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Lock-In Effects in Online Labor Markets

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ABSTRACT

Online platforms that implement reputation mechanisms typically prevent the transfer of ratings to other platforms, leading to lock-in effects and high switching costs for users. Platforms are able to capitalize on this arrangement, 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 examine switching motives in depth, differentiating between monetary motives and fairness preferences. We provide theoretical evidence for the existence of switching costs if reputation mechanisms are platform-specific. Our model predicts that reputation portability lowers switching costs, eliminating the possibility for platforms to capitalize on 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 platforms can capitalize on lock-in effects more effectively in a policy regime without reputation portability. We also find that reputation portability has a positive impact on worker mobility and 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

1 | Introduction

Most online marketplaces use reputation mechanisms to facilitate transactions between users. Reputation mechanisms facilitate the building of trust and address market inefficiencies that arise from asymmetric information (Dellarocas, Dini, and Spagnolo 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). Despite these practices being long-established, little is known about how users react when platforms capitalize on these lock-in effects. The present study, therefore, experimentally examines user reactions to the institution of a platform fee and examines what motivates users to switch to another platform after a fee is introduced. We also study the effect of reputation portability and ratings on workers' switching behavior, performance, and wages earned.

The presence of switching costs does not necessarily diminish the welfare of users. If users face switching costs, firms then may engage in fierce ex-ante competition to gain market share and, once users are locked in, relax competition ex-post (Klemperer 1987a, 1987b, 1995; Farrell and Shapiro 1988, 1989). The resulting welfare effect is ambiguous and may or may not be detrimental to users. The results of 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. Rather, 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. Dominant platforms are thus able to increase and sustain high fees over time, capitalizing on locked-in users.[1]

The present study uses a theoretical model alongside experimental analysis to investigate the effects of a platform fee on workers' switching behavior in online labor markets under two distinct policy regimes: the current status quo, which does not allow for reputation portability, and a regime with mandated reputation portability. In the latter, reputation data is fully and automatically transferred between platforms when workers switch.[2] Our focus is on online labor markets, and microtask platforms in particular. These platforms are generally used for hiring workers to perform small and repetitive tasks that are labor intensive (Durward, Blohm, and Leimeister 2020). Especially on microtask platforms, workers rely heavily on their reputation scores and often lack the opportunity to multi-home.

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 switching to another labor market platform, introducing the potential imposition of a platform fee, and analyzing the impact of these fee changes within the two policy regimes under consideration. Switching costs arise when reputation mechanisms are platform-specific. These costs are defined as the investment of effort that workers make over time to build their reputations and maximize their revenue streams. We also consider more thoroughly *why* workers switch platforms. 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, Knetsch, and Thaler 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. Workers who feel unfairly treated may also perform worse after being subjected to a fee (Fehr, Kirchsteiger, and Riedl 1993; Fehr and Falk 1999), because their utility is lowered not only by the reduction in net wages, but also by the imposition of the fee itself. Thus, if fairness preferences are not taken into account, a fee increase could lower workers' effort more than expected, thereby reducing the overall appeal of the platform from the employers' perspective.

We show theoretically that, without reputation portability, workers' reputation investments become a switching cost. Even with the promise of better economic treatment from another platform, workers may refrain from switching to avoid losing their valuable ratings. Our model predicts that workers with fairness preferences are more likely to switch than those with purely monetary motives due to the added disutility from fee impositions. Conversely, with reputation portability, switching costs disappear and workers are unwilling to pay fees to stay on the platform. Thus, workers with reputation portability are more likely to switch platforms and avoid higher fees.

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 setting allows us to examine worker behavior in a natural work environment while at the same time studying an artificial policy change and different levels of capitalization by platforms. In the experiment, participants are asked to work in a fictitious online labor market, in which switching behavior is triggered by platforms charging fees.

Experimentally, the results support the predictions from the theoretical model. The data show that a policy regime 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 respond with lower performance after the introduction of a platform fee, even when they switch platforms. Finally, a policy regime with reputation portability has a positive impact on worker mobility and wages. By decreasing lock-in effects, the right to reputation portability, among other efforts, could help improve the position of online workers.

Our paper makes several contributions to our understanding of online labor markets and platform economics. Adopting a multi-faceted approach to studying the effects of platform fees on worker behavior in online labor markets, we examine how platform fees influence not just the propensity of workers to switch platforms, but also their underlying motivations and subsequent performance. This adds a nuanced layer of understanding that is critical for platform managers as they formulate their pricing strategies. Our findings suggest that capitalizing on lock-in effects can negatively affect worker effort, providing new insights that platform managers should consider when balancing profitability and worker satisfaction. Additionally, our work has broader implications that extend to other types of online marketplaces where reputation matters but is not transferable. For example, in online marketplaces such as Amazon and eBay, the impact of platform fees on switching behavior could be similar for sellers in the policy regimes under consideration.

Our research also sheds light on a crucial yet underexplored aspect of data portability, specifically reputation portability. While legislative measures such as Article 20 of the European Union's General Data Protection Regulation (GDPR) and the California Privacy Rights Act of 2020 have been implemented to allow for the transfer of personal data between online platforms, a significant gap remains in the regulatory landscape regarding the portability of reputation data (Engels 2016; De Hert et al. 2018). As it stands, current legal interpretations exclude reputation data because ratings are provided by reviewers and not the user, such that users do not legally own their reputation data (Graef, Verschakelen, and Valcke 2013; Diker Vanberg and Ünver 2017). Consequently, online workers cannot legally own or transfer their reputation data from one platform to another, limiting their negotiating power and entrenching them in platform-specific ecosystems.

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. Section 6 concludes the paper.

2 | Related Literature

Related research can be divided into three categories: studies investigating switching costs; studies exploring reputation and, more broadly, data portability; and studies focusing on online labor markets.

Our paper is closely related to existing research on switching costs (Klemperer 1987a, 1987b, 1995; Farrell and Shapiro 1988, 1989). In online markets, switching costs may arise from learning or transaction costs, complementary services, or even psychological factors such as laziness or brand loyalty (Farrell and Klemperer 2007). When users face high switching costs, they are unlikely to switch even if the focal platform becomes relatively more expensive than competitors. Similarly to Wohlfarth (2019), in our study, reputation portability determines the degree of switching costs and, consequently, the strength of lock-in. This is because reputation has considerable economic value (Ba and Pavlou 2002; Resnick et al. 2006; Moreno and Terwiesch 2014; McDevitt 2014; Luca 2016; Saeedi 2019), and workers are inclined to invest substantial effort to build and maintain a strong reputation over time (Fehr and Goette 2007; Mason and Watts 2009; Cabral and Xu 2021). 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 showing that increased prices, data leakages, and privacy violations can lead consumers to switch to competitors despite the costs of doing so. Our work focuses on online workers' reputation formation and platform subscription choice, while also studying possible lock-in capitalization by platforms.

We also provide insights into the debate on reputation portability and data portability more generally. To date, research has focused on the influence of reputation within an online platform (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 employers 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, Angerer, and Zimmermann 2018), especially if the cross-platform signaling takes place in the same industry as the originating platform (Teubner, Adam, and Hawlitschek 2019; Hesse et al. 2020). With regard to the general idea of data portability between platforms, existing studies refer mostly to legal and technical dimensions (Dellarocas, Dini, and Spagnolo 2006; Engels 2016; De Hert et al. 2018), and the unintended effects of the GDPR and the right to data portability (Krämer and Stüdlein 2019; Wohlfarth 2019).

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 the reputation data of workers could be transferred across platforms. Thus far, none of these works have 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, low- and high-performing users might suffer differently from lock-in and benefit differently from data portability rights.

Finally, our paper extends the literature focusing on online labor markets. Due to their monopsony power (Dube et al. 2020), online labor platforms can impose lock-in effects, limiting the choice, mobility, and career development of workers, and making them vulnerable and susceptible to exploitation. Choudary (2018) argues that the design of online labor platforms has important implications for whether its workers are empowered or exploited by the organizations. For example, providers with substantial market power might demand a higher percentage of workers' wages in return for providing the platform (Kingsley, Gray, and Suri 2014). Some workers are also confronted with unstable earnings, unpredictable scheduling, unclear employment status, and a lack of social protection or voice (Degryse 2016; Berg et al. 2018; Johnston and Land-Kazlauskas 2018; Borchert et al. 2023; Wood et al. 2019; Hornuf and Vrankar 2022). Gomez-Herrera, Laitenberger, and Mueller-Langer (2022) show that online labor markets can effectively impose higher fees on a portion of workers without affecting labor demand or final prices, as workers cannot pass on costs to employers due to competition with workers who are willing to accept lower wages. We study whether the right to reputation portability might help improve the position of online workers by decreasing their platform dependency and potentially increasing their wages.

3 | Theoretical Framework

In this section, we derive formal and testable hypotheses and examine, under some simplifying assumptions, whether the platform can lock workers in using a platform-specific reputation mechanism. Our theoretical framework extends the model by Holmström (1999). Here, we provide a summary of the model; a detailed explanation is available in Appendix S1, Section A.

Our model extension incorporates reputation formation of a representative worker competing in an online labor market managed by a platform. When workers first subscribe to the platform, they have no ratings. As they start working, they establish ratings that vary according to their performance, and a higher average rating leads to higher wages.[3] In the model, the rating in each period depends on the worker's innate fixed talent and labor input, and a stochastic noise term. Both the platform and worker have incomplete information on the talent and share a common prior belief. Over time, employers learn about workers' talent by observing their ratings, which are typically visible on individual workers' profiles. We assume a competitive market and risk-neutral employers who, upon posting the labor requests on the platform, set the premium in line with the average rating of the worker. We represent the worker's atemporal utility function as follows:

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

where $\beta \in [0, 1]$ is a discount factor; c_t is the revenue scheme; $g(\cdot)$ is an increasing and convex function that represents the effort cost; and $U(\cdot,\cdot,\cdot)$ is publicly known. In contrast with the original model, we introduce the term $\phi \in [0, 1]$, which is the ad valorem fee the platform requires after each transaction applied directly to the worker's revenue. We assume that the platform increases its fee at time k, with the fee normalized to 0 before time k. The outside option for the worker is to decline work, which provides utility equivalent to 0. Ultimately, by maximizing the expected utility of the worker with respect to a_t, we obtain:

$$\sum_{s=t}^{\infty} \beta^{s-t}\alpha_s - \sum_{s=t}^{\infty} \beta^{s-t} I_s \phi \alpha_s = g'(a_t(\mathbf{r}_{t-1})), \tag{2}$$

where α_t represents the marginal return of the expected premium to labor supply for all $s \in \{1, ..., t-1\}$ in period t, and I_s is an indicator function equal to 0 when $s < k$, and equal to 1 when $s \geqslant k$. 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 the worker's innate talent. At the limit, there are no returns to trying to use labor input to bias performance evaluations, so the labor input goes to 0.

3.1 | Policy Regime Without Reputation Portability

Consider a setting in which two platforms, A and B, are initially identical and set the same fee, which we normalize to 0. Both platforms work under a regulatory regime that does not require reputation portability, and both offer a platform-specific reputation mechanism such that reputation built on one platform cannot be transferred to the other platform. Platforms remain identical until time k. Then, at time k, platform A raises the ad valorem fee to ϕ, while platform B maintains its fee at 0. Therefore, these two platforms unequally capitalize on their workers, because only one of them introduces a fee.[4] Assume workers are not aware of the fee until time k,[5] at which moment they have two choices: (1) remain on platform A to keep benefiting from the reputation investment made so far but have their income reduced by the increased fee, or (2) switch to platform B, which does not impose a fee but requires workers to rebuild their reputations from scratch. Thus, after time k, workers face a new problem and will stay on platform A if

$$\begin{aligned}&\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] \geqslant \\ &\sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)].\end{aligned} \tag{3}$$

The left-hand side of inequality (3) represents the utility to the worker, reduced by the fee, associated with the decision to stay on platform A. The right-hand side represents the utility to the worker associated with the decision to switch to platform B. The difference between the utility obtained on platform A and the utility on platform B is equivalent to the premium associated with past ratings, diminished by the fee.[6]

Our problem is similar to an ultimatum game (Güth, Schmittberger, and Schwarze 1982), where the platform acts as the proposer and the worker as the responder. If the workers' motives are purely monetary, influenced solely by the amount of their wages, then 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. We therefore anticipate that workers with purely monetary motives will switch whenever their expected utility is higher on the other platform:

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.*

However, workers' decision to switch may be influenced not only by monetary motives but also by fairness preferences; that is, switching decisions are also based on the actions of the platform. We assume that workers with fairness preferences face an additional disutility when the platform introduces a fee because they perceive it as unfair. We capture this disutility by subtracting a parameter $\delta(\phi) \in [0, \infty)$, increasing in ϕ in the left-hand side of inequality (3):

$$\begin{aligned}&\sum_{t=1}^{\infty} \beta^{t-1}[(1-\phi)c_{k+t-1} - g(a_{k+t-1})] - \delta(\phi) \geqslant \\ &\sum_{t=1}^{\infty} \beta^{t-1}[c_t - g(a_t)].\end{aligned} \tag{4}$$

Workers may exhibit varying levels of tolerance δ for the fee, which could explain their switching behavior. Workers with $\delta = 0$ have purely monetary motives. Workers with $\delta \to \infty$ always switch due to strong fairness preferences and an inability to tolerate even the smallest fee imposition. Other workers might perceive the fee increase as unfair ($\delta > 0$) but tolerable, such that they would not switch. These workers exhibit both monetary motives and fairness preferences. Workers with fairness preferences who are confronted with a platform fee yet tolerate it endure the highest losses when reputation is not transferable. Thus, a policy regime with reputation portability could be especially beneficial for these workers. We expect that some workers exhibit fairness preferences and switch platforms following a fee increase, even if it results in a wage loss. If the utility streams between the two platforms are identical, then as a tie-breaking rule, we anticipate that workers with fairness preferences will switch:

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.*

3.2 | Policy Regime With Reputation Portability

If reputation portability were mandated by regulation, extending Article 20 of the GDPR, all workers could transfer their ratings when switching to a new platform. Platforms might even implicitly enforce reputation portability by purchasing data to screen the quality of new workers before allowing them to join. Consequently, workers would not lose their reputation investments and could easily switch between platforms.[7] Assuming symmetry between platforms A and B, Bertrand competition would follow, leading platforms to set fees equal to marginal costs. Therefore, we hypothesize that workers in a reputation portability regime naturally switch more frequently:

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

This section details the experimental design used to test our hypotheses and describes the sample.[8]

4.1 | The Task

At the beginning of the experiment, participants were introduced to a new online labor market consisting of two distinct labor platforms, named Platform% and Platform# (see Figure 1).[9] The experiment was conducted over seven to ten rounds, each following a consistent structure. To mitigate potential end-round effects, a random termination mechanism was implemented from the seventh round onward. This mechanism ended the experiment with a 33.$\bar{3}$% probability after any completed round following round seven.

In each round, participants first selected the platform on which they preferred to work. Thereafter, they were tasked with counting zeros in a randomized sequence of zeros and ones. After completing the task, participants received a performance rating for that round, which ranged from 1 to 5 on each platform. Instead of displaying the rating for that specific task, we adhered to common standards in online labor markets and showed the average rating reflecting their historical performance from all previous rounds. In accordance with our theoretical model, ratings yielded a premium, such that a higher average rating was associated with a higher wage in the next round. While the base compensation for completing a task was \$0.10, participants could earn \$0.15 if their rating exceeded 3.50, and \$0.20 if it was greater than 4.50.

At the end of each round, participants received information about their average rating, the wage for the next task, the platform's introduction or increase of a fee starting in the next round, and the total wage over all rounds, separately for Platform% and Platform#. After receiving this information, participants chose which platform to work on for the next round and performed another zero-counting task. During the first three rounds, we avoided charging fees to allow participants to establish a rating, thereby creating the possibility of lock-in.

After the final round of the experiment, participants completed a questionnaire that included sociodemographic questions and details about their AMT worker profile and history. Considering the decision-making required in our experiment—where participants had to assess the potential benefits of staying on or switching between platforms under varying conditions of uncertainty—we included questions to control for individual differences in risk and ambiguity aversion. Risk-averse participants prefer outcomes with low uncertainty over those with high uncertainty (Kahneman, Knetsch, and Thaler 1991; Tversky and Kahneman 1991), and ambiguity-averse participants prefer known over unknown risks (Ellsberg 1961; Camerer and Weber 1992). To classify workers' relative risk aversion, we asked participants to choose their preferred lifetime earnings profiles (Butler, Guiso, and Jappelli 2014). To measure ambiguity aversion, we implemented a thought experiment developed by Ellsberg (1961). To further understand the motives behind platform switching, we included a question aimed at measuring negative reciprocity to determine whether decisions to

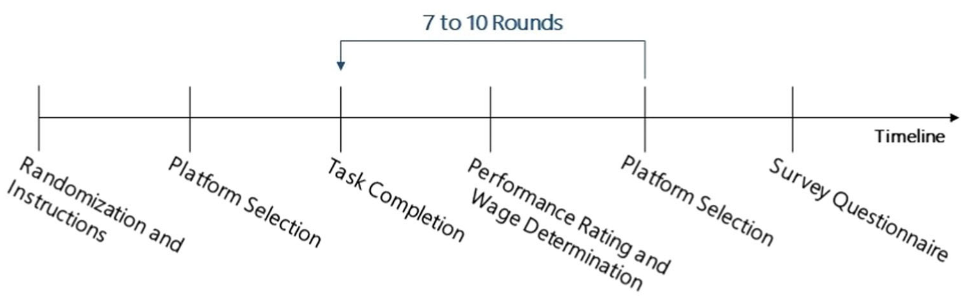

FIGURE 1 | Timeline. *Note:* The figure provides a visual overview of the experimental procedure.

switch might be influenced by participants seeking to punish the platform (Güth 1995; Kritikos and Bolle 2001), or simply perceiving the fee as unfair (Kahneman, Knetsch, and Thaler 1986; Rabin 1993). The question on negative reciprocity was derived from the 2005 personality questionnaire of the German socioeconomic panel (DIW 2023). Finally, we asked participants to rank the primary reasons for switching platforms, providing the options *boredom*, *curiosity*, *low rating*, *perceived unfairness of the fee*, *potential higher earnings on another platform*, *no switching*, and *other reason*, with the ability to specify the latter.

4.2 | Treatments

We implemented 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. First, with a probability of 50%, participants were randomly assigned to one of two policy regimes: one that allowed for the portability of participants' ratings, and one that did not. During each round, starting with round four, with a 25% probability, participants were confronted with a platform fee that remained in force after it had been introduced. Finally, to identify switching due to monetary motives or fairness preferences, participants were randomly assigned, with a 50% probability, to one of two platform conditions: (1) the platforms were perfectly identical and simultaneously charged fees of the same amount (equal platforms); and (2) the platforms were asymmetric, with only the platform the participant was currently working on charging a fee, while the other did not (asymmetric platforms).

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

With our experimental design, we can also examine second-order effects pertaining to the strength and frequency of platform capitalization due to lock-in effects. In the experiment, the platform fees took varying levels ($0.00, $0.01, $0.05), which allows comparison of 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).[10] If a platform introduced a fee of $0.01, there was a 25% probability in each subsequent round that the fee increased to $0.05, which then remained 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.

Interactions between platform provider and workers were mediated entirely through an automated mechanism that was responsible for introducing and increasing fees. This absence of direct human interaction may raise questions about the extent to which workers were influenced to switch platforms or exhibit fairness preferences. According to Blount (1995), 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. Despite this, we contend that the participants' reactions in our experiment should reflect the real-life responses of online workers, as we recreated the working conditions and environment typical of online platforms (Henrich et al. 2001). Therefore, if the platforms' machine identity influences workers' reaction, the effect sizes identified in our study could be considered conservative estimates, representing the lower bounds of the actual impacts.

4.3 | Sample

The study participants were recruited from AMT, a prominent online marketplace for crowdsourcing microtasks.[11] All participants

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
				1622

Note: 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%.

are online workers, at least 18 years of age, and either citizens or legal residents of the United States.[12] Data collection occurred between February 12 and 23, 2021. We recruited a total of 2148 participants but excluded those who provided invalid information[13] 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 1622 participants. On average, each experimental session lasted about 20 min, and participants earned an average of $1.36 plus an additional fixed amount of $1 for participating.[14]

5 | Experimental Results

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 worker mobility and wages in online labor markets. Finally, we investigate how the strength and frequency of the platform's capitalization of workers' lock-in influence switching behavior. We compare means across treatments using Fisher's exact tests, two-sample t-tests, and two-sample tests of proportions.[15]

5.1 | The Impact of a Fee Introduction on Switching Behavior

Using a within-subject analysis, we first determine if introducing a fee prompts participants to switch platforms. In the experiment, 1349 participants (83.2%) were confronted with a fee, whereas 273 participants (16.8%) never encountered these charges.[16] Figure 2 illustrates the differences in switching behavior when a platform introduces a fee, versus switching in all rounds before any fee was charged. In line with our prediction that switching behavior triggered by a platform fee differs from switching behavior in prior rounds without a fee, we find that the fraction of participants switching platforms increases from 24.4% to 38.6% following a fee, a significant increase of 14.2 percentage points (two-sample test of proportions, clustered at the worker level, $z = -10.336, p < 0.001$). Figure 3 also reveals that this effect is driven mostly by switching behaviors if platforms are asymmetric. Switching platforms before 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,[17] 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.[18]

We summarize this finding as follows:

Result 1. *If platforms are asymmetric, introducing a platform fee increases switching behavior.*

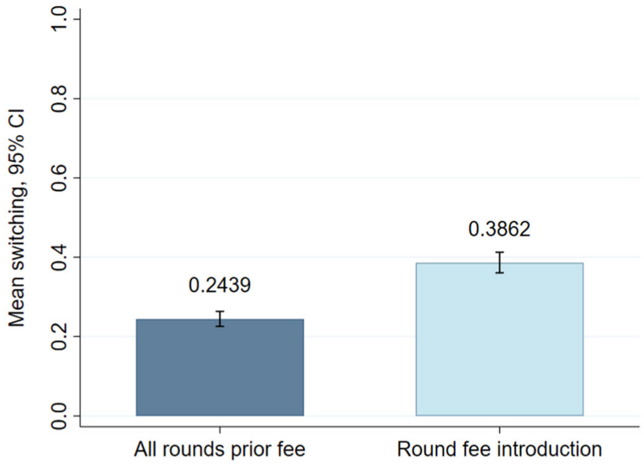

FIGURE 2 | Fee introduction. *Note:* The share of switching behavior in the round before the fee introduction and in the round when the fee is introduced. Confidence intervals are calculated with robust standard errors, clustered at the individual level. [Color figure can be viewed at wileyonlinelibrary.com]

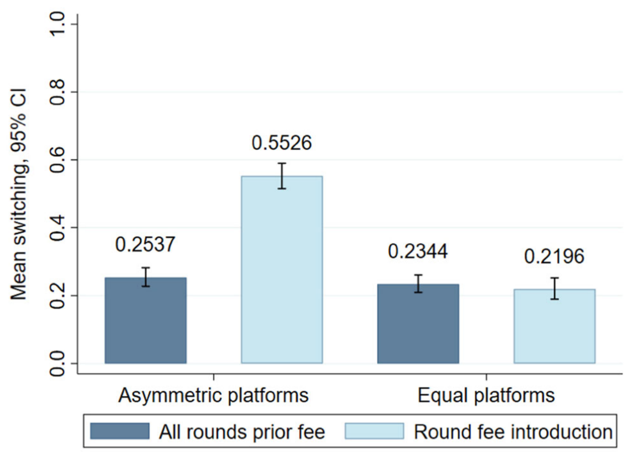

FIGURE 3 | Fee introduction and platform symmetry. *Note:* The share of switching behavior in the round before the fee introduction and in the round when the fee is introduced, separated by platform condition. Confidence intervals are calculated with robust standard errors, clustered at the individual level. [Color figure can be viewed at wileyonlinelibrary.com]

5.2 | 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 policy scenario with portability, this offers evidence that workers are vulnerable to lock-in effects arising in the absence of reputation portability. As detailed in Figure 4, switching behavior in a policy regime without reputation portability increases after a fee, from 18.3% to 23.3% (two-sample test of proportions, clustered at the worker level, $z = -2.930, p = 0.003$). In a policy regime with reputation

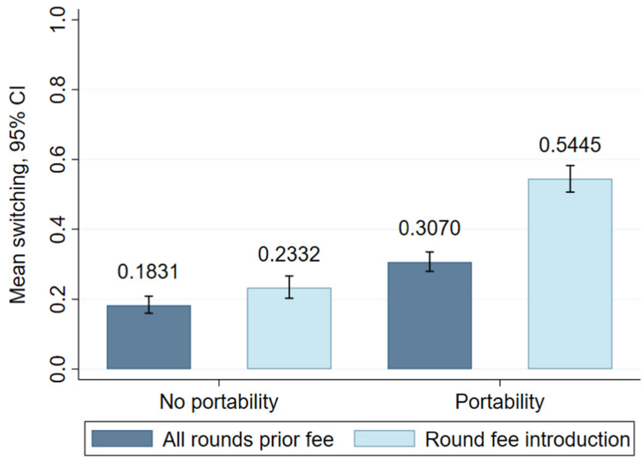

FIGURE 4 | Portability regime. *Note:* The share of switching behavior in the round before the fee introduction and in the round when the fee is introduced, separated by portability regime. Confidence intervals are calculated with robust standard errors, clustered at the individual level. [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 5 | Monetary motives and fairness preferences. *Note:* The share of switching based on monetary motives and/or fairness preferences in the round before the fee introduction and in the round when the fee is introduced. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

portability, however, switching behavior increases by 23.8 percentage points, from 30.7% to 54.5%, a finding that is statistically significant (two-sample test of proportions, clustered at the worker level, $z = -11.255, p < 0.001$). The difference between these increases (5 vs. 23.8 percentage points) also is statistically significant (Fisher's exact, $p < 0.001$), supporting Hypotheses 1 and 3. These hypotheses propose that platforms can more effectively capitalize on lock-in effects in a policy regime without portability, and that a policy regime with reputation portability increases the probability of switching platforms. Therefore,

Result 2. *Platforms can capitalize on lock-in effects more effectively in a policy regime without reputation portability, whereas a policy regime with reputation portability significantly increases switching behavior.*

5.3 | Motives for Switching 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. Their behaviors also likely depend on their tolerance level for fees.

Of the 1349 participants who encountered a fee, 417 would have earned a higher wage on the other platform; hence their platform switching might reflect monetary motives, fairness preferences, or both. As displayed in Figure 5, 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%) of these 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 purely due to 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 test of proportions, $z = -20.081, p < 0.001$). 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 6), we find a significant increase in switching behavior purely due to fairness preferences, from 15.4% to 30.2%, when reputation portability exists (two-sample test of proportions, $z = -5.363, p < 0.001$). 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. Because 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 test of proportions, $z = -1.560, p = 0.119$). 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 apparently lower for workers in a policy regime with reputation portability, as switching based purely on fairness preferences increases from* 15.4% *to* 30.2%.

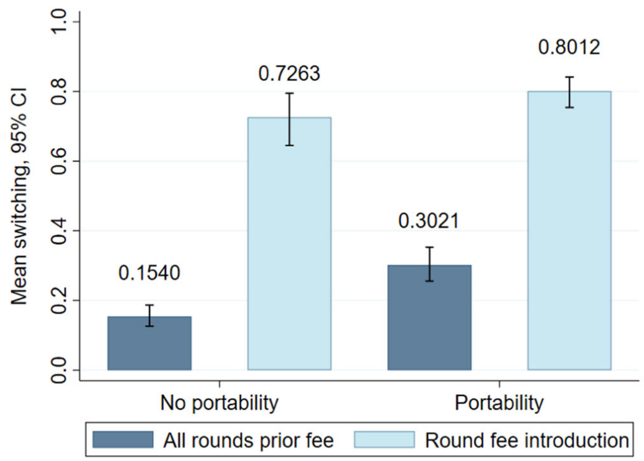

FIGURE 6 | Monetary motives, fairness preferences, and portability regime. *Note:* The share of switching based on monetary motives and/or fairness preferences in the round before the fee introduction and in the round when the fee is introduced, separated by portability regime. Confidence intervals are calculated with robust standard errors, clustered at the individual level. [Color figure can be viewed at wileyonlinelibrary.com]

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 2, we present the results of random-effects GLS 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 0.16 after the fee introduction, holding all other variables constant. We further find that workers exhibit poorer performance than they did before the fee introduction, regardless of the switching motive. Consistent with our theoretical model, workers reduce their equilibrium effort when they: (i) express fairness preferences (Column 3), (ii) face a fee and a higher wage on another platform but do not switch (Column 4), and (iii) encounter a fee and the same or lower wage on another platform and also do not switch (Column 5). This reduction is in line with findings by Fehr, Kirchsteiger, and Riedl (1993); Fehr and Falk (1999), who find that workers might reciprocate by lowering their effort in response to low wages. We also find that workers who switch platforms and earn more after a fee introduction reduce their effort level. The reduction in performance, despite the monetary gain, suggests that workers might perceive the fee introduction not just in terms of its financial impact but also as an expression of the

TABLE 2 | Performance in rounds prior a fee versus 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	−0.156***	−0.099***	−0.232***	−0.244***	−0.149***
	(0.018)	(0.034)	(0.059)	(0.094)	(0.022)
Controls					
Risk ambiguity	0.211***	0.156+	0.369***	0.179	0.156***
	(0.037)	(0.085)	(0.102)	(0.209)	(0.042)
Completed tasks AMT	0.026	0.155	−0.390	0.378***	−0.070
	(0.160)	(0.435)	(0.464)	(0.090)	(0.259)
Approval rate AMT	0.403**	0.401	0.643	−0.714***	0.487+
	(0.203)	(0.306)	(0.413)	(0.275)	(0.295)
Intercept	4.072***	4.051***	3.724***	4.887***	4.090***
	(0.199)	(0.295)	(0.404)	(0.243)	(0.290)
Number of rounds	12365	2999	1769	831	6766
Number of workers	1349	327	194	90	738
Within R^2	0.009	0.004	0.016	0.013	0.010
Between R^2	0.027	0.012	0.070	0.036	0.021
Overall R^2	0.017	0.008	0.042	0.022	0.015

Note: The table contains the results of random-effects GLS 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. Robust standard errors are clustered at the worker level and reported in parentheses. The variable *Completed tasks AMT* is scaled by #/1000000 and the variable *Approval rate AMT* is scaled by #/100. Significance levels are indicated by: $^+p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

platform's low appreciation of employees. If workers perceive the fee as unfair or as a devaluation, they could be demotivated, which impacts their performance even in a new environment where they earn more. We conclude:

Result 4. *Worker performance generally decreases after being subjected to a fee.*

To validate our findings on switching behavior influenced by monetary motives and fairness preferences, we conduct a regression analysis based on questionnaire responses to understand more deeply *why* participants chose to switch following a platform fee. The independent variables include risk aversion, ambiguity aversion, negative reciprocity, and the participants' primary ranked reasons for switching. The latter, such as "I could earn more money on the other platform" or "I perceived the fee increase as unfair," are represented as dummy variables. These variables are set to 1 if a reason for switching ranks among the top three for a worker, indicating significant influence on the decision to switch. The baseline category is *No switching*. Additionally, we control for lock-in effects by including variables such as participants' *Average rating in round k* and the *Round k* when a fee was introduced.

The probit regression involves only those participants who were confronted with 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 3 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. More specifically, 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. Notably, we find in Column 2 that negative reciprocity—a tendency to react adversely to perceived injustices—increases switching behavior by 1.6%, with all other variables held constant. Risk aversion, risk ambiguity, a poor rating, and the round in which the fee was introduced do not influence workers' switching behaviors, though boredom and curiosity increase them. We summarize the regression findings as follows:

Result 5. *The better the rating, the less likely workers are to switch. The self-reported desire to earn higher wages and perceiving a fee as unfair significantly increase workers' switching behaviors.*

TABLE 3 | Explaining switching behavior.

	(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	1349	1349
Pseudo R^2	0.244	0.243
$P = 1$	38.6%	14.4%

Note: This table contains the results of the probit regressions 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 #/1000000 and the variable *Approval rate AMT* is scaled by #/100. Robust standard errors are reported in parentheses. Significance levels are indicated by: $^{+}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Did a significantly higher proportion of participants who switch and exhibit 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 revealed 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 indeed perceived the fee as more unfair.

5.4 | The Effect of Reputation Portability on Worker Mobility and Wages

Next, we investigate the impact of a policy regime with reputation portability on workers' mobility and wages in online labor markets. Our analysis begins by examining how reputation portability influences the mobility patterns of workers, with a specific focus on variations by their average ratings. 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 7 sheds light on the differential switching behaviors. Workers with ratings below 3.50 switch significantly more often in rounds before the fee if reputation is not portable across platforms compared to when it is (two-sample test of proportions, clustered at the worker level, 66.4% vs. 39.1%, $z = 6.595$, $p < 0.001$). After a fee is introduced, the difference in switching behavior for workers with poor ratings is significant at the 5% level and differs by 17.4 percentage points between the two policy regimes, 75.6% versus 58.2% (two-sample test of proportions, clustered at the worker level, $z = 2.194$, $p = 0.028$). This finding suggests 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 cost 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 test of proportions, clustered at the worker level, for ratings between 3.50 and 4.49, 20.5% vs. 46.9%, $z = -3.892$, $p = 0.001$; for ratings greater than 4.50, 14.6% vs. 55.8%, $z = -13.683$, $p < 0.001$). In summary, a policy regime with reputation portability leads to more platform switching among high-quality workers after a fee is introduced.

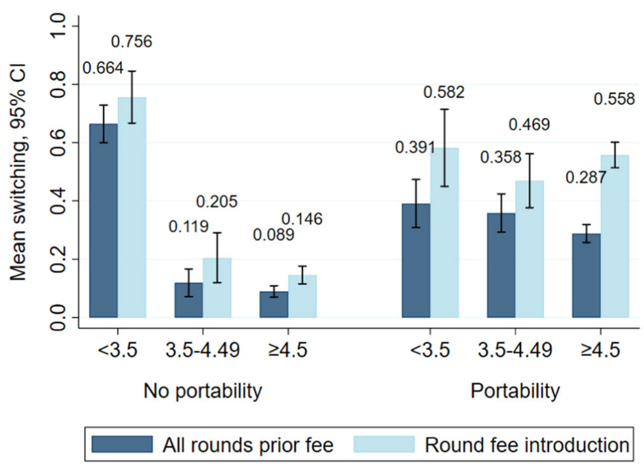

FIGURE 7 | Ratings and portability regime. *Note:* The share of switching behavior, categorized by rating, in the round before the fee introduction and in the round when the fee is introduced, separated by portability regime. Confidence intervals are calculated with robust standard errors, clustered at the individual level. [Color figure can be viewed at wileyonlinelibrary.com]

We continue by analyzing the effect of a policy regime with reputation portability on workers' wages, if these workers experience platform capitalization. In Table 4, we run several ordinary least squares regressions with the dependent variable being the *Total wage* the participant earned by the end of the experiment. 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 for empowerment, particularly for 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.*

5.5 | 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 subjected 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 8, 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 significantly by 7.1 percentage points (two-sample test of proportions, $z = -2.674$, $p = 0.008$). As detailed in Figure 9, the result

TABLE 4 | Total wage and portability regime.

	Total wage			
	(1) All ratings	(2) Ratings < 3.50	(3) Ratings ⩾ 3.50 and < 4.50	(4) Ratings ⩾ 4.50
Portability	0.030^{+}	-0.126^{***}	−0.026	0.068^{***}
	(0.016)	(0.043)	(0.034)	(0.015)
Controls				
Risk ambiguity	0.067^{***}	0.049	0.067^{+}	0.009
	(0.016)	(0.049)	(0.035)	(0.015)
Completed tasks AMT	0.074	−0.085	−0.001	0.072
	(0.065)	(0.230)	(0.177)	(0.065)
Approval rate AMT	0.085	0.104	−0.008	−0.031
	(0.070)	(0.078)	(0.097)	(0.071)
Intercept	2.235^{***}	1.892^{***}	2.229^{***}	2.441^{***}
	(0.068)	(0.072)	(0.096)	(0.070)
Number of workers	1349	122	239	988
Adjusted R^2	0.016	0.055	0.001	0.017

Note: 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 #/1000000 and the variable *Approval rate AMT* is scaled by #/100. Robust standard errors are clustered at the worker level and reported in parentheses. Significance levels are indicated by: $^{+}p < 0.10$; $^{***}p < 0.01$.

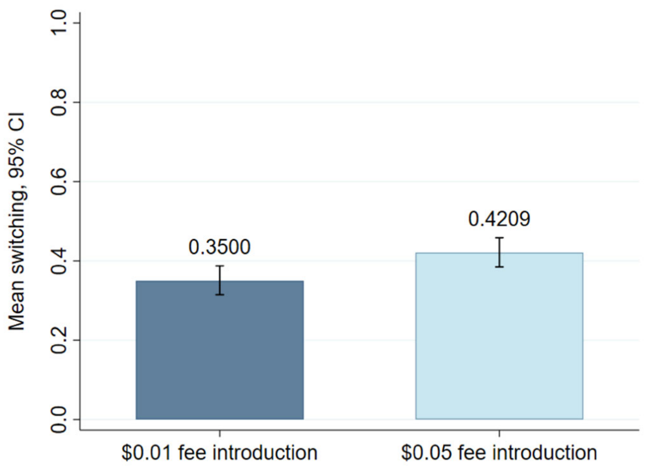

FIGURE 8 | Strength of capitalizing lock-in effects. *Note:* The share of switching behavior in the round when the platform introduces a fee of $0.01, compared to the round when a fee of $0.05 is introduced. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

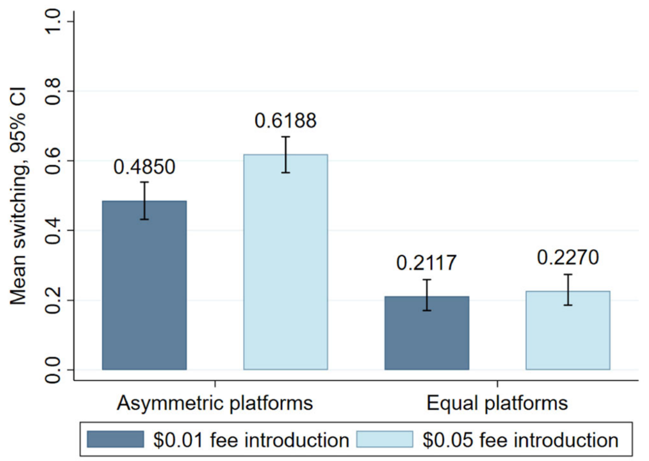

FIGURE 9 | Strength of capitalizing lock-in effects and platform symmetry. *Note:* The share of switching behavior in the round when the platform introduces a fee of $0.01, compared to the round when a fee of $0.05 is introduced, separated by platform condition. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

is driven by switching behavior if platforms are asymmetric (two-sample test of proportions, 48.5% vs. 61.9%, $z = -3.494$, $p = 0.001$). With regard to the portability regimes (see Figure 10), we find that switching significantly increases in both after a newly imposed fee (two-sample test of proportions, no portability regime, 19.6% to 26.8%, $z = -2.246$, $p = 0.025$; portability regime, 50.6% to 58.2%, $z = -1.964$, $p = 0.050$). We further 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 test of proportions, fee of $0.01, 19.6% vs. 50.6%, $z = -8.357$, $p < 0.001$; fee of $0.05, 26.8% vs. 58.2%, $z = -8.337$, $p < 0.001$). 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. Additionally, this propensity to switch in response to higher fees persists across the two portability regimes.*

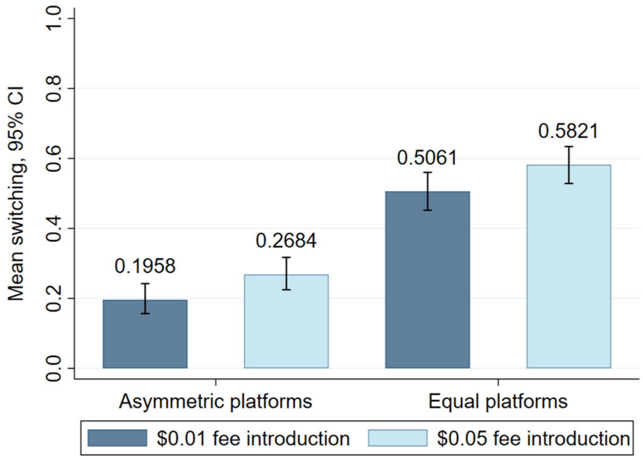

FIGURE 10 | Strength of capitalizing lock-in effects and portability regime. *Note:* The share of switching behavior in the round when the platform introduces a fee of $0.01, compared to the round when a fee of $0.05 is introduced, separated by portability regime. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

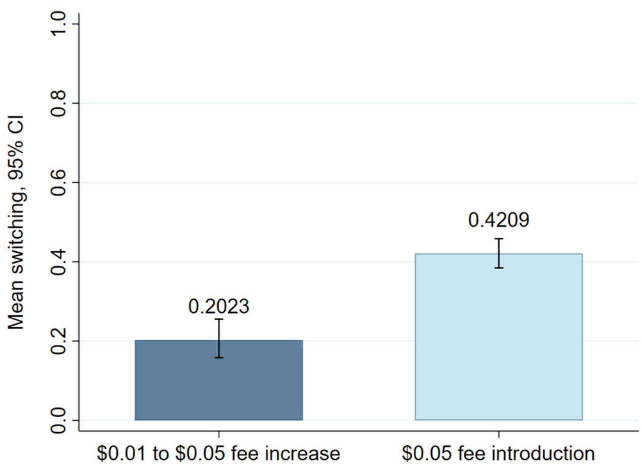

FIGURE 11 | Frequency of capitalizing lock-in effects. *Note:* The share of switching behavior among participants who are initially faced with a fee of $0.05, compared to that of participants who first encounter a fee of $0.01 and then experience an increase to a $0.05 fee in a subsequent round. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

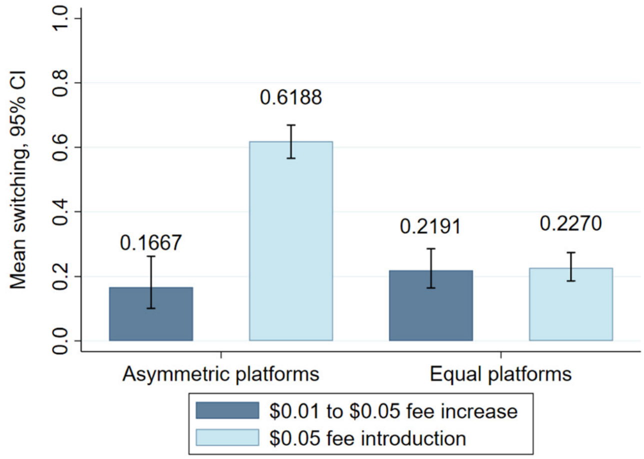

FIGURE 12 | Frequency of capitalizing lock-in effects and platform symmetry. *Note:* The share of switching behavior among participants who are initially faced with a fee of $0.05, compared to that of participants who first encounter a fee of $0.01 and then experience an increase to a $0.05 fee in a subsequent round, separated by platform condition. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

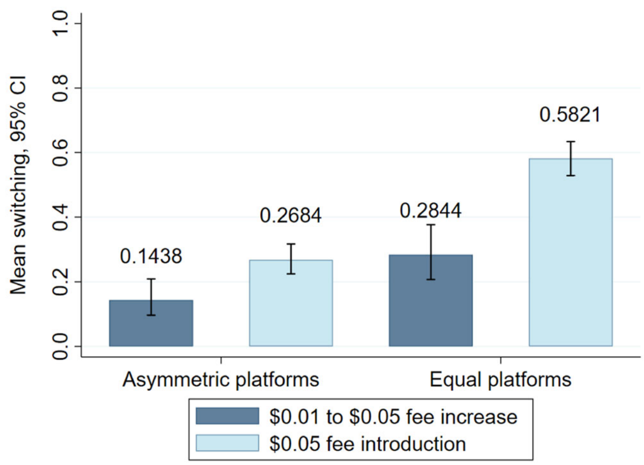

FIGURE 13 | Frequency of capitalizing lock-in effects and portability regime. *Note:* The share of switching behavior among participants who are initially faced with a fee of $0.05, compared to that of participants who first encounter a fee of $0.01 and then experience an increase to a $0.05 fee in a subsequent round, separated by portability regime. Confidence intervals are calculated with robust standard errors. [Color figure can be viewed at wileyonlinelibrary.com]

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.[19] As Figure 11 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 test of proportions, $z = -6.272, p < 0.001$). This result is explained by switching behavior if platforms are asymmetric (see Figure 12, two-sample test of proportions, 16.7% vs. 61.9%, $z = -7.436, p < 0.001$) and by switching platforms in a policy regime with and without reputation portability (see Figure 13, two-sample test of proportions, 14.4% vs. 26.8%, $z = -3.056, p = 0.002$; 28.4% vs. 58.2%, $z = -5.400, p < 0.001$). 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, the utility associated with the decision of switching is relatively low and can hardly trigger switching (see Equation 3). 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 policy regimes with and without reputation portability, workers are also less likely to switch in a situation with rising subsequent fees.*

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. We demonstrate that, without reputation portability, a platform can exploit the reluctance of locked-in workers to switch. This conclusion is supported by the results of our online lab-in-the-field decision experiment. 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. Ultimately, we find evidence that the mandated portability of reputation positively impacts wages of highly-rated workers.

Our research carries significant implications for regulatory authorities and platform managers. The findings highlight the importance of reputation portability for workers in preventing platform capitalization. This is particularly crucial in online labor markets characterized by unstable working conditions, substantial setup costs, and limits to multi-home. In line with recent regulations—such as Article 20 in the GDPR, the California Privacy Rights Act, and the Chinese Personal Information Protection Law, which require data to be easily transferable—we advocate for the implementation of reputation portability regulations in online labor markets. This would serve to alleviate lock-in effects and enhance worker mobility and wages. Regulatory action seems necessary, given that platforms do not naturally allow users to import or export their reputation data.[20, 21] Within the framework of the European legislation, introducing reputation portability would necessitate extending Article 20 of the GDPR, because reputation data is not classified as personal data and thus falls outside the purview of Article 20. We note that the European Commission proposed new regulations aimed at improving the working conditions in platform work (European Commission 2023). While the proposal addresses labor rights and algorithmic management practices, it noticeably lacks provisions for reputation portability. The absence of such measures perpetuates the lock-in effects experienced by online workers and hampers the realization of a truly competitive and socially equitable digital labor market (Kathuria and Lai 2018; Hesse and Teubner 2019). Our work also has managerial implications with regard to platform pricing. By distinguishing different switching motives, we show that workers respond with lower performance after a platform introduces a fee, even after workers have switched platforms. Therefore, the capitalization of worker lock-in through a platform-specific rating could have a non-positive effect for platforms after all.

We offer several recommendations for extending our work. First, our analysis centers on the mandatory portability of reputation. However, alternative designs—such as providing workers with the option, rather than the obligation, to transfer ratings between platforms—could have distinct effects on lock-in capitalization and switching behavior (Hesse and Teubner 2019). Further research might account for information asymmetries across platforms and users as well as the strategic decisions users make when they have the right, but not the obligation, to transfer reputation. For example, in a policy regime with voluntary reputation portability, the market might interpret a transfer of reputation data as a positive signal.

Second, it would be interesting to include employers' strategic decisions in further research on reputation portability. For example, throughout our study, we assume that the employers' side of the market reports workers' performance truthfully. However, employers could strategically reject work to avoid signaling good workers to potential competitors (Bognanno and Melero 2016; Benson, Sojourner, and Umyarov 2020), thereby lowering workers' ratings and saving money.[22] While two-sided rating systems can address this issue, fear of retaliation may hinder workers from giving bad ratings to bad employers (Sockin and Sojourner 2023), especially in markets where the employer side is concentrated. In such settings, reputation portability could further discipline employers. Employers, on top of rating workers fairly to avoid retaliation, would also be unable to reset their scores by simply switching platforms. This continuity in reputation could enhance accountability and incentivize fairer practices across the board.[23]

Third, future research could investigate how platform competition is affected when reputation portability is implemented. Reputation portability may incentivize incumbent platforms to strategically reduce investment in the informativeness of their reputation systems. Platforms might reduce these investments if they face increased competition due to portability. A comparison can be drawn with traditional network settings such as the telecommunications sector, where the effects of number portability on providers' investments in service quality have remained uncertain (Bühler, Dewenter, and Haucap 2006). However, the lower profitability resulting from reduced lock-in effects should not necessarily imperil the investments made by online platforms when reputation becomes portable, as the virtual infrastructure may have similar or even lower maintenance and development costs. Another possibility is that platforms might reduce the informativeness of their reputation systems to deter workers from switching. However, this approach could be counterproductive, as it may encourage new entrants to differentiate themselves by developing more transparent reputation systems to attract workers. Additionally, in an online market with imperfect competition or friction, the effects of reputation portability on switching behavior may differ. Reputation portability might reinforce the well-established positions of incumbent users and raise barriers to entry for new users of online marketplaces, resulting in mixed welfare effects.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author on request.

Endnotes

[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]In practice, reputation portability would likely be a user's right rather than an obligation. However, we examine these extreme cases to simplify the problem and avoid strategic behavior by workers regarding the decision to transfer reputation across platforms. For a comprehensive description of different policy regimes, see Hesse and Teubner (2019).

[3]Similar to Lambin and Palikot (2019), we consider the rating as the measure of the performance of the worker in every period.

[4]We abstract from strategic behaviors between platforms and assume that the fee increase on platform A 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% (see https://www.theguardian.com/media/2020/sep/01/googles-advertisers-will-take-the-hit-from-uk-digital-service-tax).

[5]Otherwise, they would realize that subscribing to platform B is always more profitable.

[6]In Appendix S1, Section A.2, we identify the existence of a fee that matches the inequality for some range of parameters.

[7]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.

[8]The experimental instructions and the questionnaire are available in Appendix S1, Sections B and C.

[9]In line with Hossain and Morgan (2009), we avoid using numbers or symbols that might imply a ranking or preference.

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

[11]A detailed overview of of AMT and its recruitment process can be found in Section D in Appendix S1.

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

[13]Some participants reported working a total of more than 110 h per week or responded that they work more than 150 h per week on crowdsourcing platforms. In addition, there were also workers who reported earning more than $3000 and up to $78,000 per week from crowdsourcing.

[14]Because the experiment could be completed in approximately 20 min, 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).

[15]Table 1 in Appendix S1, Section E performs a randomization check using F-tests to verify if the automated randomization produced a balanced sample. Results show that F-tests for risk ambiguity, tasks completed, and approval rate obtained on AMT are statistically significant. Consequently, we include these variables as controls in our regression analyses in Tables 2–4. Additionally, given that our experiment involves individual choices where each participant makes several decisions across multiple rounds, decisions may be correlated within individuals. To address this, whenever we consider multiple rounds, we re-run our statistical analyses based on mean comparisons in the main text using random-effects GLS and probit regressions with robust-clustered standard errors as robustness checks. Our results hold and are provided in Appendix S1, Section E.

[16]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.

[17]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."

[18]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 an average rating of 4.42, compared with an average of 4.62 for those who did not switch.

[19]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.

[20]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).

[21]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, Dini, and Spagnolo 2006).

[22]Note, however, that this may not be a viable long-term strategy, even without a two-sided rating system. Workers can use third-party rating sites or forums to flag bad employers and create block lists to avoid them in the future.

[23]To better balance the power between workers and employers in online labor markets, stricter regulations could be proposed, such as mandatory reputation portability for employers. However, voluntary portability might be sufficient to discipline employers. The decision to port ratings can itself serve as a signal. Employers who choose to port their ratings across platforms demonstrate confidence in their positive reputation, while those without a portable reputation might signal either their newness or poor performance.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.