Lock-In Effects in Online Labor Markets

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This article reports on an investigation of the role of lock-in exploitation and the impact of reputation portability on workers' switching behaviors in online labor markets. Online platforms using reputation mechanisms typically prevent users from transferring their ratings to other platforms, inducing lock-in effects and high switching costs and leaving users vulnerable to platform exploitation. With a theoretical model, in which workers in online labor markets are locked-in by their reputational data, we test the effects using an online lab-in-the-field decision experiment. In addition to comparing a policy regime with and without reputation portability, we vary lock-in exploitation using platform fees to consider how switching behavior might differ according to monetary motives and fairness preferences. Theoretically, this study reveals how reputational investments can produce switching costs that platforms can exploit. Experimentally, the results suggest that reputation portability mitigates lock-in effects, making users less susceptible to lock-in exploitation. The data further show that switching is driven primarily by monetary motives, but perceiving the fee as unfair also has a significant role.

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1. Introduction

On online platforms, lock-in effects arise from platform-specific reputation mechanisms. The reputation mechanisms function to address market inefficiencies that arise from asymmetric information (Dellarocas et al., 2006), but users generally cannot take their valuable, positive ratings with them to another platform. By building up their reputation, users may become increasingly tied to one platform; switching to another platform would risk incurring significant costs to build their reputation all over again on the new platform. In turn, platforms can exploit locked-in users by charging them higher fees.[1] In online labor markets, online workers' switching behaviors likely reflect the influences of lock-in effects linked to specific online labor platforms. We accordingly analyze whether a regulatory regime that requires reputation portability might mitigate these lock-in effects and reduce worker exploitation. Our focus in this study is on online labor markets, yet our findings likely have wider applicability to labor markets and the gig economy more generally.

Notably, reputation portability could address lock-in effects (Crémer et al., 2019), but few platforms allow users to import or export their ratings.[2] Although Amazon previously allowed sellers to import their reputational data from eBay, once eBay threatened to sue Amazon for intellectual property infringement, it halted this practice, which likely relaxed the competition for sellers (Resnick et al., 2000; Ba and Pavlou, 2002; Dellarocas et al., 2006). We also recognize that it is technically feasible to transfer reputational data, such that when Rover merged with DogVacay, it gave DogVacay's users an easy path to transfer their ratings, reviews, and transaction history to its platform (Farronato et al., 2020). However, dominant platforms such as Airbnb, Amazon, eBay, and Uber appear to prefer limiting such transfers of reputational data, likely because the switching costs created by user lock-in can mitigate competition, even if they harm users' overall welfare (Shapiro et al., 1998). If data transferability increases competition among platforms, such that it is incentive-incompatible for these powerful actors, then regulatory action likely is required.

Some relevant actions already are in place, introduced by regulators around the globe, in the form of data privacy laws (Hesse and Teubner, 2019) that aim to mitigate lock-in effects, enhance data ownership, and foster competition. For example, Article 20 (Right to Data Portability) of the European Union's General Data Protection Regulation (GDPR) stresses that individuals have the right to request their own data, as well as transfer them to other online providers without difficulty. Article 20 also seeks to promote and increase users' negotiating power by reducing lock-in effects and protecting the "*fundamental rights and freedoms of natural persons and in particular their right to the protection of personal data*" (European Commission, 2016). Many other regulators

[1] Apple, for example, takes a 30% commission on the total sale price of all paid apps (Kotapati et al., 2020).

[2] As two exceptions that prove the rule, Bonanza.com and TrueGether.com allow users to import their ratings from other platforms (Hesse et al., 2020).

have introduced data portability laws,[3] or proposed their introduction.[4]

Data privacy laws are often welcomed as a laudable step toward enhancing competition among platforms and giving users control over their personal data (Engels, 2016; De Hert et al., 2018). However, whether data portability can serve as an effective mechanism to address lock-in effects and how it should be implemented remain open questions, as do discussions of how to overcome lock-in effects and increase consumers' negotiation power to include reputational data as part of their personal data (Kathuria and Lai, 2018; Hesse and Teubner, 2019).[5] That is, reputational data do not fall under the scope of Article 20 according to current legal interpretations, because ratings and reviews are provided by reviewers and not the user, such that a user does not legally own her or his reputational data (Graef et al., 2013; Diker Vanberg and Ünver, 2017).

In an effort to understand reputation portability, exploitation by platforms, the likely effects of policy changes, and the implications for online workers, we therefore develop a theoretical framework that represents a variation of Holmström's (1999) model of managerial incentives. In this model, workers care about their future reputation and must choose the optimal effort to exert when completing a task. We extend this model by allowing these workers to consider working in a different labor market. Then we include switching costs, defined as the effort investment that workers make over time to build their reputations and maximize their revenue streams. Furthermore, we introduce a fee that the platform imposes on workers. Then we test two policy regimes, with and without reputation portability. The first regime reflects the current situation, with no right to reputation portability required by the GDPR. In the second policy scenario, we imagine a case with reputation portability, in which platforms import workers' ratings when they switch.[6] Across these regimes, we analyze workers' switching behaviors in markets in which (1) platforms are perfectly identical and charge the same fees at the same time or (2) only the focal platform (i.e., where workers currently work) charges a fee. Thus we can specify switching behavior based on monetary motives and fairness preferences that result when workers sense that they have been treated unjustly by the platform that imposes a fee increase. We test the findings from the theoretical model with an online lab-in-the-field decision experiment, conducted with actual online workers who participate on the crowdsourcing platform Amazon Mechanical Turk (AMT). Thus, we gain a natural setting for observing worker behavior, even as we manipulate policy differences in reputation portability, and levels of exploitation by platforms.

In more detail, we distinguish two types of stylized workers: those with pure *monetary motives*

[3]Examples are the Californian Consumer Privacy Act of 2018, the Brazilian General Data Protection Law of 2020, the Swiss Federal Act on Data Protection of 2020, the German Act against Restraints of Competition for a focused, proactive and digital competition law 4.0 and amending other competition law provisions of 2021, and the Chinese Personal Information Protection Law of 2021.

[4]For example, the Indian Personal Data Protection Bill, the Canadian Digital Charter Implementation Act, and the Australian Consumer Data Right.

[5]To the best of our knowledge, the only formal initiative that tries to enforce reputation portability is the one introduced by the Latium Regional Government (legge num. 4 del 12 aprile 2019).

[6]Reputation portability can be implemented via other designs too; for a comprehensive description of different scenarios, see Hesse and Teubner (2019).

and those who express *fairness preferences* (Kahneman et al., 1986). Workers with pure monetary motives are driven solely by the amount of their wages, but workers with fairness preferences care about the actions of the platform, such as the introduction of new fees. If they perceive unfair treatment, these latter workers might reciprocate by switching away from a platform that levies a fee, even if doing so causes them to lose wages. For this article, we define fairness preferences as workers' preference relative to a fee increase by the platform on which they are currently working. Our proposed theoretical model, by accounting for these features, resembles an ultimatum game (Güth et al., 1982) in which a proposer (the platform), endowed with some good, must decide how to share it with a responder (the worker). The responder can decide to accept or refuse the offer; if the responder refuses, both agents get nothing. Experimentally, we study the reaction of workers to exploitation, as imposed by a platform fee, and test whether their switching behavior is driven by monetary motives or fairness preferences.

According to prior studies, if workers regard wage decreases as unfair, they also might reciprocate by lowering their effort (Fehr et al., 1993; Fehr and Falk, 1999), even if the wage reduction resulted from exogenous causes, such as an economic recession (Bewley, 2007). Blount (1995) notes though that the perceived intentions and identity of the proposer influence the responder's reaction, such that reciprocity tends to be weaker when the proposer is a machine engaged in random assignments and stronger if the proposer is human. In our experiment, we determine the level of exploitation randomly. Because we recreate the working conditions and environment for workers on online platforms, the experimental participants' reactions should mimic the real-life responses of online workers (Henrich et al., 2001).

The theoretical and experimental results we thus obtain offer new evidence with regard to switching behavior in online labor markets. First, with our theoretical model, we establish that in a policy regime without reputation portability, reputational investments can become switching costs that platforms can exploit, given workers' reluctance to lose their valuable ratings. Second, our experimental results indicate that workers switch platforms significantly more often if the current platform introduces a fee, and this switching behavior is driven by both monetary motives *and* fairness preferences. The results further clarify that a policy regime with reputation portability significantly increases switching, such that workers are less likely to be exploited by labor platforms.

The remainder of the article is organized as follows: In Section 3, we relate our research question to existing literature. Section 3 contains our theoretical model and outlines our hypotheses. In Section 4, we detail our experimental setting and procedure. Section 5 describes the sample and summarizes the experimental results. Finally, Section 6 concludes the article.

2. Literature

The current article contributes to research into switching costs and reputation portability. We follow Wohlfarth (2019) and assume that reputation portability, defined as the ability of users to transfer their reputation from one platform to another, determines the degree of switching costs and consequently lock-in strength. Switching costs more generally might be associated with physical investments in devices, learning or transaction costs, complementary services, or even psychological costs that reflect laziness, brand loyalty, and so forth (Farrell and Klemperer, 2007). When users confront high switching costs, they are unlikely to switch even if the focal platform becomes relatively more expensive than competitors'. In addition, various studies (Klemperer, 1987a,b, 1995; Farrell and Shapiro, 1988, 1989) show that the presence of switching costs for customers triggers firms to engage in fierce ex ante competition to gain market shares but more relaxed ex post competition, once those consumers become locked in to the firm. Thus, lock-in effects enable firms to extract higher rents, as long as the difference in prices set by the firms does not exceed the barrier determined by switching costs (Gehrig and Stenbacka, 2004). In our study, workers invest effort to increase their reputation over time, and because this reputation has significant economic value (Ba and Pavlou, 2002; Resnick et al., 2006; Moreno and Terwiesch, 2014; Luca, 2016; Saeedi, 2019), the workers are inclined to devote more effort to earn higher wages by building their strong reputation and maintaining it over time (Fehr and Goette, 2007; Mason and Watts, 2009; Cabral and Xu, 2021).

Scarce literature investigates the effects of data portability though. Wohlfarth (2019) proposes a game-theoretic model that incorporates a competitive environment created by data portability rights. He demonstrates analytically that data portability generally has a positive effect on welfare but can induce negative consequences for consumers, if firms collect and reveal more of their personal data for profit, compared with a situation without data portability. Krämer and Stüdlein (2019) agree that data portability may increase firms' willingness to extract and disclose more data. On the demand side of the market, imported reputation data can increase online workers' trust in the platform (Kokkodis and Ipeirotis, 2016), as well as across platforms (Otto et al., 2018), especially if the platform that imports their ratings is active in the same sector as the platform of origin (Teubner et al., 2019; Hesse et al., 2020).

We contribute to this nascent literature on data and reputation portability by studying the supply side of online labor markets and considering what would happen if reputational data could be transferred across platforms. Thus far, the economic consequences of reputation portability on users' surpluses are unclear. Research has focused on the influence of reputation on a specific platform (Resnick et al., 2006; Kokkodis and Ipeirotis, 2016) or the general idea of data portability between platforms, which refers mostly to legal and technical dimensions (Dellarocas et al., 2006; Engels, 2016; De Hert et al., 2018; Wohlfarth, 2019). Furthermore, existing literature on switching costs tends to assume scenarios with homogeneous consumers, in the sense that they face the same switching costs (Gehrig and Stenbacka, 2004). Hesse and Teubner (2019) provide a conceptualization and review of reputation portability that leads them to call for further research on cross-platform tangible economic value, as well as more empirical and experimental approaches.

In response, we investigate individual switching costs and the resulting switching behavior exhibited by workers in a natural work environment. To the best of our knowledge, only one previous study (Eurich and Burtscher (2014)) experimentally investigates switching behavior while considering the strength of lock-in effects. They conduct an online lab experiment with students to determine that dissatisfying changes in the business-to-consumer relationship, such as increased prices, data leakages, or privacy violations, can have negative consequences for the business and lead consumers to choose a competitor, despite the costs of switching.

We study the problem of lock-in effects for online labor markets, which are characterized by high switching and set-up costs for workers, such that they typically discourage multi-homing or activity across different platforms (ILO, 2018). Due to their monopsony power (Dube et al., 2020), online labor platforms can impose lock-in effects that limit the choice, mobility, and career development of workers, making them more vulnerable and susceptible to exploitation. Choudary (2018) argues that the design of online labor platforms has important implications for whether its workers are empowered or exploited by the organizations. For example, providers with substantial market power might demand a higher percentage of workers' wages in return for providing the platform with their work (Kingsley et al., 2018). Some workers also confront unstable earnings, unpredictable scheduling, unclear employment status, and a lack of social protection or voice (Degryse, 2016; ILO, 2018; Johnston et al., 2018). Risks historically borne by companies in traditional employment relationships can be shifted to workers, who in turn earn less income than their counterparts in traditional employment relationships, at least in industrialized countries (Felstiner, 2011; Bergvall-Kåreborn and Howcroft, 2014). Furthermore, online workers' income often is reduced by inappropriately calculated working times (Borchert et al., 2018). Wood et al. (2019), evaluating job quality in the online gig economy, find that platforms' regulations often assign autonomy to workers but at the cost of irregular working hours and strong competition, which creates downward pressure on their earnings. The right to reputation portability, among other efforts, could help improve the position of online workers by decreasing their platform dependency.

3. Theoretical Framework

We first aim to derive formal, testable hypotheses, then determine, with some simplifying assumptions, whether a platform can lock in workers using platform-specific reputation mechanisms, which in turn would enable it to exploit locked-in workers by imposing a fee over some infinite time horizon. To derive testable hypotheses, we propose a model based on Holmström (1999) that accounts for reputation formation for a representative worker, competing in an online labor market managed by a monopolist platform. Present performance provides relevant information about future performance, and an average rating achieved by a worker can invoke a premium or extra remuneration the worker receives for each task, beyond any fixed wage. When workers first subscribe to the platform, they have no ratings. As they start working, they establish ratings that can change, according to their performance. A higher average rating should lead to higher wages. In other words, *ceteris paribus*, two workers who engage in the same level of labor might earn different wages if they have different average ratings.

Similar to Lambin and Palikot (2019), we consider ratings as a measure of the performance in every period t:

$$r_t = \eta + a_t + \epsilon_t, \quad t = 1, 2, ..., \tag{1}$$

where η is the worker's talent, which is fixed although the information about the worker's talent is incomplete for the worker and the platform. However, both share a common prior belief about η. This prior belief is normally distributed, with mean m_1 and precision h_1, such that precision is the inverse of the variance. Over time, learning about the talent of the worker takes place, by observing the emerging rating r_t. The labor input of the worker is $a_t \in [0, \infty)$, and ϵ_t represents a stochastic noise term, normally distributed with mean zero and precision h_ϵ.

In every period t, the worker is paid according to the following revenue scheme:

$$c_t = f + w_t(\mathbf{r}_{t-1}),$$

where $f > 0$ is an exogenous fixed amount granted to workers who have completed a task, independent of their performance,[7] and $w_t(\mathbf{r}_{t-1})$ is the premium associated with the average of past ratings ($\mathbf{r}_t = (r_1; ...; r_t)$) received by a worker. We assume this information is known to the market and used as a basis for wage payments; it usually appears next to the agent's profile in practice, as a representation of past performance. Furthermore, we assume a competitive market and risk-neutral participants, who set their premium in line with their average rating:

$$w_t(\mathbf{r}_{t-1}) = E[r_t|\mathbf{r}_{t-1}] = E[\eta|\mathbf{r}_{t-1}] + a_t(\mathbf{r}_{t-1}), \tag{2}$$

where $a_t(\mathbf{r}_{t-1})$ is the labor input, as the best response of the worker. Platforms act as intermediaries, for which service they may charge an ad valorem fee, required after each transaction.[8]

[7] Here, f does not affect the model results, because we assume the worker is risk neutral. We introduce this point in line with the experiment, in which we pay participants a minimum compensation.

[8] For example, Amazon marketplaces charges fees ranging from 7 to 45%, depending on the product category; Airbnb charges 3%; and online labor platforms such as AMT and TaskRabbit charge 20% and 15%, respectively.

We assume this fee gets applied directly to workers' premium revenue. Their atemporal utility function thus is:

$$U(c, a, \phi) = \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)] - \sum_{t=k}^{\infty} \beta^{t-1}\phi c_t, \tag{3}$$

where $\beta \in [0, 1]$ is a discount factor; $g(\cdot)$ is an increasing and convex function that represents the effort cost; and $U(\cdot, \cdot, \cdot)$ is publicly known. We assume that at time k, the platform introduces a fee $\phi \in [0, 1]$.[9] Therefore, before k, the platform's profits are zero, and all wages go to the worker.[10] The outside option for the worker is not to work, which provides utility equivalent to 0. We thus write the problem of the worker for maximizing expected utility as follows:

$$\max_{a_{(\cdot)}} \sum_{t=1}^{\infty} \beta^{t-1}[f + Ew_t(\mathbf{r}_{t-1}) - Eg(a_t(\mathbf{r}_{t-1}))] - \sum_{t=k}^{\infty} \beta^{t-1}\phi[f + Ew_t(\mathbf{r}_{t-1})]. \tag{4}$$

Together, Equations (4) and (2) determine equilibrium. The market cannot observe workers' labor input directly, but because (3) is general knowledge, we can use it to infer a_t by solving workers' maximization problem. Moreover, observing r_t is equivalent to observing the sequence

$$z_t \equiv \eta + \epsilon_t = r_t - a_t(\mathbf{r}_{t-1}). \tag{5}$$

By observing this sequence, the market learns about η, given normality and independence assumptions. The posterior distribution of η follows a normal distribution with means and precision given by, respectively,

$$m_{t+1} = \frac{h_t m_t + h_\epsilon z_t}{h_t + h_\epsilon} = \frac{h_1 m_1 + h_\epsilon \sum_{s=1}^{t} z_s}{h_1 + t h_\epsilon}, \tag{6}$$

$$h_{t+1} = h_t + h_\epsilon = h_1 + t h_\epsilon. \tag{7}$$

By applying Equation (6), we then can write Equation (2) as:

$$w_t(\mathbf{r}_{t-1}) = m_t(\mathbf{z}_{t-1}) + a_t(\mathbf{r}_{t-1}). \tag{8}$$

[9] We focus on workers' reaction to the fee introduction or increase; we do not address the optimal time k when the fee should be introduced to maximize the platform's profits.

[10] Even without analyzing platforms' business strategy, we might expect that, in a first period, it imposes no or very low fees to attract workers. This well-known firm strategy supports rapid growth and market share (Belleflamme and Peitz, 2015). In practice platforms often change their pricing structure or increase their fees over time. For example, in 2015, AMT doubled its commission fees for requests of more than ten workers (see `https://www.businessinsider.com/amazon-mechanical-turk-price-changes?r=US&IR=T`). Netflix also has increased its fees (see `https://www.cnbc.com/2020/10/31/why-netflix-will-keep-raising-prices-with-confidence.html`).

The expected premium associated with the past rating is:

$$Ew_t(\mathbf{r}_{t-1}) = \frac{h_1 m_1}{h_t} + \frac{h_\epsilon}{h_t}\sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1}). \tag{9}$$

From Equation (9), it follows that for a non-stochastic equilibrium path of labor supply, the marginal return of the expected premium to a_s for all $s \in \{1, ..., t-1\}$ in period t will be $\alpha_t = h_\epsilon / h_t$, independent of labor inputs in other periods. The maximization problem in Equation (4) is then:

$$\begin{aligned}\max_{a(\cdot)} \sum_{t=1}^{\infty} \beta^{t-1}[f + \frac{h_1 m_1}{h_t} + \alpha_t \sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1}) - Eg(a_t(\mathbf{r}_{t-1}))]- \\ - \sum_{t=k}^{\infty} \beta^{t-1}\phi[f + \frac{h_1 m_1}{h_t} + \alpha_t \sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1})].\end{aligned} \tag{10}$$

Next, we maximize Equation (10) with respect to a_t and obtain, after rearranging:

$$\sum_{s=t}^{\infty} \beta^{s-t}\alpha_s - \sum_{s=t}^{\infty} \beta^{s-t} I_s \phi \alpha_s = g'(a_t(\mathbf{r}_{t-1})), \tag{11}$$

where I_s is an indicator function that takes the following value, depending on the time:

$$I_s = \begin{cases} 0, & s < k \\ 1, & s \geq k. \end{cases}$$

As $t \to \infty$, $\alpha_s \to 0$. Therefore, the equilibrium sequence of labor inputs goes asymptotically toward 0. As long as the talent of the worker is unknown, there are returns to supplying labor. However, over time, the market learns the true value of η. At the limit, there are no returns to trying to use labor input to bias performance evaluations, so the labor input goes to 0. Comparing Equation (11) against the first-order condition in Holmström (1999),[11] we can observe that the marginal return to labor supply decreases with the fee requested by the platform.

3.1. Ratings as Switching Costs

Consider a setting with two identical platforms. In line with the current regulatory situation in Europe, we start with a regulatory regime in which no reputation portability is possible.

[11] In Holmström (1999):

$$\gamma_t \equiv \sum_{s=t}^{\infty} \beta^{s-t}\alpha_s = g'(a_t^*(y^{t-1})).$$

Then for a second, hypothetical regulatory regime, we imagine a policy scenario that features reputation portability, as if Article 20 of the GDPR were to extend from its current form to include reputational data.

Policy Regime without Reputation Portability

Two platforms (% and #)[12] are initially identical and set the same fee, which we normalize to 0. Both platforms offer a platform-specific reputation mechanism, so reputation built on one platform cannot transfer to the other platform. They remain identical until time k. Then at time k, Platform% raises the ad valorem fee to ϕ, while Platform# maintains its fee at 0. Therefore, these two platforms unequally exploit their workers, because only one of them introduces a fee. We abstract from strategic behaviors between platforms and assume that the fee increase on Platform% happens for an exogenous reason, such as a new tax that it passes through to users.[13] We further assume that workers cannot anticipate or predict the fee increase, because otherwise, they would realize that subscribing to Platform# is always more profitable.

Assume Platform% sets a fee ϕ that gets imposed from time k onward. Workers are not aware of the fee until time k, at which moment, they have two choices: (1) remain on Platform%, to keep benefiting from the reputational investment made so far but lose income equal to the cost of the fee, or (2) switch to Platform#, which does not impose a fee but requires them to rebuild their reputations from scratch. To simplify the analysis and avoid asymmetric information (i.e., the workers know more about themselves than the market), we assume that following a platform switch, the learning process depicted in Equation (6) restarts. Even if workers know their own skills, available tasks, and how the new platform works, they reasonably will remain somewhat uncertain about how their skills will be evaluated by the new market.[14] Thus, after time k, workers face a new problem but will stay on Platform% if

$$\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] \geq \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)]. \tag{12}$$

What is critical to notice here is that the difference between the utility obtained on Platform% versus the utility on Platform# is equivalent to the premium associated with past ratings, dimin-

[12]Similar to Hossain and Morgan (2009), we avoid using symbols that might be associated with an order of preference.

[13]For example, Google passed the cost of the UK's digital services tax on to British advertisers, raising its fees by 2%. See https://www.theguardian.com/media/2020/sep/01/googles-advertisers-will-take-the-hit-from-uk-digital-service-tax.

[14]Imagine a worker with a good reputation on Platform%, which informs this worker of her talent. Still, when switching platforms, this worker seems likely to exert substantial effort to gain an equally good reputation on the new platform or to impress the new employer.

ished by the fee.[15] By sticking with Platform%, at time k workers enter into a revenue scheme that accounts for past ratings obtained thus far:

$$c_k = f + w_k(r^{k-1}).$$

However, by switching platforms, all past ratings from Platform% are lost, and on Platform#, the worker has to restart from scratch. The inequality (12) implies that Platform% must set an incentive-compatible fee to retain workers on its marketplace, such that

$$\phi \leq \frac{\sum_{t=1}^{\infty} \beta^{t-1}[c_{k+t-1} - g(a_{k+t-1})] - \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)]}{\sum_{t=1}^{\infty} \beta^{t-1} c_{k+t-1}}. \tag{13}$$

Because it is not possible to find an analytical solution to Equation (13), in Appendix (A.1), we identify the existence of a fee that matches the inequality for some range of parameters β, f, m_1, h_1, and h_ϵ.

In general, our model is similar to an ultimatum game (Güth et al., 1982), in which the proposer is the platform and the responder is the worker. If the worker has pure monetary motives, the incentive-compatible fee represents the lowest offer workers are willing to accept. If the fee exceeds this value, workers refuse the offer and switch to the other platform. In the experiment, we expect workers with purely monetary motives to switch any time their expected utilities are higher on the other platform. Thus, we offer the following hypothesis:

Hypothesis 1a: *Platform switching is driven by monetary motives.*

Other factors could explain switching behavior by workers too. Considering the game structure and that of the experiment, workers' switching behavior may be motivated by monetary motives but also by fairness preferences. Workers with fairness preferences face an additional disutility when the platform introduces a fee because they also perceive it as unfair. Thus, the fee in Equation (13) would not be incentive-compatible if the platform fails to account for the fairness preferences of the worker. We capture this disutility created by workers' fairness preferences by adding a negative parameter $\delta(\phi) \in [0, \infty)$, increasing in ϕ. Then a worker with fairness preferences will remain on Platform% if

$$\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] - \delta(\phi) \geq \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)]. \tag{14}$$

[15] In the experiment, we also consider the switching behavior of workers if two platforms equally exploit them, such that both introduce the fee simultaneously. In that case, the inequality (12) becomes:

$$\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] \geq \sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_t - g(a_t)].$$

Unlike an unequal exploitation of lock-in effects, we expect that workers are less likely to switch if platforms equally exploit their workers.

Workers may have varying levels of tolerance for the fee, which could explain their switching behavior. Those workers for whom $\delta = 0$ are those with pure monetary motives, as depicted in Equation (12). Respondents with $\delta \rightarrow \infty$ always switch, because they have pure fairness preferences and cannot tolerate the imposition of even the smallest fee. Other workers might perceive the fee increase as unfair ($\delta > 0$) but tolerable, such that they would not switch if the compatibility constraint in Equation (14) is respected. These workers exhibit both monetary motives and fairness preferences. Workers with fairness preferences, who confront a platform fee but tolerate it, endure the highest losses when reputation is not transferable. Thus, a policy regime with reputation portability could be especially beneficial for workers with fairness preferences, because switching would not imply the loss of reputational investments.

We expect that some workers exhibit fairness preferences and switch platforms after a fee increase, even if they suffer a wage loss from doing so. If the utility difference between the two streams is null, we expect a worker with fairness preferences to switch. If reputation portability were mandatory and both platforms raised the fee simultaneously, by the same magnitude, the worker with fairness preferences would react and switch, even if the final economic outcome is exactly the same. Applying these considerations, we offer the following hypothesis:

Hypothesis 1b: *Platform switching is driven by fairness preferences.*

Policy Regime with Reputation Portability

If reputation portability were mandated by regulation, which would constitute an extension of Article 20 of the GDPR, all workers could import their ratings when switching to a new platform. Platforms even might implicitly enforce reputation portability by buying data to screen the quality of new workers before allowing them to join the platform. Therefore, workers do not lose their reputational investments and can easily switch between platforms.[16] In this context, we suppose that two platforms competing for workers set the lowest fees possible. Assuming symmetry between the two platforms, Bertrand competition would follow, and the platforms would set a fee equal to marginal costs, which we assume for simplicity to be 0. Therefore, we presume that workers that have access to reputation portability naturally switch more often, because switching costs are virtually nullified.

Hypothesis 2: *A policy regime with reputation portability increases switching behavior, and this effect is exacerbated if workers experience a fee introduction.*

[16] We implicitly assume that both platforms consider ratings on the other platform trustworthy. In other words, there is perfect interoperability between the reputation systems of the two platforms.

4. Experimental Design

In this section, we describe the experimental design that allows us to analyze our hypotheses, and we present the sample.

4.1. Treatments

With a fictitious online labor market, we implement three interventions, combined into a lab-in-the-field experiment with seven to ten rounds. Workers were randomly assigned to either a treatment or control condition, within a 2 × 2 × 2 between- and within-subject experimental design. In accordance with our theoretical model, ratings yield a premium, such that a higher rating is associated with a higher wage in the next round. Therefore, with a probability of 50% participants are randomly assigned to one of two policy regimes, one that allows for the portability of participants' ratings, and the other that does not. Then during each round, starting with round four, with a 25% probability, participants confront a platform fee that remains in force after it has been introduced. Finally, to identify switching due to monetary motives or fairness preferences, we compare platform switching behaviors when (1) the platforms are perfectly identical and simultaneously charge fees with the same ad valorem amount (equal exploitation of lock-in) and (2) only the platform the participant currently works on charges a fee while the other one does not (unequal exploitation of lock-in). Recall that participants are randomly assigned to these two policy conditions with 50% probability. We can identify switching based on fairness preferences if and only if, in response to a fee increase, workers switch to another platform where they earn an equal or lower wage (scenario 1). However, if workers respond to a fee increase by switching to another platform that pays them a higher wage, switching might occur because of both fairness preferences and monetary motives (scenario 2). Switching as a signal of fairness preferences can occur in every treatment condition and is subject to participants' ratings, whereas monetary motives by definition cannot arise when participants' ratings are portable and the exploitation treatments are equal.

By subtracting the fraction of workers who switch with "pure" fairness preferences (scenario 1) from the fraction of workers who switch in line with fairness preferences and/or monetary motives (scenario 2), we obtain the fraction of workers who solely switch for monetary reasons. Table 1 provides an overview of our experimental treatments and the number of observations we collected in each treatment.

— Table 1 about here —

With this experimental design, we also can examine second-order effects pertaining to the strength and frequency of exploitation due to lock-in effects. In the experiment, the platform fees take varying levels ($0.00, $0.01, $0.05), so in turn, we can compare switching behavior across conditions with an initial low fee of $0.01 (i.e., low exploitation of lock-in) versus an initial high fee of $0.05 (i.e., high exploitation of lock-in).[17] If a platform introduces a low fee, in each subsequent round and with a probability of 25%, it can charge a higher fee. Therefore, to test for second-order effects of the frequency of lock-in exploitation, we compare switching in response to an immediate high fee introduction versus a high fee increase that occurs after a low fee introduction.

4.2. Procedural Details

Our study was approved by the Ethics Commission, University of Bremen (project 2020-16), and is registered at the AEA RCT Registry (Ciotti et al., 2021). After being assigned randomly to the treatments, the study participants considered working in a new online labor market that contains two labor platforms: Platform% and Platform#. The experiment consisted of a minimum of seven and a maximum of ten rounds, each with the same structure. Starting with round seven, to prevent end round effects, a random mechanism decided with a $33.\bar{3}\%$ probability whether the study ended with the last round that had been completed. In each round, participants began by choosing the platform on which they wanted to work. After making this decision, they had to complete a task on that platform (i.e., counting zeros from a series of zeros and ones). After completing each task, participants received a performance rating, displayed as an average that reflects their past performance across all transactions in previous rounds. In each round, the minimum amount offered to complete a task was $0.10, but their ratings, based on their performance, also affected participants' wage level in the next round. Depending on their rating (ranging from 1 to 5 on each platform), participants could earn more money for a task, such that they received $0.15 if their rating exceeded 3.50 and $0.20 for a rating greater than 4.50.

Participants received information about their ratings, the platform's introduction or increase of a fee starting in the next round, wages for the next task, and the total wages over all rounds after each task, separately for Platform% and Platform#. With this information, participants again had to choose which platform to work on in the next round and perform another zero-counting task. Starting with round four, a random mechanism decided with a probability of 25% whether the platform would charge a fee for the next round. We avoided charging fees in earlier rounds so that participants could establish a rating first, which created the possibility of lock-in. To address the second-order effects pertaining to the extent and frequency of a platform fee, another random mechanism determined, with 50% probability, whether a platform that had been randomly chosen to charge a fee would charge $0.01 or $0.05. This fee would not be reduced in subsequent rounds but, again with a 25% probability, it could be increased from $0.01 to $0.05. Finally,

[17] Note that *initial* in this context indicates that the fee might be raised in later rounds; it does not refer to the first round of an experiment.

we asked participants to complete a questionnaire to control for confounding variables and individual heterogeneity.

4.3. Sample

The participants, workers we recruited from the AMT crowdsourcing platform, were all at least 18 years of age and citizens or legal residents of the United States.[18] As one of the largest online labor platforms in the world (Pittman and Sheehan, 2016), AMT provides participants who are real online workers, and it represents a much larger respondent pool than other services can offer (Sheehan, 2018), which also implies greater diversity in their backgrounds (Mason and Suri, 2012). Various studies have successfully replicated established economic and psychological effects in empirical validations of AMT as a useful data collection tool (Sprouse, 2011; Crump et al., 2013; Litman et al., 2015; Buhrmester et al., 2016).

We collected the data between February 12 and 23, 2021, using the software Unipark. We recruited a total of 2,148 participants but excluded those who provided invalid information about working hours or weekly income from online labor and who monotonously switched back and forth between platforms during the experiment. We also removed participants who received the lowest possible rating (1) in every round or who consistently failed to identify the correct number of zeros (i.e., were accurate no more than twice). Thus we can exclude bots and participants who click randomly during the task, without paying attention. The final sample includes responses from 1,622 participants. On average, each experimental session lasted about 20 minutes, and participants earned an average of $1.36 plus an additional fixed amount of $1 for participating.[19]

5. Experimental Results

In Section 5.1, we present how lock-in effects determine switching behavior and analyze workers' motives to switch platforms due to exploitation, in the form of a fee. Then we analyze the role of reputation portability on switching behavior in Section 5.2. In Section 5.3, we investigate how the strength and frequency of the platform's exploitation of workers' lock-in, as second-order effects, influence switching behavior. When comparing the means across treatments, we apply

[18] A filter applied during the tendering process on AMT and an additional query at the beginning of the experiment confirmed these criteria.

[19] Because the experiment could be completed in approximately 20 minutes, these payments correspond to an hourly remuneration ranging from $6.75 up to $8.70, above the average payment on AMT (Hara et al., 2018) and in line with the federal minimum hourly wage in the United States of $7.25 (29 USC Chapter 8, Section 206 – Minimum Wage Statutes).

two-sample chi-square tests of proportions, Fisher's exact tests, and two-sample t-tests.[20]

5.1. The Impact of Exploiting Lock-in Effects on Switching Behavior

With a within-subject analysis, we determine if introducing a fee prompts participants to switch platforms. In the experiment, 1,349 participants (83.2%) confronted a fee, whereas 273 participants (16.8%) never encountered these charges. Figure 5 illustrates the differences in switching behavior when a platform introduces a fee, versus switching in all rounds before any fee was charged. In line with our prediction that switching behavior triggered by a platform fee differs from switching behavior in prior rounds without a fee, we find that the fraction of participants switching platforms increases from 24.4% to 38.6% following a fee, a significant increase of 14.2 percentage points (two-sample chi-square test of proportions, $z = 6.025, p < 0.001$). Figure 6 also reveals that this effect is driven mostly by switching behaviors in response to a fee charged by the focal platform (unequal exploitation). Switching behaviors prior to a fee might be explained by curiosity, a strategic desire to build good ratings on multiple platforms to avoid the issues related to a lack of reputation portability,[21] or an effort to avoid the negative implications of a poor rating received in earlier rounds, which also requires a policy regime without reputation portability.[22] We summarize this finding as follows:

Result 1. *Introducing a platform fee increases switching behavior.*

— Figures 5 to 6 about here —

With Figure 7, we can analyze *why* participants switch platforms in response to a fee. In our experimental design, workers may be motivated by monetary reasons and/or have fairness preferences, such that they might react to platform fees even in the absence of monetary incentives to switch (Dhami, 2016). If workers with fairness preferences perceive the fee as unfair, they thus might switch to another platform, even if they earn the same or a lower wage. But if they earn a higher wage on the other platform, participants could be motivated by both their fairness preferences and their monetary motives. Their behaviors also should depend on their tolerance level for fees.

[20] In Table 2, we also present the results of a test for whether the computerized randomization created a balanced sample using F-tests. These results indicate that the F-tests for risk ambiguity, the tasks completed and the approval rate obtained on AMT are statistically different from zero at the 10% level, so we include these variables as control variables for the regression analyses.

[21] Prompted by an item in the questionnaire, a participant offered a reason for switching platforms: "I felt it was wise to create a high rating on each platform. That way if there was a difference in the fee or I made a mistake, I could use the platform with the highest rating since it would be saved from when I switched from it."

[22] We check whether the rating differs systematically across participants who switched and those who did not, in rounds before the fee increase, and find that they are significantly different (two-sample t-test, $t = 26.563, df = 5,049, p < 0.001$). That is, some workers left the focal platform due to a poor rating. Those who switched had a rating of 3.60, compared with an average of 4.62 for those who did not switch.

Of the 1,349 participants who encountered a fee, 417 (30.9%) would have earned a higher wage on the other platform, so their platform switching might reflect monetary motives, fairness preferences, or both. We find that 327 (78.4%) workers switched platforms in this setting. For 932 participants, the fee increase coincided with an equal or lower wage available on the other platform; specifically, 447 workers would have earned the same wage in the next round, and 485 would have earned less, had they switched platforms. Exhibiting their fairness preferences, 194 (20.8%) workers switched platforms (148 who earned an equal wage and 46 participants who earned less).

Next, to calculate the fraction of workers who switched solely for monetary reasons, we subtract the 20.8% fraction of workers who switched due to "pure" fairness preferences (t-test against zero, $t = 16.465, df = 968, p < 0.001$) from the 78.4% fraction of workers whose switching behavior signaled fairness preferences and/or monetary motives (t-test against zero, $t = 38.495, df = 445, p < 0.001$). The difference, of 57.6 percentage points, identifies workers who switched solely for monetary reasons and reveals that the difference in switching motives is statistically significant (two-sample chi-square test of proportions, $z = 12.837, p < 0.001$). Overall, our findings are in line with Hypothesis 1a, in which we predicted that platform switching behavior is driven by monetary motives, and with Hypothesis 1b, in which we anticipated that it is driven by fairness preferences.[23] Therefore,

Result 2. *If a platform introduces a fee, 57.6% of workers switch based on monetary motives, and 20.8% switch due to fairness preferences.*

— Figures 7 and 8 about here —

Workers also might perform differently after encountering a newly imposed or increased fee, which we test according to their ratings. In Table 3, we present the results of ordinary least squares regressions and assess the average ratings in round k on the platform on which the participant currently works as the dependent variable. Workers charged a fee who switch, but without monetary incentives to do so, exhibit poorer performance than they did before the fee introduction (column (2)). More precisely, their average rating decreases by 0.44 in the rounds after the fee introduction (*After Fee Introduction*), holding all other variables constant.[24] These results are in line with our theoretical model, in which workers who confront a lower wage reduce their equilibrium effort accordingly. This effect even becomes exacerbated if workers

[23]When we consider switching behavior after a fee introduction for each portability regime separately (see Figure 8), we find a significant increase in "pure" switching behavior due to fairness preferences, from 15.4% to 30.2%, when reputation portability exists (two-sample chi-square test of proportions, $t = 2.437, p = 0.015$). If participants earn more on the other platform after the fee is introduced, switching behavior increases from 72.6% to 80.1%. However, this difference is not statistically significant (two-sample chi-square test of proportions, $z = 1.346, p = 0.178$).

[24]If we control for the size of the fee, we find that workers with fairness preferences perform significantly worse after they encounter the platform fee. These results are available on request.

express fairness preferences, because the fee introduction constitutes an additional disutility for them. We therefore conclude:

Result 3. *Workers with fairness preferences perform more poorly after they confront a fee.*

— Table 3 about here —

To confirm our findings related to switching behavior based on monetary motives and fairness preferences, we also run a regression analysis, informed by responses to the questionnaire, such that we analyze in depth *why* participants chose to switch after being charged a fee. According to prior experimental research, risk-averse people tend to prefer outcomes with low uncertainty over those with high uncertainty (Kahneman et al., 1991; Tversky and Kahneman, 1991), and ambiguity-averse people prefer known over unknown risks (Ellsberg, 1961; Camerer and Weber, 1992). In addition to testing for the effects of risk attitudes (i.e., risk aversion and ambiguity aversion) and perceptions on switching behavior, we investigate whether switching behavior might constitute a form of negative reciprocity, such that workers seek to respond to the fee by punishing the platform, even at a cost to themselves (Güth, 1995; Kritikos and Bolle, 2001), or if they simply regard the fee as unfair, which is sufficient to prompt them to switch platforms (Kahneman et al., 1986; Rabin, 1993).

First, to classify workers according to their relative risk aversion (Butler et al. (2014)), we asked participants to choose their preferred lifetime earnings profiles. Second, we implemented a thought experiment developed by Ellsberg (1961) that requires participants to choose between two urns. Third, with measures of negative reciprocity from the 2005 personality questionnaire of the German socioeconomic panel, we asked participants how much they agreed with six self-descriptive statements, on 7-point Likert scales ranging from "does not apply to me at all" to "applies to me perfectly." Fourth, we solicited the main reasons participants switched by offering a list of seven options, then asking them to rank the reasons that applied, in order of importance.[25] The dummy variables *Boredom*, *Curiosity*, *Poor Rating*, *Earn Higher Wages*, and *Fee Perceived as Unfair* were derived from their responses. All these dummy variables equal 1 if participants rank that reason for switching among the top three, suggesting that it represented a relevant consideration for them. In addition, we control for the extent of lock-in by including participants' ratings in round k and the round the fee was introduced. The probit regression includes *Switching* as the dependent variable and involves only those participants who confronted a fee at some point during the experiment.

The results in Table 4 corroborate our main findings. Participants' average rating has a negative effect on their switching behavior after the fee introduction. If the average rating increases by one unit, the probability of switching decreases by 7.7% in response to a platform fee, all

[25]These choices were "I was bored," "I was curious," "I had a low rating," "I perceived the fee increase as unfair," "I could earn more money on the other platform," "I did not switch platforms," and "other reason."

else being equal. This result confirms that reputation can lock-in workers. We also find strong support for our predictions about monetary motives and fairness preferences; both a desire to earn higher wages and the perception that the fee is unfair significantly increase the likelihood that participants switch platforms. In detail, an opportunity to earn higher wages increases switching behavior by 27.6%, holding all other variables constant. Perceiving the fee as unfair increases this behavior by 18.1%, all else being equal. In a comparison of switchers *with* fairness preferences against all other participants subject to a fee, we find that 39.7% of workers with fairness preferences, but only 27.5% of other workers, regard the fee as unfair. This difference is statistically significant (Fisher's exact, $p = 0.001$), so workers with fairness preferences perceive the fee as more unfair. Risk aversion, risk ambiguity, negative reciprocity, a poor rating, and the round in which the fee was introduced do not influence workers' switching behaviors, though boredom and curiosity increase them. We summarize the regression findings as follows:

Result 4. *The better the rating, the less likely workers are to switch. The desire to earn higher wages and perceiving a fee as unfair significantly increase workers' switching behaviors; risk aversion, risk ambiguity, negative reciprocity, and a poor rating do not.*

— Table 4 about here —

5.2. The Effect of Reputation Portability on Switching Behavior

Can a policy regime that mandates reputation portability mitigate the lock-in effects that we identify in online labor markets? To answer this question, we compare switching behavior after a platform introduces a fee in regimes without and with reputation portability. As noted previously, if switching increases more in the latter policy scenario, it offers evidence that workers are exploited by the lock-in effects that arise in the absence of reputation portability. As detailed in Figure 9, switching behavior in a policy regime without reputation portability increases after a fee, from 18.3% to 23.3%. However, the 5 percentage point increase is not significant (two-sample chi-square test of proportions, $z = 1.380, p = 0.168$), in line with our theoretical finding that platforms exploit their workers in the absence of reputation portability. In a policy regime with reputation portability though, switching behavior increases by 23.8 percentage points, from 30.7% to 54.5%, which is statistically relevant (two-sample chi-square test of proportions, $z = 7.643, p < 0.001$). The difference between these increases (5 versus 23.8) also is statistically significant (Fisher's exact, $p < 0.001$), which offers support for Hypothesis 2, because the policy regime with reputation portability increases the probability of switching platforms. Formally,

Result 5. *Platforms can exploit lock-in effects more effectively in a policy regime without reputation portability, whereas a policy regime with reputation portability significantly increases switching behavior and reduces the chances that workers in online labor markets will be exploited by the imposition of a platform fee.*

— Figure 9 about here —

Figure 10 also sheds light on the differential switching behaviors of workers, depending on the strength of the lock-in effects. In our experimental setup, a rating greater than 3.50 is associated with higher wages, and we anticipate that the lock-in effects might be particularly strong for highly rated workers. Whether we consider switching in all rounds prior to the fee or only in the round in which the fee has been introduced, workers with ratings higher than 3.50 switch significantly more if they can take their reputation score with them (i.e., reputation portability) than do workers with comparable ratings but without reputation portability. The difference is consistently statistically different from 0 at a 5% level. In contrast, workers with ratings below 3.50 switch significantly less often in rounds prior to the fee (two-sample chi-square test of proportions, 66.4% vs. 39.1%, $z = -4.596, p < 0.001$). After the fee is introduced, the difference in switching behavior for workers with poor ratings is only weakly significant at the 10% level and decreases by 17.4 percentage points, from 75.6% to 58.2% (two-sample chi-square test of proportions, $z = -1.769, p = 0.077$). A policy regime with reputation portability leads to more platform switching among highly rated workers. Arguably, it also could increase the quality of information available in the market.

To gain further insights, we investigate whether a policy regime with reputation portability has a positive effect on workers' wages. We compare the total wages, defined as the total amount participants have received by the end of the experiment, between policy regimes. As Figure 11 shows, the average total wage increases by $0.03 from $2.38 to $2.41 in a policy regime with reputation portability. If we control for risk ambiguity, the tasks completed and the approval rate obtained on AMT, this difference is only weakly significant at the 10% level (Table 5, column (1)). If we run the same regression for workers with a rating greater than 3.50 in the last round of the experiment (column (2)), we find that a policy regime with portability increases these high-quality workers' total wages by $0.04, holding all other variables constant. Thus, we offer strong evidence that a regulatory regime with reputation portability can function as a mechanism to empower workers in online labor markets, by making them less vulnerable to being exploited by platforms. We summarize these findings as follows:

Result 6. *Lock-in effects affect highly rated workers more than poorly rated workers. A policy regime with reputation portability increases the switching behavior of highly rated workers and reduces the switching behavior of poorly rated workers. In addition, a policy regime with reputation portability increases highly rated workers' wages.*

— Figures 10 to 11 and Table 5 about here —

5.3. The Strength and Frequency of Exploiting Lock-in Effects

Recall that during the experiment, starting with round 4, a random mechanism decided, with a 25% probability, whether the platform introduced a fee of \$0.01 (low exploitation of lock-in effects) or \$0.05 (high exploitation). Once participants were subject to this platform fee, it remained in effect, but we also allowed platforms that introduced the low fee of \$0.01 to raise it to the high level in each following round, with a probability of 25%. With this mechanism, we can determine if high initial exploitation of lock-in effects triggers significantly more switching than a lower level of exploitation. Furthermore, we test whether the frequency of this exploitation affects switching behaviors, according to the fraction of switchers from a platform that immediately introduces a \$0.05 fee versus one that charges a fee of \$0.05 only after it introduced a fee of \$0.01 in previous rounds.

As we argued previously, if workers switch significantly more often in response to a fee of \$0.05 compared with a fee of \$0.01, it constitutes evidence that workers switch more if they perceive they are being highly exploited. As depicted in Figure 12, 35% of participants switch platforms on average if the platforms introduce a low fee of \$0.01, whereas 42.1% switch if the platform directly introduces a fee of \$0.05. This increase in switching behavior differs by 5.6 percentage points, which is only weakly significant at the 10% level (two-sample chi-square test of proportions, $z = 1.649, p = 0.099$). Formally:

Result 7. *The strength of the exploitation of lock-in effects barely influences switching behavior.*

— Figure 12 about here —

To determine if the frequency of this form of exploitation further affects switching behavior, we test for a difference in platform switching between participants immediately confronted with the high fee (\$0.05) versus those who receive notice of a low fee first (\$0.01) and then a further increase to the high fee (\$0.05) in a later round.[26] As Figure 13 shows, workers switch significantly more often if a platform initially introduces a fee of \$0.05, compared with the step-up situation in which the platform initially introduced the \$0.01 fee and then increased it to \$0.05 (two-sample chi-square test of proportions, $z = 3.004, p = 0.003$). Because the platforms are not perfectly identical in this case, and only the focal platform charges a fee, this finding reconfirms the notion that fairness preferences are at play (Figure 14). If the markets are perfectly identical and charge fees of the same amount at the same time, workers instead switch less often, in line with our theoretical model (Equation 12). In summary,

[26] If both platforms are perfectly identical and equally exploit lock-in effects, it does not matter if the worker is currently active on Platform% or Platform#. However, in the case of unequal exploitation of lock-in effects, only the platform on which the worker was active at the time of the fee introduction might charge \$0.01, so we only consider those participants on that same platform when the fee increases to \$0.05.

Result 8. *If only the platform on which workers currently work charges a fee, workers are less likely to switch platforms if they experience rising subsequent fees. If the platforms are identical, switching behavior does not depend on the frequency of fees.*

— Figures 13 to 14 about here —

6. Conclusion

This article presents a theoretical model and empirical evidence that online labor markets can exploit the lock-in effects generated by platform-specific reputation mechanisms; a policy regime with reputation portability would mitigate such lock-in effects and their exploitation by platforms. To the best of our knowledge, this study represents the first effort to investigate lock-in effects in conjunction with reputation portability, as well as whether workers might switch platforms for monetary reasons or due to fairness preferences. Theoretically, we show that a platform can impose a fee on workers and sustain it over an infinite horizon, without losing workers, if reputation portability is not made mandatory. Because its workers are locked in, the platform can exploit their reluctance to switch. Experimentally, the online lab-in-the-field decision experiment relied on actual workers from the crowdsourcing platform AMT to test whether a policy regime with or without reputation portability affects their switching behaviors in response to newly introduced fees. As we show, platforms exploit lock-in effects more intensely when reputation portability mechanisms are absent. A policy regime with reputation portability instead substantially increases workers' switching behaviors, mainly due to monetary incentives, though fairness preferences also play a role. These results likely apply to various online marketplaces in which multi-homing is difficult and reputation is not transferable across platforms.

Our study thus extends research on switching costs and reputation portability by investigating why workers switch to other platforms, how they react when they feel exploited, and whether reputation portability is necessary. The results indicate that reputation portability is a valuable means for workers to be able to avoid exploitation, a goal that is particularly important in online labor markets where workers rely on valuable ratings of their quality and face precarious working conditions, significant setup costs, and limits to their multi-homing. The current analysis also informs questions about whether reputational data should be regulated. In line with the purposes of recent regulations such as the GDPR, the Californian Consumer Privacy Act, or the Chinese Personal Information Protection Law, we recommend the imposition of reputation portability rules to mitigate lock-in effects and improve online working conditions. In addition, introducing reputation portability in online labor markets could increase competition among platforms, which improves the bargaining power of workers.

As relevant extensions to our theoretical model and experimental design, we offer several potentially interesting options. First, we consider reputation portability specifically, but other designs pertaining to reputational data also might influence switching behaviors (Hesse and Teubner, 2019). Second, researchers might address how platform competition changes when regimes implement reputation portability. When lock-in effects are likely, firms usually compete fiercely in a first stage, then relax their competition later, and it is unclear if a situation that mitigates these lock-in effects is worse in terms of overall welfare. In the presence of reputation portability, platforms may have greater incentives to coordinate on prices but less drive to invest in the overall quality of their marketplaces and reputation systems. In traditional network settings, such as telecommunications, the outcomes of number portability on providers' investments in quality remain uncertain (Bühler et al., 2006), and in any case, the cost of maintaining or developing the infrastructure for online marketplaces would be significantly lower than required in traditional network settings. Third, an online market with imperfect competition or frictions also might affect switching behavior differently. Allowing for reputation portability could reinforce the well-established positions of incumbent users and raise barriers to entry for new users of online marketplaces. Here again, these impacts might affect overall welfare in the market. Fourth and finally, further research might account for information asymmetries across platforms and users, as well as strategic choices by users to transfer their reputation when they have the right, but not the obligation, to reputation portability. For example, in a policy regime with voluntary reputation portability, the market might interpret a transfer of reputational data as a positive signal. We leave this question for further research.

References

Ba, S. and Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quarterly*, pages 243–268.

Belleflamme, P. and Peitz, M. (2015). *Industrial organization: Markets and strategies*. Cambridge University Press.

Bergvall-Kåreborn, B. and Howcroft, D. (2014). Amazon mechanical turk and the commodification of labour. *New Technology, Work and Employment*, 29(3):213–223.

Bewley, T. F. (2007). Fairness, reciprocity, and wage rigidity. *Behavioral Economics and Its Applications*, pages 157–188.

Blount, S. (1995). When social outcomes aren t fair: The effect of causal attributions on preferences. *Organizational Behavior and Human Decision Processes*, 63(2):131–144.

Borchert, K., Hirth, M., Kummer, M. E., Laitenberger, U., Slivko, O., and Viete, S. (2018). Unemployment and online labor. *ZEW-Centre for European Economic Research Discussion Paper*, (18-023).

Bühler, S., Dewenter, R., and Haucap, J. (2006). Mobile number portability in europe. *Telecommunications Policy*, 30(7):385–399.

Buhrmester, M., Kwang, T., and Gosling, S. D. (2016). Amazon's mechanical turk: A new source of inexpensive, yet high-quality data?

Butler, J. V., Guiso, L., and Jappelli, T. (2014). The role of intuition and reasoning in driving aversion to risk and ambiguity. *Theory and Decision*, 77(4):455–484.

Cabral, L. and Xu, L. (2021). Seller reputation and price gouging: Evidence from the COVID-19 pandemic. *Economic Inquiry*, 59(3):867–879.

Camerer, C. and Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty*, 5(4):325–370.

Choudary, S. P. (2018). The architecture of digital labour platforms: Policy recommendations on platform design for worker well-being. *ILO Future of Work Research Paper Series*, 3.

Ciotti, F., Hornuf, L., and Stenzhorn, E. (2021). Lock-in effects in online labor markets. *AEA RCT Registry*.

Crémer, J., de Montjoye, Y.-A., and Schweitzer, H. (2019). Competition policy for the digital era'. *Luxembourg: Publications Office of the European Union*.

Crump, M. J., McDonnell, J. V., and Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PLoS ONE*, 8(3):e57410.

De Hert, P., Papakonstantinou, V., Malgieri, G., Beslay, L., and Sanchez, I. (2018). The right to data portability in the GDPR: Towards user-centric interoperability of digital services. *Computer Law & Security Review*, 34(2):193–203.

Degryse, C. (2016). Digitalisation of the economy and its impact on labour markets. *ETUI Research Paper-Working Paper*.

Dellarocas, C., Dini, F., and Spagnolo, G. (2006). Designing reputation (feedback) mechanisms.

Dhami, S. (2016). *The foundations of behavioral economic analysis*. Oxford University Press.

Diker Vanberg, A. and Ünver, M. B. (2017). The right to data portability in the GDPR and EU competition law: Odd couple or dynamic duo? *European Journal of Law and Technology*, 8(1).

Dube, A., Jacobs, J., Naidu, S., and Suri, S. (2020). Monopsony in online labor markets. *American Economic Review: Insights*, 2(1):33–46.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, pages 643–669.

Engels, B. (2016). Data portability among online platforms. *Internet Policy Review*, 5(2).

Eurich, M. and Burtscher, M. (2014). The business-to-consumer lock-in effect. *Working Paper*.

European Commission (2016). Article 1 GDPR: Subject-matter and objective. `https://gdpr-info.eu/art-1-gdpr/`. [Online; accessed 2020-05-23].

Farrell, J. and Klemperer, P. (2007). Chapter 31 coordination and lock-in: Competition with switching costs and network effects. volume 3 of *Handbook of Industrial Organization*, pages 1967–2072. Elsevier.

Farrell, J. and Shapiro, C. (1988). Dynamic competition with switching costs. *The RAND Journal of Economics*, pages 123–137.

Farrell, J. and Shapiro, C. (1989). Optimal contracts with lock-in. *American Economic Review*, pages 51–68.

Farronato, C., Fong, J., and Fradkin, A. (2020). Dog eat dog: Measuring network effects using a digital platform merger. *NBER Working Paper*, (28047).

Fehr, E. and Falk, A. (1999). Wage rigidity in a competitive incomplete contract market. *Journal of Political Economy*, 107(1):106–134.

Fehr, E. and Goette, L. (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *American Economic Review*, 97(1):298–317.

Fehr, E., Kirchsteiger, G., and Riedl, A. (1993). Does fairness prevent market clearing? An experimental investigation. *The Quarterly Journal of Economics*, 108(2):437–459.

Felstiner, A. (2011). Working the crowd: Employment and labor law in the crowdsourcing industry. *Berkeley Journal of Employment & Labor Law*, 32:143.

Gehrig, T. and Stenbacka, R. (2004). Differentiation-induced switching costs and poaching. *Journal of Economics & Management Strategy*, 13(4):635–655.

Graef, I., Verschakelen, J., and Valcke, P. (2013). Putting the right to data portability into a competition law perspective. *Law: The Journal of the Higher School of Economics, Annual Review*, pages 53–63.

Güth, W. (1995). On ultimatum bargaining experiments—A personal review. *Journal of Economic Behavior & Organization*, 27(3):329–344.

Güth, W., Schmittberger, R., and Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization*, 3(4):367–388.

Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C., and Bigham, J. P. (2018). A data-driven analysis of workers' earnings on Amazon Mechanical Turk. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pages 1–14.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., et al. (2001). Cooperation, reciprocity and punishment in fifteen small-scale societies. *American Economic Review*, 91(2):73–78.

Hesse, M., Lutz, O. H.-M., Adam, M., and Teubner, T. (2020). Gazing at the stars: How signal discrepancy affects purchase intentions and cognition.

Hesse, M. and Teubner, T. (2019). Reputation portability—Quo vadis? *Electronic Markets*, pages 1–19.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. *The Review of Economic Studies*, 66(1):169–182.

Hossain, T. and Morgan, J. (2009). The quest for qwerty. *American Economic Review*, 99(2):435–40.

ILO (2018). Digital labour platforms and the future of work: Towards decent work in the online world. International Labour Office.

Johnston, H., Land-Kazlauskas, C., et al. (2018). Organizing on-demand: Representation, voice, and collective bargaining in the gig economy. *Conditions of Work and Employment Series*, 94.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1986). Fairness and the assumptions of economics. *The Journal of Business*, 59(4):S285–S300.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, 5(1):193–206.

Kathuria, V. and Lai, J. C. (2018). User review portability: Why and how? *Computer Law & Security Review*, 34(6):1291–1299.

Kingsley, S., Gray, M.-L., and Suri, S. (2018). Monopsony and the crowd: Labor for lemons? *Working Paper*.

Klemperer, P. (1987a). The competitiveness of markets with switching costs. *The RAND Journal of Economics*, pages 138–150.

Klemperer, P. (1987b). Markets with consumer switching costs. *The Quarterly Journal of Economics*, 102(2):375–394.

Klemperer, P. (1995). Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. *The Review of Economic Studies*, 62(4):515–539.

Kokkodis, M. and Ipeirotis, P. G. (2016). Reputation transferability in online labor markets. *Management Science*, 62(6):1687–1706.

Kotapati, B., Mutungi, S., Newham, M., Schroeder, J., Shao, S., and Wang, M. (2020). The antitrust case against apple. *Available at SSRN*.

Krämer, J. and Stüdlein, N. (2019). Data portability, data disclosure and data-induced switching costs: Some unintended consequences of the general data protection regulation. *Economics Letters*, 181:99–103.

Kritikos, A. and Bolle, F. (2001). Distributional concerns: Equity-or efficiency-oriented? *Economics Letters*, 73(3):333–338.

Lambin, X. and Palikot, E. (2019). The impact of online reputation on ethnic discrimination. *Working Paper*.

Litman, L., Robinson, J., and Rosenzweig, C. (2015). The relationship between motivation, monetary compensation, and data quality among us-and india-based workers on Mechanical Turk. *Behavior Research Methods*, 47(2):519–528.

Luca, M. (2016). Reviews, reputation, and revenue: The case of yelp. com. *Com* (*March 15, 2016*). *Harvard Business School NOM Unit Working Paper*, (12-016).

Mason, W. and Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods*, 44(1):1–23.

Mason, W. and Watts, D. J. (2009). Financial incentives and the “performance of crowds”. In *Proceedings of the ACM SIGKDD Workshop on Human Computation*, pages 77–85.

Moreno, A. and Terwiesch, C. (2014). Doing business with strangers: Reputation in online service marketplaces. *Information Systems Research*, 25(4):865–886.

Otto, L., Angerer, P., and Zimmermann, S. (2018). Incorporating external trust signals on service sharing platforms. *Research Papers*, 78.

Pittman, M. and Sheehan, K. (2016). Amazon’s mechanical turk a digital sweatshop? transparency and accountability in crowdsourced online research. *Journal of Media Ethics*, 31(4):260–262.

Rabin, M. (1993). Incorporating fairness into game theory and economics. *American Economic Review*, pages 1281–1302.

Resnick, P., Kuwabara, K., Zeckhauser, R., and Friedman, E. (2000). Reputation systems. *Communications of the ACM*, 43(12):45–48.

Resnick, P., Zeckhauser, R., Swanson, J., and Lockwood, K. (2006). The value of reputation on ebay: A controlled experiment. *Experimental Economics*, 9(2):79–101.

Saeedi, M. (2019). Reputation and adverse selection: Theory and evidence from eBay. *The RAND Journal of Economics*, 50(4):822–853.

Shapiro, C., Carl, S., Varian, H. R., et al. (1998). *Information rules: A strategic guide to the network economy*. Harvard Business Press.

Sheehan, K. B. (2018). Crowdsourcing research: Data collection with Amazon’s Mechanical Turk. *Communication Monographs*, 85(1):140–156.

Sprouse, J. (2011). A validation of amazon mechanical turk for the collection of acceptability judgments in linguistic theory. *Behavior Research Methods*, 43(1):155–167.

Teubner, T., Adam, M., and Hawlitschek, F. (2019). Unlocking online reputation: On the effectiveness of cross-platform signaling. *Business & Information Systems Engineering*.

Tversky, A. and Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, 106(4):1039–1061.

Wohlfarth, M. (2019). Data portability on the internet. *Business & Information Systems Engineering*, 61(5):551–574.

Wood, A. J., Graham, M., Lehdonvirta, V., and Hjorth, I. (2019). Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 33(1):56–75.

Appendix A.

A.1. Existence of an incentive-compatible fee

Because it is not possible to find an analytical solution to Equation (13), we use hypothetical values of β, f, m_1, h_1, and h_ϵ to find a fee that can fit with this inequality. For a sufficiently low value of β, several periods after the introduction of ϕ on Platform%, the additional discounted value of another completed contract is ≈ 0.

Consider a setting in which the effort cost function is quadratic:

$$g(a_t) = \frac{1}{2} a_t^2(\mathbf{r}_{t-1}). \tag{A-1}$$

Then we can derive an explicit function of both the effort and the labor input in inequality (13). Assume the worker stays on Platform%. Following the steps detailed in Section 3, we find the first-order condition:

$$\sum_{s=1}^{\infty} \beta^{s-1}(1-\phi)\alpha_{k+s-1} - \beta^{t-1} g'(a_{k+t-1}(\mathbf{r}_{k+t-2})) = 0.$$

Rearranging and assuming quadratic effort costs yields:

$$a_{k+t-1}(\mathbf{r}_{k+t-2}) = \sum_{s=t}^{\infty} \beta^{s-t}(1-\phi)\alpha_{k+s-1}. \tag{A-2}$$

We then look for the equilibrium labor input when the worker switches to Platform#. The first-order condition in this case is:

$$\sum_{s=1}^{\infty} \beta^{s-1}\alpha_s - \beta^{t-1} g'(a_t(\mathbf{r}_{t-1})) = 0.$$

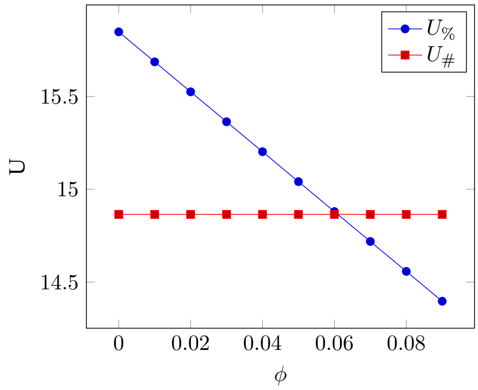
By rearranging and assuming quadratic effort costs, it follows that

$$a_t(\mathbf{r}_{t-1}) = \sum_{s=t}^{\infty} \beta^{s-t}\alpha_s. \tag{A-3}$$

With this explicit form of the effort cost function, inequality (13) can be expressed entirely in terms of $\beta, f, m_1, h_1, h_\epsilon$, and ϕ. Figure 1 depicts the incentive-compatible fee introduced after four rounds, with some previously established parameters.

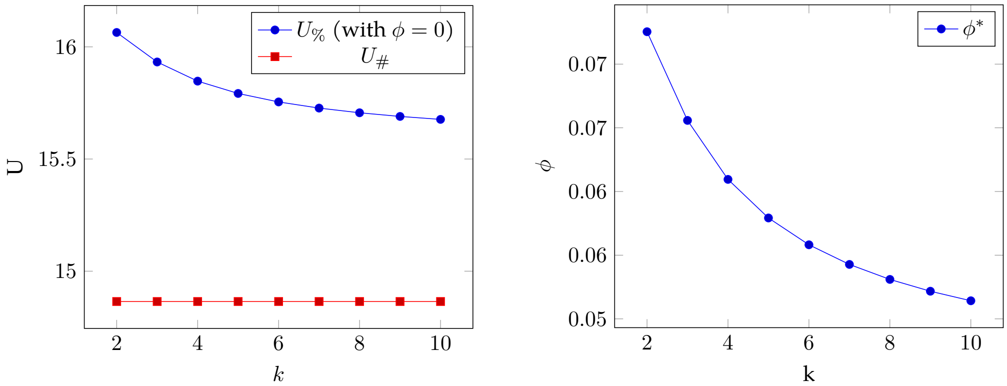
Figure 2 then indicates the incentive-compatible ϕ, depending on the time the worker has spent on Platform%. The more time the worker spends on Platform%, the lower the surplus that

Figure 1: Incentive compatible ϕ



$$t = 10 \quad k = 4 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_1 = 2 \quad h_\epsilon = 5$$

Figure 2: Variations of k



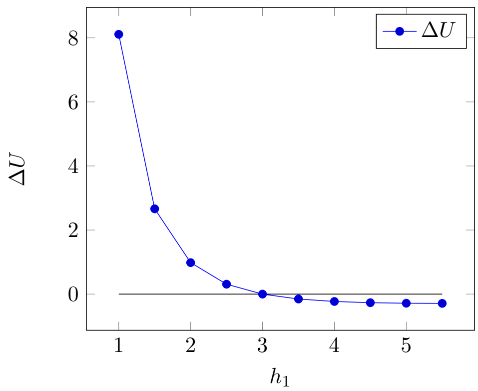
$$t = 10 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_1 = 2 \quad h_\epsilon = 5$$

the platform can extract; this effect is nullified even more when $k \to \infty$ (with the values from Figure 2, where $k = 1000000000$, and then $\phi^* = 0.044413846$). The more time workers have spent on the initial platform, the more the market knows about their talent, and the lower the workers' incentive to bias their evaluations. Thus, switching to another platform becomes slightly less unattractive with more time spent on the initial platform.

Figure 3 reveals how the difference in utilities between Platform% and Platform# depends on the precision term h_1. A straightforward interpretation of h_1 is that it represents the inverse of the variance of talent η in the market. We also can interpret it as the precision of the platforms' reputation systems. When h_1 is lower, there is a lower incentive to switch to another platform too. Due to the poor precision of assessments of workers' talent in early rounds, it becomes less interesting for workers to switch, which would require them to start building a new reputation by supplying costly, large amount of labor. Therefore, with lower precision, the platform can impose a larger fee.

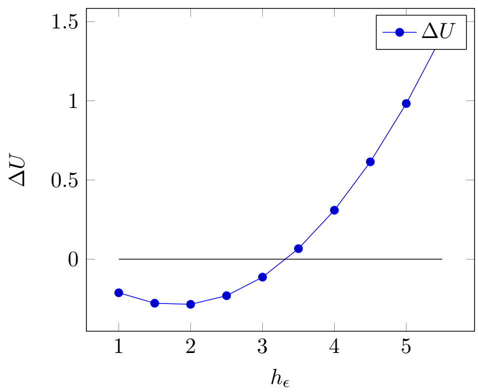
Figure 4 indicates the difference of utilities between Platform% and Platform#, according to the

Figure 3: Variations of h_1



$$t = 10 \quad k = 4 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_\epsilon = 5 \quad \phi = 0$$

Figure 4: Variations of h_ϵ



$$t = 10 \quad k = 4 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_1 = 2 \quad \phi = 0$$

precision term h_ϵ. In contrast with the example in Figure 3, the incentive to stay on the initial platform is higher when the variance of the noise term is lower.

A.2. Experimental Results

Figure 5: Fee Introduction

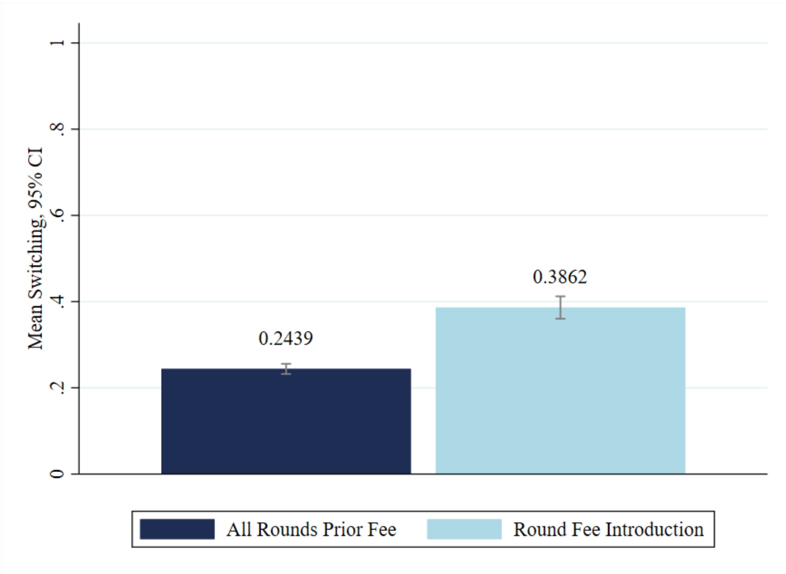


Figure 6: Exploiting Lock-in Effects

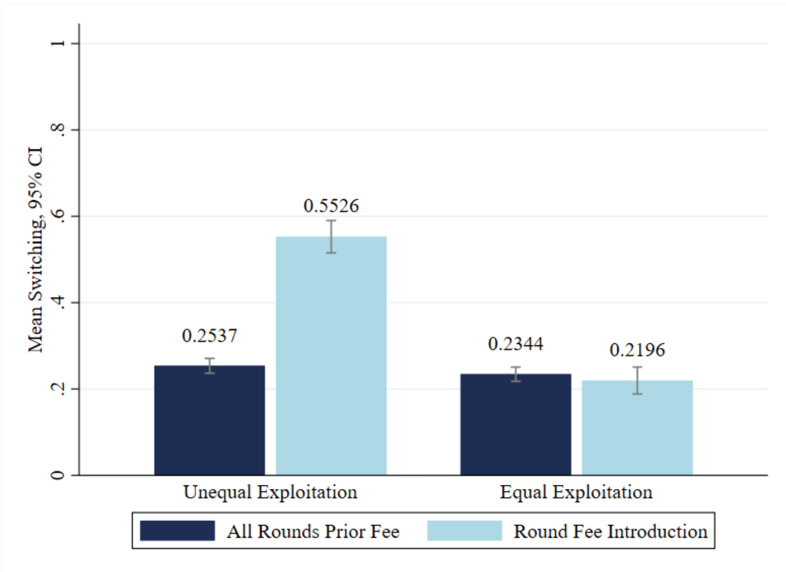


Figure 7: Monetary Motives and Fairness Preferences

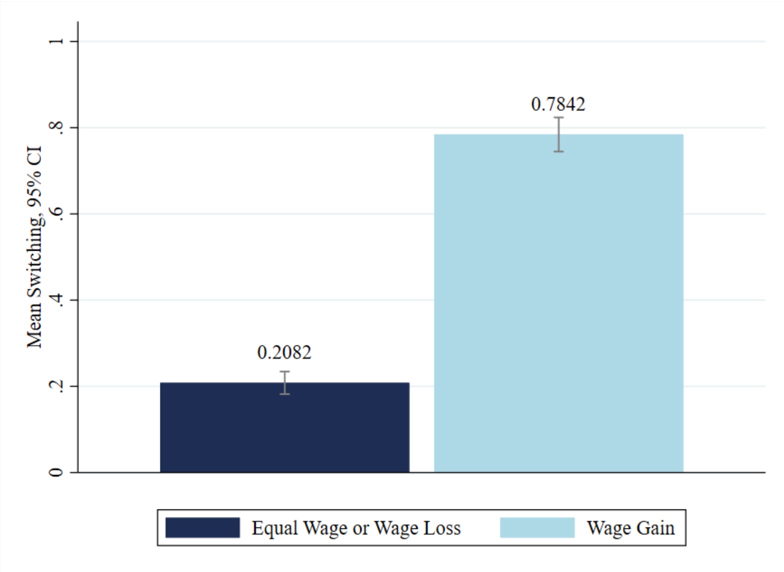


Figure 8: Portability Regime, Monetary Motives, and Fairness Preferences

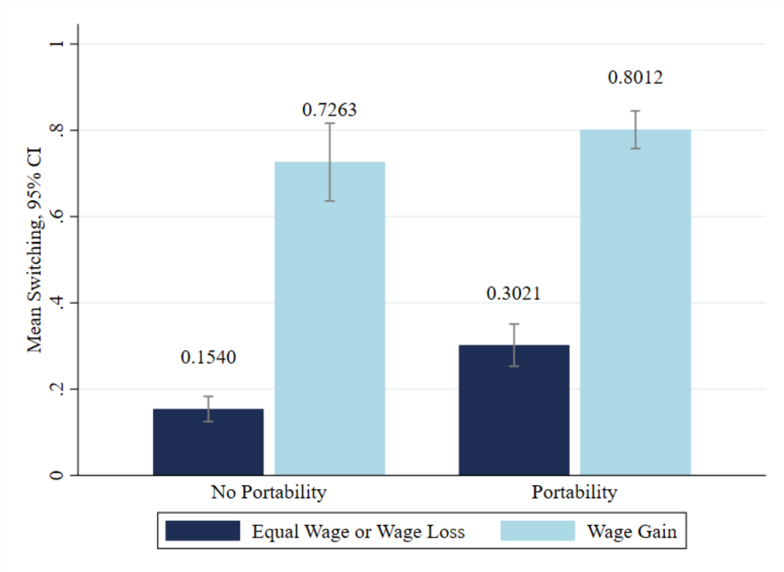


Figure 9: Portability Regime

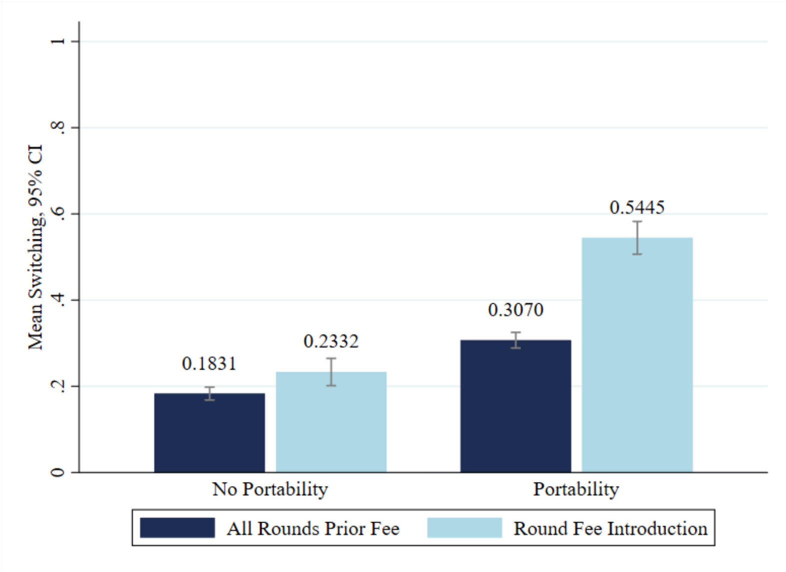


Figure 10: Portability Regime and Ratings

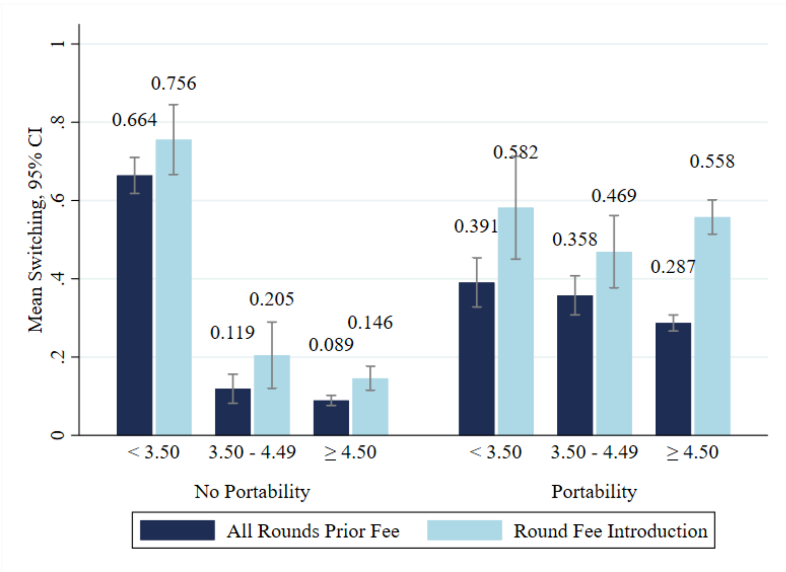


Figure 11: Portability Regime and Total Wage

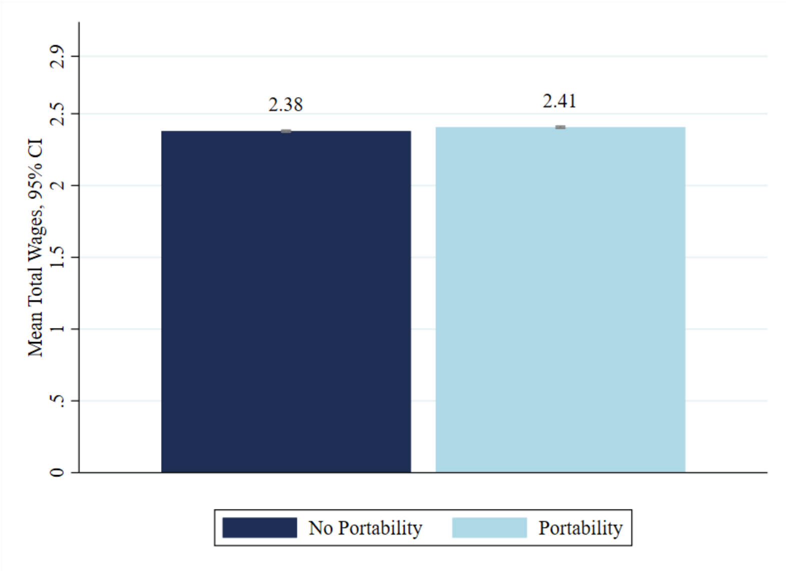


Figure 12: The Strength of Exploiting Lock-in Effects

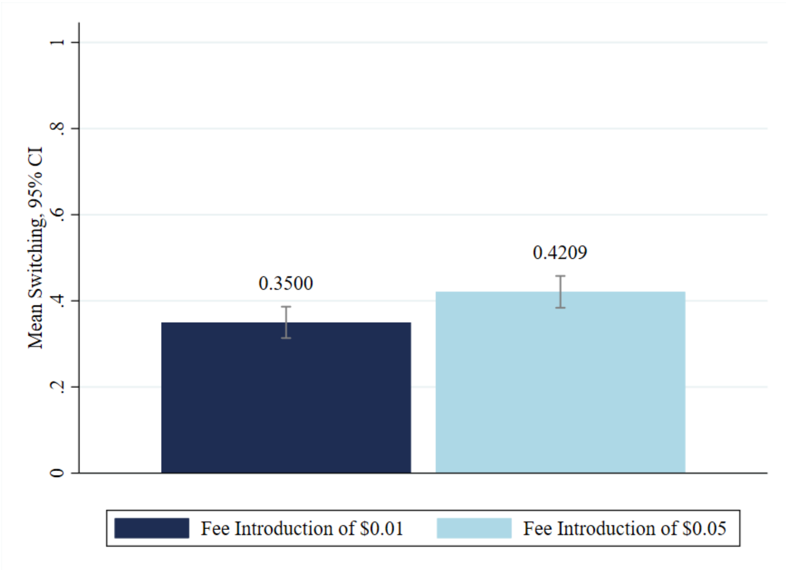


Figure 13: The Frequency of Exploiting Lock-in Effects

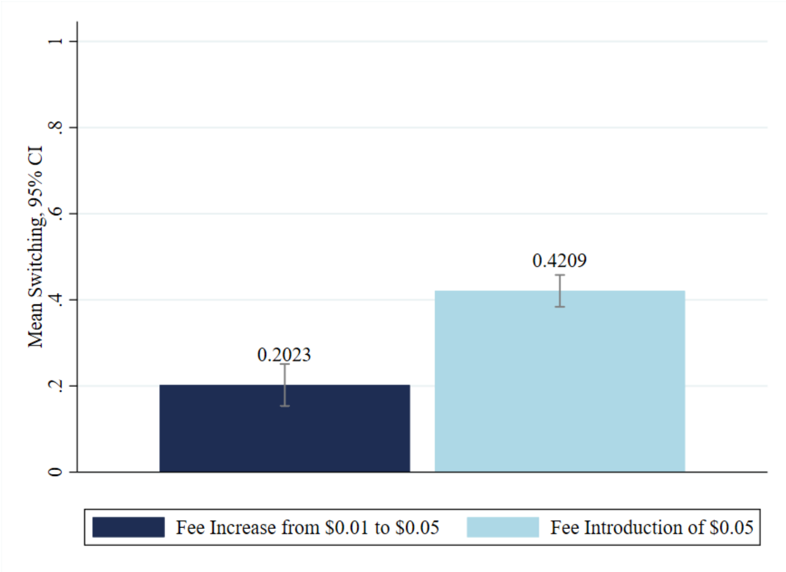


Figure 14: The Frequency of Exploiting Lock-in Effects by Exploitation Treatment

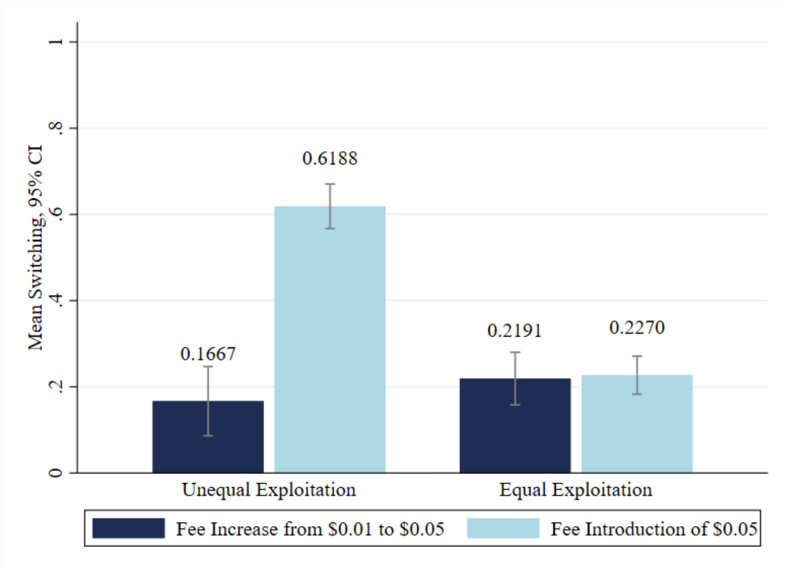


Table 1: Experimental Conditions

Conditions	Portability Regime	Exploitation of Lock-in Effects	Fee	N
1	No Portability	Equal	No	64
2	No Portability	Equal	Yes	334
3	No Portability	Unequal	No	72
4	No Portability	Unequal	Yes	352
5	Portability	Equal	No	65
6	Portability	Equal	Yes	340
7	Portability	Unequal	No	72
8	Portability	Unequal	Yes	323
				1,622

Notes: The table shows the experimental treatment conditions. Participants in treatment conditions 1, 3, 5, and 7 were not affected by a fee introduction or a fee increase, reflecting the randomized mechanism that decided before each round, starting in round 4, whether the platform would introduce a fee, with a probability of 25%.

Table 2: Randomization Check

	Conditions								
	1	2	3	4	5	6	7	8	R^2	F-test
Socio-Economic Background										
Age (yrs)	37.469	0.771	2.559	0.673	-2.423	-0.466	0.253	-0.661	0.006	0.221
Female and Diverse (y/n)	0.547	-0.136	-0.075	-0.098	-0.131	-0.106	-0.099	-0.157	0.005	0.363
Education (yrs)	15.75	-0.178	-0.083	-0.071	-0.119	-0.062	0.347	-0.199	0.004	0.458
Weekly Working Hours	34.845	1.830	1.517	2.776	3.433	2.086	-0.760	1.627	0.002	0.752
Annual Inc. ($)	34,297	3,622	3,411	4,680	972	5,696	3,342	2,932	0.002	0.799
Work Experience										
Hours Online Labor	19.266	-0.355	-1.224	-1.428	0.365	-0.133	-2.738	-0.086	0.003	0.755
Weekly Inc. Online Labor ($)	76.875	2.667	-7.833	4.483	21.679	3.269	26.569	1.633	0.004	0.786
Platform Registrations	1.953	0.724	-0.120	-0.050	0.847	0.088	0.186	-0.139	0.006	0.489
Completed Tasks AMT	10,428	14,388	30,288	16,677	19,913	17,387	-1,415	15,009	0.003	0.000
Approval Rate AMT (%)	97	0.042	1	-0.152	0.692	-0.956	-3.139	-0.947	0.005	0.061
Preferences										
Risk Aversion (0-1)	0.125	0.016	0.014	0.057	-0.033	0.054	0.000	0.005	0.005	0.245
Risk Ambiguity (0-1)	0.672	-0.172	-0.130	-0.180	-0.118	-0.187	-0.067	-0.146	0.008	0.056

Notes: This table provides the results from ordinary least squares regressions with treatment dummies as independent variables. The questionnaire, completed by participants after the experiment, is the source of the dependent variables. The treatment conditions are in Table 1. The omitted treatment condition is condition 1, a policy regime without reputation portability, equal exploitation of lock-in effects, such that both platforms are perfectly identical, and no fee. The first column shows the mean values of this treatment condition. The last column shows the p-values of the F-test of joint significance of the treatment dummies. Gender is coded 1 if participants reported being female and/or gender-diverse $(n = 6)$ and 0 if male. Robust standard errors (not shown). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Performance in Rounds Prior a Fee vs. After Fee Introduction

	(1) Rating in Round t	(2) Rating in Round t
After Fee Introduction	-0.027	-0.443***
	(0.037)	(0.129)
Round k	0.046***	0.132***
	(0.007)	(0.024)
Risk Ambiguity	0.233***	0.257**
	(0.040)	(0.107)
Completed Tasks AMT	0.003	0.022
	(0.020)	(0.042)
Approval Rate AMT	0.370	0.943+
	(0.233)	(0.507)
Intercept	3.727***	2.706***
	(0.230)	(0.498)
Observations	11,016	1,575
Adjusted R^2	0.022	0.048

Notes: The table contains the results of the probit regression for switching behavior. The dependent variable is the participant's average rating in round t. In column (1), we consider all participants who confronted a fee. In column (2), we only include participants who confronted a fee and had no monetary incentive to switch. In column (1), standard errors are clustered by worker and reported in parentheses; in column (2), robust standard errors are reported in parentheses. The variable *Completed Tasks AMT* is scaled by #/100,000 and the variable *Approval Rate AMT* is scaled by #/100. $+\ p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Channels

	Switching
Average Rating in Round k	-0.077***
	(0.009)
Risk Aversion	-0.019
	(0.031)
Risk Ambiguity	0.019
	(0.023)
Negative Reciprocity	-0.006
	(0.008)
Completed Tasks AMT	-0.007
	(0.010)
Approval Rate AMT	-0.071
	(0.088)
Round k	-0.004
	(0.007)
Most important self-reported switching motives as a response to fee introduction	
Earn Higher Wages	0.276***
	(0.021)
Fee Perceived as Unfair	0.181***
	(0.024)
Curiosity	0.153***
	(0.023)
Boredom	0.085**
	(0.032)
Poor Rating	-0.015
	(0.031)
Observations	1,349
Pseudo R^2	0.241
P=1	38.6%

Notes: This table contains the results of the probit regression for switching behavior. The dependent variable is a dummy variable that indicates whether the participant switched platforms after the fee introduction. The coefficients are average marginal effects. The variable *Completed Tasks AMT* is scaled by #/100,000 and the variable *Approval Rate AMT* is scaled by #/100. Robust standard errors are reported in parentheses. + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Total Wage and Portability Regime

	(1) Total Wage	(2) Total Wage
Portability	0.030+	0.040***
	(0.016)	(0.015)
Risk Ambiguity	0.067***	0.032**
	(0.016)	(0.015)
Completed Tasks AMT	0.007	0.007
	(0.007)	(0.007)
Approval Rate AMT	0.085	0.040
	(0.073)	(0.070)
Intercept	2.235***	2.332***
	(0.071)	(0.069)
Observations	1,349	1,227
Adjusted R^2	0.016	0.008

Notes: This table contains the results of the ordinary least squares regression for total wages, in line with the robustness results presented in Figure 11. The dependent variable is the total wage each participant had received by the end of the experiment. In column (1), we consider all participants subject to a fee. In column (2), we consider participants who confronted a fee but also earned a rating greater than 3.50 by the end of the experiment. The variable *Completed Tasks AMT* is scaled by #/100,000 and the variable *Approval Rate AMT* is scaled by #/100. Robust standard errors are reported in parentheses. + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.3. Experimental Instructions

[*Note: These are the written instructions, presented to participants in the treatment without reputation portability and unequal exploitation of lock-in effects. Amendments to the other treatment conditions are enclosed in square brackets.*]

Instructions

To earn the highest possible amount during this study, please carefully read this introductions page. The study begins immediately thereafter.

Thank you for participating in this study. The instructions will provide you with all the information you require for participation in the study. The instructions accurately reflect how decisions and processes will unfold. We will not deceive or lie to you in any way.

In this study, the duration of your participation will vary between 7 and 10 rounds. Each round has the same structure. From the 7$^{\text{th}}$ round onward, a random mechanism will decide whether the study ends or not. After the 7$^{\text{th}}$ round, there is a 2/3 probability that another round will take place. At the end of your last round, you will be asked to fill out a questionnaire and will receive your study completion code.

Market Environment

- Imagine a fictitious crowdsourcing market that consists of two online labor platforms, **Platform%** and **Platform#**, and a **requester**. Platform%, Platform#, and the requester are programmed.
- You enter this new market as a **worker**.
- In each round, the requester publishes the **exact** same task on **both** platforms.
- You can perform the task only on **one** platform.
- You can earn money for each task you complete.
- Platform% and Platform# each have an integrated reputation system to evaluate your performance. You will automatically receive a rating for each task you complete.
- Your **earnings** depend on the **average rating** you build up during the study and a possible fee Platform% and Platform# can charge its workers.
- **Platform% and Platform# use an identical reputation system and they have the same payment structure. Platform% and Platform# differ only in terms of how they increase their fees.**
- [*Equal exploitation of lock-in effects treatment condition:* **Platform% and Platform# are perfectly identical: They have the same payment structure, reputation system, and platform fee.**]

- **Your rating is platform-dependent** (i.e., it is stored on the respective platform and cannot be transferred to the other platform). This means that if you have established a rating on one platform and decide to switch to the other, you will need to rebuild a new rating. However, after you have built a rating on a platform, it will be stored on that platform until the end of the study. Thus, if you decide to switch platforms and return to the first platform later on, the rating that you built up before you switched will be stored there.
- [*Reputation portability treatment condition:* **Platform% and Platform# use a cross-platform reputation system.** This means you only have one rating that is applicable for both platforms. As soon as you build a rating on one platform, it will be transferred to and displayed on the other platform as well.]

Details on the payment structure, rating, and platform fees will be provided below.

Study Procedure

All rounds follow an identical scheme:

- **Step 1 – Make a decision:** You decide on which platform you want to work during the next round. Registration on a platform is not necessary. You can directly start working.
- **Step 2 – Work on a task:** Your task is to count the number of zeros in a table. Your performances will be rated, and you will receive a new average rating after completing a task.
- **Step 3 – Receive information:** After completing the task, you will be informed separately for each platform about (a) your current rating, (b) your wage in the next round, (c) the fee the platform will charge you in the next round (if any), and (d) your net earnings for the task in the next round.

You will receive all necessary information before each round. The information will be shown in a table. The following figure provides an example:

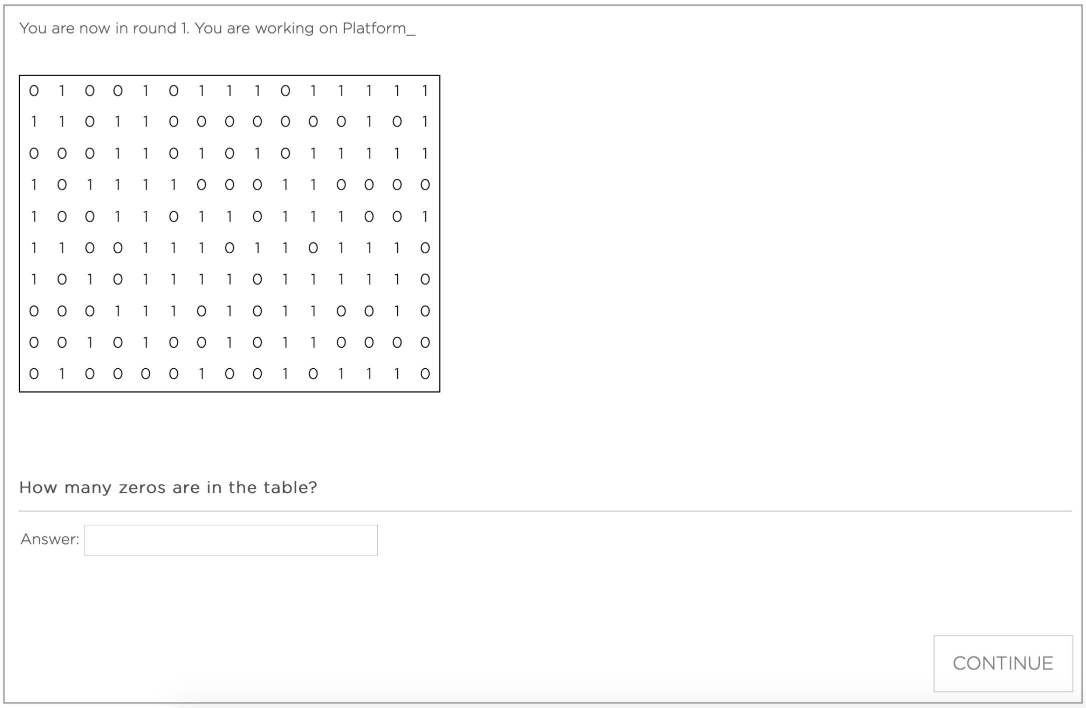
For Platform% and Platform#, the following box summarizes your current rating, your wage in the next round, the fee (if any) applied in the next round by the platforms, and your net earnings for completing the next task:

	Platform%	Platform#
Your current rating		
Your wage next round	USD 0.10	USD 0.10
Platform fee next round	USD 0.00	USD 0.00
Your net earnings next round	USD 0.10	USD 0.10

Your total earnings over all rounds are USD 0.00.

Your Task

Your task is to count the zeros in a table that lists a series of zeros and ones. The following figure shows the work screen you will use later on:



You will always see whether you are currently working on Platform% or Platform#. Enter the number of zeros into the "Answer" field at the bottom of the screen. After you have entered the number, click the "Continue" button. In each round, you will have only one try to solve the task.

Rating, Platform Fee, and Earnings

In each round, your earnings depend on your rating and whether or not the platform you are currently working on increased its platform fee.

Rating

The procedure for calculating your reputation is identical on both platforms and will result in a rating ranging from 1.00 to 5.00. A rating of **1.00** is given for the worst performance and a rating of **5.00** for the best performance. Your rating in each individual round depends on how accurately you count the number of zeros in the table:

- If you count the **correct** number, you will receive a rating of **5.00**.
- If your counted number differs by **+/− 1**, you will receive a rating of **4.00**.
- If your counted number differs by **+/− 2**, you will receive a rating of **3.00**.
- If your counted number differs by **+/− 3**, you will receive a rating of **2.00**.

- If your counted number differs by **more than +/– 4**, you will receive a rating of **1.00**.

Example: Assume that the correct number of zeros in a table is 10. You counted 9 zeros (i.e., you miscounted by 1). This means your rating in that round is 4.00.

Furthermore, platforms will consider your **average rating** (i.e., the average of your past performance across all transactions in the past rounds). That means that each round is important for your next and final payoff. The rating is always rounded to two decimal places.

Example: Assume that you receive a rating of 5.00 in the first round, 4.00 in the second round, and 5.00 in the third round. Your average rating is therefore (5.00 + 4.00 + 5.00) / 3 = 4.67.

Platform Fee

During the study and starting with round 4, the **platforms may charge a fee to its workers**. A fee is introduced with a 1/4 probability by a random mechanism. The fee will be automatically deducted from your earnings per completion of a task. The fee is announced at the end of a round and always takes effect in the next round. After a fee increase is introduced, it will not be reduced in the following rounds.

Earnings in a round

In each round, the **minimum amount offered** for a task is **USD 0.10**. Depending on your rating, however, you can also earn more money in the next round for completing the task:

- USD **0.10** for a rating **less than 3.50**.
- USD **0.15** for a rating **of at least 3.50**.
- USD **0.20** for a rating **of at least 4.50**.

Your net earnings in each round are given by USD 0.10 but increase depending on your rating minus the platform fee (if any). In other words, for each platform, your net earnings are calculated in each round as follows:

(USD 0.10 + increase due to your rating) – platform fee.

In the first round, or the first time you switch to the other platform, you will earn USD 0.10 for completing the task, as you have not yet established a rating.

[*Equal exploitation of lock-in effects treatment condition:* In the first round, you will earn USD 0.10 for completing the task, as you have not yet established a rating.]

Total Earnings

Your total earnings are the sum of your net earnings on both platforms from all rounds plus USD 1 for taking part in this study.