rehabilitate the reputation mechanism by amplifying the incentives for type separation.

References

[1] Akerlof, GA. (1970). The market for ‘Lemons’: Quality uncertainty and the market mechanism. Quarterly Journal of Economics, 84(3), 488-500.

[2] Ba, S., Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. MIS quarterly, 26(3), 243-268.

[3] Brown, J., Morgan, J. (2006). Reputation in online markets: some negative feedback. University of California, Berkeley. // URL: https://faculty.haas.berkeley.edu/rjmorgan/Reputation%20in%20Online%20Markets.pdf

[4] Chechulina M. (2016). Freelancing as a Developing Form of the Economic Activity Modernizan. Russian Journal of Labor Economics, 3(3), 291–306.

[5] Chevalier, J. A., Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of marketing research, 43(3), 345-354.

[6] Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. Management science, 49(10), 1407-1424.

[7] Dellarocas, C. (2005). Reputation mechanism design in online trading environments with pure moral hazard. Information systems research, 16(2), 209-230.

[8] Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. Management science, 52(10), 1577-1593.

[9] Dini, F., Spagnolo, G. (2009). Buying reputation on eBay: Do recent changes help?. International Journal of Electronic Business, 7(6), 581-598.

[10] Filippas, A., Horton, J. J., Joseph, M. Golden. (2019). Reputation inflation. NBER Working Paper, (No. 25857).

[11] Fudenberg, D., Tirole, J. (1991). Game theory, 1991. Cambridge, Massachusetts, 393(12), 80.

[12] Greif, A. (1993). Contract enforceability and economic institutions in early trade: The Maghribi traders' coalition. The American economic review, 525-548.

[13] Gu, G., Zhu, F. (2021). Trust and disintermediation: Evidence from an online freelance marketplace. Management Science, 67(2), 794-807.

[14] Inc., Study: in Russia freelancers earn more than most full-time employees, 2019 // URL: https://incrussia.ru/news/frilansery-zarabatyvayut-bolshe/

[15] Kahneman, D., Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-292.

[16] Kauffman, R. J., Wood, C. A. (2000). Running up the bid: Modeling seller opportunism in Internet auctions. AMCIS 2000 Proceedings, 376, 929-935.

[17] Lucking−Reiley, D., Bryan, D., Prasad, N., Reeves, D. (2007). Pennies from eBay: The determinants of price in online auctions. The journal of industrial economics, 55(2), 223-233.

[18] Ma, Y., Zhang, Z., Li, D., Tang, M. (2021). Deflated reputation using multiplicative long short-term memory neural networks. Future Generation Computer Systems, 118, 198-207.

[19] Milgrom, P. R., North, D. C., Weingast*, B. R. (1990). The role of institutions in the revival of trade: The law merchant, private judges, and the champagne fairs. Economics and Politics, 2(1), 1-23.

[20] Nosko, C., Tadelis, S. (2015). The limits of reputation in platform markets: An empirical analysis and field experiment. National Bureau of Economic Research. Working Paper (No. w20830).

[21] Smirnov, A., Starkov, E. (2022). Bad news turned good: reversal under censorship. American Economic Journal: Microeconomics, 14(2), 506-60.

[22] Tadelis, S. (1999). What's in a Name? Reputation as a Tradeable Asset. American Economic Review, 89(3), 548-563.

[23] Tadelis, S. (2016). Reputation and feedback systems in online platform markets. Annual Review of Economics, 8, 321-340.

[24] TASS, Survey: more than 40% of Russians want to change their job, 2020. // URL: https://tass.ru/ekonomika/9608771

[25] Thompson, N. (2003). More companies pay heed to their 'word of mouse' reputation. The New York Times, 6(23), 1-3.

[26] Yoganarasimhan, H. (2013). The value of reputation in an online freelance marketplace. Marketing Science, 32(6), 860-891.

Corresponding author:

Marina Sandomirskaia

Department of Theoretical Economics, Faculty of Economic Sciences, HSE University, Russian Federation

E-mail: msandomirskaya@hse.ru, sandomirskaya_ms@mail.ru