How Do Intermediaries Shape Labor Market Efficiency? An Equilibrium Model and Experimental Evidence *

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Abstract

This paper studies labor markets where intermediaries hold market power over workers and firms, charge fees on successful hires, and can sell preferential treatment in matching. To do so, we partnered with a large online job platform to conduct an advertising field experiment with 465,000 employers. Ads that boosted "premium membership" workers to the top of search results successfully steered employers' attention but lowered overall hiring by 0.9%. Guided by the experimental results, we develop and calibrate a continuous-time search and matching model in which platforms endogenously enter, set fee structures, and choose how much to distort matches toward premium workers. This type of match-steering can either increase or decrease aggregate employment, depending on the intensity of congestion externalities coming from non-paying workers. Given the parameters inferred from the experiment, we find that it lowers employment in our setting; banning premium memberships increases welfare by 4.2%. We also characterize optimal platform entry, quantify how premium memberships shift the Beveridge curve, and show that platforms' endogenous choice of revenue-raising strategies can alter the implications of pro-competitive policies. Finally, we discuss our model's applicability to two additional markets—seasonal migrants and entertainment industry workers—in which regulations limiting intermediaries' revenue-raising strategies are common.

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1 Introduction

Workers and firms use intermediaries to facilitate matching. Examples include job posting boards, university career fairs, union hiring halls, labor recruiters managing seasonal migrant work, and hiring agencies. This paper investigates how such intermediation affects labor-market efficiency. More specifically, we study the consequences of three features that are present in many markets: (i) intermediaries compete with each other and may have market power over workers and firms; (ii) they can steer matches toward specific individuals; and (iii) they have discretion over their monetization strategies, including the possibility of charging market participants for preferential treatment in the matching process.

These features may have significant, but theoretically ambiguous, effects on welfare. On the one hand, participants willing to pay for preferential treatment may be positively selected: when paired with a counterparty, they are more likely to form a productive job relationship. In this case, steering matches toward those individuals can be welfare-improving. On the other hand, intermediaries may promote lower quality matches to extract rents from workers with high willingness to pay, akin to a monopolist introducing an inferior version of a product to implement second-degree price discrimination (Deneckere and McAfee, 1996). In that case, match rates may fall, leading to lower welfare. Our primary contribution is to develop a framework for understanding and quantifying these welfare effects and, more broadly, for examining the implications of match-steering for labor market performance.

We begin with a descriptive analysis of the market we study in detail: short-term labor services delivered remotely, with intermediaries being online job platforms. The primary revenue source for most platforms is a proportional fee on workers' earnings, collected only on successful matches. However, many also feature "premium memberships" that promise higher match rates for workers or firms who pay for them. In principle, both of the welfare possibilities described above are plausible in this market. Because almost all platforms allow workers to join for free, it is possible that non-paying workers are weakly engaged with the platform, and that paying for premium memberships acts as a costly signal of openness to matches. At the same time, platforms implement premium memberships by restricting non-paying participants' access to resources that have zero marginal cost, such as information, messaging, and job applications. If these technological choices primarily serve to induce upgrades and extract rents, their welfare consequences can be negative.

To better understand the implications of premium memberships, we partnered with a large platform to conduct a field experiment involving 465,000 employers. The platform already offered premium memberships before the experiment. Our intervention increased the relative visibility advantage granted to premium over basic-tier workers. Specifically, the platform randomly assigned employers searching for workers to treatment and control groups. Treated employers were shown advertisements featuring premium-tier workers whenever they initiated search queries. Using click-level data, we show that this intervention successfully redirected employer attention. Treated employers were significantly less likely to hire basic-tier workers. However, this reduction was not offset by increased hiring of premium-tier ones, resulting in a statistically significant 0.9% decline in the probability of hiring anyone. The finding that employment falls when the platform increases the advantage of the premium tier suggests that the marginal worker being redirected is negatively rather than positively selected, consistent with the hypothesis that premium memberships reduce welfare.

Although these descriptive results are informative, they are not sufficient for a complete welfare analysis for four reasons. First, the experiment features spillovers: control employers are indirectly affected because they share the same pool of workers as treated employers. Second, employment and welfare may sometimes move in opposite directions—for instance, if premium memberships significantly lower hard-to-observe search costs. Third, the fact that an increase in match distortions reduces hiring does not necessarily imply that the optimal level of distortion is zero; some degree of match-steering may still be efficient. Fourth, the experiment provides a partial-equilibrium view of a single platform. To evaluate broader counterfactuals, such as the consequences of banning premium memberships, we must adopt a general-equilibrium framework that incorporates competition among platforms and their choice of revenue channels.

We design a continuous-time search and matching model to overcome these limitations. Our extension of the Diamond, Mortensen and Pissarides framework (1984; 1994, henceforth DMP) includes platforms as profit-maximizing agents that choose whether to enter the market, set fee structures, and determine how much to distort matches in favor of premium-tier workers. We provide a microfoundation for the platform's matching technology that describes how this distortion choice affects job-finding and vacancy-filling rates. When the worker pool is less suitable on average and the platform cannot perfectly screen suitability, premium tiers can increase efficiency by improving sorting—concentrating attention on workers who are more likely to form productive matches. On the other hand, the second-degree price discrimination motive is introduced by modeling the endogenous evolution of workers on a platform, which increases their stickiness over time. Recent joiners are unsure whether the platform is a good fit; they experiment on the platform and leave after an optimal stopping time if they are not successfully matched to an employer. “Experienced” workers, on the other hand, are more invested in the platform and have more to lose if they separate from it. We show that if the platform implements a premium membership, it is designed such that experienced workers choose to enter that tier, while recent joiners do not. We also show that platforms may not always implement a premium tier, as there is significant substitutability between revenue sources. Thus, our model is consistent with the diversity in revenue strategies observed in real-world intermediaries.

After calibrating our model to match internal data from the platform and the experimental results, we conduct a series of counterfactual simulations to understand the implications of match steering. We report four key findings. First, if platforms were prohibited from implementing premium-membership fees, welfare (output net of search costs) would improve by 4.2%, with gains stemming primarily from higher employment rates. This result is robust to alternative modeling and calibration choices. We also show that, consistent with the intuition described above, there exists a direct link between the magnitude of experimental effects on hiring and the model-implied welfare gains from this policy.

Second, we consider a centralized benchmark. A planner chooses platform entry, fee structure, and the extent of match distortion subject to the same search frictions. In all the cases we analyze, the planner would eliminate the premium membership tier. Decentralized entry is in general not optimal; it could be either above or below the planner’s choice due to within-platform thin markets effects and the platform’s market power. Nevertheless, when the planner’s optimal number of platforms is within 20% of the decentralized equilibrium, the gains from banning premiums are at least 85% of those from moving all the way to the planner’s allocation.

Third, we examine the Beveridge curves implied by the calibrated model under the baseline and under the prohibition of premium memberships. Despite platform frictions and thin markets effects within individual platforms, the aggregate Beveridge curves remain decreasing and weakly convex, as in standard search models. A comparison of the two curves shows that employment losses from premium memberships are largest when match output is low relative to search costs; when match output is high, platforms optimally forgo premium tiers, and the curves converge.

Fourth, we study how competition between platforms interacts with premium memberships.

We simulate counterfactuals with less market power by reducing the idiosyncratic platform-joining costs faced by workers and firms. When premium memberships are prohibited, match fees fall and welfare rises, as expected. However, when premium memberships are allowed, welfare falls instead. The mechanism is substitution across revenue margins: when premium tiers are allowed, platforms offset revenue losses from match fees by increasing match distortion and premium fees, which in turn lower welfare.

In the final section of this paper, we illustrate the broader applicability of our model through a qualitative discussion of two additional intermediated labor markets: non-established workers in the entertainment industry and seasonal migrant work in developing countries. We argue that our modeling assumptions apply in these contexts as well. We also document, in both markets, regulations and other institutional features that limit intermediaries' monetization strategies—including prohibitions on worker-paid fees for preferential access to employers. Our model provides a tool for predicting the equilibrium consequences and welfare implications of such policies.

Related literature. To our knowledge, we are the first to jointly study the labor market implications of intermediaries' market power, their ability to steer matches toward particular workers, and their revenue-raising strategies. Our findings on platforms' optimal entry in the presence of market power echo the theoretical insights of Farboodi, Jarosch and Shimer (2023) and Farboodi et al. (2025), although these studies analyze different environments. Shimer and Wu (2023) also examine platform competition, but focus on private information and sorting rather than platform choices on monetization and steering.

Our paper also contributes to the literature on how the internet and online platforms shape labor-market efficiency (e.g., Kuhn and Skuterud, 2004; Autor, 2008; Stevenson, 2008; Bhuller et al., 2023). Our focus on premium tiers and matching distortions connects most closely to studies of displacement effects, in which limited employer attention in frictional markets can generate inefficiencies (Crépon et al., 2013; Pallais, 2014; Cheron and Decreuse, 2016). We explicitly model the "matching with phantoms" problem highlighted by Cheron and Decreuse (2016) and relate our findings to Pallais (2014) in the discussion of counterfactuals.

A growing strand of literature uses online labor markets as field laboratories. Randomized experiments have examined algorithmic recommendations (Horton, 2017), information access (Barach and Horton, 2021), minimum-wage floors (Horton, 2025), sponsored advertising (Filippas et al., 2025*b*), and capacity signaling (Horton, Barach and Golden, 2020;

Filippas et al., 2025*a*). We contribute to this literature in two ways. First, our experiment shows that advertising workers is effective at redirecting employer attention, yet the impact on overall hiring may be negative. Second, we provide a theoretical framework that can be used to extrapolate the general-equilibrium implications of interventions studied in these experiments, as well as to measure welfare effects that may not always align with employment.

The literature at the intersection of Marketing and industrial organization uses field experiments on digital platforms to study how advertising design and sponsored placements shape consumer attention, search, and demand. Empirical evidence highlights the importance of prominence and position effects in both organic rankings and sponsored listings (Narayanan and Kalyanam, 2015; Ursu, 2018; Abhishek, Jerath and Sharma, 2025) and documents substantial substitution/crowd-out between paid and unpaid traffic for some keywords and advertisers (Blake, Nosko and Tadelis, 2015; Simonov, Nosko and Rao, 2018). There is evidence for both efficiency-increasing and rent-extraction functions of advertising. For example, ads may serve as informative signals (Sahni and Nair, 2019), reducing the prominence of ads on a search engine can lower its usage and consumers' information discovery (Sahni and Zhang, 2024), while removing sponsored listings on retail media can reduce the retailer's total revenue even when it increases transactions (Moshary, 2025). We complement these findings by providing a search-and-matching framework that clarifies when prioritization improves efficiency by sorting through a noisy pool versus when it primarily functions as rent extraction from relatively inelastic participants.

Finally, we contribute to the industrial organization literature on intermediation markets (Rochet and Tirole, 2003; Lee, 2014; Rosaia, 2025). Our work is most closely related to models of competition between intermediaries that choose pricing strategies (Caillaud and Jullien, 2003), can steer matches (Hagiu and Jullien, 2014), or make optimal entry decisions (Atkeson, Eisfeldt and Weill, 2015). However, it differs from existing approaches in several ways. First, it simultaneously incorporates platform choices on monetization, steering, and entry. Second, it features endogenous differentiation between market participants in a dynamic setting, based on past successful matches. Third, it replicates detailed features of the data and can serve as the basis for quantitative policy analysis. Tractability follows from our focus on markets with many intermediaries, which allows us to make two simplifying assumptions: a "monopolistic competition" limitation on strategic interactions and ignoring granularity concerns by treating the number of operating platforms as a continuous variable.[1]

[1]Our focus on competition between intermediaries differentiates our work from interesting papers that study related design choices in models with a single platform, such as Hagiu and Jullien (2011), Hagiu and

The paper is organized as follows. The following section describes the empirical setting and the experiment. The third section presents the model. The fourth section reports the quantitative analysis. The fifth section discusses broader applicability. The last section concludes with directions for future research.

2 Online Job Platforms and Experimental Evidence

2.1 Description of the Market

Since their emergence at the turn of the century, online labor markets have experienced rapid growth. By 2009, workers in this market earned around \$700 million annually (Horton, 2010), and this figure reached \$1 billion by the end of 2012 (Agrawal et al., 2015). More broadly, the so-called gig economy currently involves tens of millions of workers and generates hundreds of billions of dollars in gross volume of transactions (Statista Research Department, 2022).

In short, online labor markets are digital platforms through which individual employers can hire the services of independent workers for specific tasks. These platforms are not passive marketplaces, as they operate the matching process between workers and employers and facilitate transactions between them. Typically, employers can post and describe vacancies and search for workers, whereas workers can search and apply for jobs. More information about agents on both sides of the market is also made publicly available.

Platforms compete against one another, and there are several options available to workers and employers. Whereas some platforms specialize in specific types of service, others host workers of varied backgrounds. Nevertheless, the monetization tools of all these platforms are roughly similar, as summarized in Table 1.

Most often, platforms charge a fee on successful matches between workers and employers. However, they also commonly offer premium memberships that grant access to additional features unavailable to non-paying users. These features are advertised as tools for increasing job-finding or vacancy-filling rates. Examples include higher limits on the number of job applications or messages that can be sent to potential counterparties, access to additional information about these counterparties, and maintaining a high ranking in search results

Wright (2015), de Cornière (2016), Dinerstein et al. (2018), de Cornière and Taylor (2019), Marx and Schummer (2021), Teh, Wang and Watanabe (2024), Horton, Johari and Kircher (2024), and Lee and Musolff (2025).

Table 1: Monetization Features of Some Online Labor Platforms

Platform	Fees on Matches	Premium for Workers	Premium for Employers	Participation Fee
99designs	Yes	No	Yes	No
Care.com	No	Yes	Yes	Yes
Catalant	Yes	No	Yes	No
DesignCrowd	Yes	No	Yes	No
Fiverr	Yes	Yes	Yes	No
Freelancer	Yes	Yes	Yes	No
Guru	Yes	Yes	Yes	No
Handy	Yes	No	No	No
Hubstaff Talent†	No	No	No	No
Outsourcely	No	Yes	Yes	Yes
PeoplePerHour	Yes	Yes	No	No
Rover	Yes	Yes	No	No
TaskRabbit	Yes	No	No	No
Thumbtack	Yes††	No	No	No
Toptal	Yes	No	No	No
Truelancer	Yes	Yes	No	No
Upwork	Yes	Yes	Yes	No
WeGoLook	Yes	No	No	No
Wonolo	Yes	No	No	No
Workana	Yes	Yes	Yes	No

Notes: Information from each platform was obtained by browsing their websites as of May 2025. † Hubstaff Talent does not charge fees because they function as an advertising tool for Hubstaff's time-tracking and workforce management paid products. †† On Thumbtack, workers pay fees on "leads," that is, when employers try to contact them after seeing their profile on the website.

even when the platform detects limited recent activity.

An important observation from Table 1 is that very few platforms require participation fees; most allow employers and job seekers to create accounts and match at no cost. This observation motivates one of our modeling assumptions: we do not allow intermediaries to charge such fees. Appendix B.1 provides an extended discussion of the theoretical reasons why it may not be optimal for platforms to levy participation fees.

2.2 The Platform: Searching, Matching, and Hiring

We partnered with a large online platform to run our experiment, which we describe in more detail in the next section. This platform does not specialize in specific types of tasks; it hosts workers from several areas, including marketing, IT, and translation.

In this platform, an employer creates listings with the job description and a range of prices that they are willing to pay. Employers can also search for workers and invite specific ones to apply for their job, and the platform provides employers with algorithmic recommendations based on machine learning models. Employers can observe workers' profiles, portfolios, and reviews, and they have the ability to interview workers. In addition, the platform offers a premium option for employers that offers enhanced support in exchange for additional fees.

Workers create a profile and search for jobs. They can submit proposals for specific jobs, which may require the payment of an internal currency amount that has to be purchased. This currency can also be used to increase visibility and show availability. Following the completion of jobs and reviews, workers can be awarded specific badges that indicate their high quality. Furthermore, the platform also offers a premium tier for a monthly payment, which gives workers additional internal currency and other benefits.

Workers and employers must come to terms for a match to be successful. The platform allows for both fixed-price contracts and hourly contracts, whose respective rates must be agreed upon by the two parties. The platform charges a fee on earnings in addition to potential additional payments from elective premium options.[2]

2.3 Experiment

We leverage data from an experiment conducted by the platform between May and July 2019. In this experiment, the platform introduced ads for the first time. More specifically, the platform boosted workers that belonged to the premium-tier to the top of the page, where they were displayed as an ad, based on the order in which they showed up as an organic result. The experiment randomized employers into treatment and control groups equiprobably. Employers who belonged to the control group saw the platform as it had always been, without advertisements. In turn, treated employers were eligible to be exposed to advertised workers. We provide more details about the data and the experiment in Appendix A.

We interpret this experiment as tracing the "possibility frontier" of the platform's matching technology, specifically with respect to its ability to steer matches towards a selected subgroup of workers. As the platform directs employers toward premium workers, we should expect the hiring rates of basic-membership workers to fall. The key question is what happens to total hiring. If it remains roughly constant, this would indicate that the platform can

[2] The platform can effectively retain fees from matches because one of the services it provides is facilitating the payment for labor services. Firms and workers benefit from using the platform for settlement because they offer dispute resolution services. Additionally, the platform offers monitoring tools for workers engaged in online-only work.

Table 2: Experimental Results, Employer-Level Regressions

	All workers	Sometimes premium	Never premium
Panel A: dependent variable is ***any clicks on these workers***			
Treatment	-0.00413***	0.0155***	-0.0121***
	(0.00147)	(0.00128)	(0.00133)
Constant	0.485***	0.248***	0.299***
	(0.00104)	(0.000897)	(0.000951)
Panel B: dependent variable is ***log(1 + number of clicks on these workers)***			
Treatment	-0.0107**	0.0173***	-0.0173***
	(0.00294)	(0.00159)	(0.0184)
Constant	0.769***	0.267***	0.350***
	(0.00209)	(0.00111)	(0.00132)
Panel C: dependent variable is ***any hire***			
Treatment	-0.00263**	0.0000115	-0.00252***
	(0.00133)	(0.000941)	(0.00102)
Constant	0.293***	0.117***	0.143***
	(0.000945)	(0.000666)	(0.000728)
Panel D: dependent variable is ***log(1 + number of hired workers)***			
Treatment	-0.00286**	-0.000195	-0.00211**
	(0.00138)	(0.000771)	(0.000917)
Constant	0.271***	0.0914***	0.119***
	(0.000981)	(0.000547)	(0.000652)
N	464,986	464,986	464,986

Data sources: Internal data from the platform. Note: the "Constant" rows in Panels B and D, Columns (2) and (3) do not add up to the value in Column (1) because there are workers in the platform for whom premium-membership status is not observed, such that they are included in the first column but do not appear in the others. See Appendix A.3 for details on the measurement of premium-membership status.
Heteroskedasticity-robust standard errors are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

reallocate matches across worker types with little effect on the average employment rate. Indeed, overall employment effects could even be positive if prioritizing paying workers improves match efficiency—for example, due to strong congestion externalities generated by non-paying workers. Conversely, if the experiment reveals a decline in total hiring, that would suggest that premium memberships are associated with welfare losses.[3]

Table 2 reports the experimental results for outcomes measured at the employer level. The first two panels show the employer's interaction with search results in the form of clicks. The dependent variable in Panel A is an indicator for whether the employer clicked in the profile of a particular worker in a period of 60 days starting from the employer's assignment to an experimental group (which happens upon their first interaction with the platform during the experimental window). Panel B's dependent variable is the logarithm of one plus the total number of clicks in the same interval. While the first column shows clicking behavior for all workers, the second and third columns condition on the employer clicking on particular subsets of workers: those that sometimes had a premium membership during the experimental period, and those who never had a premium membership in the same period.

The results show that ads seem to successfully divert employer attention during the search process toward premium-membership workers. Compared to control employers, treated ones are more likely to click on premium workers and less likely to click on basic-membership ones. The overall effect is negative.

Next, we turn to hiring outcomes in Panels C and D, where we limit hiring outcomes to the same 60-day interval used for clicks. Treated employers' probability of hiring any worker falls by 0.263 percentage points, which is a relative decline of 0.9 percent. The analysis by worker group shows that this decline is concentrated on workers who never had a premium membership. The point estimate suggests no effects on the probability of "sometimes premium" workers being hired, with standard errors small enough to reject both an increase or a reduction of the same relative magnitude as that observed observed for non-premium workers.

[3]The large scale of the experiment gave the platform strong incentives to carry it out carefully, consistent with our interpretation that it traces the possibility frontier rather than reflecting a suboptimal modification of its interface or recommendation systems. A back-of-the-envelope calculation illustrates the stakes: with 465,000 employers, a 0.9% reduction in hiring among treated users—the magnitude we estimate—would imply more than four million dollars in foregone match fees over the three-month experimental period, under the assumption that the average employment spell lasts one full-time month.

2.4 Discussion

The experiment provides strong evidence that premium memberships can effectively redirect employers' attention toward paying workers, as reflected in their click-level behavior. The fact that overall hiring is lower for treated employers suggests a reduction in match efficiency arising from premium memberships. However, as discussed in the introduction, descriptive results alone are not sufficient for a complete understanding of their implications for labor market efficiency for four reasons. First, control users may be indirectly affected because both groups interact with the same pool of workers. Second, employment and welfare may not necessarily move in the same direction. Third, a marginal increase in distortion toward premium users may be inefficient even when a lower, but still positive level is socially optimal. Fourth, because the experiment covers only one platform, it provides limited insight into the equilibrium implications of premium memberships.

The model developed in the next section is designed to overcome these limitations. However, before turning to it, we rule out alternative explanations for our experimental results, as identifying the specific channel through which premium memberships affect hiring is important for determining the appropriate model structure.

Are experimental results driven by signaling about worker quality? Existing literature shows that when consumers lack perfect information about product quality, advertising can operate not only through saliency, but also through signaling. For example, Sahni and Nair (2019) design an experiment to disentangle these channels and find that advertising conveys a positive quality signal in the market they study (restaurants). Signaling effects can also be negative. In our context, employers might infer that a worker who needs to advertise is struggling to find work, possibly because they have lower ability. That could explain the absence of a positive treatment effect on premium workers' hiring rates.

This interpretation appears inconsistent with the increase we observe in the click rate for premium workers, which signals greater employer interest. To provide an even stronger test of this hypothesis, we use data on whether employers invite specific workers to apply to one of their job postings. The results, reported in Appendix Table A2, show that treated employers are significantly more likely to invite premium workers to apply, with a magnitude similar to the corresponding decline for basic-tier workers. Thus, it does not appear that employers down-weight or disregard advertised workers; they show greater interest in them, but this additional interest does not translate into higher hiring rates.

Are treated employers exposed to different workers? Another potential explanation is that the experiment introduces differences in the sets of workers encountered by treated employers. As discussed in Appendix A, the experiment was designed to minimize this possibility. To further establish that the results are not driven by selection into the pool of workers considered by each group, we estimate an alternative regression where the unit of analysis is the worker–employer pair. The data are constructed using workers who appear on the first page of search results viewed by employers upon entering the experiment. This design eliminates selection concerns, as the advertising treatment has no effect before an employer's initial search. Importantly, it also allows us to include worker fixed effects, exploiting the fact that the same workers appear before both treated and control employers.

Appendix Table A3 reports the results. We find qualitatively similar patterns: treated employers are significantly less likely to hire basic-tier workers relative to control employers, but their likelihood of hiring premium-tier workers is unchanged.

Takeaways. These additional exercises support the view that premium memberships influence employers' hiring decisions primarily through a saliency mechanism—namely, which workers are noticed and seriously considered, given employers' limited attention. This motivates us to build a model that emphasizes this aspect of the search process rather than one in which employers infer worker quality from premium status in a standard signaling framework. That said, in an extension introduced in Section 4.1, we will consider a different signaling role for premium memberships: the possibility that workers may use them to convey information to the platform, rather than to employers, about being more promising than the average worker and therefore deserving of higher priority in the search process. Before turning to that extension, we first present the basic version of the model.

3 Model

We develop a continuous-time frictional model of job search with profit-maximizing intermediaries, which we refer to as platforms. The model provides a framework for explaining the factors that impact the platforms' monetizing decisions and analyzes how they shape labor-market outcomes and welfare. Although the model is dynamic, we focus on steady-state equilibria. In addition, throughout the paper, we restrict attention to symmetric equilibria where platforms make identical choices.

Our goal is to study the cases where platforms manipulate the matching mechanism to favor some workers relative to others, aligning with the experiment described in the previous subsection. Although the same kind of steering can also exist towards specific firms (as shown in Table 1), we abstract from that dimension to keep the model as simple as possible.

3.1 Preliminaries: Workers, Firms, and Platforms

The economy is populated by N_w workers and a large number of potential employers. Throughout the paper, we use the terms "firms" and "employers" interchangeably. Workers and firms are ex-ante identical, infinitely-lived, and risk-neutral. Not every worker-firm combination is productive and assessing match quality is costly and time-consuming. Platforms facilitate this process. The matching technology is fully presented in the following section.

Risk-neutral entrepreneurs must pay a flow cost F to operate a productive platform. Throughout the paper, we will index platforms by i and denote the endogenous number of operating platforms in the economy by I. Platforms are horizontally differentiated, giving them some degree of power over workers and firms. This differentiation will be modeled through idiosyncratic utility costs to be described in Section 3.3.

Platforms can raise revenues in two ways. The first is through a match fee f_m that is extracted from successful job matches. The second is a "premium membership" fee f_p paid by workers who choose that tier if the platform chooses to offer it. Importantly, we do not allow platforms to charge participation fees; that is, they must allow workers and firms to join them and have a chance to be matched without paying any upfront costs. This assumption, which will be formalized in Section 3.3, is central to our results. It is consistent with the fact that very few platforms charge this type of fee, as shown in Table 1. In Appendix B.1, we discuss how zero participation fees could emerge endogenously in augmented versions of the model with additional mechanisms. We do not add these microfoundations to the baseline model for the sake of simplicity.

3.2 Search Frictions and the Platform's Matching Technology

Workers and firms in the platform. The search process begins with firms creating open vacancies, which require a flow cost of c to be sustained. Employers must then join a platform, a process described in detail in the next section. Unemployed workers must also join a platform before they can find jobs.

Workers and firms can belong to at most one platform at a time and can only be matched to counterparties on the same platform. In other words, our model does not allow for *multi-homing*. In the context of online labor platforms, this is not an unreasonable assumption; see, for example, Horton (2025). In Section 4.1, we incorporate an extension that partially accounts for the possibility of multi-homing in the data. Workers can be matched only when unemployed; each job spell should be interpreted as a short-term but full-time position.

When a worker joins a platform, an unobservable random variable $x \in \{0,1\}$ is drawn with $\Pr(x=1) = \bar{x}$. If $x = 0$, the worker is "unsuitable," meaning that they cannot form a productive match with any firm on that platform. Crucially, neither the worker nor the platform observes x, although both can infer that $x = 1$ after the worker's first successful match. Suitability plays a central role in the model, generating an "experimentation" phase in the worker's platform experience and creating the possibility that premium memberships increase welfare. For the purposes of this section, it suffices to note that both workers and platforms are uncertain about suitability, and that $x = 0$ implies a match cannot be formed.[4]

Matching. The platform's matching technology works as follows. At an exogenous Poisson rate λ, the platform receives a "match-making opportunity." It begins by randomly selecting an open vacancy. Then, for every worker on the platform, a latent "match distance" variable $d \sim U[0,1]$ is drawn. This variable captures horizontal differentiation between the firm's needs and the worker's abilities. It may also reflect temporary worker unavailability for reasons outside of the model.

The platform can identify the worker with the lowest d and direct them to the firm. A match is formed under two conditions: the worker must be suitable ($x = 1$), and the mismatch must be sufficiently small ($d < 1/D$, with $D > 1$ exogenous). Importantly, neither x nor d is revealed in the event of a failed match. Combined with the fact that D is large in typical applications (e.g., $D = 13{,}500$ in our baseline calibration), this assumption implies that failed matches do not convey information on suitability.

The platform may also choose to skew matches toward premium workers. When a match-making opportunity arrives, it can restrict attention to premium workers when identifying

[4] The extension presented in Section 4.1 allows workers to have private information about their suitability. Suitability may represent worker–platform idiosyncratic factors that are difficult to observe before engaging with the platform, such as whether the worker finds the interface intuitive and can use it effectively. Suitability may also reflect unmodeled sorting of employers with different skill requirements or geographies across platforms, as long as such sorting is not easily observable before a period of experimentation.

the worker with the lowest d. We allow mixed strategies in which the platform randomly determines whether to impose this restriction with probability $\gamma_i \in [0,1]$. We refer to γ as the "match distortion," and it will be one of the platform's choice variables in its profit-maximization problem. In Appendix B.2 we further discuss this microfoundation and its connection to our empirical setting and the experiment.

Vacancy-filling and job-finding rates. We use lowercase n to denote the counts of workers and firms within a platform. Specifically, $n_{V,i}$ is the number of firms with open vacancies, $n_{J,i}$ is the number of filled job positions, $n_{b,i}$ is the number of unemployed workers with a basic membership, and $n_{p,i}$ is the number if unemployed workers with a premium membership. Therefore, the total number of firms on the platform is $n_{V,i}+n_{J,i}$, while the total number of works workers is $n_{b,i}+n_{p,i}+n_{J,i}$.

We consider environments in which both the number of workers and the number of vacancies are large and in which the mismatch parameter D is also large. In Appendix B.2, we show that under these assumptions, the vacancy-filling rate can be approximated as:

$$q_i \; = \frac{\lambda}{n_{V,i}} \left\{ \gamma_i \left[1 - e^{-n_{p,i}/D} \right] \; + \; (1-\gamma_i) \left[1 - e^{-(n_{b,i}+n_{p,i})/D} \right] \phi_i \right\}, \tag{1}$$

where ϕ_i is the share of suitable workers among all unemployed workers in the platform, which we will derive below. This expression assumes that every unemployed worker in the premium pool is suitable, which we will show to be true in equilibrium. The corresponding job-finding rates for *suitable* workers in the basic and premium tiers are given by

$$h_{b,i} = \frac{\lambda(1-\gamma_i)\left(1 - e^{-(n_{b,i}+n_{p,i})/D}\right)}{n_{b,i}+n_{p,i}} \tag{2}$$

$$h_{p,i} = h_{b,i} + \frac{\lambda\gamma_i\left(1 - e^{-n_{p,i}/D}\right)}{n_{p,i}}. \tag{3}$$

Note that $\gamma_i > 0$ implies $h_{p,i} > h_{b,i}$, that is, higher job-finding rates for premium-membership workers. This difference in match rates is what allows the platform to charge premium membership fees, as we explain in the following section.

Discussion. We make four important remarks regarding that vacancy-filling expression (1), which is a core component of the model. First, it may be either increasing or decreasing in

γ_i. On the one hand, restricting attention to premium workers means that there would be situations where a suitable basic-membership worker could form a match, but none of the premium-membership ones are good enough. On the other hand, this kind of restriction may be efficient if contacts originating from the unrestricted pool often fail to form matches because many of them are unsuitable (that is, ϕ_i is low). Thus, our formulation of the matching process does not imply that the existence of premium tiers is necessarily detrimental to market efficiency. The extensions presented in Section 4.1 provide additional mechanisms through which premium memberships could increase match efficiency by allowing workers to reveal private information.

Second, if the platform chooses $\gamma_i > 0$, the vacancy-filling rate is strictly increasing in the share of the platform's workers who belong to the premium tier. This is because having more workers in that tier makes the conditioning to that pool less restrictive. This observation has an important implication for the profit-maximizing problem of the platform. As we will show below, conditional on implementing a premium membership, the platform will want to induce all experienced workers to participate in it, in order to make it less distortionary.

Third, the vacancy-filling rate increases with the number of workers in the platform. With few workers, match probabilities become small due to a "thin markets" effect: even when the platform is able to identify the most suitable worker, that worker may still not be a good enough match. The ratio D/λ regulates the strength of this effect. When we solve the problem of a welfare-maximizing central planner in this economy in Section 4.4, we will show that a higher D/λ is associated with larger optimal platform sizes.

Finally, one may be concerned that this thin markets effect implies a fundamental difference between our model and the standard search-and-matching framework. However, note that even though thin markets effects exist within individual platforms, they may not exist at the aggregate level. In Section 4.5, we show that the Beveridge curve implied by our calibrated model is decreasing and convex, as in the textbook DMP model with a concave, constant-returns-to-scale matching function.

3.3 States, Transitions, Value Functions, and Wage-Setting

Employers. Employers can be in one of *three* states. The first is a newly created vacancy. In this stage, the firm has to *search for a platform* and has the option of joining it or not. The second stage is an open vacancy within the platform. At this point, the firm searches for workers, but may also receive an exogenous vacancy destruction shock. The third and final stage is reached after matching with a worker, at which point the firm has a filled job that is subject to a job destruction shock. These states are illustrated as the orange and green boxes in Figure 1.

In the first state, firms receive the opportunity of being matched to a randomly-drawn platform i at Poisson rate λ_0. When this happens, they draw an idiosyncratic cost ε of joining the platform from an Exponential distribution with mean $1/\sigma_\varepsilon$. The value of being a searching firm is equal to the expected discounted value of continuing to pay c per unit of time while occasionally getting opportunities to join a platform that may or may not be worth paying for. This flow value is given by

$$rV_0^e = -c + \lambda_0 \int_0^\infty \left[\frac{1}{I} \sum_i \max \left\{ V_i^e - \varepsilon - V_0^e, 0 \right\} \right] \sigma_\varepsilon e^{-\sigma_\varepsilon \varepsilon} d\varepsilon,$$

where r is the discount rate.

The flow value of being an employer in the second state—an open vacancy at platform i—is given by

$$rV_i^e = -c + q_i \left[J_i^e - V_i^e \right] + s_V \left[V_0^e - V_i^e \right],$$

where q_i is the platform's vacancy-filling rate from the previous section, J_i^e is the value of a filled vacancy at platform i, and s_V is an exogenous rate of separations from the platform while in the open vacancy stage.

Finally, J_i^e is defined by

$$rJ_i^e = y - w_i + \delta \left[0 - J_i^e \right],$$

where y is the raw match output, w_i is the bargained wage, and δ is the job destruction rate. When the job is destroyed, the firm goes back to the pool of potential entrants not yet matched to a platform, with present value normalized to zero.

Workers. Workers may be in one of *five* states. Like firms, the beginning of the match process is the search for a platform. In that stage, they face similar joining frictions as firms. Upon joining a platform, they remain in the second state—an *inexperienced* worker—until they are matched to an employer or, alternatively, if they decide to leave the platform. Employed workers (the third state) leave that state following job-destruction shocks. At that point, they remain in the platform and can choose between one of the two last states: an experienced unemployed worker with either a basic or a premium membership. The

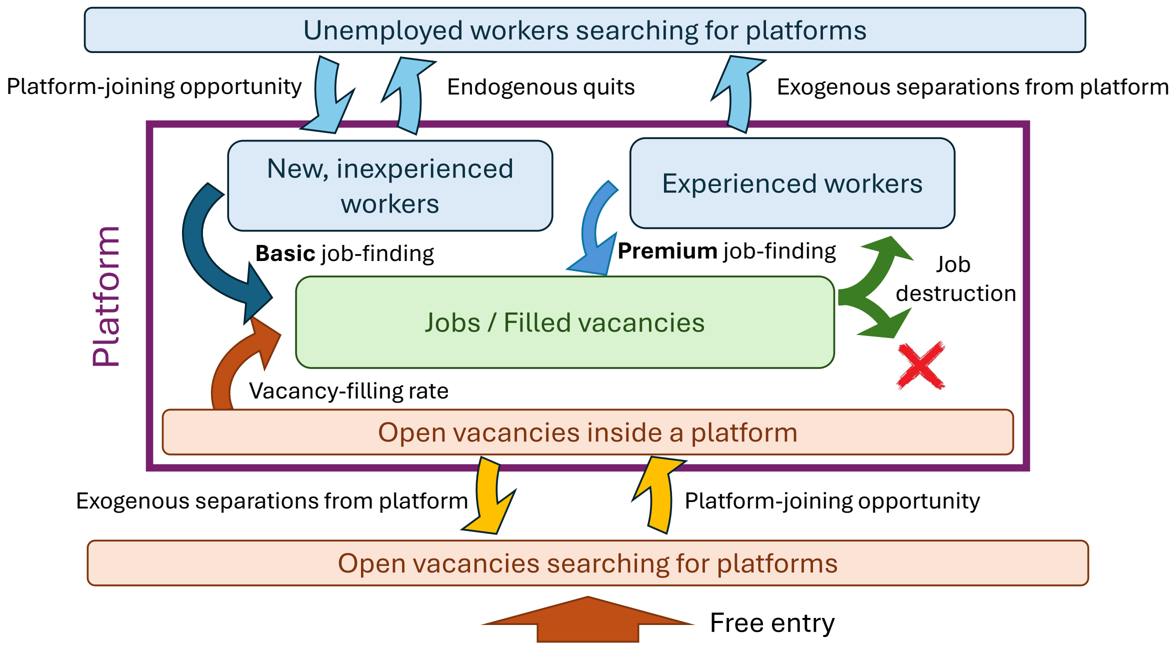

Figure 1: States and Transitions for Workers and Firms

difference between inexperienced and experienced workers is that the former do not know their own suitability x, while the latter know that $x = 1$ because they have been previously matched to a firm in that platform.

Fee structure. Before proceeding to the corresponding value functions for workers, we formalize our assumptions regarding fee structure. We impose that (i) inexperienced workers would not join the platform or would leave the platform if they were required to pay any fees other than match fees; (ii) match fees are a fixed proportion of wages received by workers, with the proportion being the same for every worker in the platform; and (iii) premium-membership fees are identical for all workers. These assumptions imply that every inexperienced worker chooses the basic membership and prevent any form of price discrimination other than the possibility of experienced workers self-selecting into premium memberships. As discussed in Section 2.2 and Appendix B.1, we believe these assumptions provide a useful approximation to this market. Investigating richer forms of contracts would be interesting, but is left for future work.

Worker value functions and transitions. We start with the equation that defines the flow value of the platform-search state,

$$rV_0^w = \lambda_0 \int_0^\infty \left[\frac{1}{I} \sum_i \max \left\{ \tilde{V}_i^{iw}(0) - V_0^w - \varepsilon, 0 \right\} \right] \sigma_\varepsilon e^{-\sigma_\varepsilon \varepsilon} d\varepsilon,$$

where $\tilde{V}_i^{iw}(t)$ corresponds to the *perceived* value of being an inexperienced worker who has been in the platform for t units of time without having received a match. This instantaneous return to waiting on a platform equals the expected gain from finding a job (weighted by the worker's belief of being suitable) plus the gradual decline in value over time as that belief falls. That value function is defined by

$$r\tilde{V}_i^{iw}(t) = \bar{h}_b \left[\tilde{J}_i^w - \tilde{V}_i^{iw}(t) \right] \Pr\left(x = 1 | t, \bar{h}_b \right) + \frac{d\tilde{V}_i^{iw}(t)}{dt}.$$

where $\tilde{J}_i^w$ is the perceived value of being an employed worker in platform i.

This expression defines a *perceived* value, rather than an actual value, for two reasons. First, because inexperienced workers do not know their suitability x, the value function reflects their posterior probability of being suitable given how long they have stayed in the platform. For workers who just join the platform, that perceived probability is $\Pr\left(x = 1 | t = 0, \bar{h}_b\right) = \bar{x}$. As time passes with no matches arriving, that probability falls, approaching zero as $t \to \infty$. When $\tilde{V}_i^{iw}(t)$ falls so much that it becomes lower than the outside value V_0^w, it becomes optimal for the worker to leave the platform and return to the platform-search stage.

Second, we assume that inexperienced workers cannot observe the platform-specific job-finding rate for basic-membership workers, $h_{b,i}$. Instead, workers infer that the platform's job-finding rate is equal to the average rate across all platforms, denoted by $\bar{h}_b$. In a symmetric equilibrium, workers' beliefs regarding job-finding rates are correct. However, this assumption has implications for the platform's optimal choices, as we discuss below. Appendix C.5 contains an extended discussion regarding this assumption. There, we show that it is more consistent with our data than the alternative assumption that inexperienced workers are fully informed about job-finding rates. We also verify the robustness of our main quantitative result as we allow a fraction of inexperienced workers to be well-informed about match rates.

The value function for employed workers is given by

$$rJ_i^w = (1 - f_{m,i})w + \delta \left[\max\left\{V_i^b, V_i^p\right\} - J_i^w \right]$$

where $f_{m,i}$ is the platform-specific fee collected as a share of payments from the firm to the worker (referred to as "match fees"). V_i^b and V_i^p denote the values of being an experienced but unemployed worker in the platform with either a basic or a premium membership, respectively.

Before presenting the equations defining these last two value functions, we must introduce the process of separations from the platform. At an exogenous rate s_U, an unemployed, experienced worker receives a "separation shock" ν that can represent frustration, fatigue, or outside opportunities, which is drawn from an Exponential distribution with mean $1/\sigma_\nu$. The worker has then the choice of incurring an instantaneous utility loss of ν or returning to the platform-search stage. The resulting asset values then satisfy:

$$\begin{aligned} rV_i^b &= h_{b,i}\left[J_i^w - V_i^b\right] + s_U \int_0^\infty \max\left\{-\nu, V_0^w - V_i^b\right\} \sigma_\nu e^{-\sigma_\nu \nu} d\nu \\ rV_i^p &= -f_{p,i} + h_{p,i}\left[J_i^w - V_i^p\right] + s_U \int_0^\infty \max\left\{-\nu, V_0^w - V_i^p\right\} \sigma_\nu e^{-\sigma_\nu \nu} d\nu, \end{aligned}$$

where $f_{p,i}$ is the premium membership fee and $h_{p,i}$ is the premium job-finding rate. We introduce the separation shocks ν to regulate the platform's market power over experienced workers, making their retention responsive to $\max\left\{V_i^b, V_i^p\right\}$. We abstract from these separation shocks for inexperienced workers for simplicity.

Wages. We end this section by describing wage setting in the platform. As in the standard DMP model, wages are set by Nash bargaining. The threat points for both workers and firms correspond to returning to the search stage within the platform. Denoting the worker's bargaining power parameter by β, that means the bargained wage at platform i is the implicit solution to the equation

$$(1-\beta)\left[J_i^w(w) - \max\left\{V_i^b, V_i^p\right\}\right] = \beta\left[J_i^e(w) - V_i^e\right]. \tag{4}$$

Note that wages do not depend on whether it's the worker's first match in the platform or not. That is because upon the first match, the worker learns that $x = 1$, and thus the threat point is to return to the platform as an experienced worker.[5]

3.4 Firm and Worker Choices and Steady-State Quantities

We now begin characterizing an equilibrium in this model. The following macroeconomic variables are taken as given in this stage: the value functions for platform-searching workers and firms, V_0^w and V_0^e, the number of operating platforms, I, and the stocks of workers and firms in the platform-search stage, denoted by N_0^w and N_0^e. The variables $(f_{m,i}, f_{p,i}, \gamma_i)$ represent arbitrary choices for a given platform i. In this section, we discuss how the model's key stock variables, such as the steady-state number of workers with premium memberships, are determined as functions of these arbitrary choices. The following section will use these results to discuss the platform's profit-maximization problem.

Firms and workers in the platform-search stage who receive the opportunity to join a platform will do so as long as the joining cost, ε, is low enough. That condition is $\varepsilon < V_i^e - V_0^e = V_i^e$ for firms and $\varepsilon < \tilde{V}_i^{iw}(0) - V_0^w$ for workers. Thus, we can calculate expressions for inflows of firms and workers into the platform, respectively

$$\psi_i^e = \frac{N_0^e}{I}\lambda_0\Big[1 - \exp\big(-\sigma_\varepsilon V_i^e\big)\Big] \tag{5}$$

$$\psi_i^w = \frac{N_0^w}{I}\lambda_0\Big[1 - \exp\big(-\sigma_\varepsilon(\tilde{V}_i^{iw}(0) - V_0^w)\big)\Big]. \tag{6}$$

It is easy to show that the elasticities of inflows into a platform with respect to the platform value are strictly positive, strictly decreasing, diverge to positive infinity as $V_i^e \to V_0^e$ or $\tilde{V}_i^{iw}(0) \to V_0^w$, and converge to zero as V_i^e or $\tilde{V}_i^{iw}(0)$ grow large. The parameters λ_0 and σ_ε regulate the degree of competitiveness between platforms.

The number of open vacancies within a specific platform i is pinned down by equating inflows to total outflows,

$$\psi_i^e = (q_i + s_V)n_{V,i}, \tag{7}$$

where the right-hand side of this expression includes two types of outflows: vacancy-filling and exogenous separations from the platform.

[5] When we defined the value for inexperienced workers $\tilde{V}_i^{iw}(t)$ above, we used a *perceived* value for the value of a job $\tilde{J}_i^w$, rather than the real J_i^w. The values for $\tilde{J}_i^w$, $\tilde{V}_i^b$, and $\tilde{V}_i^p$ are obtained by solving a system of equations given by the non-tilde definitions, but using the perceived job-finding rates $\bar{h}_b, \bar{h}_p$ instead of the real ones. For computational simplicity, we assume that workers observe the true bargained wage w_i, but are not sophisticated enough to use this information to "back out" other platform-specific outcomes from it.

Inexperienced workers stay in the platform for a certain amount of time but leave if it takes too long to be matched to a firm. In Appendix B.3, we derive the optimal stopping time

$$T_i \;=\; \max\left\{0,\; \frac{1}{\bar{h}_b}\left[\ln\!\Big(\frac{\bar{x}}{1-\bar{x}}\Big) + \ln\left(1+\frac{\bar{h}_b}{r}\frac{\tilde{J}_i^w - V_0^w}{V_0^w}\right)\right]\right\}. \tag{8}$$

To calculate the equilibrium number of inexperienced workers, we need to consider inflows and outflows for two subgroups: those who are suitable ($x=1$) and those who are not ($x=0$). The balance equation that determines the number of suitable inexperienced workers, $n_{siw,i}$, is

$$\psi_i^w \bar{x} = n_{siw,i} h_{b,i} + \psi_i^w \bar{x} \exp\left(-h_{b,i} T_i\right). \tag{9}$$

The first term in the right-hand side represents exits due to workers finding their first jobs in the platform. The second term corresponds to voluntary exits at the end of the optimal waiting time.[6]

In turn, the expression for unsuitable, inexperienced workers is

$$\psi_i^w (1-\bar{x}) = \frac{n_{uiw,i}}{T_i}. \tag{10}$$

For these workers, there is no job finding; they simply exit the platform at rate $1/T_i$.

The pools of employed ($n_{J,i}$) and experienced but unemployed workers ($n_{ew,i}$) are pinned down by

$$\begin{aligned} n_{siw,i} h_{b,i} + n_{ew,i} h_{ew,i} =& \,\delta n_{J,i} \\ \delta n_{J,i} =& \,(h_{ew,i} + \bar{s}_U)\, n_{ew,i}, \end{aligned}$$

where $\bar{s}_U \equiv s_U \exp\left(-\sigma_V(\max\{V_i^b, V_i^p\} - V_0^w)\right)$ is the effective separation rate for experienced unemployed workers, and $h_{ew,i} \equiv (1-\rho_{ew,i}) h_{b,i} + \rho_{ew,i} h_{p,i}$ is the average job-finding rate for experienced workers, with $\rho_{ew,i}$ denoting the share of those workers who choose the premium membership tier. Note that this share must be zero if $V_i^b > V_i^p$ and one if $V_i^b < V_i^p$. If $V_i^b = V_i^p$, then any $\rho_{ew,i} \in [0,1]$ is consistent with worker's optimal behavior. In that case, we will assume that the platform chooses $\rho_{ew,i}$.

[6] An alternative way to derive this expression is to apply Little's law, such that the number of workers is the product of the inflow rate $\psi_i^w \bar{x}$ multiplied by the expected time a worker remains in that state. To get that expected time, model the total time spent in the inexperienced state as a random variable $\bar{\mathbb{T}} = \min\{\mathbb{T}, T_i\}$, where $\mathbb{T} \sim \text{Exp}(h_{b,i})$, then integrate $\mathbb{E}[\bar{\mathbb{T}}]$.

We can rewrite the expressions for the pools of experienced and employed workers as

$$n_{ew,i} = \frac{h_{b,i}}{\bar{s}_U} n_{siw,i} \tag{11}$$

$$n_{J,i} = \frac{h_{ew,i} + \bar{s}_U}{\delta} n_{ew,i}. \tag{12}$$

Finally, the numbers of workers in each membership tier, along with the share of suitable workers among unemployed workers, are

$$n_{b,i} = n_{siw,i} + n_{uiw,i} + (1 - \rho_{ew,i}) n_{ew,i} \tag{13}$$

$$n_{p,i} = \rho_{ew,i} n_{ew,i} \tag{14}$$

$$\phi_i = \frac{n_{siw,i} + n_{ew,i}}{n_{uiw,i} + n_{siw,i} + n_{ew,i}}. \tag{15}$$

3.5 Optimal Platform Choices

Our model is designed to approximate empirical settings where intermediaries have some market power but the intermediation market is not too concentrated; that is, the number of platforms is not too small. Given this intended application and to make the problem tractable, we make a "monopolistic competition" assumption: platforms take the macroeconomic variables $(V_0^w, V_0^e, N_0^w, N_0^e, I)$ as given.[7]

Under that assumption, we can write the platform's profit-maximizing problem as

$$\Pi = \max_{f_{m,i},\ f_{p,i},\ \gamma_i,\ \rho_{ew,i}} \quad f_m w(\cdot) n_J(\cdot) + f_p n_p(\cdot) - F$$
$$\text{s.t.} \quad V_i^b(\cdot) > V_i^p(\cdot) \Rightarrow \rho_{ew,i} = 0 \quad \text{and} \quad V_i^b(\cdot) < V_i^p(\cdot) \Rightarrow \rho_{ew,i} = 1,$$

that is, the platform maximizes steady-state profit flows by choosing fees $f_{m,i}$ and $f_{p,i}$, and match distortion γ_i. If experienced workers are indifferent between basic and premium membership tiers, then the platform also chooses $\rho_{ew,i}$ (the share of experienced workers picking premium memberships).

The endogenous terms $w(\cdot)$, $n_J(\cdot)$, and $n_p(\cdot)$ are functions of the macroeconomic variables and of platform choices. They are found by solving a system of equations that determine the

[7] Burdett, Shi and Wright (2001) show that, in frictional markets with a finite number of sellers, equilibrium properties differ depending on whether one considers strategic interactions between sellers or not, but that the two approaches converge as the number of sellers becomes large.

internal mechanics of the platform. More concretely, the tuple of fifteen endogenous variables $(w_i, q_i, h_{b,i}, h_{p,i}, T_i, \psi_i^e, n_{V,i}, \psi_i^w, n_{siw,i}, n_{uiw,i}, n_{ew,i}, n_{b,i}, n_{p,i}, n_{J,i}, \phi_i)$ solves the system of Equations (1) through (15). It is not possible to obtain simple expressions for these endogenous variables in terms of macroeconomic aggregates and platform choices. However, we can still obtain a few economic insights into this problem before proceeding to the numerical simulations that constitute our main results.

Discussion. The first insight is that, if the platform chooses to implement a premium tier, it designs it so that every experienced worker picks that option: $\rho_{ew,i} = 1$. The proof is provided in Appendix B.4. The basic intuition follows from the discussion of the matching technology in Section 3.2. If the platform distorts matches at all by setting $\gamma_i > 0$, then match rates become strictly increasing in the share of workers belonging to the premium tier. That makes total premium membership revenues $f_p n_p(\cdot)$ increase with $\rho_{ew,i}$ even if the platform has to reduce per-capita fees $f_{p,i}$ to make that strategy incentive-compatible.

The second insight is that there is no guarantee of an internal solution in $(f_{m,i}, f_{p,i}, \gamma)$. The problem admits solutions where revenues come solely from match fees, others where the platform uses both sources of revenue, and others still where there are no match fees and only premium fees are charged. We view this result as a key validation of our theory. This is because although the absence of participation fees is a nearly universal characteristic of online labor platforms, we do observe a variety of revenue strategies in the market. Among the platforms in Table 1 that do not charge participation fees, 11 use both match fees and premium fees of some kind, but six only use match fees. Thus, we believe it is proper to use a theoretical framework that does not require the existence of a premium tier to be profit-maximizing. The fundamental reason why the model is able to rationalize these different possibilities is that there is some degree of substitutability in revenue strategies: an increase in match distortion tends to reduce the marginal benefit of match revenues, and an increase in match fees reduces the marginal benefit of premium revenues.

This flexibility also brings some threats to our quantitative analysis. Specifically, we cannot assume that the optimal solution is internal or that the maximand is strictly concave. That said, because the choice space is compact, the problem is guaranteed to have a well-defined solution, which is unique except for knife-edge cases. Our numerical procedures include a series of checks to ensure the validity of our quantitative results, both for the estimation steps and in counterfactual simulations. See Appendix C.2 for more details.

When is the platform more likely to implement premium membership fees? An important determinant is the separation margin. All else equal, low values for the s_U and σ_v parameters make premium memberships more likely to be optimal. A low s_U increases the expected duration of an experienced worker's spell in the platform, increasing the share of workers in that state, and hence the potential revenues to be tapped from them. A low σ_v makes separations less elastic to the value V_i^p, increasing the platform's market power over those workers.

Another key determinant for the optimality of premium memberships is the ex-ante probability of workers being suitable to a particular platform, $\bar{x}$. This is because, as discussed in Section 3.2, distorting matches toward premium workers is guaranteed to decrease the vacancy-filling rate q_i when $\bar{x} = 1$, but those negative effects become less significant as $\bar{x}$ becomes smaller—potentially even switching sign for low-enough $\bar{x}$ under specific parameter sets. Finally, we will show in Section 4.5 that premium memberships are more likely to be optimal when search costs are high relative to match output.

In Section 4.1, we extend the model to incorporate additional mechanisms that help rationalize the existence of premium memberships. But before we get there, we will finish the exposition of the model with a discussion of the economy-wide equilibrium.

3.6 Equilibrium

We focus on symmetric equilibria in which all platforms make identical choices. When referring to platform-related variables, we will use $-i$ for the single value chosen by all other platforms where needed, and we will omit subscripts where the distinction is not necessary. In addition, because we focus on applications with several intermediaries, we will treat the number of platforms I as a continuous variable for computational simplicity, as it allows us to abstract from granularity issues.

There are five macroeconomic variables to be pinned down: the platform-searching values V_0^e and V_0^w, the numbers of platform-searching vacancies N_0^e and workers N_0^w, and I. We start by imposing free entry of firms, which implies that the value of a platform-searching vacancy is zero. Using the expression we derived in Section 3.3, and imposing symmetry between firms, we obtain an equation that can be used to pin down the number of platform-searching firms:

$$0 = -c + \lambda_0 \int_0^\infty \max\left\{V^e - \varepsilon, 0\right\} \sigma_\varepsilon e^{-\sigma_\varepsilon \varepsilon} d\varepsilon. \quad (16)$$

The worker-related variables are pinned down by:

$$rV_0^w = \lambda_0 \int_0^\infty \max\left\{\tilde{V}^{iw}(0) - V_0^w - \varepsilon, 0\right\} \sigma_\varepsilon e^{-\sigma_\varepsilon \varepsilon} d\varepsilon \tag{17}$$

$$N^w = N_0^w + (n_{siw} + n_{uiw} + n_{ew} + n_J) I, \tag{18}$$

with the first equation derived previously and the second equation representing labor market clearing.

Finally, the number of operating platforms is pinned down by a free entry condition for platforms, which imposes that steady-state profit flows must be zero:

$$f_m w n_J + f_p n_p - F = 0 \tag{19}$$

Given a guess for the symmetric platform choices platforms $(f_{m,-i}, f_{p,-i}, \gamma_{-i})$, one can simultaneously solve for endogenous variables within other platforms and macroeconomic variables using Equations (1) through (19). Then, an individual platform solves:

$$\begin{bmatrix} f_{m,i} \\ f_{p,i} \\ \gamma_i \end{bmatrix} = \Phi\left(f_{m,-i}, f_{p,-i}, \gamma_{-i}\right) = \underset{f_{m,i},\ f_{p,i},\ \gamma_i}{\arg\max}\ f_m w(\cdot) n_J(\cdot) + f_p n_{ew}(\cdot) - F,$$

where $(\cdot)$ denotes dependency on own platform choices and indirect dependence on other platform choices through the five macroeconomic variables, which can be solved for given $(f_{m,-i}, f_{p,-i}, \gamma_{-i})$.

We define equilibrium platform choices as the solution to the fixed-point problem

$$\begin{bmatrix} f_m \\ f_p \\ \gamma \end{bmatrix} = \Phi\left(f_m, f_p, \gamma\right).$$

Some of the considerations from the previous section apply here—for example, the solution to this problem may be a corner solution. There are also additional concerns, such as the possibility of non-existence of equilibria, of multiplicity of equilibria, and that solutions to the fixed point are not stable, such that counterfactual analysis are not well-defined. Although we do not have formal proofs regarding these issues, we take them seriously in our quantitative analysis. See Appendix C.2 for details on specific assumptions made in the estimation process and how we thoroughly check for potential problems in our analysis.

4 Quantitative Exercises

Now we proceed to apply the model to the data. First, we augment the model to include additional mechanisms that are likely present in online labor platforms and that could impact the welfare implications of premium memberships. Next, we explain the calibration procedure and discuss our counterfactual simulations which constitute the core results of the paper.

4.1 Extended Empirical Model

Phantoms. Cheron and Decreuse (2016) study the possibility that some of the participants in a matching market may turn out to be inactive accounts generated by previous search activity of a real agent. These "phantoms" decrease search efficiency, as counterparties may lose time trying to match with them. This problem is likely to be present in online job platforms, since creating accounts is very cheap and there are no incentives for a worker to delete their account should they leave the platform.

We model phantom accounts in the following way. Whenever a worker leaves the platform for any reason, that event generates a phantom account. Phantoms disappear from the platform at an exogenous rate $s_{\dagger}$, reflecting the average speed with which the platform can identify that the account is not active anymore and stop redirecting potential employers to them. Crucially, we will assume that phantom accounts always choose the basic membership, as workers who leave the platform would have no incentives to keep paying for a premium membership.

Phantoms degrade match efficiency because they make the ϕ_i term in Equation 1 smaller. That is, the share of suitable workers in the platform pools mechanically decreases once phantom accounts are added to the pool of basic-membership accounts. This provides an additional channel through which premium memberships can enhance match efficiency: by prioritizing premium-membership workers in the matching process, the platform makes it less likely that a potential employer is directed to a phantom instead of a real worker.

Phantom accounts can also be interpreted as a device to incorporate the consequences of multi-homing among inexperienced workers, which we do not model explicitly. Suppose that inexperienced workers may simultaneously participate in several platforms, but doing so reduces their match rates as they must split their attention across multiple platforms. The mathematical consequences of this possibility are similar to what is achieved with the addition of phantoms in the model, because the $s_\dagger$ parameter has two main effects: it decouples the quantity of accounts to the quantity of workers (which could reflect either phantom accounts or multi-homing) and reduces match rates among basic-membership accounts (reflecting either an employer being directed to a phantom or a match failing to be formed because the worker diluted his attention across multiple platforms).

Private information regarding suitability. In the baseline model, immediately after a worker joins a platform, the suitability shock x is realized, leading to two possibilities: either the worker is suitable or unsuitable. In both cases, neither the platform nor the worker is informed about x. We now extend the model to account for an additional third possibility. With probability θ, the worker is suitable ($x = 1$) and privately knows it. With probability $(1-\theta)\bar{x}$, the worker is suitable but does not know it. Finally, with probability $(1-\theta)(1-\bar{x})$, the worker is not suitable and does not know it.

The difference between this version of the model and the baseline is that, with probability θ, the recently-joined worker is mathematically equivalent to an experienced, unemployed worker, rather than an inexperienced worker. This is because the fundamental difference between these two groups of workers is the knowledge that $x = 1$. Thus, the recently-joined workers who know they are suitable behave in the same way as experienced workers, in particular with respect to tier choices. Following the same logic, it is optimal for the platform to induce all of them to choose the premium membership.

This mechanism provides another realistic channel through which premium memberships can increase market efficiency. Without premium memberships, workers who receive the private information shock are pooled with every other worker in the matching process. When premium memberships exist, they have a credible way to convey their private information to the platform, which will in turn give them some degree of priority in the matching process relative to other recently-joining workers.

Model adjustments. The mechanics of the expanded model are similar to those of the base model presented in the previous section. There are two additional parameters, $s_\dagger$ and θ, which regulate the strength of the two additional mechanisms. The extensions require adjustments to the equations that define steady-state stocks within platforms. These adjustments are explained in Appendix C.1. There, we present a more general formulation that also allows a fraction of workers to be informed about platform-specific match rates. That generalization of the model is used in the robustness exercises presented in Appendix C.5.

4.2 Calibration

To evaluate the welfare implications of premium memberships, we calibrate the model with three sources of information: (i) parameter values drawn from the literature, (ii) direct calibration based on institutional knowledge of the platform and its market, and (iii) an indirect inference procedure. The unit of time in the model is a month.

The Experiment Through the Lens of the Model. We use data from the platform—including the experimental data—in the indirect inference procedure that we describe below. This requires a clear conceptual mapping between the model and the experiment. We begin with the assumption that the platform for which we have data is one of many operating platforms in the symmetric market equilibrium. The experiment is modeled as an exogenous increase $\Delta\gamma > 0$ in the distortion parameter, holding fees f_m and f_p fixed. This implies that, in implementing the experiment, the platform deviates from its profit-maximizing choices. The increase in γ applies only to firms randomly assigned to the treatment group.

To analyze the implications of the experiment for the internal outcomes of the platform, we extend the model to track treated and untreated vacancies separately. Although the inflow of firms into each pool is equalized by design (each firm is assigned to treatment with probability 0.5 at its first search during the experimental period), the *stocks* of vacancies in the treatment and control groups need not be the same. This is because the experiment may generate different vacancy-filling rates. Indeed, given the experimental results, we should expect fewer control vacancies, as they are successfully matched to a worker slightly faster than treated firms.

In contrast, the worker pools are *not* split between the treatment and control groups. Hence, our modeling explicitly allows for spillover effects that treated firms can have on control firms through their shared interactions with workers.

Externally-calibrated parameters. The first subset of parameters appears in Table 3, along with brief justifications for each choice. We model a labor market of 10,000 workers, which should be viewed as a segmented, easily-observable category of workers in the overall market (for example, "C# .NET programmers"). We choose a high value for the arrival

Table 3: Externally Calibrated Parameters

Parameter	Value	Rationale
r	0.004	Yearly discount of 5%
δ	1.00	Av. emp. spell of one month (see Appendix)
N_w	10000	Normalization
y	100.0	Normalization
β	0.50	Symmetric bargaining
λ_0	150.00	Five arrivals per day while platform-searching
D	13500.00	Other values considered in additional exercises.

Notes: See text for a detailed explanation of the rationale for these choices. Calibrations with alternative values for the "thin markets effect" parameter D are explored in Section 4.4.

rate of platform offers in the platform-search stage, so that most of the time spent in search occurs inside platforms. We calibrate the job destruction δ so that job spells last one month in expectation. This duration is calibrated such that, when all the internal calibration targets in Table 4 are satisfied, the monthly price for a premium membership, measured as a fraction of the full-time monthly wage, matches the same number in the data. See Appendix A.3 for a detailed explanation.

Our data do not provide a credible approach for identifying the mismatch parameter D, which regulates the strength of thin markets effects within platforms conditional on the match arrival rate λ. The value of 13,500 is chosen so that platform entry in the decentralized market equilibrium matches the choices of a welfare-maximizing planner, which we describe later in Section 4.4. This choice allows us to focus on the match-efficiency mechanisms emphasized as we described the model, abstracting from potential interactions between premium memberships and optimal platform entry. That said, we are also interested in exploring optimal entry. To that end, we will use alternative calibrations with different values for D.

Internal calibration through indirect inference. The remaining 11 parameters, listed in Table 4, are chosen by simulating the model and matching a corresponding number of targets. The indirect inference targets are also listed in Table 4. Although all calibration targets affect all parameter estimates, the table is ordered so that the target on the right is particularly informative about the corresponding parameter on the left. Appendix C.2 presents additional details on our numerical methods.

The first two targets are normalized rather than taken from the data. We consider that our market of 10,000 workers is served by 10 platforms. This number corresponds to half the number of platforms listed in Table 1. It reflects the relatively large number of platforms

Table 4: Internally Calibrated Parameters

Parameter	Value	Target	Data	Sim.
F	920.0	Number of platforms	*10.00*	10.00
s_U	0.923	Probability that an experienced worker does not change state in one month	*0.600*	0.600
s_V	0.311	Share of platform vacancies filled in two months	0.190	0.190
λ	2406.6	Average number of jobs found by workers over two months	0.054	0.054
c	5.505	Ratio of workers to firms in platform	3.549	3.549
σ_ε	0.017	Match fees as fraction of gross wage	0.150	0.150
σ_v	0.235	Premium fees as fraction of platform revenue	0.100	0.100
$\bar{x}$	0.691	Share of premium-membership workers in platform	0.095	0.095
θ	0.152	Share of one-month workers choosing premium	0.122	0.122
$\Delta\gamma$	0.0180	Treatment effect on probability of hiring a basic membership worker	-0.0176	-0.0176
$s_\dagger$	0.127	Treat. effect on prob. hiring any worker	-0.0090	-0.0090

Notes: *Italicized numbers* correspond to calibration targets that are normalized rather than taken from the data. Appendix C.4 presents robustness exercises where we consider alternative targets for the probability that an experienced worker does not change state in a month. The last two targets correspond to experimental treatment effects from Table 2, stated in relative terms (that is, the estimated coefficient divided by the mean outcome in the control group).

that we observe operating in the United States, while also noting that some of them cater to specific workers or firms—such that the number of platforms that would cater to any given worker is less than the overall number of platforms. Matching the number of operating platforms allows us to recover the fixed costs associated with platform operation.

The second target represents the probability that an unemployed experienced worker in the platform remains in that state for one month, that is, in that interval, they are neither hired nor separate from the platform. This number is difficult to observe in the data because we do not observe whether a given account is active or a phantom. However, it is important to target this number to capture the fact that workers often stay in the platform for more than one employment spell. In Appendix C.4, we re-calibrate the model using alternative values for this calibration target and show that our central welfare results are robust to those alternative choices.

The remaining targets are observable; Appendix A describes how we calculate them. The match arrival rate λ is identified from the average number of jobs found by workers over two months, while the vacancy separation rate s_V is used to match the share of vacancies that are filled in the same period conditional on λ. The vacancy-posting flow cost c is a key determinant of the vacancy creation tradeoff and is thus backed out from the equilibrium ratio of worker accounts to employers in the platform.

The parameters σ_ε and σ_ν, which regulate the dispersion of idiosyncratic shocks related to platform-joining and platform separations, are critical determinants of platform market power. The first one is particularly important for firms and recently-joined workers, while the second is only relevant for experienced workers. Thus, we back them out from how much revenue platforms are able to extract from successful matches and from premium memberships, respectively.

The parameters $\bar{x}$ and θ regulate platform suitability and worker's private information about it. The first is backed out from the overall share of premium memberships among worker accounts in the platform, while the second is related to the same share but conditional on accounts being created very recently: exactly 30 days old. The latter target helps discipline θ because workers who receive the private information shock quickly choose premium memberships shortly after joining. We estimate $\theta = 0.152$, suggesting that a sizable share of joining workers have private information and signal it through premium memberships.

The last two parameters are identified from two experimentally-recovered differences between treated and control employers presented in Table 2. The first corresponds to the relative difference in the probability of hiring at least one basic-membership worker in a period of two months following entering the experiment, while the second corresponds to the relative difference in the probability of hiring at least one worker of any tier. The first target pins down the size of the additional distortion induced by advertising, $\Delta\gamma$. Conditional on $\Delta\gamma$, the effect on the probability of hiring any worker helps recover the speed with which platforms can eliminate phantom accounts, $s_\dagger$. We make this link more explicit in Section 4.3.

Note that none of the indirect inference targets pertains to observed differences between premium-membership workers and basic-membership workers in the platform. This was a deliberate choice. It is reasonable to expect that, in the data, premium-membership workers are selected in dimensions other than experience in the platform; for example, they may be systematically more or less skilled. Because we do not model ex-ante worker heterogeneity, we would be unable to replicate such selection. Thus, if we were to, say, target differences in job-finding between basic- and premium-tier workers, our model would entirely attribute to platform distortion what in the data is coming from differential skills. Our approach allows us to sidestep these concerns while keeping the model as simple as possible.

Before proceeding, we note that our model can perfectly match all of the indirect inference targets. There is nothing in the model that ensures this outcome; indeed, it is easy to picture scenarios where changes in one of the targets lead a parameter to the boundary of the parametric space, preventing the model from matching that target and possibly others. Moreover, different modeling assumptions could also have prevented the model from matching the data well; Appendix C.5 provides a concrete example. Thus, we view our model's ability to match the data as a positive signal about its usefulness.

The baseline equilibrium. To further verify whether the model provides a reasonable lens through which to view online platforms, we characterize the equilibrium implied by our baseline calibration. Those endogenous outcomes are presented in Appendix Table A4. The employment rate in this market is 10%, which implies that workers spend most of their time not matched to an employer as a freelancer. This is consistent with the low hiring rates documented by Kässi, Lehdonvirta and Stephany (2021). It suggests that the probability that a randomly-drawn worker can be effectively matched to a randomly-drawn vacancy, $1/D$, is low in part because workers may be temporarily engaged in unmodeled forms of work outside of online platforms.

The model also implies that total search costs—including vacancy-posting, platform operation costs, platform-joining costs, and platform-separation shocks for experienced workers—amount to 58.6% of aggregate output. Although we do not have direct evidence for this number in the context of online job platforms, it appears reasonable. The fact that the platform charges 15% of worker earnings as match fees and that premium fees account for 10% of platform revenues means that platform operation costs alone amount to around 9% of aggregate output (given that wages are 54.7% of output in the baseline equilibrium). Firm vacancy-posting costs constitute most of the remainder. The personnel economics literature often finds that total hiring costs for permanent skilled workers typically amount to at least one month of pay (Dube, Freeman and Reich, 2010; Blatter, Muehlemann and Schenker, 2012; Kuhn and Yu, 2021). Thus, it may be profitable to hire remote freelancers for temporary tasks even if the firm has to spend significant resources to search for and screen them because it would probably be even more expensive to hire permanent workers instead.

Moving on to internal platform outcomes, the model implies that the platform's optimal

Table 5: Counterfactual Simulations: Premium Membership Prohibition Policy

Outcome	Mkt. Equilibrium	Premium Prohibition
Panel A: Aggregate metrics		
Welfare gains (%)	-	4.2
Welfare gains relative to initial aggregate payroll (%)	-	3.2
Employment rate	0.100	0.103
Search costs as share of output	0.586	0.582
Panel B: Market outcomes		
Number of platforms	10.0	10.2
Match fees	0.150	0.163
Match distortion γ	0.046	-
Premium membership fee	0.34	-

Notes: The first column shows characteristics of the baseline equilibrium, while the second column shows a simulated equilibrium where platforms are forced to set $\gamma = f_p = 0$. Welfare gains are total output net of total search costs, which include platform joining costs, vacancy-posting costs, platform separation shocks for experienced workers, and platform operation costs. The second row shows the difference in welfare between the two scenarios divided by the aggregate payroll in the market equilibrium.

choice of distortion is $\gamma = 0.046$. This level of distortion implies that a premium worker's job-finding rates are about 5% higher than those of a suitable basic-membership worker. The optimal wait time T is a bit more than three months. Overall, none of those numbers gives us reason to doubt the usefulness of the model for evaluating the welfare implications of premium memberships.

4.3 Policy Counterfactual: Prohibiting Premium Memberships

Table 5 presents our key counterfactual policy result: what would happen to this market if platforms were prohibited from using premium-membership fees? Specifically, they are forced to choose $\gamma = f_p = 0$. The first row in Panel A presents the change in welfare resulting from this counterfactual policy. We define aggregate welfare flow as total output net of platform operation costs, vacancy-posting costs, joining costs for workers and firms, and separation costs for experienced workers. We find that welfare would increase by 4.2% following the prohibition. We can also measure the welfare gains as a share of initial aggregate payroll in the market, as opposed to initial welfare. The result is similar: a 3.2% increase.

The result that welfare would increase if premium memberships were prohibited shows that the "match quality degradation for rent extraction" possibility is the most important one in our empirical setting. This finding confirms the intuition coming from our experimental results, where we argued that the statistically-significant employment losses induced by advertising suggested that the marginal worker being redirected to employers was negatively selected. We make this link more explicit in the following section.

The remainder of Table 5 details how this policy would affect the market. In principle, welfare gains could come from either rising employment or lower search costs. The last two rows in Panel A show that, in our setting, gains come from both margins, though rising employment is quantitatively more important. Panel B shows that this policy does not induce significant changes in the number of platforms operating in the market. Match fees increase as platforms have to offset foregone revenue from premium memberships.

It is informative to interpret the finding that premium memberships reduce welfare in light of Pallais (2014). That paper's analysis suggests that, once one accounts for the possibility of inefficient hiring of inexperienced workers, interventions that encourage employers to hire such workers can be welfare-improving. Premium memberships push the market in the opposite direction: they increase experienced workers' hiring rates while decreasing hiring rates for inexperienced workers. We therefore conjecture that incorporating the channel highlighted by Pallais (2014) would strengthen our main conclusion.

How does the experiment inform this welfare result? Recall that the estimation procedure uses two outcomes from the experiment: the treatment effect on the hiring of any type of worker (a reduction of around 0.9%) and the treatment effect on the hiring of workers with a "basic" membership (a reduction of around 1.8%). Table 6 shows alternative scenarios in which we change the value of these calibration targets, rerun the indirect inference procedure, and recalculate the counterfactual scenario without premium memberships.

In the second column, we reduce the magnitude of both targets by 10%. A comparison between the first two columns in Panel A shows that this does not make any difference for the magnitude of welfare gains associated with the premium-prohibition policy. Panels B and C clarify why this is the case. When both calibration targets fall in the same proportion, the model infers that the experiment corresponded to a smaller change in the matching technology, that is, $\Delta\gamma$ is 10% smaller. The parameters that regulate the welfare effects of premium memberships remain unchanged.

The third column considers the case where only the "treatment effect on any hiring" target falls by 10%, while the other target is kept constant. That is, the targets become closer to a hypothetical case where advertising mostly redirects matches from the basic to the premium tier, while leaving overall hiring unchanged. In that case, the predicted welfare gains

Table 6: How Does the Experiment Inform Counterfactual Results?

Outcome	Baseline estimation	Both outcomes 10% lower	Any hiring 10% lower
Panel A: Predicted gains from prohition of premium memberships			
Welfare gain (%)	4.21	4.22	3.76
Panel B: Estimated parameters			
$\bar{x}$	0.691	0.692	0.676
$s_{\dagger}$	0.127	0.127	0.119
$\Delta\gamma$	0.018	0.016	0.018
Panel C: Composition of basic accounts in the platform			
Suitable inexperienced workers	0.16	0.16	0.13
Unsuitable inexperienced workers	0.07	0.07	0.06
Phantoms	0.77	0.77	0.80

Notes: This table clarifies how the experimental estimates impact the main welfare result regarding the premium membership prohibition policy. **Panel A** compares welfare gains from that policy in three different scenarios. The first column replicates the baseline results. The second column considers an alternative calibration where both experimental targets—treatment effects on the probability of hiring a basic-membership worker or any worker—are reduced by 10% in magnitude. The third column considers another alternative calibration where only one of the two targets is reduced: the treatment effect on the probability of hiring any worker. Only in the latter case welfare effects become smaller. **Panels B and C** explain why treatment effects become smaller. All else equal, a less negative effect on "any hiring" informs the model that diverting attention away from basic-membership workers is not so detrimental to match efficiency. The model interprets this result as showing that basic-membership accounts are marginally more likely to be phantoms rather than active workers. The estimator then recovers a lower phantom destruction rate $s_{\dagger}$.

decrease by about 10% relative to the baseline estimation. The model-backed explanation for the lower effects on "any hiring" is that the basic-membership pool is more heavily populated by phantoms. More phantoms in that pool means that giving premium-membership workers an advantage is not as distortionary as in the baseline model, which in turn implies that the welfare gains of eliminating premium memberships altogether are smaller.

4.4 Thin Markets and Optimal Platform Creation

As a benchmark for studying inefficiencies introduced by imperfect competition between platforms and thin markets effects, we introduce the concept of a planner who can control platform creation and operation. However, the planner cannot implement lump-sum transfers, control firm and worker behavior directly, nor overcome informational frictions by fiat. We also assume that the planner is subject to the same fee structure constraints from the baseline model; in particular, they cannot implement participation fees.

Table 7: Counterfactual Simulations: Different Assumptions on Thin Markets Effects

Outcome	$D = 8437.5$	$D = 13500.0$	$D = 21600.0$
Panel A: Planner solution			
Welfare gain (%)	4.9	4.2	4.8
Change in employment rate (%)	6.3	3.2	1.9
Change in gross output (%)	6.3	3.2	1.9
Change in search costs as share of output (p.p.)	-0.4	-0.4	-0.5
Number of platforms	12.8	10.0	7.9
Match fees	0.195	0.161	0.130
Match distortion γ	0.000	0.000	0.000
Premium membership fee	0.00	0.00	0.00
Panel B: Premium membership prohibition policy			
Welfare gain (%)	4.1	4.2	4.2
Change in employment rate (%)	3.1	3.4	3.5
Change in gross output (%)	3.1	3.4	3.5
Change in search costs as share of output (p.p.)	-1.4	-0.3	0.4
Number of platforms	10.1	10.2	10.2
Match fees	0.162	0.163	0.163

Notes: Each column in this table corresponds to a different calibration of the model. Using different values for the externally-calibrated parameter *D*, the target-matching calibration procedure is run again, so that all columns match all calibration targets perfectly. **Panel A** describes the optimal solution for a central planner that chooses platform fee structure and the number of operating platforms. Larger values of *D* imply more significant thin markets effects, such that the planner creates fewer, but larger platforms. In all cases, the planner eliminates the premium membership tier. **Panel B** replicates the premium prohibition policy results from Table 5 for the different calibrations.

The planner chooses the number of platforms in the economy I and their design choices (f_m, f_p, γ) with the goal of maximizing welfare. As with the individual platform's problem, the planner's problem is constrained. Given a choice of (I, f_m, γ), premium fees f_p must be low enough so that experienced unemployed workers weakly prefer premium memberships. In addition, given (I, γ), match fees f_m must be such that the planner's budget is balanced, that is, platforms make zero profits in the aggregate.

The planner's optimal solution is likely to depend on the calibrated choice of D, as larger values for this parameter imply stronger thin markets effects within platforms. To see this mechanism in action, we consider what happens to the vacancy-filling rate, Equation (1), in a limit where D and λ diverge to infinity, but λ/D remains constant. We obtain

$$q_i \;\to\; \frac{1}{n_{V,i}} \frac{\lambda}{D} \left[\gamma_i n_{p,i} \;+\; (1-\gamma_i)\phi_i \left(n_{b,i} + n_{p,i}\right) \right].$$

When D is very large, vacancy-filling rates would remain unchanged if all workers and firms were concentrated on a single platform (that is, $n_{V,i}$, $n_{p,i}$, and $n_{b,i}$ all grew in the same proportion). This is surprising given that the arrival of match-making opportunities is fixed at the *platform* level; that is, having only one platform operating instead of 10 means that the aggregate arrival of match-making opportunities falls tenfold. This is because thin markets effects are so strong that they completely offset the reduction in match-making opportunities. In that limit, there would be no reason for the central planner to create multiple platforms; they would choose to create a single one to avoid paying platform operation costs.

In our quantitative analysis, we study less extreme scenarios. We consider a lower and a higher value for D corresponding to shifting our baseline calibration by a factor of 1.6. We then rerun the indirect inference procedure, recalculate the previous counterfactual results regarding the premium prohibition policy, and find the solution of the planner's problem.

The results are reported in Table 7. As expected, the planner's choice on the number of platforms is decreasing in D. Consistent with the premium prohibition policy results, the planner chooses to eliminate premium memberships in all cases. The welfare gains from moving to the planner's solution are smallest for the baseline value $D = 13,500$. This is because, when D is either lower or higher, the planner can improve market allocation not only by eliminating premium memberships but also by correcting platform entry.

We make two additional notes on these results. First, the welfare gains from the premium prohibition policy are remarkably robust to the choice of D. Second, for the two cases we analyze, the additional gains from correcting entry are small relative to those achieved by the premium prohibition policy. Thus, unless the optimal entry level is very far from the decentralized equilibrium's, the premium prohibition policy achieves most of the gains from moving all the way to the planner's solution.

4.5 Premium Memberships and the Beveridge Curve

Following the previous discussion, one may be concerned that the existence of thin markets effects implies fundamentally different macroeconomic properties compared to the standard DMP framework. We now show that this is not the case. In Figure 2, we plot Beveridge curves implied by this model. To plot those curves, we calculate counterfactual equilibria where the log match output $\log y$ is shifted up or down by 0.12, starting from the calibrated equilibrium. The blue curve corresponds to the full model. The green curve represents a constrained model corresponding to the premium prohibition policy, that is, with $\gamma = f_p = 0$.

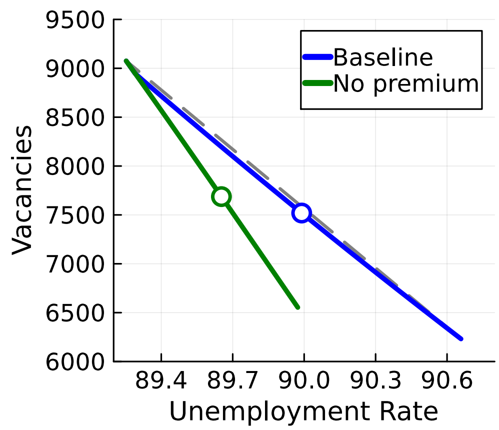

Figure 2: Premium Memberships and the Beveridge Curve

Notes: The blue curve is the model-implied Beveridge curve, created by shifting the log match output $\log y$ by plus or minus 0.12 starting from the baseline market equilibrium (which corresponds to the blue circle). The green curve is analogous, but corresponds to equilibria where platforms are forced to set $\gamma = f_p = 0$, eliminating premium memberships. When productivity is high enough (or equivalently, when search costs are small), platforms choose not to implement premium memberships, such that the two curves coincide. Lower productivity relative to search costs magnify employment losses from premium memberships. The dashed gray lines highlight that despite the presence of thin markets effects in the model, the aggregate Beveridge curves are still weakly convex, as in standard search models.

Our first observation is that both curves are decreasing and (weakly) convex. This shows that the aggregate matching function implied by our model is well-behaved despite thin markets effects within individual platforms. Key to this result is the fact that match arrivals λ are fixed per platform, rather than increasing in the number of workers or firms within the platform.

Second, note that the difference between the two curves is mostly horizontal rather than vertical. This is consistent with the findings shown in Table 5, where the welfare gains come from increased employment rather than falling search costs.

Finally, the differences between the two curves are large for low levels of vacancies (correspondingly, low levels of productivity), whereas the two curves converge when the market is tight. This is because, in the latter case, platforms optimally choose not to implement premium memberships even if they have the option to do so. Note that, as we change $\log y$ in the model, all sources of search costs remain constant. Thus, we can interpret this finding in terms of the relative intensity of search frictions relative to match output. Specifically, the platform's ability to use match distortions and premium memberships to extract rents is higher when search costs are more sizable.

4.6 Premium Memberships and Competition Between Platforms

In our final quantitative exercise, we explore the broader implications of modeling platform's revenue-raising strategies, including the possibility of charging premium membership fees, for analyzing competition in the intermediation market. In Table 8, we report the implications of counterfactuals where we dampen the idiosyncratic costs workers and firms face when they join platforms. We do so by increasing σ_ε by 10%. This is analogous to reducing the degree of differentiation between products in a discrete-choice framework. In our model, we should expect some welfare gains to appear mechanically, as the idiosyncratic shocks enter negatively in workers and firms' value functions. We should also expect match fees—the main price chosen by platforms—to fall.

Panel A reports results for the restricted model where premium memberships are prohibited. This model is easier to analyze, as platforms only choose match fees f_m. As expected, welfare rises and match fees fall. The equilibrium number of operating platforms also falls, reflecting reduced revenues per worker from lower match fees. This means that platform sizes must be larger to offset operating costs. Welfare gains are larger in the calibration with a large value for D, as in this case the optimal number of operating platforms is lower than in the baseline equilibrium.

Panel B studies the richer case where premium memberships are allowed. Surprisingly, welfare falls, despite a larger decline in match fees. The explanation for both facts is the substitutability between revenue sources, emphasized in the discussion of the problem of the platform in Section 3.5. More stiff competition in the platform-entry margin leads to lower match fees. That makes premium memberships fees more attractive from the platform's point of view, which makes them increase their reliance on them. The associated increase in match distortions explains why welfare falls even with reduced platform-entry costs.

These findings point to a potential pitfall for empirical studies assessing the impact of pro-competitive reforms in intermediated markets. Specifically, a researcher using reduced-form policy evaluation designs could erroneously conclude that the reform has stronger positive impacts on markets where premium tiers are prevalent, based on the higher responsiveness of match fees on those markets. That observation highlights the importance of accounting for intermediaries' choices of revenue sources when analyzing competition in these markets.

Table 8: Increasing Competition by Dampening Idiosyncratic Platform-Joining Costs

Outcome	$D = 8437.5$	$D = 13500.0$	$D = 21600.0$
Panel A: Restricted model with premium memberships prohibited			
Welfare gains from falling joining costs (%)	0.08	0.41	0.65
Change in number of platforms I (%)	-1.99	-1.95	-1.97
Change in match fees f_m (%)	-1.53	-1.74	-1.93
Panel B: Baseline model with premium memberships			
Welfare gains from falling joining costs (%)	-0.80	-0.58	-0.40
Change in number of platforms I (%)	-2.22	-2.38	-2.48
Change in match fees f_m (%)	-3.37	-3.89	-4.26
Change in premium membership fees f_p (%)	21.94	23.98	25.20

Notes: This table shows the results of counterfactual simulations where the σ_ε parameter grows by 10%, meaning that the mean and standard deviation of the exponentially-distributed platform joining costs fall in the same proportion. **Panel A** analyzes the simpler case where memberships are prohibited, such that platforms only choose match fees f_m. Increased competition due to falling idiosyncratic joining costs drive platforms to reduce fees. As platforms need to cover the same fixed costs of operation with reduced margins, they become larger in equilibrium, reducing the number of operating platforms. Welfare increases, with larger gains when the reduction in the number of platforms is also desirable due to strong thin markets effects (third column). **Panel B** considers the richer case where platforms also use premium memberships. Welfare falls, as platforms rely more on premium memberships when competition in the entry margin is stiff. However, due to substitutability between revenue sources, match fees fall by more than in Panel A.

5 Discussion: Applicability to Other Labor Markets

Our model's main objective is to study labor markets where intermediaries have market power, the ability to steer matches, and the discretion to monetize access to attention. It is particularly well-suited for markets with many intermediaries and where worker–intermediary relationships span multiple short spells. These conditions hold in the online freelance market we study in detail. Here we argue that the same logic carries over to other intermediated markets as well, using two settings as examples: intermediation for non-established talent in the entertainment industry and seasonal migrant work in developing countries.

Non-established actors, models, screenwriters, and other talent markets. Previous literature has documented that these labor markets feature short employment spells (Christopherson and Storper, 1989; Menger, 1999) and that intermediaries play a central role in them (Bielby and Bielby, 1999). Intermediaries' power arises from substantial horizontal differentiation in workers' attributes (looks, accent, demeanor, style) and in employer needs. These markets are also characterized by what has been described as an "excessive supply" of workers (Frank and Sohn, 2011), leading to an environment potentially similar to online platform markets: average employment rates are low, and aspiring workers may generate significant congestion externalities.

Our model can be used to evaluate the optimality of important institutional features present in these markets. For example, a major union-negotiated contract in the United States specifies in its baseline terms that casting agencies are prohibited from charging workers fees in exchange for preferential access to "background actor" jobs. Instead, agencies may only accept union-negotiated commissions that are analogous to match fees in our model.[8] In addition, California's Labor Code prohibits talent agencies, or other agents acting on behalf of employers, from charging workers upfront fees of any kind in exchange for interviews or hiring.[9] Despite these provisions, there are multiple reports of intermediaries requesting both pecuniary and non-pecuniary payments from workers in exchange for preferential treatment in the matching process, analogous to premium fees in our model (Syam, 2017; Salomon, 2019; Rice, 2024). Our model provides a tool for evaluating whether these rules are welfare-improving and, if so, for quantifying potential welfare losses arising from imperfect compliance.

Seasonal migrant work in developing countries. Seasonal migration in agriculture, construction, and hospitality also features many intermediaries, repeated short spells, and the possibility of match-steering. This type of work can be a valuable source of income, especially for poor households, but also entails substantial risk if workers cannot secure a job at their destination (Bryan, Chowdhury and Mobarak, 2014). That opens space for intermediaries to improve welfare by effectively matching workers and firms.

Gibson and McKenzie (2014) document that a program in New Zealand facilitating seasonal migrant work from Tonga and Vanuatu had large positive impacts on migrant-sending households. Notably, the program allowed agents to match workers to employers while also imposing restrictions on monetization strategies. Specifically, neither employers nor agents could charge workers upfront fees. Naidu, Nyarko and Wang (2023) evaluate a program that facilitated seasonal migration from India to the United Arab Emirates and find more ambiguous results. They emphasize that intermediaries play an important role in these markets but are relatively under-studied. In their context, intermediaries are essential for securing a job

[8]See the 2014 Codified Basic Agreement between the Alliance of Motion Picture and Television Producers and the Screen Actors Guild-American Federation of Television and Radio Artists, Schedule X-I, 43.C, available at https://amptp.org/contracts/.

[9]California Labor Code, Sections 1700.40 and 450.

but absorb a significant share of the match surplus, with average agent fees amounting to 40% of annual household income in their sample.

We believe that our model can be a useful tool for evaluating and improving the design of these programs, particularly for predicting the equilibrium consequences of regulations that restrict intermediaries' monetization strategies.

6 Conclusion

In this paper, we develop a search-and-matching model to study labor markets in which intermediaries charge users for preferential treatment in the matching process. Our theory clarifies the trade-offs intermediaries face when deciding to offer premium memberships and highlights the resulting welfare consequences. Using internal data from an online job platform and results from a large-scale experiment, we show that the model can replicate detailed features of the data and serve as a quantitative tool for analyzing policies aimed at regulating intermediaries' behavior.

Our modeling framework can be extended to study other aspects of labor market intermediation. For example, Horton (2017) provides experimental evidence that well-calibrated recommendation algorithms can increase match efficiency. A version of our model that includes endogenous investment in match quality could shed light on the equilibrium effects of such investments and their interaction with imperfect competition among platforms. More broadly, we believe that our model can be used to study other forms of labor market intermediation where workers interact repeatedly with intermediaries and those intermediaries are allowed to charge fees in return for preferential treatment in the matching process. Potential examples include staffing agencies, international labor recruiters, union halls with dues-based priority, or creative talent agencies.

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Online Appendix
How Do Intermediaries Shape Labor Market Efficiency? An Equilibrium Model and Experimental Evidence

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Table of Contents

A Data and Experiment

A.1 Details on the Implementation of the Experiment

Our data come from a large online labor platform with which we partnered to run a large-scale advertising experiment from 29 April 2019 to 31 July 2019. Potential employers were randomly assigned with equal probability to one of two groups: treatment and control. Treated employers were eligible to be exposed to a particular form of advertising, described in more detail below. Control employers experienced the status quo version of the platform, without advertising. The existence of the experiment was not concealed; the platform's public blog featured short posts about it. However, the platform's interface did not provide any cues or disclosures indicating that an experiment was underway.

The experiment was designed as follows. Upon receiving a recommendation-page or search-page request from a treated employer, the platform first retrieved the organic list of results. The order of the workers in this list was determined by the platform's internal algorithms, which are designed primarily to maximize the probability of successful matches. Next, the platform identified the subset of freelancers in the organic list who had premium membership. On the first page of results, the premium freelancer with the highest organic position was displayed as an ad above the organic listings. On the second page, the second-highest premium freelancer was displayed as an ad, and so on. Importantly, the ads added an extra listing rather than replacing the organic one. Figure A1 illustrates the difference between the listings seen by treated and control employers.

The experiment also introduced ads into the worker recommendations shown to employers after they created a job posting. The process operated similarly to the search results: the platform's algorithm generated an organic list of workers to recommend based on the job characteristics provided by the employer, and then selected premium-membership workers appearing in that organic list to be displayed as ads. However, the share of ads was smaller in recommendations than in search results: overall, 1.8% of recommendations shown to treated employers contained ads, compared with 6.7% of search results. In addition, employers received, on average, twice as many search results as recommendations. Combining these two factors, the number of ads stemming from search results was about seven times larger than the number stemming from recommendations. This is why we emphasize the search mechanism in the main text.

During the design stage of the experiment, we did not rule out the possibility that the same

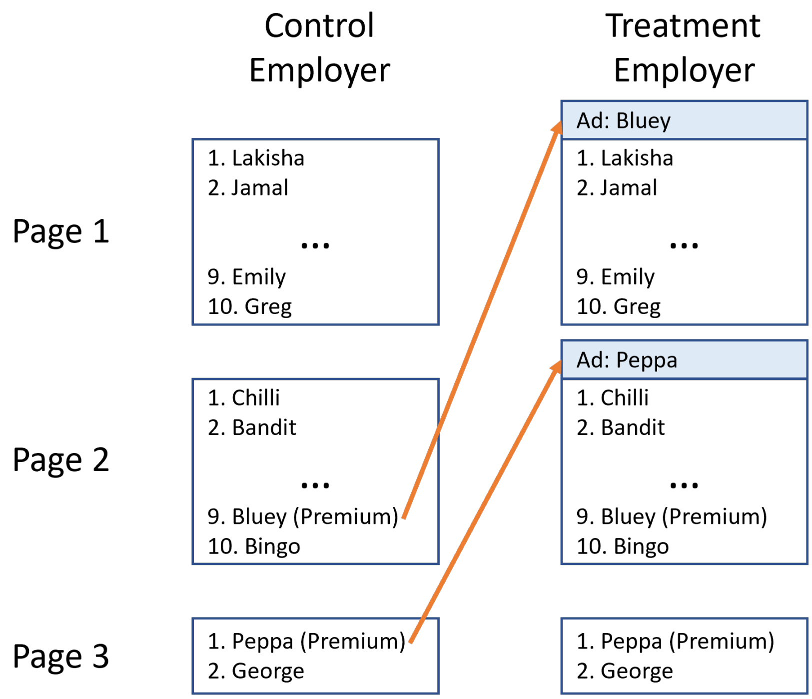

Figure A1: Premium Workers Featured as "Ads" in Search Results

freelancer could appear twice on a page—once as an ad and once as an organic listing. After analyzing the data, we observed that in many cases (but not all), the platform's algorithm removed one of the repeated listings. This occurred because the listings shown to employers are determined through a sequence of algorithmic steps: the experimental design was implemented at one of the intermediate steps, while following steps sometimes removed duplicate listings and reordered results. These downstream adjustments occasionally led to cases in which the advertised worker did not appear to have a premium membership at the time of the listing. Such cases are relatively rare, occurring in approximately 11% of page prints for the treatment group. In other instances, the later-stage algorithms removed the organic listing but retained the ad, resulting in cases where a premium worker appeared only as an ad and not in the organic results. Ads could also not appear if the search queries were too specific, such that no worker in the organic listing had a premium membership.

These implementation details do not appear to pose problems for our analysis; the experiment was highly successful in shifting employers' attention toward premium workers, as evidenced by click behavior (Table 2) and job-invitation outcomes (Table A2). To further ensure that these issues do not affect the experiment's internal validity, we verified that the likelihood of an advertised worker not appearing as an organic listing is uncorrelated with

Table A1: Randomization Checks

Variable	Treatment Mean	Control Mean	P-value
Number of Searches	1.2805	1.3051	0.0191^{**}
Has Searched (1/0)	0.3044	0.3046	0.8627
Number of Invitations	1.8419	2.0377	0.0641^{*}
Has Invited (1/0)	0.1303	0.1313	0.2811
Number of Hires	0.3749	0.3757	0.9157
Has Hired (1/0)	0.1337	0.1350	0.2173
Number of Posts	8.8312	8.8424	0.9207
Has Posted (1/0)	0.4202	0.4216	0.3596
Total Spent	4,915.86	4,882.39	0.8839
Has Spent (1/0)	0.3204	0.3209	0.6818
Experience at Entry	522.06	524.06	0.4321
US (1/0)	0.4351	0.4359	0.5754
Joint Test	–	–	0.3654

This table shows the outcomes of t tests applied to each of the variables. The joint test is performed based on a SUR model with standard errors clustered at the employer level. There are 464,986 employers.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

employers' predetermined characteristics.

More importantly, we conducted a series of tests to confirm that employers were indeed randomly allocated to treatment and control. We compared employer characteristics measured prior to the start of the experiment between the two groups; results are reported in Table A1. These characteristics include: the number of times the employer searched for workers, invited a worker for an interview, hired a worker, or posted a job, along with indicators for whether these quantities were positive; the amount the employer spent on the platform and an indicator for whether they spent at all; the employer's experience, measured as the number of days between registration and the start of the experiment; and an indicator for whether the employer was based in the United States.

We begin by conducting t-tests to compare the means of these variables between treatment and control. Except for the number of searches and invitations, none of these tests indicate statistically significant differences at conventional levels. However, because the tests are not independent and raise the usual concerns about multiple hypothesis testing, we estimate a SUR model and conduct a joint test of equality between treatment and control means, clustering at the employer level (464,986 employers in total). This joint test yields a p-

Table A2: Experimental Results on Employers Inviting Workers to Apply for Jobs

	All workers	Sometimes premium	Never premium
Panel A: dependent variable is ***any invitation sent to these workers***			
Treatment	-0.00168	0.00566***	-0.00543***
	(0.00142)	(0.00116)	(0.00124)
Constant	0.377***	0.193***	0.237***
	(0.00101)	(0.000819)	(0.000883)
Panel B: dep. var. is ***log(1 + number of invitations sent to these workers)***			
Treatment	-0.00742***	0.00673***	-0.00879***
	(0.00285)	(0.00146)	(0.0173)
Constant	0.624***	0.210***	0.283***
	(0.00203)	(0.00103)	(0.00124)
N	464986	464986	464986

Data sources: Internal data from the platform. Note: the "Constant" rows in Panel B, Columns (2) and (3) do not add up to the value in Column (1) because there are workers in the platform for whom premium-membership status is not observed, such that they are included in the first column but do not appear in the others. Heteroskedasticity-robust standard errors are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

value of 0.3654, indicating that there are no statistically significant differences between the treatment and control groups across all variables.

A.2 Additional Experimental Results

In this section, we present additional evaluations of the experiment's effects. We begin with Table A2, which follows the same structure as Table 2 in the main text but examines a different outcome: whether employers invite workers to apply for one of their job postings. The results show that treated employers are significantly more likely to invite premium-membership workers and less likely to invite basic-membership workers.

Next, Table A3 reports results from an alternative regression specification. In this design, the unit of observation is an employer–worker pair. The workers paired with each employer are those who appear on the first page of search results that the employer viewed during the experimental period. We restrict attention to this pool because it is not a selected sample: the decision to view additional pages of results may itself be endogenous to treatment. In addition, we include only workers whose premium-membership status can be verified on the

Table A3: Experimental Results, Pairwise Regressions (First Page of Search Results)

	Hired	Clicked
Treatment$_j$	-0.000448***	-0.00315***
	(0.000149)	(0.000575)
Treatment$_j$ $\times$ Premium$_{i,t}$	0.000502*	0.00238**
	(0.000267)	(0.000948)
Premium$_{i,t}$	-0.000191	
	(0.000554)	(0.00185)
Constant	0.00175***	0.0203***
	(0.000232)	(0.000784)
N	415566	
r2	0.143	0.120
Unique employers	223187	
Unique workers	22040	
Worker fixed effects	✓	✓

Data sources: Internal data from the platform. Standard errors clustered at the employer level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

day of the search.

A third sample restriction is that we include only workers who appear as organic listings on that first page; we exclude workers who appear solely as ads. Including the latter could introduce differences in match quality, as workers shown in the first-page organic results are those the platform's algorithm identifies as the best matches for that employer and search query. Workers shown only as ads may be individuals who would have appeared organically on subsequent pages, potentially reflecting lower match quality. It is possible that some premium-membership workers appear twice in the first page, as discussed in the previous section. This duplication is intentionally introduced by the treatment and constitutes part of the variation we exploit in this specification.

The regressions include worker fixed effects, a dummy for whether firm j is treated, a dummy for whether worker i has a premium membership on day t, and the interaction between these two variables. Note that the number of employers used in this design is less than half of those who were assigned to the experiment. That is because not all employers use the search feature; some may rely on recommendations from their platform shown after they create the job posting, while others may passively wait for workers to apply to their jobs.

The results support the interpretation that the experiment diverted employers' attention without increasing net hiring of premium workers. This can be seen by noting that the coefficient on the treatment dummy is negative and statistically significant, while the sum of that coefficient and the interaction term is very close to zero.

A.3 Details on the Calculation of Calibration Targets

This section provides details on the calculation of the target statistics shown in Table 4, along with a discussion of the calibration of the job destruction rate.

Before describing each target individually, we offer a few general observations on the mapping between the data and the model. Vacancies correspond to every employer account assigned to the experiment—a total of 464,986 accounts. However, because treatment is not assigned at the worker level, defining the set of worker accounts used in the calculation of target statistics requires careful consideration. Recall that worker accounts in the model include inexperienced workers, experienced workers, and phantom accounts. The key conceptual features to keep in mind are: (i) experienced workers correspond to premium-membership workers; (ii) the platform cannot distinguish suitable inexperienced workers, unsuitable inexperienced workers, and phantoms; and (iii) all such workers are included in the platform's matching mechanism.

Based on these observations, our pool of worker accounts corresponds to those that the platform actively directs to employers during the experiment. Specifically, we include every worker shown to an employer within 60 days after the employer's assignment to the treatment or control group. Workers may be shown either as search results or as recommendations following a job posting. This procedure yields 1,650,153 worker accounts.

We also need a clear concept of hiring. In the data, the same employer may hire multiple workers or hire the same worker multiple times. This differs from the model, where each firm has a single vacancy. Our approach is to consider only the first hire (if any) made by an employer after entering the experiment and to disregard subsequent hires. We then adjust other variables—for example, the duration of a job spell—to compensate for the missing hires.

We now describe each calibration target.

Share of platform vacancies filled in two months. Of the 464,986 employers in our pool, 135,669 hire someone within 60 days of entering the experiment. However, 47,274 of these hires correspond to workers outside of our sample. To ensure consistency across worker and employer sides, we consider only the 88,395 hires involving workers in our pool. This yields a target value of $88,395/135,669 = 0.19$.

Average number of jobs found by workers over two months. This is given by the ratio of hires to worker accounts: $88,395/1,650,153 = 0.054$.

Ratio of workers to firms on the platform. This follows directly from the number of employer accounts and the number of workers in our selected pool.

Match fees as a fraction of gross wages. We take this target value of 15% directly from the platform's match fee at the time of the experiment.

Premium fees as a fraction of platform revenue. We take this value from a publicly available report that indicates that 90% of the platform's revenue comes from match fees.

Share of premium-membership workers on the platform. Due to data-access limitations, we do not observe comprehensive premium-membership information. However, we have access to browsing data indicating when workers visit pages where they can adjust account settings, including opting into or out of premium membership. This allows us to observe premium status on a few dates for a subset of workers.

We extrapolate membership rates as follows. First, whenever all browsing visits by a worker on a given day indicate the same membership type, we assign that membership type to the worker for that day. Next, if we observe the same membership type on two visits at most three weeks apart, with no intermediate visits, we assume that type applied throughout the interval. This yields an unbalanced worker–day–level dataset on premium status. This is the dataset used to determine whether freelancers are "sometimes premium" or "never premium" in the regressions reported in Tables 2 and A2.

We then merge this dataset with the pool of workers used for estimation. For each day of the experimental period, we compute the average premium-membership rate among workers for whom we have information. To correct for the fact that this subsample is positively selected on platform activity, we assume that the premium-membership rate among workers with missing information is half that of the observed subsample. Using this imputation, we compute the average premium-membership rate among all workers in the estimation pool.

Share of one-month-old workers choosing premium. To measure this target, we use an internal dataset that records account registration dates. We observe this information for over 95% of the workers in the estimation pool, allowing us to ignore the small unmatched remainder. Using the registration dates and the same imputation procedure as above, we calculate the premium-membership rate among workers who are exactly 30 days old during the experimental period, with premium membership being measured (or imputed) exactly at that day.

Experimental treatment effect targets. These come directly from the estimates in Table 2. We set the targets as relative effects: the treatment dummy coefficients divided by the mean rate in the control group (the constant term).

External calibration of the job destruction rate δ. We do not observe hours worked for all hires on the platform. Even if we did, calibrating the job destruction rate would not be straightforward, given the conceptual differences between "hiring" in the model and in the data. Our solution is to choose a value that ensures consistency between the calibrated model and the data from an accounting perspective.

Specifically, while we use the share of platform revenue coming from premium memberships as one of the indirect inference targets, we do not use the monthly premium price relative to wages, even though it is observed. Setting $\delta = 1$ ensures consistency between these perspectives. We verify this by inferring total revenue from premium memberships in the calibrated model, using the observed monthly premium cost, and comparing this to total match-fee revenue using the observed average hourly rate (for a subset of contracts) and the average number of worker hires over 60 days. Crucially, computing the latter requires an estimate of the average number of hours per hire, which depends directly on the job destruction rate.[10]

[10] Workers purchase premium memberships in two ways: through a monthly plan with automatic renewal and by purchasing platform currency that can be used for the same purposes (and may be purchased even by monthly subscribers who have exhausted their allotment). When measuring premium-membership rates, we use the former concept, but to account for some premium-membership revenue comes through currency purchases, setting $\delta = 1$ is consistent with average monthly payments from premium workers being about 46% higher than the listed monthly subscription price at the time of the experiment.

B Model

B.1 Discussion of Platform Participation Fees

As we illustrate in Table 1, the vast majority of platforms allow workers and firms to join for free. This observation constitutes *prima facie* evidence that there exist institutional factors that make it optimal for platforms to offer membership options that do not require upfront or periodic payments, while still allowing workers and firms to use the platform and potentially match with each other. In the main text, for simplicity of exposition, we exogenously ruled out the possibility of participation fees. In this section, we discuss two possible microfoundations that we could have added to the model to endogenously generate this result.

Fraudulent platforms. The first microfoundation is predicated on the idea that the platform's choice not to charge a participation fee can act as a costly signal of the platform's ability to match workers and firms, given that match rates are hard to observe. We now present a simple model that conveys this idea. Suppose that, in addition to the possibility of creating well-functioning platforms at flow cost F, entrepreneurs may also operate fraudulent platforms by paying a small but positive flow cost F_{fraud}. A fraudulent platform is able to attract workers in the same way that normal platforms can, but it does not possess the ability to match workers and firms. In addition, suppose that in this version of the model, platforms can choose not only match fees and premium membership fees, but also a participation fee f_0: a flow cost paid by all workers on the platform, regardless of premium membership status.

Now consider a candidate equilibrium with positive participation fees. If the entry cost F_{fraud} is sufficiently low, it is easy to show that entrepreneurs could make strictly positive profits by creating fraudulent platforms. They would choose exactly the same fee structure used by real platforms so that platform-searching workers would be unable to distinguish between real and fraudulent platforms. The platform would receive revenue from the participation fees of those "inexperienced" workers before they left at the end of the optimal waiting period, but then no real platforms would be created and the market would unravel. The only candidate equilibria that cannot be unraveled in this way are those with zero participation fees.

Note that this argument does not rely on fraudulent platforms being able to deceive workers in perpetuity. To see why, consider a modification where, after a period T_{fraud}, the fraudulent platform is forced to shut down, possibly because of "word of mouth" effects that inhibit its ability to attract more workers. This only reduces the total lifetime profits from operating the fraudulent platform, but they will still be strictly positive.

A possible counterpoint to this argument is that workers could use information from the platform's observable history to infer which platforms are fraudulent. We believe that, although this surely happens to some extent, there are limitations to its practical effectiveness. One is based on bounded rationality, where it may be costly for workers to collect that information. The second is the introduction of additional dynamic elements to the model, such as the presence of innovation with creative destruction. In that case, sticking to older, "proven" platforms may lead workers to miss out on higher match rates offered by newer platforms.

For a more extensive discussion of fraud in a somewhat similar context, see Cumming et al. (2023). Dyck, Morse and Zingales (2010) discuss the prevalence of corporate fraud among large companies.

Hassle costs. The second argument is the presence of "hassle costs" that lead to a discontinuous decrease in the inflow of users into the platform if it decides to charge a participation fee. That is, if the platform charges a participation fee $f_0 > 0$, the inflow of workers into the platform-search stage is reduced by a constant factor $p_{hassle} \in (0,1)$. If p_{hassle} is sufficiently low, there will be no equilibrium with positive participation fees.

There are several justifications for the hassle factor p_{hassle}. Consider, for example, a worker who visits a platform's website after seeing an advertisement for it. If the platform does not charge a participation fee, the worker can join immediately and start experimenting with it. If, however, there is a participation fee, then the worker may not join because they may not have the payment information at hand. When they return to the computer with payment information and search for platforms, they may see a different ad and join a different platform instead.

Another justification for hassle costs comes from the dynamic version of the "fraudulent platforms" argument presented above. In a richer model where some new platforms are fraudulent in equilibrium, the request for payment information may prompt the worker either to make efforts to extract more information from the platform—which may lead to a posterior belief that the platform is fraudulent—or to disregard the platform altogether if trying to acquire that information would be too costly.

B.2 Platform's Matching Mechanism in Detail

In this section, we derive the expressions for the vacancy-filling and job-finding rates in the platform. Before presenting these mathematical results, it is helpful to discuss how this structure captures the key elements of the actual search and matching process within the platform, in addition to being tractable and straightforward.

We view the "match-making opportunities" as a combination of technical design choices by the platform—such as the quality of the matching algorithm and website design—and the effort and attention of users. The platform's ability to identify the closest match along the d dimension represents the platform's matching algorithm, which determines how workers are sorted in search results, which workers are recommended to firms when they create a vacancy, and which vacancies the platform shows to workers who search for them. The fact that the platform does not observe specific values for d represents a limit to the platform's information. The best it can do is offer recommendations and order search results based on predictive models. However, the platform ultimately does not know if that specific firm will actually hire the best-ranked workers. Often, the proposed match will fail and the firm will continue searching.

There are different mechanisms that the platform can use to implement distortion, that is, $\gamma_i > 0$. Consider, for example, a restriction on a basic worker's ability to access information about a particular job posting or apply for it. In a counterfactual scenario without these artificial constraints, they would have applied for the job, meaning they would have been the worker connected with the firm in our modeling of the match process. However, with the restrictions in place, that worker will not be able to connect with that potential employer; instead, the employer will focus on another worker with a premium membership. Note that the platform continues to use its recommendation algorithm to determine which *premium-membership* workers to recommend to an employer. This is why we assume that the platform will select the lowest-d worker within the premium group.

This discussion implicitly assumes that firms consider only one worker at a time; there is no possibility that they will simultaneously evaluate the lowest-d worker in both pools. That is a simple way to incorporate the idea that screening workers requires time and effort for firms. Spending time reviewing one particular worker incurs an opportunity cost such that when the platform chooses to promote one worker over another, it has real consequences—as demonstrated in our experimental results.

The advertising experiment can be interpreted similarly. Consider a control-group employer reviewing one or two pages of search results for a query such as "*Search engine optimization*," then clicking on two or three of the listed candidates to analyze their profiles in detail, and finally selecting one to invite for an interview. The "lowest-d" event corresponds to a combination of two factors: the platform's use of predictive algorithms along with the employer's screening process, which includes some degree of rational inattention (as they do not have the time to click, review, and interview all candidates). The model's randomness regarding whether a match occurs or not—the combination of the lowest d being low enough and the worker being suitable—corresponds to whether the worker selected for an interview was eventually hired or not.

Now, compare this situation to that of a treated employer. There may be cases where advertising does not make any difference because the advertised worker would still appear among the top results and would be selected for the interview anyway. This situation corresponds to the lowest-d worker belonging to the premium tier, such that the γ_i event does not introduce any distortion. However, in the presence of partial inattention, seeing the ad may prompt the employer to click and then select a different worker. That is the case where restricting to the premium tier is consequential.

How does that affect the probability of a hire? As explained earlier in the paper's introduction, there are two possibilities. The modeling of the platform's γ_i mechanism ensures that the lowest-d worker in the restricted premium pool will, on average, have a higher mismatch than that in the general pool. This feature captures the "match efficiency degradation" hypothesis. On the other hand, workers in the premium pool may be positively selected on their suitability x; for example, they are more likely to be available for work or less likely to be phantom accounts (introduced in Section 4.1). In that case, setting $\gamma_i > 0$ can increase match efficiency.

We now proceed to the formal mathematical derivation of the matching mechanism. As described in the main text, we use lowercase n to denote the number of workers and firms in the platform. Specifically, $n_{V,i}$ is the number of firms with open vacancies, $n_{J,i}$ is the number of filled job positions, $n_{b,i}$ counts unemployed workers with a basic membership, and $n_{p,i}$ counts unemployed workers with a premium membership. The total number of firms in the platform is thus $n_{V,i} + n_{J,i}$, while the total number of worker accounts is $n_{b,i} + n_{p,i} + n_{J,i}$.

We assume that every worker in the premium membership pool is suitable, that is, they have $x = 1$. This assumption is consistent with the optimal behavior of workers, as described in the main text. On the other hand, the basic-membership pool has a heterogeneous composition:

$$n_{b,i} = \underbrace{n_{siw,i}}_{\substack{\text{Inexperienced}\\ \text{but suitable}}} + \underbrace{n_{uiw,i}}_{\substack{\text{Inexperienced}\\ \text{and unsuitable}}} + \underbrace{(1-\rho_{ew,i})n_{ew,i}}_{\substack{\text{Experienced}\\ \text{choosing basic}}} + \underbrace{n_{\dagger,i}}_{\substack{\text{Phantom}\\ \text{accounts}}}$$

where the phantom accounts are introduced in Section 4.1, and presented in detail in Appendix C.1. In that appendix, we derive the extended model's expression for the share of suitable workers in the complete worker pool,

$$\phi_i = \frac{n_{siw,i} + n_{ew,i}}{n_{uiw,i} + n_{siw,i} + n_{ew,i} + n_{\dagger,i}}. \tag{15.a}$$

Given this structure, the vacancy-filling rate is

$$q_i = \frac{1}{n_{V,i}} \left\{ \gamma_i \lambda \left[1 - \left(1 - \tfrac{1}{D}\right)^{n_{p,i}} \right] + (1-\gamma_i)\, \lambda \left[1 - \left(1 - \tfrac{1}{D}\right)^{n_{b,i}+n_{p,i}} \right] \phi_i \right\}.$$

The first term inside curly brackets corresponds to potential matches restricted to the premium pool. The term in square brackets represents the probability that at least one worker in the premium pool has a low enough d, so that when the platform recommends the lowest-d worker in that pool, it results in a productive match. The second term is the analog for the case where the match is unrestricted. Multiplication by ϕ_i accounts for the fact that, in addition to having a low-enough d, the recommended worker must be suitable.

We will focus on cases where platforms have large pools of workers, but the potential mismatch D is also large. Formally, we take a limit where all n quantities and D grow to infinity at the same rate. That leads to the following approximation for the vacancy-filling rate,

$$q_i \;=\; \frac{\lambda}{n_v} \left\{ \gamma_i \left[1 - e^{-n_{p,i}/D} \right] \;+\; (1-\gamma_i) \left[1 - e^{-(n_{b,j}+n_{p,i})/D} \right] \phi_i \right\}, \tag{20}$$

which is the expression presented in the main text.

To calculate the job-finding expressions for suitable workers in each pool (Equations 2 and 3), one needs to multiply each of the two components of q_i by $n_{V,i}$ to obtain the total flow of matches that are formed in the selected and unrestricted pools; and then divide by the number of suitable workers in the corresponding pool.

B.3 Stopping Time

Recall that the worker's initial prior is $\bar{x} = \Pr(x = 1)$, which means that with probability $\bar{x}$, the platform is suitable, and with probability $1 - \bar{x}$, it is not. If $x = 1$, successful matches arrive at Poisson rate $h_{b,i}$, which in this derivation we will denote just by h for simplicity. The present value of a successful match is J_i^w as perceived by inexperienced workers, which will appear as J^w below. Let $t \geq 0$ denote time on the platform. At any t, the worker has the option of returning to the platform-searching state, which has discounted present value V_0^w.

The law of motion for the Bayesian beliefs in the absence of job arrivals is

$$\Pr(x_{ij} = 1|t) \equiv \tilde{x}(t) \; = \; \frac{\bar{x}\mathrm{e}^{-ht}}{\bar{x}\mathrm{e}^{-ht} + 1 - \bar{x}},$$

which evolves according to

$$\frac{\mathrm{d}\tilde{x}}{\mathrm{d}t} \; = \; -h\tilde{x}(1 - \tilde{x}).$$

This downward drift reflects the updating that happens when the worker observes no matches over an infinitesimal time interval.

In the main text, we defined the value of inexperienced workers in the platform as

$$r\tilde{V}_i^{iw}(t) = \Pr\left(x = 1|t, h_{b,i}\right) h_{b,i} \left[J_i^w - \tilde{V}_i^{iw}(t)\right] + \frac{d\tilde{V}_i^{iw}(t)}{dt}$$

which in the notation introduced here becomes

$$r\tilde{V}^{iw}(t) = \tilde{x}(t)h\left[J^w - \tilde{V}^{iw}(t)\right] + \frac{d\tilde{V}^{iw}(t)}{dt}.$$

We can use the monotonic mapping $\tilde{x}(t)$, and a small abuse of notation, to rewrite this value as a function of the posterior probability instead:

$$r\tilde{V}^{iw}(\tilde{x}) \; = \; h\tilde{x}\big(J^w - \tilde{V}^{iw}(\tilde{x})\big) \; + \; \frac{\mathrm{d}\tilde{x}}{\mathrm{d}t}\frac{\mathrm{d}\tilde{V}^{iw}}{\mathrm{d}\tilde{x}}.$$

This expression means that if an arrival occurs, the worker collects J^w at that moment, learning that the platform is indeed correct. If there is no match, the perceived value decreases due to the decay of the Bayesian posterior $\tilde{x}$.

Substituting $\mathrm{d}\tilde{x}/\mathrm{d}t = -\lambda\tilde{x}(1-\tilde{x})$ in the value function gives

$$r\tilde{V}^{iw}(\tilde{x}) \;=\; h\tilde{x}\left(J^w - \tilde{V}^{iw}(\tilde{x})\right) \;-\; h\tilde{x}(1-\tilde{x})\,\frac{\mathrm{d}\tilde{V}^{iw}}{\mathrm{d}\tilde{x}}.$$

Rearranging terms, factoring out h, and letting $\alpha = r/h$ leads to

$$\tilde{x}(1-\tilde{x})\,\frac{\mathrm{d}\tilde{V}^{iw}}{\mathrm{d}\tilde{x}} \;+\; \left(\alpha+\tilde{x}\right)\tilde{V}^{iw}(\tilde{x}) \;=\; \tilde{x}J^w.$$

This is a first-order linear differential equation in $\tilde{V}^{iw}(\tilde{x})$. Its general solution can be written as

$$\tilde{V}^{iw}(\tilde{x}) \;=\; \frac{J^w}{\alpha+1}\,\tilde{x} \;+\; C\,\tilde{x}^{-\alpha}\,(1-\tilde{x})^{\alpha+1},$$

where C is a constant of integration to be found via boundary conditions. The worker abandons the platform at some cutoff $\tilde{x}_{min} \in (0,1)$, at which point the worker is exactly indifferent between continuing and switching. This gives the *value-matching condition*,

$$\tilde{V}^{iw}(\tilde{x}_{min}) \;=\; V_0^w.$$

Moreover, because the optimal $\tilde{x}_{min}$ maximizes expected lifetime value, it must be chosen so that there is no "kink" in $\tilde{V}^{iw}(\tilde{x})$ at the exit boundary, leading to the *smooth-pasting condition*,

$$\left.\frac{\mathrm{d}\tilde{V}^{iw}}{\mathrm{d}\tilde{x}}\right|_{x=x_{min}} \;=\; 0.$$

We now derive two separate expressions for C from these conditions and then set them equal, yielding a single equation in $\tilde{x}_{min}$. First, substituting $\tilde{x} = \tilde{x}_{min}$ into the value function gives

$$\frac{J^w}{\alpha+1}\,\tilde{x}_{min} \;+\; C\,\tilde{x}_{min}^{-\alpha}\left(1-\tilde{x}_{min}\right)^{\alpha+1} \;=\; V_0^w,$$

which we rearrange to isolate C

$$C \;=\; \frac{V_0^w - \dfrac{J^w}{\alpha+1}\,\tilde{x}_{min}}{\tilde{x}_{min}^{-\alpha}\left(1-\tilde{x}_{min}\right)^{\alpha+1}} \;\equiv\; C_1.$$

Next, the smooth-pasting condition requires that

$$\frac{\mathrm{d}}{\mathrm{d}\tilde{x}}\left[\tfrac{J^w}{\alpha+1}\,\tilde{x}+C\,\tilde{x}^{-\alpha}\left(1-\tilde{x}\right)^{\alpha+1}\right]_{\tilde{x}=\tilde{x}_{min}} \;=\; 0.$$

After some straightforward algebra, one obtains

$$\frac{J^w}{\alpha+1} \;-\; C\left(\alpha+\tilde{x}_{min}\right)\tilde{x}_{min}^{-\alpha-1}\left(1-\tilde{x}_{min}\right)^{\alpha} \;=\; 0,$$

hence

$$C \;=\; \frac{\frac{J^w}{\alpha+1}}{\left(\alpha+\tilde{x}_{min}\right)\tilde{x}_{min}^{-\alpha-1}\left(1-\tilde{x}_{min}\right)^{\alpha}} \equiv C_2.$$

Equating C_1 and C_2 provides the single equation that determines the optimal cutoff $\tilde{x}_{min}$. After a few steps of more algebraic manipulations, and changing back from α to the original model variables, we find

$$\tilde{x}_{min} \;=\; \frac{r\,V_0^w}{h\left(J^w-V_0^w\right)}.$$

The optimal stopping time T, follows by solving $\tilde{x}\big(T\big) \;=\; \tilde{x}_{min}$, yielding

$$T \;=\; \frac{1}{h}\ln\!\left(\frac{\bar{x}\left[1-\tilde{x}_{min}\right]}{\left(1-\bar{x}\right)\tilde{x}_{min}}\right).$$

This expression can be rewritten in terms of original model parameters, yielding the expression shown in the main text

$$T\left(J_i^w,V_0^w,h_b\right) \;=\; \max\left\{0,\;\frac{1}{h_b}\left[\ln\!\left(\frac{\bar{x}}{1-\bar{x}}\right)+\ln\left(1+\frac{h_b}{r}\,\frac{J^w-V_0^w}{V_0^w}\right)\right]\right\}, \qquad (21)$$

where we added the max term to account for the possibility that, under some parameter values, the initial value at the platform $\tilde{V}^{iw}(0)$ could be greater than J^w, in which case workers would have no reason to stay there.

B.4 Profit-Maximizing Platforms Induce Experienced Workers to Choose Premium Memberships

In this section, we prove the result stated in its title.

There are two types of possible solutions to the platform's problem, depending on whether the match distortion chosen by the platform is strictly positive or not. If $\gamma_i = 0$, the platform does not offer any advantage to premium workers and, therefore, they would not pay positive fees $f_{p,i} > 0$ for it. In this case, we assume without loss that the optimal choice also has $f_{p,i} = 0$ and that experienced workers choose premium memberships, which are identical to the basic membership. Thus, for these kinds of solutions the desired result is just a normalization.

In the remainder of this proof, we will consider candidate solutions to the platform's profit-maximizing problem that have $\gamma_i > 0$. We will analyze three cases, depending on whether V_i^p is smaller than, greater than, or equal to V_i^b when evaluated at the candidate solution.

If $V_i^p < V_i^b$, then experienced workers must choose basic memberships: $\rho_{ew,i} = 0$. Given that $\gamma_i > 0$, we have $h_{p,i} > h_{b,i}$. So, we can conclude that this candidate solution has $f_p > 0$. It is then possible to choose a specific $f_p' \in (0, f_{p,i})$ such that experienced workers become indifferent between tiers, that is, $V'^p_i = V'^b_i$. This alternative solution is guaranteed to increase profits, as the platform obtains an additional source of revenue.[11] Thus, we can conclude that the original candidate solution with $V_i^p < V_i^b$ is not optimal.

In the second case with $V_i^p > V_i^b$, every experienced worker chooses the premium membership and there is nothing else to prove.

The last and most interesting case is when the premium-membership incentive-compatibility constraint binds, that is, when $V_i^p = V_i^b$. This is the case for the calibrated model used in our quantitative exercises. Equalizing $V_i^p = V_i^b$ yields

$$\begin{aligned} f_{p,i} =& (h_{p,i} - h_{b,i})(J_i^w - V_i^b) \\ =& \frac{\lambda \gamma_i \left(1 - e^{-n_{p,i}/D}\right)}{n_{p,i}} (J_i^w - V_i^b). \end{aligned}$$

That is, the premium fee must be proportional to the increase in the match rate provided by the premium membership. The right-hand side is thus the willingness to pay for premium memberships. It is decreasing in $n_{p,i}$ because the more workers belong to that tier, the more "diluted" the benefits in match rates. Thus, starting from a candidate solution where the $V_i^p \geq V_i^b$ constraint binds, if the platform chooses to increase $\rho_{ew,i}$, it must reduce $f_{p,i}$.

[11] Additionally, given that no workers were choosing premium memberships, vacancy-filling rates also rise following the shift to $f'_{p,i}$, given that when the platform restricts matches to the premium set, those potential matches are no longer wasted. The increase in q_i provides a further boost to platform revenues coming from premium revenues if $f_{m,i} > 0$, but the argument above holds even if the original candidate solution has $f_{m,i} = 0$.

To derive our main result, we reformulate the problem of the platform in a sequential manner. In the first stage, the platform chooses $f_{m,i}$ and γ_i. In the second stage, it chooses $\rho_{ew,i}$. Finally, it sets $f_{p,i}$ to the value that solves the above equation. Formally,

$$\Pi = \max_{f_{m,i},\ \gamma_i} \left\{ \max_{\rho_{ew,i}} \left[f_m w(\cdot) n_J(\cdot) + \lambda \gamma_i \left(1 - e^{-n_{p,i}/D}\right) \left[J_i^w(\cdot) - V_i^b(\cdot) \right] - F \right] \right\},$$

where we have substituted the utility constraint into the objective function.

Note from the equations in Section 3.3 that conditional on $f_{m,i},\ \gamma_i$, and under the assumption that $V_i^p(\cdot) = V_i^b(\cdot)$ binds, $J_i^w(\cdot)$, $V_i^b(\cdot)$, and $w_i(\cdot)$ do not depend on either $\rho_{ew,i}$ or $f_{p,i}$. This is because we can use $V_i^b(\cdot)$ in place of $\max\{V_i^b, V_i^p\}$. Thus, those variables are exogenous to the inner problem. Because $n_{b,i} + n_{p,i} = n_{iw,i} + n_{ew,i}$ does not change with $\rho_{ew,i}$, $h_{b,i}$ is also invariant in the inner problem. If $J_i^w(\cdot)$ and $h_{b,i}$ are exogenous in the inner problem, so is $n_{iw,i}$. Furthermore, given that $n_{iw,i}$, $h_{b,i}$, and V_i^b are invariant, $n_{ew,i}$ is also invariant.

With that, we can write:

$$\begin{aligned} n_{J,i} &= \frac{h_{ew,i} + s_U \exp\left(-\sigma_v(\max\{V_i^b, V_i^p\} - V_0^w)\right)}{\delta} n_{ew,i} \\ &= \left[(1-\rho_{ew,i})h_{b,i} + \rho_{ew,i} h_{p,i} + sep_i\right] K_J \end{aligned}$$

where sep_i and K_J are invariant in the inner problem. Also denoting $K_w = f_m w(\cdot)$ and $K_p = \lambda \gamma_i \left[J_i^w(\cdot) - V_i^b(\cdot)\right]$, the sequential profit-maximization problem becomes:

$$\Pi = \max_{f_{m,i},\ \gamma_i} \left\{ \max_{\rho_{ew,i}} \left[\left[(1-\rho_{ew,i})h_{b,i} + \rho_{ew,i} h_{p,i} + sep_i\right] K_J K_w + \left(1 - e^{-\frac{\rho_{ew,i} n_{ew,i}}{D}}\right) K_p - F \right] \right\}.$$

Now it becomes evident that the inner problem is strictly increasing in $\rho_{ew,i}$, because $h_{p,i} > h_{b,i}$ and $n_{ew,i}$ is a non-negative constant in the inner problem and that we must have either $K_w > 0$ or $K_p > 0$ (at an optimal solution, the platform raises revenues in at least one way). That suffices to prove that the solution to the inner problem is at the boundary $\rho_{ew,i} = 1$.

The intuition for this result is that a larger pool of premium workers makes the matching mechanism more efficient conditional on $\gamma_i > 0$. Hence, if the firm wants to distort the matching process to extract rents from premium workers, the most efficient way to do so is to charge fees that are low enough to induce all experienced workers to join that tier, making the preference awarded to them less distortionary.

C Quantitative Exercises

C.1 Extended Model: Phantoms, Private Information, and Inattention

In this section, we provide the full characterization of the quantitative model, including phantom accounts, some workers having private information about their own suitability when joining, and some workers being attentive to the platform's job-finding rates when deciding whether to join. These changes correspond to the extensions described in Section 4.1 and the robustness exercises in Appendix C.5.

These additional model components work as follows. Consider a worker in the platform-search stage who is matched to a potential platform and must decide whether to join. This prompts a series of events:

1. With probability Ξ, the worker is fully informed about platform characteristics, including the true job-finding rates. With probability $1-\Xi$, they instead believe the platform's job-finding rates are equal to the market averages. The baseline model corresponds to $\Xi = 0$.

2. The worker decides whether to join the platform based on their expectation of the value delivered by the platform relative to the draw of the joining cost ε (which is known at that point).

3. If the worker joins, one of the following three events occurs.

   (a) With probability θ, the worker is suitable ($x = 1$) and knows it privately, but cannot costlessly convey that information to the platform in a credible manner. As explained in the main text, this worker's state is equivalent to that of an experienced but unemployed worker. If the platform offers a premium membership and sets it optimally, they will join it.

   (b) With probability $(1-\theta)\bar{x}$, the worker is suitable but has no private information about it. These workers will opt for the basic-membership tier given their uncertainty about their own x.

   (c) With probability $(1-\theta)(1-\bar{x})$, the worker is unsuitable and does not know it. These workers will also join the basic-membership tier in equilibrium.

Before redefining the model equations, note that we are fairly specific in how we model private information. To begin with, we do not allow workers to have correct private information when $x = 0$. If this was possible, informed workers would separate from the platform immediately after joining. Including this feature would not yield additional insights, which is why we adopt a simpler structure.

A potentially more interesting possibility would be for joining workers to have mistaken beliefs about their suitability—for instance, workers with $x = 0$ incorrectly believing that $x = 1$. These workers would choose the premium tier, but would never be matched, remaining on the platform until they received a sufficiently strong separation shock. We do not include this possibility because it would be difficult to identify the relative frequency of such mistakes jointly with that of the "correct" type of private-information shock. Our choice to assume that all private information is correct is conservative, as it works against our main finding that premium-membership tiers are welfare-decreasing. Having workers join that tier due to mistaken beliefs would constitute an additional channel through which welfare could fall when those tiers are offered.

We now proceed to the equations. We start by splitting the worker-inflow expressions by whether workers are informed about platform-specific job-finding rates.

$$\psi_i^{w,informed} = \frac{N_0^w}{I}\lambda_0 \Xi \Big[1 - \exp\big(-\sigma_\varepsilon(EV_i^{iw} - V_0^w)\big)\Big] \tag{6.a}$$

$$\psi_i^{w,uninformed} = \frac{N_0^w}{I}\lambda_0 (1-\Xi) \Big[1 - \exp\big(-\sigma_\varepsilon(\tilde{EV}_i^{iw} - V_0^w)\big)\Big]. \tag{6.b}$$

There are three differences between these expressions and Equation (6) in the main text. First, the value of being a recently joined worker on the platform is represented by expected utilities denoted EV_i^{iw} (defined below) instead of V_i^{iw}. Second, informed workers choose based on true expected utilities, whereas uninformed ones choose based on perceived expected utility $\tilde{EV}_i^{iw}$. Finally, the inflow equations are adjusted to account for the probabilities of being informed or uninformed, according to Ξ.

The expected utilities at the time of the platform decision, before the realization of the private-information shock, are given by

$$EV_i^{iw} = \theta \max\{V_i^b, V_i^p\} + (1-\theta)V_i^{iw}(0)$$
$$\tilde{EV}_i^{iw} = \theta \max\{\tilde{V}_i^b, \tilde{V}_i^p\} + (1-\theta)\tilde{V}_i^{iw}(0),$$

where the difference between the two is that, as explained in the main text, the terms with tildes are calculated using the average job-finding rates across platforms rather than the true job-finding rates for platform i.

The definition of optimal waiting time for workers who do not receive the private-information shock—and thus join the basic tier—is the same, except that informed workers use true job-finding rates and employment values, while uninformed workers use those from the basic model. For consistency of notation, denote the waiting times by T_i and $\tilde{T}_i$, respectively.

To find the number of suitable and unsuitable inexperienced workers, it is easiest to write separate balance equations for informed and uninformed workers. Starting with suitable inexperienced workers:

$$\psi_i^{w,informed}(1-\theta)\bar{x} = n_{siw,inf,i}h_{b,i} + \psi_i^{w,informed}(1-\theta)\bar{x}\exp\left(-h_{b,i}T_i\right). \quad (9.a)$$

$$\psi_i^{w,uninformed}(1-\theta)\bar{x} = n_{siw,uninf,i}h_{b,i} + \psi_i^{w,uninformed}(1-\theta)\bar{x}\exp\left(-h_{b,i}\tilde{T}_i\right). \quad (9.b)$$

$$n_{siw,i} = n_{siw,inf,i} + n_{siw,uninf,i}. \quad (9.c)$$

Although we must use different stopping times—since informed and uninformed workers remain on the platform for different durations, and thus have different probabilities of finding a job before leaving—we use the true platform-specific job-finding rate $h_{b,i}$ in both expressions, as that rate determines actual flows.

The expressions for unsuitable, inexperienced workers are:

$$\psi_i^{w,informed}(1-\theta)(1-\bar{x}) = \frac{n_{uiw,inf,i}}{T_i}. \quad (10.a)$$

$$\psi_i^{w,uninformed}(1-\theta)(1-\bar{x}) = \frac{n_{uiw,uninf,i}}{\tilde{T}_i}. \quad (10.b)$$

$$n_{uiw,i} = n_{uiw,inf,i} + n_{uiw,uninf,i}. \quad (10.c)$$

The balance equation defining the number of employed workers $n_{J,i}$ is the same as in the main text; we repeat it below for convenience. However, we need a new expression for experienced but unemployed workers ($n_{ew,i}$):

$$n_{siw,i}h_{b,i} + n_{ew,i}h_{ew,i} = \delta n_{J,i}$$

$$\delta n_{J,i} + \psi_i^{ew} = (h_{ew,i} + \bar{s}_U)\, n_{ew,i},$$

where $\psi_i^{ew} \equiv \left(\psi_i^{w,informed} + \psi_i^{w,uninformed}\right)\theta$ is the inflow of workers who receive the private-information shock immediately after joining the platform.

We can rewrite the expressions for the pools of experienced and employed workers as:

$$n_{ew,i} = \frac{h_{b,i} + \psi_i^{ew}}{\bar{s}_U} n_{siw,i} \tag{11.a}$$

$$n_{J,i} = \frac{(h_{ew,i} + \bar{s}_U)\, n_{ew,i} - \psi_i^{ew}}{\delta}\,. \tag{12.a}$$

The numbers of workers in the basic-membership tier, along with the share of suitable workers among unemployed workers, must be adjusted to account for phantom accounts.

$$n_{b,i} = n_{siw,i} + n_{uiw,i} + (1-\rho_{ew,i}) n_{ew,i} + n_{\dagger,i} \tag{13.a}$$

$$\phi_i = \frac{n_{siw,i} + n_{ew,i}}{n_{uiw,i} + n_{siw,i} + n_{ew,i} + n_{\dagger,i}}. \tag{15.a}$$

The pool of phantom workers is pinned down by:

$$\begin{aligned} \psi_i^{w,informed}(1-\theta)\left[\bar{x}\exp\left(-h_{b,i}T_i\right) + (1-\bar{x})\right] \\ + \psi_i^{w,uninformed}(1-\theta)\left[\bar{x}\exp\left(-h_{b,i}\tilde{T}_i\right) + (1-\bar{x})\right] \\ + n_{ew,i}\bar{s}_U = n_{\dagger,i}s_{\dagger}, \end{aligned} \tag{22}$$

which equates inflows into and outflows from the phantom pool. The first two inflow sources correspond to inexperienced workers who do not receive the private-information shock and leave at the end of their optimal waiting time, either because they are unsuitable or because they were suitable but did not find a job in time. The last term corresponds to separations of experienced unemployed workers (including recently joined workers who received the private-information shock).

C.2 Details on the Numerical Procedures

We develop a series of numerical procedures to calibrate the model, ensure the validity of solutions, and simulate counterfactual scenarios. All procedures are implemented in the Julia programming language (Bezanson et al., 2017). We now provide an overview of these procedures, paying particular attention to potential pitfalls of our economic model, such as the possibility that the platform's problem described in Section 3.5 may not be strictly concave.

Solving for endogenous variables given platform choices. This procedure, named *solveForEquilibriumExPlatformProfits* in our code, is used as an intermediate step in several other procedures. It takes as arguments the model parameters and the choices of match fees and distortions, and it outputs endogenous variables that are consistent with internal platform dynamics and aggregate equilibrium conditions, except for platform profit maximization. To do so, it solves a square system of nonlinear equations. It imposes two assumptions. The first is that the experienced worker's incentive-compatibility constraint holds, that is, $V_i^b = V_i^p$ (as opposed to experienced workers strictly preferring premium memberships, $V_i^b < V_i^p$). We test the validity of this assumption later. The second assumption, which we maintain in all exercises, is that all platforms make identical choices in equilibrium.

Because this procedure is a central component of our exercises, we speed it up by keeping track of the solutions to the system of equations after every successful call. These solutions are saved in a file and then retrieved whenever the procedure is called again, at which point they can be used as starting points.

Internal platform variables given the platform's own choices and those of other platforms. This procedure, named *solveForPlatformSpecificRates* in our code, calculates platform-specific variables such as job-finding rates and stocks. It differs from the previous procedure in that it allows individual platforms to deviate from the equilibrium choices of other platforms, making it the appropriate procedure for analyzing the platform profit-maximization problem. We also develop a closely related procedure, named *solveForPlatformSpecificRates_experiment* in our code, which achieves the same goal but accounts for the case in which the individual platform increases the advantage given to premium workers for a random subsample of vacancies, as in the experiment described in the paper. It takes an additional argument, $\Delta\gamma$, denoting the increase in distortion for treated vacancies.

Equilibrium-finding procedure. The procedure *solveForMarketEquilibrium* calls the two previous procedures to find an equilibrium of the model under two assumptions: (i) the platform's profit-maximization problem is solved at a unique point where first-order conditions hold, and (ii) the incentive-compatibility constraint binds (see "Verifying platform optimality" and "Verifying the incentive-compatibility assumption" below). It solves a system of two equations where the choice variables are f_m and γ, and the two equations correspond to the first-order conditions. We also implement modified versions of this procedure that impose either $f_m = 0$ or $\gamma = 0$, so that we can find equilibria where platforms employ only one of the two revenue strategies.

Calibration objective function. This procedure, named *estimationObjFun*, takes as inputs a guess for the 11 estimated parameters listed in Table 4, plus a guess of the baseline equilibrium level of distortion γ. It returns a vector of 12 outputs corresponding to errors in 12 equations that must be satisfied for a successful calibration. The first 10 outputs correspond to deviations between the internal calibration targets and their model-implied counterparts, with one exception: match fees as a fraction of gross wage, which we use as a direct input.

In the first step, we call *solveForEquilibriumExPlatformProfits* to find all endogenous variables as a function of the guessed model parameters, the guessed input for the platform's distortion choice γ, and the level of match fees observed in the data ($f_m = 0.15$). In the second step, we use these endogenous variables to simulate eight of the calibration targets (all in Table 4 except for match fees and the experimental targets). Next, we use *solveForPlatformSpecificRates_experiment* to find internal platform variables for a platform that implements an experiment with strength $\Delta\gamma$, which allows us to simulate the final two calibration targets. Finally, we use *solveForPlatformSpecificRates* to calculate two quantities corresponding to the first-order conditions of the platform's problem. Specifically, we calculate marginal profits associated with changes in either f_m or γ, assuming that all other platforms play the equilibrium values. Thus, a solution to this system of 12 equations ensures that all calibration targets are met and that platform choices of f_m and γ are consistent with zero marginal profits.

Baseline calibration procedure. As explained in the main text, we find an exact solution in the calibration procedure, corresponding to a perfect match of all calibration targets and of the platform's first-order conditions. Nevertheless, there remains a concern that the solution to this system of equations may not be unique. We address this concern in two ways. First, we run the estimation procedure with 200 randomly generated starting points that exhibit sizable deviations between them. Second, we use a gradient-descent method for half of these starting points and a Nelder–Mead procedure for the other half, as the latter can be more robust in less smooth regions of the parameter space. We verify that all solutions are identical.

Alternative calibrations. We rerun the calibration procedure for seven alternative models: two different values of D, two different values for the experimental calibration targets, two different values for the persistence target, and a version of the model in which some workers are fully informed about platform-specific match rates. For each of the first six, we try 10 different starting points, beginning with the baseline calibration's optimum. For the last case, where we cannot achieve a perfect match for all calibration targets, we use 40 starting points. Again, we apply a gradient-descent method for half of them and Nelder–Mead for the other half. In all cases, the solution is unique.

Verifying platform optimality. As described above, our calibration procedure assumes that first-order conditions are sufficient for platform profit maximization, which is not guaranteed for two reasons. First, the platform's profit function may not be strictly concave. Second, the model may admit corner solutions.

To address the first issue, we develop another procedure, *maximizePlatformProfits*, which solves the platform's problem directly as a maximization problem rather than as a system of equations. This procedure takes the estimated model parameters as given and assumes that all other platforms choose the estimated equilibrium values of f_m and γ. We use the Nelder–Mead method for this maximization, as it is more robust when the problem is not globally concave or includes corner solutions. We also try five different starting points: the estimated equilibrium's platform choices and four additional points obtained by doubling or halving each choice variable. We perform this analysis for all eight versions of the calibration procedure. In all cases, the platform's optimal choice coincides with the calibrated equilibrium value obtained under the assumption that first-order conditions are sufficient.

To address the second issue, we test for alternative equilibria with corner solutions. Specifically, we attempt to solve for an equilibrium where all platforms set $f_m = 0$, and another where all platforms set $\gamma = 0$, using the *solveForMarketEquilibrium* procedure described above. In all versions of the calibration, we fail to find such alternative equilibria. Specifically, when one control is set to zero and we solve for zero marginal profit in the other, the former control's marginal profit is strictly positive, indicating that the corner is not a solution.

Verifying the incentive-compatibility assumption. The calibration and counterfactual exercises assume that the incentive-compatibility constraint $V_i^b \leq V_i^p$ binds. To test for the possibility of a slack solution, we develop an alternative procedure, *maximizePlatformProfits_diffVs*, which relaxes this assumption. Using each version of the calibrated model, we optimize individual platform problems assuming all other platforms play the estimated equilibria. If we were to find an equilibrium where $V_i^b < V_i^p$ and platform profits exceeded the baseline level, the bindingness assumption would be invalid. However, in all cases, we find that profits are higher in the unconstrained problem, but $V_i^b > V_i^p$, confirming that the calibration procedure is valid.

Premium-prohibition policy counterfactuals. These correspond to solving for equilibria using the restricted version of *solveForMarketEquilibrium* that imposes $\gamma = 0$.

Planner's problem. We use *solveForEquilibriumExPlatformProfits* to construct an objective function where the inputs are guesses for f_m and γ and the output is aggregate welfare. Note that *solveForEquilibriumExPlatformProfits* yields a level of entry I consistent with zero profits, which is equivalent to the planner's budget constraint. We maximize this objective function using the Nelder–Mead method, employing five different starting points corresponding to those described above in the "Verifying platform optimality" section. This increases the likelihood of finding a global solution even if the welfare objective function is not globally concave.

Reduced platform differentiation and Beveridge curves. These exercises correspond to solving for equilibria with the *solveForMarketEquilibrium* procedure under different parameter sets, using the $\gamma = 0$ constraint when considering scenarios with the premium-prohibition policy in place.

C.3 Additional Characteristics of Estimated Equilibria

Table A4 presents additional information on the estimated models for different levels of D.

C.4 Robustness with Respect to Premium-Membership Worker's Persistency on the Platform

Table A5 reports the results of these robustness exercises. Panel A shows how different assumptions regarding the persistence target translate into different parameters governing the separation process for experienced users, along with the corresponding separation rates. The exercise spans a fairly wide range of parameter values, particularly for s_U. The last row in this panel reports the probability that an initially unemployed experienced worker remains

Table A4: Additional Information Regarding Estimated Equilibria

Outcome	$D = 8437.5$	$D = 13500.0$	$D = 21600.0$
Panel A: Aggregate outcomes			
Employment rate (%)	10.0	10.0	10.0
Search costs as share of output (%)	57.6	58.6	59.2
Number of platforms	10.0	10.0	10.0
Share of workers outside platforms (%)	4.4	5.2	5.7
Share of firms outside platforms (%)	6.1	7.0	7.6
Panel B: Platform-specific outcomes			
Match fees, f_m	0.150	0.150	0.150
Match distortion, γ	0.046	0.046	0.046
Premium membership fee, f_p	0.35	0.34	0.34
Vacancy-filling rate, q	0.145	0.145	0.144
Basic membership job-finding rate, h_b	0.147	0.154	0.159
Premium membership job-finding rate, h_p	0.155	0.162	0.167
Wage relative to match output (%)	55.3	55.1	55.0
Optimal wait time for inexperienced workers, T (months)	3.5	3.4	3.4
Cutoff prob. for posterior $\Pr(x=1\|t)$, $\tilde{x}_{min}$	0.620	0.569	0.537
Pr(Premium worker still active after one month)	0.72	0.72	0.72

Table A5: Main Results Under Different Persistency Calibration Targets

	Target premium worker persistency		
Outcome	55%	60% (Baseline)	65%
Panel A: Separation-related estimates			
Separation shock arrival s_U	1.178	0.923	0.663
Inverse mean of separation utility cost σ_v	0.254	0.235	0.220
Effective separation rate for premium users	0.423	0.349	0.281
Pr(Premium worker still active after one month)	0.67	0.72	0.77
Panel B: Welfare implications			
Welfare gain from premium prohibition policy (%)	4.3	4.2	4.0
Welfare gain in planner's optimum (%)	4.3	4.2	4.0
Number of platforms in planner's optimum	9.7	10.0	10.4
Match distortion γ in planner's optimum	0.000	0.000	0.000

active on the platform after one month, either as an unemployed (non-phantom) worker or as an employed worker.

Panel B reports the main counterfactual results of these robustness exercises. The central conclusion is that our estimates of welfare gains associated with the premium-prohibition policy are similar across calibrations. In all cases, the central planner would choose to eliminate premium memberships.

C.5 Inexperienced Workers' Inattention With Respect to Job-Finding

In the baseline model, we assume that when a worker in the platform-search stage is matched to a potential platform and considers joining, they fully observe that platform's fees but cannot observe its job-finding rates. Instead, they make their decision under the assumption that the platform's job-finding rate is equal to the market average across all platforms. As mentioned in the main text, because we focus on symmetric equilibria, this implies that workers' beliefs about job-finding rates are correct in equilibrium. Nevertheless, the assumption remains consequential, as it determines the responsiveness of workers' joining decisions when an individual platform changes its fees or match distortion γ_i. Workers fully learn about job-finding rates only after becoming experienced on the platform or if they receive the private information shock introduced in Section 4.1.

We believe that this assumption is realistic in the context of online job platforms. However, it is difficult to provide direct empirical support for it. Instead, in this Appendix we examine the implications of adopting an alternative assumption about workers' attentiveness in our model.

Specifically, we assume that, when having the opportunity to match with a platform, a fraction Ξ of workers are fully informed about platform-specific job-finding rates, while with probability $1-\Xi$ they are inattentive and believe that the platform's job-finding rate is equal to the market average. Appendix C.1 describes how the model equations are modified under this extension.

We then re-calibrate the model imposing $\Xi = 25\%$. This deviation is quantitatively meaningful while still close enough to the baseline calibration that the latter serves as a useful starting point for the indirect inference procedure. We use a total of 40 starting points: one identical to the baseline calibration and the remaining 39 consisting of random perturbations around that benchmark.

Table A6: Alternative Calibration with 25% of Workers Fully Attentive

Parameter	Value	Moment	Target	Sim.
F	1225.1	Number of platforms	*10.00*	10.00
s_U	0.213	Prob. experienced worker does not change state in one month	*0.600*	0.689
s_V	0.150	Share of platform vacancies eventually filled	0.190	0.190
λ	2469.3	Average number of jobs found by workers over two months	0.054	0.056
σ_ε	0.011	Match fees as fraction of gross wage	0.150	0.150
σ_ν	0.000	Premium fees as fraction of platform revenue	0.100	0.100
c	4.739	Ratio of workers to firms in platform	3.549	3.528
$\bar{x}$	1.000	Share of premium-membership workers in platform	0.095	0.089
θ	0.111	Share of one-month workers choosing premium	0.122	0.123
$\Delta\gamma$	0.0182	Treat. effect on prob. hiring a basic membership worker	-0.0176	-0.0180
$s_\dagger$	0.025	Treat. effect on prob. hiring any worker	-0.0090	-0.0082

Table A7: Prohibition Policy with 25% of Workers Fully Attentive

Outcome	Mkt. Equilibrium	Premium Prohibition
Panel A: Aggregate metrics		
Welfare gains (%)	-	3.1
Welfare gains relative to initial aggregate payroll (%)	-	2.5
Employment rate	0.131	0.134
Search costs as share of output	0.539	0.534
Panel B: Market outcomes		
Number of platforms	10.0	10.3
Match fees	0.150	0.166
Match distortion γ	0.043	-
Premium membership fee	0.32	-

Under this alternative assumption, the model's ability to match the calibration targets deteriorates. Table A6 reports the calibrated parameters, calibration targets and the corresponding simulated values. The model does not match the persistence target for experienced workers, implying excessive persistence. More importantly, it cannot replicate the experimentally estimated treatment effects. Specifically, the model underestimates the ratio of treatment effects on overall hiring relative to that on basic-membership workers' hiring. This discrepancy is problematic because, as we discuss in Section 4.3, this ratio is a key determinant of the welfare implications of the premium-prohibition policy. The failure to match these targets is associated with the parameters σ_v and $\bar{x}$ converging to their lower and upper bounds, respectively.

The lack of a perfect fit using this alternative model suggests that the baseline version where all workers are inattentive provides the best approximation to this market. Still, for the sake of evaluating the robustness of our results, we simulate our main counterfactual policy using the alternative model. The results, presented in Table A7, show that while the magnitude of the welfare change falls, it remains positive.