Lock-In Effects in Online Labor Markets

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April 2023

Online platforms that implement reputation mechanisms usually prevent the transfer of ratings to other platforms, leading to lock-in effects and high switching costs for users. This situation can be capitalized by platforms, for example, by charging their users higher fees. In this paper, we theoretically and experimentally investigate the effects of platform pricing on workers' switching behavior in online labor markets and analyze whether a policy regime with reputation portability could mitigate lock-in effects and reduce the likelihood of worker capitalization by the platform. We further examine switching motives more thoroughly and differentiate between monetary motives and fairness preferences. Theoretically, we provide evidence for the existence of switching costs if reputation mechanisms are platform-specific. The model predicts that reputation portability lowers switching costs, eliminating the possibility for platforms to capitalize lock-in effects. We test our predictions using an online lab-in-the-field experiment. The results are in line with our theoretical model and show that the absence of reputation portability leads to worker lock-in, which can be capitalized by platforms. Moreover, reputation portability has a positive impact on the wages of highly rated workers. The data further show that the switching of workers is primarily driven by monetary motives, but perceiving the platform fee as unfair also plays a significant role for workers.

JEL Classification: D40, D91, J24, J40, L51
Keywords: crowdsourcing, online labor markets, platform fees, reputation portability, switching costs
Data Availability Statement: The data that support the findings of this study are available from the corresponding author on request.

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1. Introduction

Most online marketplaces use reputation mechanisms to facilitate transactions between users. Reputation mechanisms build trust and address market inefficiencies that arise from asymmetric information (Dellarocas et al., 2006; Kokkodis and Ipeirotis, 2016). However, many platforms employ platform-specific reputation mechanisms and do not allow users to transfer their ratings to other platforms. Because ratings have an economic value (Resnick et al., 2006; Saeedi, 2019), platform-specific ratings can create lock-in effects and in turn cause high switching costs, which can make users more vulnerable to platform exploitation (Choudary, 2018). To this day we know little about how users react when platforms capitalize on these lock-in effects. In this paper, we therefore experimentally examine user reactions to a platform fee and examine what motivates users to switch to another platform after a fee is introduced. Moreover, we study the effect of reputation portability and ratings on workers' switching behavior, performance, and wages earned.

The presence of switching costs is not necessarily welfare decreasing for users. If users face switching costs, firms then may engage in fierce ex-ante competition to gain market shares, and relax competition ex-post, once users are locked-in (Klemperer, 1987a,b, 1995; Farrell and Shapiro, 1988, 1989). The resulting welfare effect is ambiguous and may or may not be detrimental to users. Policy interventions, such as the European Union's (EU) Digital Market Act, suggest that ex-ante competition may not offset the negative ex-post effects on welfare. Possibly, the presence of dominant platforms may exacerbate the negative impacts of lock-in effects because these platforms do not need to compete much for new users. Thus, dominant platforms are able to increase and sustain high fees over time, capitalizing on locked-in users.[1]

Hereinafter, we use a combination of a theoretical model and an experimental analysis to investigate the effects of a platform fee on workers' switching behavior in online labor markets in two policy regimes: a regime without reputation portability—the status quo—and a regime with reputation portability, which could be mandated by regulation. In the second policy scenario, we imagine a case with reputation portability, in which platforms import workers' ratings when they switch. In practical terms, we consider the case where reputation data is entirely and automatically exported from one platform to another.[2] Our focus is on online labor markets, in particular microtask platforms. These platforms are generally used to hire workers to perform small and repetitive tasks that are labor intensive (Durward et al., 2020). Especially on microtask platforms, workers rely heavily on their reputation scores and lack the opportunity to multi-home in the presence of platform-specific reputation mechanisms.

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

[2] Reputation portability can be implemented via other designs as well. Another prominent example is the use of Personal Information Management Systems, which are supposed to provide users with a central online storage system to manage and share their personal data (Krämer, 2021). For a comprehensive description of different scenarios, see Hesse and Teubner (2019).

Workers on microtasking platforms are typically classified as independent contractors (Prassl and Risak, 2015) and research suggests that these workers may also face precarious working conditions, amongst others, in the form of insecure and low earnings (Berg et al., 2018; Hornuf and Vrankar, 2022).

Our theoretical framework 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 Holmström's model by allowing workers to consider joining a different labor market platform. Switching costs arise when reputation mechanisms are platform-specific. These costs are defined as the effort investment that workers make over time to build their reputations and to maximize their revenue streams. Since the market is organized by a platform, we also introduce the possibility to impose a fee on workers' revenues and study the impact of a fee change in two policy regimes on reputation portability. We also consider more thoroughly *why* workers switch platforms, because different motives may have strong economic implications that are difficult to foresee. We distinguish two types of stylized workers: those with *monetary motives* and those who express *fairness preferences*. Workers with monetary motives are driven by the amount of their wages, while workers with fairness preferences have a preference for being treated fairly (Kahneman et al., 1986). Workers with fairness preferences care about the actions of the platform, such as the introduction of new fees. If they perceive unfair treatment, these workers may reciprocate by leaving the platform that levies a fee, even if doing so causes them to lose their ratings and, in turn, wages. In addition, workers with a preference for fairness may not only be less willing to pay a higher fee to stay on the platform, but may also perform worse after experiencing a fee (Fehr et al., 1993; Fehr and Falk, 1999), because their utility is lowered not only by the reduction in net wages, but also by the introduction of the fee itself. Thus, if fairness preferences are not taken into account, a fee increase could lower workers' effort more than expected and thus the overall appeal of the platform from a contractors' perspective.

Theoretically, we show that in a policy regime without reputation portability, the reputation investments of workers can become a switching cost. Moreover, even in the presence of an alternative platform offering better economic treatment, workers may refrain from switching because of their reluctance to lose their valuable ratings. However, our model predictions indicate that workers with fairness preferences are more susceptible to switch, compared to workers with pure monetary motives, because they face an additional disutility from the introduction of a fee. Instead, when reputation portability is enforced, workers do not incur switching costs and, thus, the fee they are willing to pay to stay in the platform is zero. Therefore, we expect that workers being treated with reputation portability will be more likely to switch and to avoid paying higher fees on the focal platform.

For our experimental evaluation, we conducted an online lab-in-the-field decision experiment with actual online workers from the crowdsourcing platform Amazon Mechanical Turk

(AMT). This allows us to examine worker behavior in a natural work environment, and, at the same time, to study artificial policy changes and different levels of capitalization by platforms. In the experiment, participants are asked to work in a fictitious online labor market. Switching behavior is triggered by platforms charging fees. Our proposed design 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, the results support the predictions from the theory model. The data show that a policy regime without reputation portability creates lock-in effects, which can be capitalized by the platform. In turn, a scenario with reputation portability significantly increases switching, such that workers are more likely to avoid paying higher fees. Furthermore, we evidence that switching behavior is driven by both monetary motives and fairness preferences. Workers expressing fairness preferences responded with lower performance after the introduction of a platform fee, even when they switched platforms. Finally, a policy regime with reputation portability has a positive impact on working conditions in terms of wages. By decreasing lock-in effects, the right to reputation portability, among other efforts, could help improve the position of online workers.

A key contribution of this paper is that we study not only the impact of a platform fee on switching behavior, but also workers' motivation to switch, and their performance after a fee is introduced. The study therefore has direct managerial implications with regards to platforms' business strategy, because it sheds light on the negative effect of capitalization of lock-in effects on workers' effort levels. Notably, our results may also be applicable to other online marketplaces where users rely on reputation, but reputation is not portable across platforms and multi-homing is difficult. For example, on e-commerce platforms like Amazon and eBay, the impact of platform fees on switching behavior could be similar for sellers in the policy regimes under consideration.

We further contribute to the current regulatory debate on data portability. To address lock-in effects and switching costs generated by data, regulators have already taken actions in the form of data privacy laws (Hesse and Teubner, 2019). The objective of such regulations is to both enhance data ownership and foster competition (Engels, 2016; De Hert et al., 2018). The most notable example is Article 20, the Right to Data Portability, of the European Union's General Data Protection Regulation (GDPR), which stresses that individuals have the right to request their own data, and transfer them to other online providers without difficulty.[3] According to current legal interpretations, reputation data do not fall under the scope of Article 20 because ratings are provided by reviewers and not the user, such that a user does not legally own their reputation data (Graef et al., 2013; Diker Vanberg and Ünver, 2017).

[3]Other 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.

According to Kathuria and Lai (2018) and Hesse and Teubner (2019), reputation portability as outlined in Article 20 could help overcome lock-in effects and increase users' negotiation power.

However, further regulatory action may be necessary, because platforms do not naturally allow users to import or export their reputation data.[4] Although Amazon previously allowed sellers to import their reputation 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). Still, it is technically feasible to transfer reputation data: when the dog sitting platform Rover merged with DogVacay, it gave DogVacay's users an easy path to transfer their ratings and transaction history to its platform (Farronato et al., 2020). Our study makes an important contribution to this debate by showing that reputation portability reduces lock-in effects of workers in online labor markets and also demonstrates the positive effects of a portability regime on workers' wages.

The remainder of the paper is organized as follows: In Section 2, we relate our research question to the 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 paper.

2. Related Literature

Related research can be divided into three categories: studies that investigate switching costs, studies that explore data portability, and studies that focus on online labor markets.

First, our paper is closely related to research studying switching costs (Klemperer, 1987a,b, 1995; Farrell and Shapiro, 1988, 1989). 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 the strength of lock-in. Switching costs can result from 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. To the best of our knowledge, only one study experimentally investigates switching behavior while considering the strength of lock-in effects. Eurich and Burtscher (2014) conduct an online lab experiment with students to determine the consequences of changes in the business-to-consumer relationship. Increased prices, data leakages, and

[4] 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).

privacy violations can have negative consequences for the business and lead consumers to choose a competitor, despite the costs of switching. In our setting, online 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 build a strong reputation and maintaining it over time (Fehr and Goette, 2007; Mason and Watts, 2009; Cabral and Xu, 2021). Our work is therefore complementary to the working paper by Eurich and Burtscher (2014), because it focuses on online workers' reputation formation and platform subscription choice, while at the same time studying possible lock-in capitalization by platforms.

Second, we provide insights into the debate on reputation portability and, more generally, data portability. To date, research has focused on the influence of reputation within an online platform, examining buyers willingness-to-pay for vintage postcards on eBay (Resnick et al., 2006) or the necessity of reputation mechanisms to provide category-specific feedback in online labor markets (Kokkodis and Ipeirotis, 2016). On the demand side of the market, reputation portability across task categories can help contractors make better hiring decisions (Kokkodis and Ipeirotis, 2016). In addition, a star rating on one platform can serve as an additional signal to build trust in service providers who have not yet received a rating on another platform (Otto et al., 2018), especially if the cross-platform signaling takes place in the same industry as the originating platform (Teubner et al., 2019; Hesse et al., 2020). With regards to the general idea of data portability between platforms, existing studies refer mostly to legal and technical dimensions (Dellarocas et al., 2006; Engels, 2016; De Hert et al., 2018; Krämer and Stüdlein, 2019; Wohlfarth, 2019).

Theoretical papers suggest that data portability generally has a positive effect on user welfare and can increase platform competition in online markets (Krämer and Stüdlein, 2019; Wohlfarth, 2019). However, data portability may also increase platforms' willingness to extract and disclose more data. Our study is conceptually different from all these previous works, because we analyze the supply side of online labor markets and consider lock-in capitalization by platforms and what would happen if reputation data of workers could be transferred across platforms. Thus far, none of these works studied the economic consequences of reputation portability on workers' surpluses. Hesse and Teubner (2019) provide a conceptualization and review of reputation portability that leads them to call for empirical and experimental studies to assess the economic value of cross-platform reputation mechanisms. Furthermore, existing literature on switching costs tends to assume scenarios with consumers being homogeneous with respect to their switching costs (Gehrig and Stenbacka, 2004). In reality, however, weak and high-performing users might suffer from lock-in differently and benefit differently from data portability rights. The Right to Data Portability under the GDPR has been in force since 2018, but so far there are only few empirical and theoretical studies on its economic consequences and none focuses on the consequences for online workers, which is also emphasized in an article by Krämer (2021), assessing the economic implications of Article 20 GDPR.

Finally, our paper also relates to the literature that focuses on online labor markets. 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 vulnerable and susceptible to capitalization. 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; Berg et al., 2018; Johnston et al., 2018). Risks historically borne by employees 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 (Borchert et al., 2018; Hornuf and Vrankar, 2022). Wood et al. (2019) evaluate job quality in online labor markets and 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. Gomez-Herrera et al. (2022) show that online labor markets can effectively impose higher fees on a portion of its workers without affecting labor demand or final prices. Workers are unable to pass on costs to contractors because they are competing with workers who are able to accept lower wages. The right to reputation portability, among other efforts, could help improve the position of online workers by decreasing their platform dependency. In an effort to understand switching behavior when lock-in effects are capitalized by platforms and to study the impact on reputation portability, we show that a policy regime with reputation portability can affect switching costs. Moreover, such a policy regime might not only reduce the likelihood of workers being capitalized by platforms, but also improve workers online working conditions in terms of higher wages.

3. Theoretical Framework

We first aim to derive formal, testable hypotheses. Second, we determine, with some simplifying assumptions, whether a platform can lock workers in using platform-specific reputation mechanisms, which in turn would enable it to capitalize locked-in workers. 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 that 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. The worker and the platform have incomplete information about the worker's talent and they share a common prior belief about η. This prior belief is normally distributed, with mean m_1 and precision h_1, with precision being defined as the inverse of the variance. Over time, the demand side of the platform learns about the talent of the worker 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:

$$c_t = f + w_t(\mathbf{r}_{t-1}), \tag{2}$$

where $f > 0$ is an exogenous fixed amount granted to workers who have completed a task, independently of their performance,[5] and $w_t(\mathbf{r}_{t-1})$ is the premium associated with the average of past ratings ($\mathbf{r}_{t-1} = r_0; ...; r_{t-1}$) 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 contractors (i.e., the demand side of the platform), who, upon posting the labor requests on the platform, set the premium in line with the average rating of the worker:

$$w_t(\mathbf{r}_{t-1}) = E[r_t|\mathbf{r}_{t-1}] = E[\eta|\mathbf{r}_{t-1}] + a_t(\mathbf{r}_{t-1}), \tag{3}$$

where $a_t(\mathbf{r}_{t-1})$ is the labor input, as the best response of the worker. Platforms act as intermediaries, and they charge an ad valorem fee, required after each transaction, for the intermediation service.[6] We assume this fee is applied directly to the workers' premium

[5]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.

[6]For example, Amazon marketplaces charges fees ranging from 7 to 45%, depending on the product category (https://sellercentral.amazon.com/help/hub/reference/external/200336920); Airbnb charges 3% (https://www.airbnb.com/resources/hosting-homes/a/how-much-does-airbnb-charge-hosts-288?_set_bev_on_new_domain=1664465164_YTM4OWM2OTk2MGYz&locale=en); and online labor platforms such as AMT (https://www.mturk.com/pricing) and TaskRabbit (https://support.taskrabbit.com/hc/en-us/articles/204411610-What-s-the-TaskRabbit-Service-Fee-) charge 20% and 15%, respectively.

revenue. A worker's atemporal utility function is thus:

$$U(c,a,\phi) = \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)] - \sum_{t=k}^{\infty} \beta^{t-1}\phi c_t, \tag{4}$$

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 increases its fee to $\phi \in [0,1]$,[7] and before k, the fee is normalized to 0.[8] The outside option for the worker is to not work, which provides utility equivalent to 0. Using Equations (2), and (4), we can write the problem of the worker for maximizing expected utility as follows:

$$\max_{a(\cdot)} \sum_{t=1}^{\infty} \beta^{t-1}[f + Ew_t(\mathbf{r}_{t-1}) - Eg(a_t(\mathbf{r}_{t-1}))] - \sum_{t=k}^{\infty} \beta^{t-1}\phi[f + Ew_t(\mathbf{r}_{t-1})]. \tag{5}$$

The contractors cannot observe workers' labor input directly, but because Equation (4) is general knowledge, we can use it to infer a_t by solving the workers' maximization problem. Moreover, observing r_t is equivalent to observing the sequence

$$z_t \equiv \eta + \epsilon_t = r_t - a_t(\mathbf{r}_{t-1}). \tag{6}$$

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 m_{t+1} and precision h_{t+1} given by, respectively,

$$m_{t+1} = \frac{h_t m_t + h_\epsilon z_t}{h_t + h_\epsilon} = \frac{h_1 m_1 + h_\epsilon \sum_{s=1}^{t} z_s}{h_1 + t h_\epsilon}, \tag{7}$$

$$h_{t+1} = h_t + h_\epsilon = h_1 + t h_\epsilon. \tag{8}$$

By applying Equation (7), we then can write Equation (3) as:

$$w_t(\mathbf{r}_{t-1}) = m_t(\mathbf{z}_{t-1}) + a_t(\mathbf{r}_{t-1}). \tag{9}$$

[7]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.

[8]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). In 2022, five thousands sellers on Etsy.com went on 'strike' after the platform announced record revenues and a 30% fee increase (see https://www.theverge.com/2022/3/30/23001727/etsy-seller-strike-boycott-fee-increase).

The expected premium associated with the past rating is:

$$Ew_t(\mathbf{r}_{t-1}) = \frac{h_1 m_1}{h_t} + \frac{h_\epsilon}{h_t}\sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1}). \tag{10}$$

From Equation (10), 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 $\alpha_t = h_\epsilon / h_t$, irrespective of labor inputs in other periods. The maximization problem in Equation (5) is then:

$$\begin{aligned}\max_{a(\cdot)} \sum_{t=1}^{\infty} \beta^{t-1}[f + \frac{h_1 m_1}{h_t} + \alpha_t \sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1}) - Eg(a_t(\mathbf{r}_{t-1}))] - \\ - \sum_{t=k}^{\infty} \beta^{t-1}\phi[f + \frac{h_1 m_1}{h_t} + \alpha_t \sum_{s=1}^{t-1}(m_1 + a_s - Ea_s(r^{s-1})) + Ea_t(\mathbf{r}_{t-1})].\end{aligned} \tag{11}$$

Next, we maximize Equation (11) with respect to a_t and obtain, after rearranging:

$$\sum_{s=t}^{\infty} \beta^{s-t}\alpha_s - \sum_{s=t}^{\infty} \beta^{s-t} I_s \phi \alpha_s = g'(a_t(\mathbf{r}_{t-1})), \tag{12}$$

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 tends to infinity, α_s tends 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 (12) against the first-order condition in Holmström (1999),[9] we can observe that the marginal return to labor supply decreases with the fee requested by the platform.

[9] In Holmström (1999):

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

3.1. Ratings as Switching Costs

Consider now a setting with two identical platforms. In line with the current regulatory situation in Europe, we start with a scenario in which no reputation portability is possible. Then for a second, hypothetical regulatory regime, we imagine a policy setting that features reputation portability. Then we presume the right to data portability provided by Article 20 of the GDPR would also include reputation data.

Policy Regime without Reputation Portability

Two platforms (% and #)[10] 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 be transferred to the other platform. Platforms 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 capitalize on 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 is passed on to users. For example, Google passed the cost of the UK's digital services tax on to British advertisers, raising its fees by 2%.[11]

Assume workers are not aware of the fee until time k,[12] at which moment, they have two choices: (1) remain on Platform%, to keep benefiting from the reputation investment made so far but have their income reduced by the increased fee, or (2) switch to Platform#, which does not impose a fee but requires workers 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 (7) 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.[13] Thus, after time k, workers face a new problem and will stay on Platform% if

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

The left-hand side of inequality (13) represents the utility of the worker, reduced by the fee, associated to the decision of staying on the platform. The right-hand side, instead, represents

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

[11] See https://www.theguardian.com/media/2020/sep/01/googles-advertisers-will-take-the-hit-from-uk-digital-service-tax.

[12] Otherwise, they would realize that subscribing to Platform# is always more profitable.

[13] Imagine a worker with a good reputation on Platform%, which informs this worker of their 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.

the utility of the worker associated with the decision of switching to the other platform. 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, diminished by the fee.[14] 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 (13) implies that the fee increase does not trigger switching provided that the following inequality is satisfied:

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

Because it is not possible to find an analytical solution to Equation (14), in Online 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.

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 maximum fee compatible with no switching 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 1: *A policy regime without reputation portability enables the creation of switching costs, implying that workers are willing to pay a positive fee to stay on the platform they have built their reputation on.*

Other factors could explain switching behavior by workers. Considering the game structure and that of the experiment, workers' switching behavior may be motivated by monetary motives *and* fairness preferences. It is important to study and verify if workers feel they are treated unfairly because it not only influences the possible switching decision, but it can negatively affect workers' performance, which, in turn, can decrease the overall appeal of online labor markets. Workers with fairness preferences face an additional disutility when the

[14] In the experiment, we also consider the switching behavior of workers if two platforms equally capitalize on them, such that both introduce the fee simultaneously. In that case, the inequality (13) 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 capitalization of lock-in effects, we expect that workers are less likely to switch if platforms equally capitalize on their workers.

platform introduces a fee because they also perceive it as unfair. Thus, the fee in Equation (14) would not be compatible with the no switching condition 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

$$\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] - \delta(\phi) \geq \sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)]. \tag{15}$$

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 (13). Respondents with $\delta \rightarrow \infty$ always switch, because they have strong 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 (15) 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 reputation 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 streams between the two platforms are identical, then, as a tie-breaking rule, we expect workers with fairness preferences to switch. Applying these considerations, we offer the following hypothesis:

Hypothesis 2: *Workers with fairness preferences are ceteris paribus willing to pay a lower fee to stay on the platform they have built their reputation on.*

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 reputation investments and can easily switch between platforms.[15] 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 0.

[15] 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.

Hypothesis 3: *In a policy regime with reputation portability, workers that have built a reputation do not accept any fee because there are no switching costs.*

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 $2 \times 2 \times 2$ 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. 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 amount (equal platforms) and (2) platforms are asymmetric, because only the platform the participant currently works on charges a fee while the other one does not (asymmetric platforms). Recall that participants are randomly assigned to these two platform conditions with 50% probability.

In our experiment, there was no human interaction between platform provider and worker, because a pre-programmed mechanism decided to introduce and increase a fee. Therefore, it could be argued that workers may not have been prompted to switch platforms or show fairness preferences. Blount (1995) notes 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. We nevertheless assume that the participants' reactions should mimic the real-life responses of online workers, because we recreate the working conditions and environment for workers on online platforms (Henrich et al., 2001). Finally, if the proposer's machine identity influences the responder's reaction, the effect sizes we identify would form lower bounds and represent conservative estimates.

We 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 be elicited when participants' ratings are portable and the platforms 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 platform capitalization due to lock-in effects. In the experiment, the platform fees take varying levels ($0.00, $0.01, $0.05), which allows to compare switching behavior with an initial fee of $0.01 (i.e., low capitalization of lock-in) versus an initial fee of $0.05 (i.e., high capitalization of lock-in).[16] If a platform introduces a fee of $0.01, there is a 25% probability in each subsequent round that the fee will increase to $0.05, which will remain in effect until the end of the experiment. To test for second-order effects of the frequency of lock-in capitalization, 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, which consisted of 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

[16]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.

complete a task was $0.10. The rating, which is based on participants' performance, also affected their 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. During the first three rounds, we avoided charging fees so that participants could establish a rating first, which created the possibility of lock-in.

4.3. Sample

The study participants were recruited from AMT, an online marketplace for crowdsourcing microtasks, i.e. small and repetitive tasks including answering surveys, testing websites or categorizing images (Amazon Mechanical Turk, 2022c). On AMT, contractors post tasks, called Human Intelligence Tasks (HITs), in the form of an open call to geographically dispersed workers. Workers can choose between the available HITs for which they will be paid. Contractors can then either accept or reject the completed task. To signal the quality of workers, AMT uses different qualification types: the HIT approval rate—the rate of approved tasks that workers have completed in the past—and the master qualification, which is awarded to workers who have demonstrated excellence by completing a wide range of HITs on AMT (Amazon Mechanical Turk, 2022b). The resulting qualification types can serve as exclusion criteria for contractors, because they indicate certain qualifications of workers before HITs are posted. For each HIT, contractors have to pay a 20% fee on the amount they pay workers, plus an additional 20% fee if more than ten HITs are published (Amazon Mechanical Turk, 2022a). While the fees are paid by contractors, we assume a full pass through of the fee from the contractors to the workers. In a similar vein, Semuels (2018) has noted that AMT has doubled its fees since 2015, which resulted in workers complaining about contractors offering less money.

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 (Paolacci et al., 2010; Sprouse, 2011; Crump et al., 2013; Litman et al., 2015; Buhrmester et al., 2016; Hillebrand et al., 2023).

The participants were all at least 18 years of age and citizens or legal residents of the United States.[17] 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[18] 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 of 1 in every round or who consistently failed to identify the correct number of zeros (i.e., were accurate no more than twice). This allowed us to 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, we first present evidence whether platform fees trigger switching behavior of online workers. Then we analyze the role of reputation portability on switching behavior. Next, we examine workers' motives to switch platforms and concentrate our analysis on monetary motives and fairness preferences. We then focus on the effect of reputation portability on working conditions in online labor markets. Finally, we investigate how the strength and frequency of the platform's capitalization of workers' lock-in influence switching behavior. When comparing the means across treatments, we apply two-sample chi-square tests of proportions, Fisher's exact tests, and two-sample t-tests.[20]

The Impact of a Fee Introduction on Switching Behavior

With a within-subject analysis, we first 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.[21] Figure 1 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

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

[18] Some participants reported working a total of more than 110 hours per week or responded that they work more than 150 hours per week on crowdsourcing platforms. In addition, there were also workers who reported earning more than $3,000 and up to $78,000 per week from crowdsourcing.

[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).

[20] Table 2 provides a randomization check using F-tests to determine whether the computerized randomization created a balanced sample. 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. We therefore include these variables as control variables in our regression analyses presented in Tables 3 to 5.

[21] In the round the fee was introduced, 10.8% had a rating of less than 3.50, 14.9% had a rating between 3.50 and 4.49, and 74% had a rating greater than 4.50.

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 2 also reveals that this effect is driven mostly by switching behaviors if platforms are asymmetric. Switching platforms prior to a fee might be explained by curiosity, a strategic desire to build good ratings on multiple platforms to avoid the costs related to a lack of reputation portability,[22] 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.[23] We summarize this finding as follows:

Result 1. *Introducing a platform fee increases switching behavior, if platforms are asymmetric.*

— Figures 1 to 2 about here —

The Effect of Reputation Portability on Switching Behavior

Can a policy regime that mandates reputation portability mitigate the lock-in effects in online labor markets? To answer this question, we compare switching behavior after a platform introduces a fee in regimes with and without reputation portability. As noted previously, if switching increases more in the a policy scenario with portability, it offers evidence that workers are vulnerable to lock-in effects that arise in the absence of reputation portability. As detailed in Figure 3, 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, $z = 1.380, p = 0.168$), which is in line with Hypothesis 1, stating that platforms can capitalize lock-in effects in a policy regime without 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 significant (two-sample chi-square test of proportions, $z = 7.643, p < 0.001$). The difference between these increases (5 versus 23.8 percentage points) also is statistically significant (Fisher's exact, $p < 0.001$), supporting Hypothesis 3 that the policy regime with reputation portability increases the probability of switching platforms. Therefore,

Result 2. *Platforms can capitalize 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 at risk from the imposition of a platform fee.*

[22] 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."

[23] 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, $t = 5.975, df = 5,049, p < 0.001$). 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.

— Figure 3 about here —

The Motives to Switch Platforms

We now analyze more thoroughly *why* participants switch platforms in response to a fee, and how reputation portability affects these switching motives. 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 might switch to another platform, even if they earn the same or a lower wage. But if workers earn a higher wage on the other platform, they could be motivated by both their fairness preferences and their monetary motives. Additionally, their behaviors also should depend on their tolerance level for fees.

Of the 1,349 participants who encountered a fee, 417 would have earned a higher wage on the other platform, so their platform switching might reflect monetary motives, fairness preferences, or both. As displayed in Figure 4, 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. Overall, 194 (20.8%) workers switched platforms (148 who earned an equal wage and 46 participants who earned less), exhibiting their fairness preferences.

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, $t = -59.512, df = 931, p < 0.001$) from the 78.4% fraction of workers whose switching behavior signaled fairness preferences and/or monetary motives (t-test against zero, $t = -10.700, df = 416, p < 0.001$). The difference of 57.6 percentage points identifies workers who switched solely for monetary reasons. 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 2, in which we predicted that workers with fairness preferences are ceteris paribus willing to pay a lower fee to stay on the platform they have build their reputation on. When we consider switching behavior after a fee introduction for each portability regime separately (see Figure 5), 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, $z = 2.437, p = 0.015$). Interestingly, this result may suggest that workers with fairness preferences are more willing to punish the platform by switching if they are allowed to take their data with them. Since workers do not lose their ratings when they switch, punishment costs are lower. If participants earn more on the other platform after the fee is introduced, switching behavior in a policy regime with reputation portability increases from 72.6% to 80.1%. However, this difference is not statistically significant (two-sample chi-square test of proportions, $z = 1.346, p = 0.178$). Formally:

Result 3. *If a platform introduces a fee, 57.6% of workers switch based on monetary motives, and 20.8% switch due to fairness preferences. Moreover, the costs of "punishing" the platform by switching are lower for workers in a policy regime with reputation portability, as switching based on pure fairness preferences increases from 15.4% to 30.2%.*

— Figures 4 to 5 about here —

By investigating differences in their ratings in each round before and after a fee introduction, we test if workers perform differently after a newly imposed fee than before the fee. In Table 3, we present the results of ordinary least squares regressions and assess the *Rating in Round t* on the platform on which the participant currently works as the dependent variable. Our variable of interest is *Period after Fee*, which is equal to 1 in the rounds after the fee was introduced and 0 in prior rounds. In column 1, we investigate differences in performance for all workers who encountered a fee. Their rating in each round decreases significantly by 0.13 after the fee introduction, holding all other variables constant. In addition, we find that workers exhibit poorer performance than they did before the fee introduction if they (i) expressed fairness preferences (column 3), (ii) confronted a fee and a higher wage on the other platform but did not switch (column 4), and (iii) confronted a fee and the same or lower wage on the other platform and also did not switch (column 5). For workers who switched to a platform with a higher wage after the introduction of a fee (column 2), the difference in lowered performance is only weakly significant at the 10% level. These results are in line with our theoretical model, in which workers who confront a lower wage reduce their equilibrium effort accordingly, and with Fehr et al. (1993) and Fehr and Falk (1999), who find that workers might reciprocate by lowering their effort in response to low wages.We conclude:

Result 4. *Except for workers who switch due to monetary motives when a platform introduces a fee, workers performance generally decreases after experiencing a fee.*

— Table 3 about here —

To validate 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 participants tend to prefer outcomes with low uncertainty over those with high uncertainty (Kahneman et al., 1991; Tversky and Kahneman, 1991), and ambiguity-averse participants prefer known over unknown risks (Ellsberg, 1961; Camerer and Weber, 1992). In addition to testing for the effects of risk attitudes, that is 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 we asked participants to choose their preferred lifetime earnings profiles (Butler et al., 2014). 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 socio-economic panel (DIW, 2023), 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.[24] The dummy variables *Boredom*, *Curiosity*, *Poor Rating*, *Earn Higher Wages*, *Fee Perceived as Unfair*, and *Other Reason* 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. The baseline category is *No Switching*. In addition, we control for the extent of lock-in by including participants' *Average Rating in Round k* and the *Round k*, i.e., the round the fee is introduced.

The probit regression involves only those participants who confronted a fee at some point during the experiment. The dependent variable is the dummy variable *Switching*, which indicates whether the worker switched platforms during the round of the fee introduction. The results in Table 4 corroborate our main findings. In column 1 participants' average rating has a negative effect on their switching behavior after the fee introduction. If the average rating (*Average Rating in Round k*) increases by one unit, the probability of switching decreases by 7.7% in response to a platform fee, all 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 (*Fee Perceived as Unfair*) significantly increase the likelihood that participants switch platforms. In detail, an opportunity to earn higher wages increases switching behavior by 27.8%, holding all other variables constant. Perceiving the fee as unfair increases this behavior by 18.2%, all else being equal. Our findings regarding fairness preferences remain consistent in column 2, where we specifically focus on participants who expressed pure fairness preferences. 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:

[24] 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.″

Result 5. *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 —

Did a significantly higher proportion of participants who switched and exhibited fairness preferences report perceiving the fee in the questionnaire as unfair compared to other participants who were also confronted with the fee? We conduct a Fisher's exact test and find that 39.7% of workers with fairness preferences, but only 27.5% of all other workers, reported that they perceived the fee as unfair in the questionnaire. This difference is statistically significant ($p = 0.001$), which implies that workers who expressed fairness preferences perceived the fee indeed as more unfair.

The Effect of Reputation Portability on Working Conditions

Next, we investigate the effect of a policy regime with reputation portability on working conditions in online labor markets. We begin with an analysis of switching behavior in both policy regimes, accounting for worker reputation. In our experimental setup, a rating greater than 3.50 is associated with higher wages. We thus anticipate that the lock-in effects might be particularly strong for highly rated workers. Figure 6 sheds light on the differential switching behaviors. Workers with ratings below 3.50 switch significantly more often in rounds prior to the fee if reputation is not portable across platforms compared to when that is the case (two-sample chi-square test of proportions, 66.4% vs. 39.1%, $z = -4.596, p < 0.001$). After a fee is introduced, the difference in switching behavior for workers with poor ratings is only weakly significant at the 10% level and differs by 17.4 percentage points between the two policy regimes, 75.6% versus 58.2% (two-sample chi-square test of proportions, $z = -1.769, p = 0.077$). One could argue that a policy regime that allows for reputation portability could potentially increase the quality of the signal of workers' talents. In such a scenario, poorly rated workers are less likely to switch frequently, because they are unable to erase their rating history. However, high-quality workers switch more often after the introduction of a fee because expressing their preferences is associated with less costs than in a policy regime without reputation portability. When confronted with a fee, we find that workers with ratings higher than 3.50 switch significantly more often in a policy regime with reputation portability than do workers with comparable ratings but without reputation portability (two-sample chi-square test of proportions, for ratings between 3.50 and 4.49, 20.5% vs. 46.9%, $z = 1.978, p = 0.048$; for ratings greater than 4.50, 14.6% vs. 55.8%, $z = 6.304, p < 0.001$). In summary, a policy regime with reputation portability leads to more platform switching after a fee is introduced among high-quality workers.

We continue by analyzing the effect of a policy regime with reputation portability on workers' wages, if these workers experienced platform capitalization. In Table 5, we run several ordinary least squares regressions with the *Total Wage* the participant earned by the end of the experiment as dependent variable. Our variable of interest is *Portability*, which is a dummy variable equal to 1 if the worker was assigned to the a policy regime with portability and 0 otherwise. Considering all ratings by the end of the experiment in column 1, the effect of portability on earnings is only weakly significant at the 10% level. In column 2, we run the same regression for workers with a rating of less than 3.50 at the end of the experiment. We find that a policy regime with portability decreased these workers' total wages by $0.13, holding all other variables constant. For workers that encountered a rating between 3.50 and 4.49 in the last round, we do not find an effect of reputation portability on wages (column 3). Lastly, we evidence that a rating greater than 4.50 at the end of the experiment significantly increased workers' total wages by $0.07, all else equal. Our findings suggest that a regulatory regime with reputation portability can function as a mechanism to empower in particular highly rated workers in online labor markets. We summarize these findings as follows:

Result 6. *Lock-in effects affect high-quality workers more than poorly rated workers. In addition, a policy regime with reputation portability increases high-quality workers' wages and significantly decreases wages of workers with a poor rating.*

— Figures 6 and Table 5 about here —

The Strength and Frequency of Capitalizing 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 capitalization of lock-in) or $0.05 (high capitalization of lock-in). Once participants were subject to this platform fee, it remained in effect, but we also allowed platforms that introduced a fee of $0.01 to raise it to the $0.05 in each following round, again with a probability of 25%. With this mechanism, we can determine if high initial capitalization of lock-in effects triggers significantly more switching than a lower initial level of capitalization. Furthermore, we test whether the frequency of fee increases 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.

We start our investigation with the role of fee size on switching behavior. As depicted in Figure 7, 35% of participants switch platforms on average if the platforms introduce a 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 7.1 percentage points, which is only weakly significant at the 10% level (two-sample chi-square test of proportions, $z = 1.649, p = 0.099$). As detailed in Figure 8, the result is driven by switching behavior if platforms are asymmetric (two-sample chi-square test of proportions, 48.5% vs. 61.9%, $z = 2.581, p < 0.001$). With regards to the portability regimes, we do not find a significant effect between switching behavior and the levels of capitalization of lock-in (Figure 9. However, regardless of the size of the fee introduction, we evidence that switching is significantly larger in a policy regime with reputation portability, which again highlights that workers are less vulnerable to platform capitalization (two-sample chi-square test of proportions, fee of \$0.01, 19.6% vs. 50.6%, $z = 4.299, p < 0.001$; fee of \$0.05, 26.8% vs. 58.2%, $z = 5.019, p < 0.001$). Formally:

Result 7. *If platforms are asymmetric, workers are more likely to switch when the platform they work on immediately introduces a high fee rather than a low fee.*

— Figures 7 and 9 about here —

To determine if the frequency of lock-in capitalization by platforms affects switching behavior, we test for a difference in platform switching between participants immediately confronted with a \$0.05 fee versus those who first experienced a fee of \$0.01 and then a fee of \$0.05 in a later round.[25] As Figure 10 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, $z = 3.004, p = 0.003$). This result is explained by switching behavior if platforms are asymmetric (see Figure 11, two-sample chi-square test of proportions, 16.7% vs. 61.9%, $z = 3.332, p < 0.001$) and by switching platforms in a policy regime with reputation portability (see Figure 12, two-sample chi-square test of proportions, 28.4% vs. 58.2%, $z = 3.090, p < 0.001$). In a policy regime without reputation portability, or if the platforms are perfectly identical, we do not find a significant effect. This finding is in line with our model prediction: as platforms equally capitalize on their workers, or as workers are unable to transfer their ratings, the utility associated with the decision of switching is relatively low and can hardly trigger switching (see Equation 13). In summary,

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. In a policy regime with reputation portability, workers are also less likely to switch in a situation with rising subsequent fees, whereas in a policy regime without reputation portability, the frequency of fees does not affect switching behavior.*

— Figures 10 to 12 about here —

[25] If both platforms are perfectly identical, it does not matter if workers are currently active on Platform% or Platform#, because they have to pay the fee on both platforms regardless of their switching behavior. Recall that if platforms are asymmetric, only the platform the worker currently works on introduces (and potentially later increases) a fee, while the other platform never charges a fee. Therefore, in the case of asymmetric platforms, we consider participants who did not switch platforms after the \$0.01 fee introduction and thus faced a fee increase to \$0.05.

6. Conclusion

This study represents a first effort to investigate the capitalization of lock-in effects by online platforms and the influence of reputation portability on lock-in effects and lock-in capitalization of workers. 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 capitalize their reluctance to switch. Experimentally, we conduct an online lab-in-the-field decision experiment and evidence that platforms can capitalize lock-in effects more intensely when reputation portability mechanisms are absent. Moreover, by disentangling switching behavior based on monetary motives and fairness preferences, we find that a policy regime with reputation portability substantially increases workers' switching behaviors, mainly due to monetary incentives, though fairness preferences also play a role. Our data further show that a fee charge has a negative impact on worker performance.

Our paper has direct implications for regulatory authorities and platform managers. First, the results show that reputation portability is valuable for workers to avoid platform capitalization, a goal that is particularly important in online labor markets where workers rely on valuable ratings of their quality and often face precarious working conditions, significant setup costs, and limits to multi-homing. The current analysis also informs questions about whether reputation 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 to make data easily transferable, we recommend the imposition of reputation portability rules to mitigate lock-in effects and improve the working conditions of high-quality online workers. In the European context, the introduction of reputation portability would mean to extend Article 20 GDPR, the Right to Data Portability, because reputation data do not fall within the scope of Article 20. In addition, introducing reputation portability in online labor markets could increase competition among platforms, which improves the bargaining power of workers. Second, our work also has managerial implications with regards to platform pricing. By distinguishing different switching motives, we show that workers respond with a lower performance after a platform introduces a fee, even after workers switched platforms. Therefore, the capitalization of worker lock-in through a platform specific rating could have a non-positive effect for platforms after all.

As relevant extensions to our work, we offer several potential options. First, we consider specifically the portability of reputation data mandated by regulation, but other designs, such as the right but not the obligation to transfer ratings to other platforms, also might influence lock-in capitalization and thus switching behavior (Hesse and Teubner, 2019). Second, researchers might address how platform competition changes when regimes implement reputation portability. In the presence of reputation portability, platforms may have greater incentives to coordinate on prices but are less motivated 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). Lower profit because of lower lock-in effects should a priori not jeopardize online platforms' investments when reputation becomes portable, as the virtual infrastructure may have similar or even lower maintenance and development costs. 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 reputation data as a positive signal. We leave this question for further research.

Acknowledgements

This research paper evolved as part of the research project "Crowdsourcing as a new form of organizing labor relations: regulatory requirements and welfare effects," supported by the Deutsche Forschungsgemeinschaft (DFG) under grant DFG HO 5296/3-1. Financial support from FNRS-FRESH is gratefully acknowledged by Fabrizio Ciotti. The authors thank Paul Belleflamme, Andreas Engert, Rosa Ferrer, Ximena Garcia-Rada, Johannes Johnen, Christoph Merkle, Sharon Parker, Johannes Rincke, Michelangelo Rossi, Geza Sapi, Martin Spann, Leonard Treuren, Georg Weiszäcker, Lauri Wessel, Youngjin Yoo, Gül Yüksel, and Stefan Zeisberger, as well as workshop and seminar participants at Maastricht University, the MaCCI Annual Conference 2023, the 5$^{\text{th}}$ IDSC of IZA Workshop, the 16$^{\text{th}}$ International Conference on Competition and Regulation (CRESSE), the Humboldt University Behavioral/Experimental Economics Reading Group, the LMU conference in honor of Andreas Haufler's 60$^{\text{th}}$ birthday, the Padova DaTEPP Seminar, the CESifo Area Conference on the Economics of Digitization 2021, the Oxford Platform Economy Seminar, the XXXV Jornadas de Economía Industrial, the 9$^{\text{th}}$ Competition and Innovation Summer School, the Research Seminar at Skema Business School Paris, the 3$^{\text{rd}}$ Crowdworking Symposium, the Diginomics Brownbag Seminar, and the Field Day in Field Experiments at the University of Bremen for their valuable comments and suggestions. They also thank the online Amazon Mechanical Turk workers for participating in the experiment. Jannik Althof provided excellent research support.

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Figures and Tables.

Figure 1: Fee Introduction

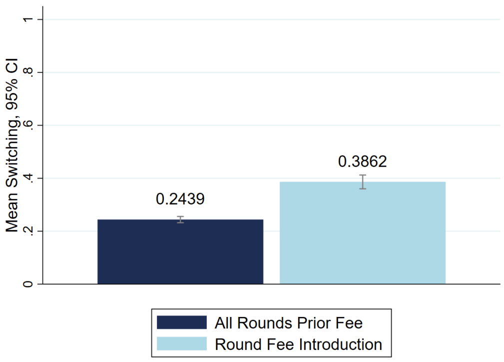


Figure 2: Fee Introduction and Platform Symmetry

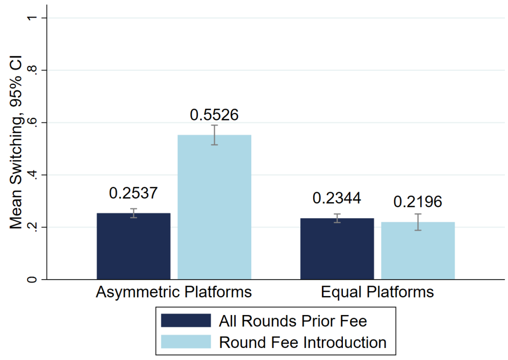


Figure 3: Portability Regime

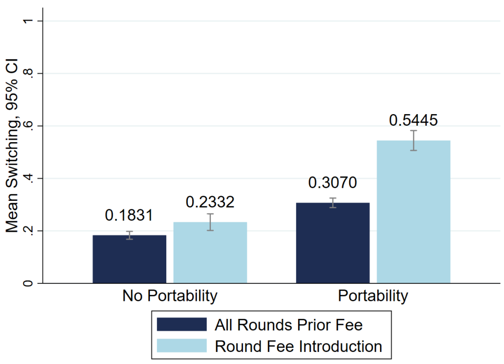


Figure 4: Monetary Motives and Fairness Preferences

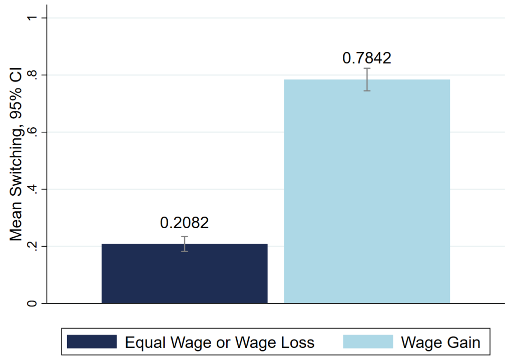


Figure 5: Monetary Motives, Fairness Preferences, and Portability Regime

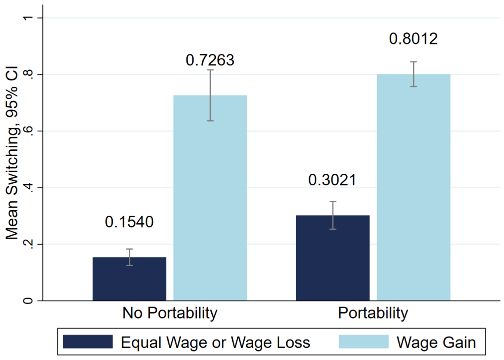


Figure 6: Ratings and Portability Regime

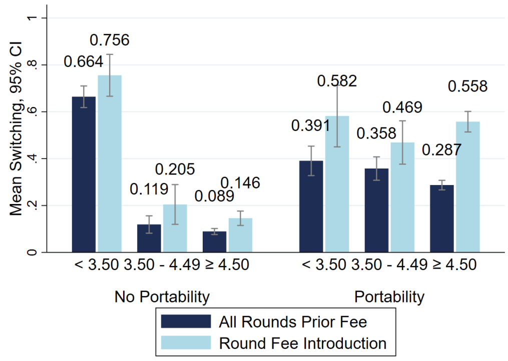


Figure 7: The Strength of Capitalizing Lock-In Effects

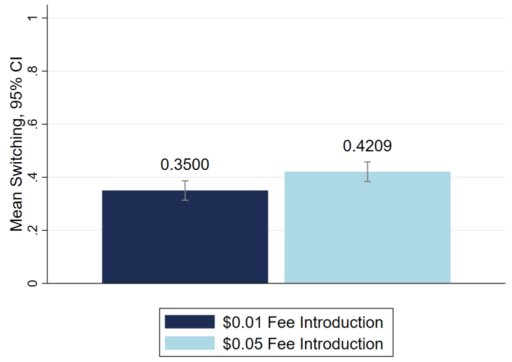


Figure 8: The Strength of Capitalizing Lock-In Effects and Platform Symmetry

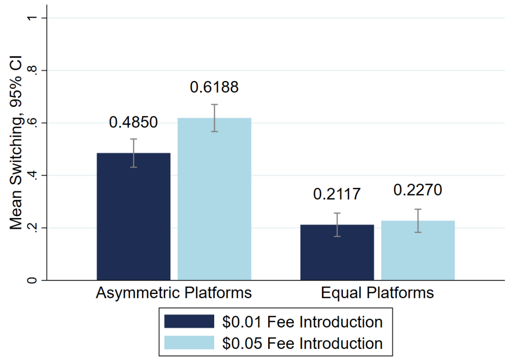


Figure 9: The Strength of Capitalizing Lock-In Effects and Portability Regime

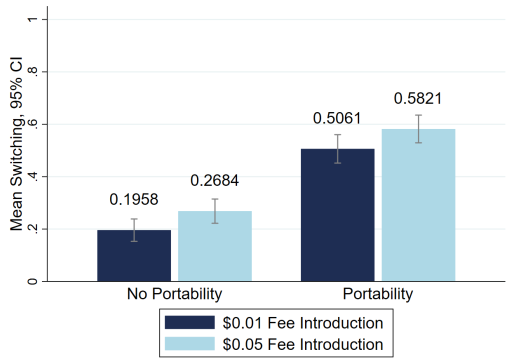


Figure 10: The Frequency of Capitalizing Lock-In Effects

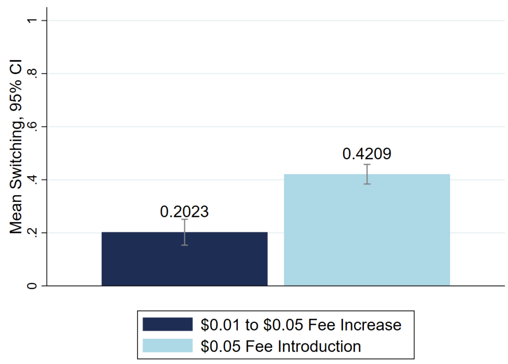


Figure 11: The Frequency of Capitalizing Lock-In Effects and Platform Symmetry

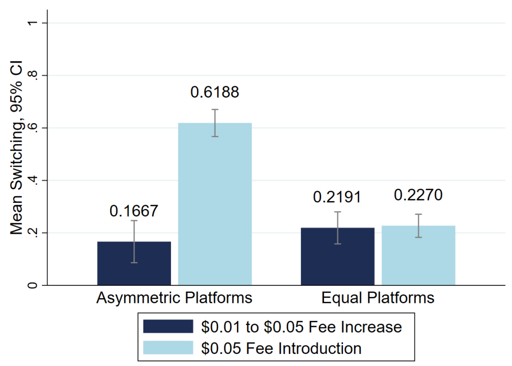


Figure 12: The Frequency of Capitalizing Lock-In Effects and Portability Regime

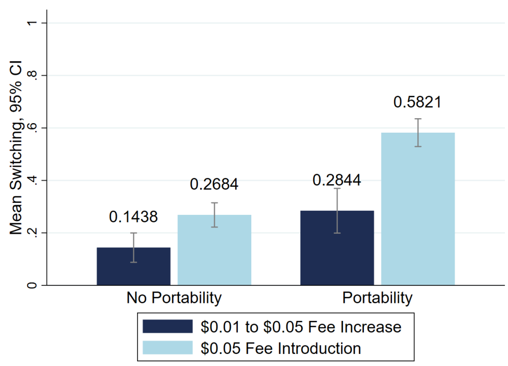


Table 1: Experimental Conditions

Conditions	Portability Regime	Platforms	Fee	N
1	No Portability	Equal	No	64
2	No Portability	Equal	Yes	334
3	No Portability	Asymmetric	No	72
4	No Portability	Asymmetric	Yes	352
5	Portability	Equal	No	65
6	Portability	Equal	Yes	340
7	Portability	Asymmetric	No	72
8	Portability	Asymmetric	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 platforms, 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

	Rating in Round t				
	(1) Full Sample	(2) Wage Gain	(3) Equal Wage or Wage Loss	(4) Wage Gain Situation	(5) Equal Wage or Wage Loss Situation
Period after Fee	-0.129***	-0.073+	-0.191***	-0.241**	-0.123***
	(0.022)	(0.043)	(0.073)	(0.108)	(0.027)
Controls					
Risk Ambiguity	0.214***	0.155+	0.382***	0.157	0.161***
	(0.037)	(0.086)	(0.101)	(0.216)	(0.043)
Completed Tasks AMT	0.002	0.023	-0.041	0.037***	-0.008
	(0.016)	(0.042)	(0.047)	(0.009)	(0.027)
Approval Rate AMT	0.401+	0.397	0.635	-0.725***	0.509+
	(0.205)	(0.308)	(0.412)	(0.267)	(0.304)
Intercept	4.061***	4.043***	3.708***	4.902***	4.054***
	(0.201)	(0.298)	(0.403)	(0.234)	(0.299)
Observations	12,365	2,999	1,769	831	6,766
Number of Workers	1,349	327	194	90	738
Adjusted R^2	0.017	0.007	0.040	0.018	0.014

Notes: The table contains the results of the ordinary least squares regressions for the *Rating in Round t*. The variable of interest is *Period after Fee*, a dummy variable equal to 1 in rounds after a fee is introduced and 0 otherwise. In column 1, we consider all participants who confronted a fee. In column 2, we only include participants who expressed monetary motives. Column 3 includes only participants who expressed fairness preferences. In column 4, participants were confronted with a situation in which they could have earned more money on the other platform after a fee was introduced but did not switch, and in column 5, participants were confronted with a fee and a situation in which they could have earned the same amount or less on the other platform and did not switch. Standard errors are clustered by worker and reported in parentheses. The variable *Completed Tasks AMT* is scaled by #/1,000,000 and the variable *Approval Rate AMT* is scaled by #/100. + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Channels

	(1) Switching	(2) Switching with Fairness Preferences
Most important self-reported switching motives as a response to fee introduction		
Earn Higher Wages	0.278***	-0.004
	(0.021)	(0.018)
Fee Perceived as Unfair	0.182***	0.052**
	(0.024)	(0.018)
Curiosity	0.152***	0.113***
	(0.023)	(0.018)
Boredom	0.081*	0.091***
	(0.032)	(0.022)
Poor Rating	-0.011	0.033
	(0.031)	(0.022)
Other Reason	0.083*	0.098***
	(0.040)	(0.026)
No Switching	*Baseline*	*Baseline*
Controls		
Average Rating in Round k	-0.077***	-0.068***
	(0.009)	(0.005)
Round k	-0.004	-0.003
	(0.007)	(0.005)
Negative Reciprocity	-0.006	0.016**
	(0.008)	(0.006)
Risk Aversion	-0.021	0.037+
	(0.031)	(0.021)
Risk Ambiguity	0.019	-0.030+
	(0.023)	(0.017)
Completed Tasks AMT	-0.065	-0.033
	(0.100)	(0.075)
Approval Rate AMT	-0.046	-0.060
	(0.089)	(0.060)
Number of Workers	1,349	1,349
Pseudo R^2	0.244	0.245
P=1	38.6%	14.4%

Notes: This table contains the results of the probit regression for switching behavior. The dependent variable in column 1 is a dummy variable that denotes whether the participant switched platforms after the introduction of a fee. In column 2, the dependent variable is also a dummy variable, which takes the value 1 if the participant demonstrated pure fairness preferences by switching after the fee introduction and 0 if participants were confronted with a fee introduction. The coefficients are average marginal effects. The baseline category of the most important self-reported switching motives is *No Switching*. The variable *Completed Tasks AMT* is scaled by #/1,000,000 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

	Total Wage			
	(1)	(2)	(3)	(4)
	All Ratings	Ratings < 3.50	Ratings ≥ 3.50 & < 4.50	Ratings ≥ 4.50
Portability	0.030+	-0.126***	-0.026	0.068***
	(0.016)	(0.044)	(0.034)	(0.015)
Controls				
Risk Ambiguity	0.067***	0.049	0.067+	0.009
	(0.016)	(0.050)	(0.035)	(0.015)
Completed Tasks AMT	0.074	-0.085	-0.001	0.072
	(0.070)	(0.652)	(0.202)	(0.080)
Approval Rate AMT	0.085	0.104	-0.008	-0.031
	(0.073)	(0.100)	(0.110)	(0.078)
Intercept	2.235***	1.892***	2.229***	2.441***
	(0.071)	(0.093)	(0.108)	(0.076)
Number of workers	1,349	122	239	988
Adjusted R^2	0.016	0.055	0.001	0.017

Notes: This table contains the results of the ordinary least squares regressions for total wages. The dependent variable is the *Total Wage* each participant, who experienced a fee, 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 earned an average rating of less than 3.50 in the final round. In column 3, we consider participants with average ratings greater than 3.50 and smaller 4.50 in the final round. In column 4, we consider participants with an average rating greater than 4.50 at the end of the experiment. The variable *Completed Tasks AMT* is scaled by #/1,000,000 and the variable *Approval Rate AMT* is scaled by #/100. Robust standard errors are reported in parentheses. + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix.

A.1. Existence of an incentive-compatible fee

Because it is not possible to find an analytical solution to Equation (14), 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 (14). 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 (14) 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 the platform can extract; this effect is nullified even more when $k \to \infty$ (with the values

Figure 1: Incentive compatible ϕ
$t = 10 \quad k = 4 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_1 = 2 \quad h_\epsilon = 5$

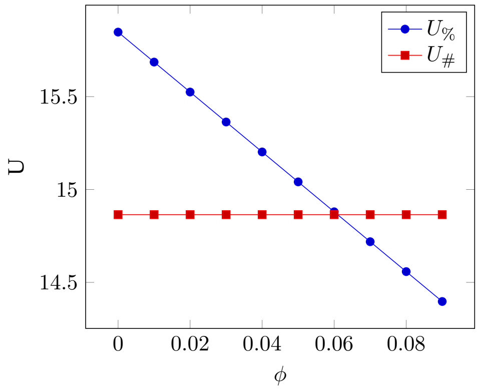
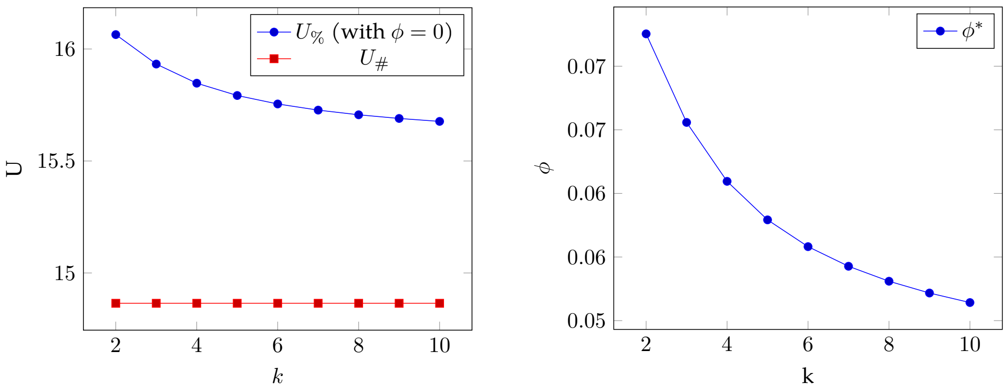


Figure 2: Variations of k
$t = 10 \quad \beta = 0,1 \quad f = 10 \quad m_1 = 4 \quad h_1 = 2 \quad h_\epsilon = 5$



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 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.

Figure 3: Variations of h_1

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

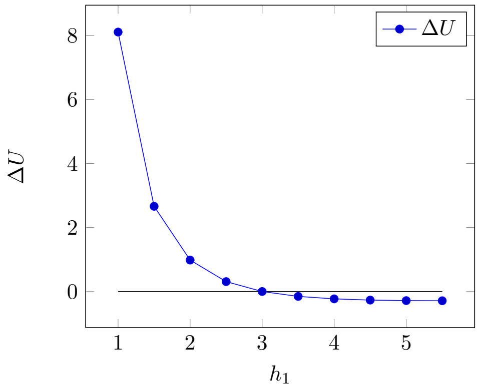
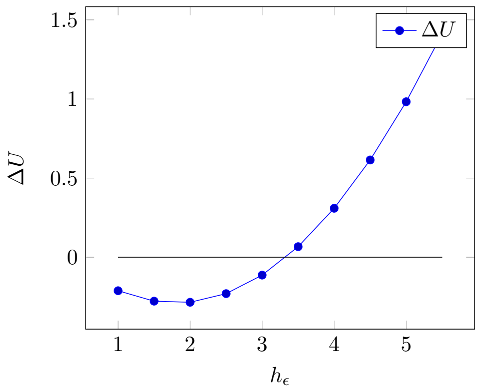


Figure 4: Variations of h_ϵ

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



A.2. Experimental Instructions

[*Note: These are the written instructions, presented to participants in the treatment without reputation portability and asymmetric platforms. 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^{th} round onward, a random mechanism will decide whether the study ends or not. After the 7^{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 platform 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:

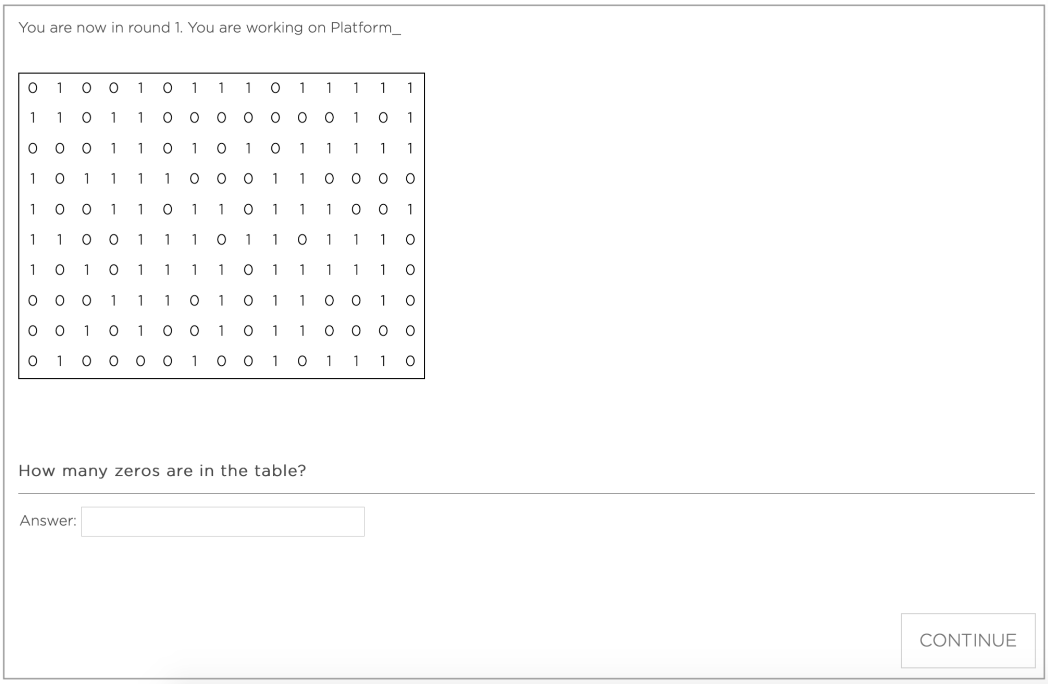
For Platform% and Platform#, the following box summarizes your current rating, your wage in the next round, the fee (if any) applied in the next round by the platforms, and your net earnings for completing the next task:

	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 platform 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.