Hunting for talent: Firm-driven labor market search in the United States*

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May 31, 2021

Abstract

Research suggests that increased digitization of the labor market, combined with the changing demand for skill, has altered the job-search process. This article argues that these changes have led to increased investments in firm-driven search for talent (or 'outbound recruiting'). We investigate this question by proposing a two-sector labor market model and using two data sets, one new, to corroborate our predictions. First, we conduct a nationally representative survey of over 13,000 American workers. We find that nearly 18 percent of all employed workers in the US were hired into their present company by their employer's outbound recruiting effort, a substantial increase over the 4.2 percent observed in prior surveys. Using a post-COVID survey, we find similar results. Moreover, the share of hiring driven by firm-driven search is greatest among higher-income workers, at 20.3 percent, and those with STEM and business degrees, at 20 percent. Considerable regional variation also exists with over a quarter of Silicon Valley workers hired in this manner, but only 14.5 percent of those in Rochester. Second, we complement our worker-level results by analyzing a large sample of job postings in the US economy over the past decade. We find that firms, especially those relying on high-skilled labor, are increasingly developing capabilities to better hunt for talent—hiring more recruiters with skill in online search. Given the growth of this practice, we discuss implications for research on firm strategy and labor markets.

*Author names are listed in alphabetical order. The authors thanks Duke University's Fuqua School of Business, Harvard Business School and the Kauffman Foundation for their generous financial support for this project.

1 Introduction

A firm's performance relies on finding, hiring, and retaining talented workers (Coff and Kryscynski, 2011). However, much of the existing research on human capital strategy implicitly assumes firms rely on the search behavior of workers to find talent. The framework in which workers drive search is embedded in theoretical models of job search behavior (e.g., Mortensen and Vishwanath, 1994; Jovanovic, 1979) as well as in expansive empirical work on firms' hiring decisions (e.g., Fernandez and Sosa, 2005; Bertrand and Mullainathan, 2004) and human resource capabilities (e.g., Coff and Kryscynski, 2011; Barney, 1991). In most theories, firms 'search' for workers in so far as they post job openings, choose among applicants and sometimes rely on existing employees' referrals (Fernandez, Castilla and Moore, 2000; Petersen, Saporta and Seidel, 2000). Increasingly, however, digitization and the internet have enabled firms to take a more active role in finding talent—via access to vast databases of updated worker profiles (Elfenbein and Sterling, 2018; Autor, 2001). Such data has the potential to reduce the costs of finding workers, especially those not actively searching. Yet, there remains a considerable gap in our understanding of how widespread firm-driven search is, which workers and firms participate, and the consequences for labor market outcomes.

In recent years, the growth of firm-driven search or "outbound" recruiting —the practice of firms finding and reaching out to potential candidates and inviting them to their recruiting process, as opposed to worker-driven search or "inbound" recruiting, which pertains to workers responding to job postings with applications— has been highlighted by many in industry and academia. A Federal Reserve report, for example, indicated that nearly 1 in 3 workers who switched employers were not actively searching—a finding the authors attribute to high rates of outbound recruiting by firms

(Carrillo-Tudela et al., 2015). Researchers have also highlighted this trend. In a recent novel survey of job search behavior of both employed and unemployed workers, Faberman et al. (2020) find that around 22 percent of of the employed report searching for work on-the-job in the prior four weeks. Cappelli (2019) argues that firms increasingly prefer to hire "passive candidates" and scour online databases (e.g., LinkedIn) for people to poach. Despite an emerging constellation of suggestive patterns and anecdotes, there remains no systematic study of this phenomenon.

This article proposes a two-sector labor market model highlighting the interplay between firms' skill requirements and inbound or outbound recruiting costs. We take a firm-side approach, whereby firms adapt their optimal hiring choices according to skill requirement heterogeneity and industry-level changes in recruiting costs, while workers simply accept the best offer. We generate predictions to guide our empirical analyses. we predict that firms will engage more in outbound recruiting when (a) they face more binding skill requirements; (b) they face higher costs of screening applications; or (c) they have access to a lower cost of finding workers outside their applicant pool (lower cost of "hunting") and, as a result, high-skill workers will be paid higher wages.

We analyze two new data sources that provide insight into the prevalence and impact of outbound recruiting in the United States' labor market. To better understand the effects on workers, we conduct a nationally representative survey of working Americans to assess the prevalence of different modes —e.g., inbound, outbound, referrals— of finding a job. Next, we complement our survey by analyzing a large sample of job postings between 2010 and 2018 to understand temporal and firm-level heterogeneity in firm-led worker search investments.

Our analyses provide several new facts about the prevalence of this practice and firms' increasing investment in it. First, we show that over 18 percent of all employed workers in the US in January 2020 were hired into their present company by the outbound recruiting effort of their employer, either directly or through a headhunter.[1] Moreover, hiring through outbound recruiting is greatest among higher-income workers, at 20.3 percent, and those with STEM and business degrees, at 22.5 percent. Finally, we find that the percentages we find in our January 2020 survey remain consistent after the COVID-19 pandemic at 16.09 percent overall and at 18.85 percent for those who switched jobs during the pandemic.

Additionally, there is considerable regional, firm, and demographic variation. Over 25 percent of Silicon Valley workers are hired in this manner, but only 15 percent in Sacramento are. While outbound recruiting varies across regions, referrals do not, sticking near 33 percent across all the labor markets in our sample. For workers at firms with fewer than 100 employees, 22 percent got their jobs through outbound recruiting, only about 15 percent at firms with more than 100 workers. Finally, 18.9 percent of men landed their current position by being recruited, against 16 percent of women.

In our analysis of tens-of-millions of job-postings and two-hundred-thousand US firms, we find that firms are developing capabilities to better hunt for talent. They are increasingly hiring recruiters with considerable skill in searching databases such as LinkedIn—nearly tripling the rate at which they employ this type of worker relative to other workers, even general HR staff. Finally, we see that the most significant demand for recruiting talent is among firms that rely on high-skilled technical and managerial labor.

These findings hold several important implications for research on human capital strategy and labor markets (Barney, 1991; Coff, 1997). If we take the firm's perspective, research must better understand the capabilities that lead some firms to more successfully find, vet, and retain talent (Coff and Kryscynski, 2011). Such capabilities

[1]While we do not have a comparable historical reference point for this figure, our data does suggest a decline in the use of formal applications as compared known figures from past research. Namely, the General Social Survey places the incidence of firm-driven search around 4.2 percent in 1991.

are especially important in an environment where competitors are actively recruiting a firm's workers. These capabilities may be especially crucial for small or new firms with little visibility in the labor market (Cardon and Stevens, 2004). Second, our findings also highlight the importance of recruiters as essential intermediaries between firms and workers (e.g., Fernandez-Mateo and Fernandez, 2016; Finlay and Coverdill, 2007). While a voluminous literature exists about the behavior of employee referrers on individual hiring decisions, recruiters both in-house and outsourced are critical for understanding how firm-driven search operates (e.g., Fernandez-Mateo and Fernandez, 2016). A growing literature on the labor market frictions introduced by recruiters is emerging. Our findings provide novel and crucial macro-level empirical evidence of their increasing importance. Third, we also contribute to the literature in search and match in the labor market. In particular, we add to the recent literature on firms' recruiting practices (e.g., Wolthoff, 2018; Baydur, 2017), by proposing a model in which firms choose between inbound and outbound recruiting. Our paper also builds on the recent findings of Faberman et al. (2020), who develop the first survey distinguishing job search behavior of the employed and unemployed. While they model the workers' side and focus on job search behavior, we take a firm-side approach to the question of hiring modes.

Furthermore, since nearly 18 percent of Americans are hired through the outbound recruiting efforts of firms, we must understand the factors that lead individuals to be more effective *passive candidates* (Cappelli, 2019). That is, what leads workers to be easily discovered, understood, and recruited? Those impacted by this shift appear to be workers in remunerative occupations requiring STEM and management skills (Deming and Kahn, 2018). Owing to this shift, researchers must also understand the biases and frictions that hunting for passive candidates introduces, especially the effects on workforce composition and wages. Finally, there is a possibility that this change will lead to more inequality and further entrench segregation across occupations and firms (e.g., Rubineau and Fernandez, 2013; Barbulescu and Bidwell, 2013; Ferguson and Koning, 2018). In particular, we may see a gap between those who are hunted by firms and those who search independently. While these lie outside of this paper's scope, we believe they would be important avenues for future research.

The rest of the manuscript is organized as follows. Section 2 reviews relevant literature; Section 3 develops a theoretical model of the labor market in which firms choose between inbound and outbound recruiting; Section 4 details the empirical methodology used; Section 5 presents its results and Section 6 concludes.

2 Labor market strategy of firms: literature

Management scholars have developed a rich literature on strategic human capital (e.g., Coff, 1997; Lee and Miller, 1999; Williams, Chen and Agarwal, 2017; Belenzon and Schankerman, 2015). This literature has primarily focused on identifying conditions under which human capital can be a source of sustained competitive advantage for firms (Barney, 1991; Coff, 1997; Felin, Zenger and Tomsik, 2009). Many scholars have progressively unpacked the individual, firm, and industry-level mechanisms that allow organizations to create and capture value from their employees. Existing studies have focused on a range of levers that firms have at their disposal to get workers to perform better—e.g., incentives (Bandiera, Barankay and Rasul, 2007), organizational structure (Puranam, 2018), purpose and identity (Burbano, 2016), and managerial practices (Chatterji et al., 2019). An important stream of this research focuses on the strategic implications of hiring practices, including *who*, to hire as well as emerging literature on *how* to hire (Fernandez, Castilla and Moore, 2000; Burks et al., 2015; Pallais and Sands, 2016).

2.1 Why do firms invest in outbound search for labor?

The literature has traditionally argued that two primary factors determine whether a firm gains advantage from its people (Coff and Kryscynski, 2011; Bidwell, 2011). First, companies that rely on firm-specific human capital, consisting of skills and knowledge more useful to them than their competitors, will fare better. The latter is because workers with a higher proportion of firm-specific capital are not as valuable to other companies and are less likely to be poached (Jovanovic, 1979). A second means through which firms derive competitive advantage from human capital is if their cost of getting talent is lower than their competitors (Bidwell, 2011).

In recent years, scholars have observed that firms may be less reliant on firm-specific human capital and increasingly demand workers with transferable skill and knowledge (Cappelli, 2012). Research suggests that one mechanism driving this change is firms' decreasing investments in on-the-job training (Cappelli, 2015). This shift has several consequences for human capital strategy. First, firms may substitute lower-skilled candidates whom they train internally for higher-skilled external ones. Second, given the rising expectations for new hires' skills, firms may seek candidates from narrower pools of workers who *already* do similar jobs at competitor firms. The latter should lead firms to prefer employed, and therefore passive, candidates who may not be actively searching for jobs. Finally, if firms' skill requirements are indeed general, then we should see increased competition among firms for the same pool of workers.

A second factor that may drive the rise of outbound recruiting is the potentially decreasing returns from network hiring. A large body of research suggests that firms rely on their employees' networks to recruit (Granovetter, 1973; Castilla, 2005; Burks et al., 2015). Hiring through network referrals helps solve many information problems for the firm (Pallais and Sands, 2016). However, while the networks of existing employees might help firms distinguish high- and low-quality workers, they constrain the consideration set, limiting the pool of talent and the firm's growth potential (Black and Hasan, 2020). As a result, firm-driven search may be a partial solution to the decreasing returns from network hiring.

Finally, another major transformation in the labor market has been its mass digitization (CITES). While online job-boards have been around for several decades, in recent years, many more people have gotten access to the Internet and created online profiles that showcase their skills and experience (Autor, 2001). Nowadays, over 163 million Americans use LinkedIn, a prominent online career platform that allows workers to post profiles and apply for jobs. A necessary consequence of the mass digitization of the labor market is a reduced cost of finding workers, especially those that are not actively looking for a job. However, much like any other type of technological change, firms who have complementary capabilities in place will benefit most from this information.

These three factors—the increasing demand for transferable and high-level skill, decreasing returns from network hiring *and* the mass availability of information on workers—we hypothesize will lead to more outbound recruiting by firms. Specifically, we should see firms increasingly invest in outbound recruiting capabilities. That is, they will hire more recruiters with skills that allow them to scour vast online databases. Moreover, we should especially see higher levels of outbound recruiting among highly skilled workers in managerial and technical occupations. Lastly, because of digitization, we should anticipate the most substantial proportion of workers affected by outbound recruiting to be ones on career platforms such as LinkedIn.

2.2 Which firms invest in outbound recruiting?

Not all firms will likely engage in outbound recruiting at similar levels. Theoretically, the firms that have the greatest incentive to use this practice are ones for whom the cost of the vacancy remaining open is higher. Consequently, we should expect both firm size and the human capital needs of firms to impact their use of outbound recruiting.

Regarding firm size, research suggests that large high-status firms have an advantage in the labor market. For example, Bidwell et al. (2015) find that, in the early stages of workers' careers, high-status firms can attract higher-quality employees without changing wages. On the other hand, smaller or less established firms may need outbound recruiting to increase brand awareness with candidates that would otherwise not be in their normal applicant pool—a pool drawn from job postings or referrals (Rubineau and Fernandez, 2013; Fernandez and Sosa, 2005). As a consequence, we predict that smaller firms are more likely to recruit via outbound searches.

3 Theoretical Framework

In this section, we use insights from prior literature described above to develop a labor market model that focuses on the firm's decision regarding recruiting modes, given the trade off between firms' skill requirements and the cost of recruiting the right workers. As highlighted in Section 2, the literature has recently documented a decrease in on-the-job training and a rise in demand for high-skill workers. Simultaneously, digitization has changed both the cost of screening incoming candidate applications and finding potential candidates, or *hunting* for talent. We underscore the interaction between these features in a model with two labor markets corresponding to different skill levels.

Our model follows the Diamond-Mortensen-Pissarides (DMP) framework (Diamond, 1982; Mortensen, 1982; Pissarides, 1985) of labor market matching while introducing two innovations. First, the economy is composed of two different skill sectors, and the production function in one of the sectors is skill-specific. Second, firms can choose other hiring mechanisms to fill their vacancies. We employ an approach similar to Baydur (2017), in that we augment the DMP by adding a stage between vacancy posting and wage bargaining, which in our case is the stage corresponding to the firm's choice of hiring mechanism.

3.1 Environment and Assumptions

Consider an economy that is populated by firms and workers. Both agent types are risk-neutral and maximize their expected sum of payoffs. Time is discrete, and the discount factor associated is β. There are two sectors in the economy — low-skill (l) and high-skill (h) — each comprised of identical firms. Each sector has a total labor force of L_i, with $i \in \{l, h\}$. We think of the low-skill sector as comprised of jobs that required less formal training, whereas the high-skill sector includes jobs that require tertiary education (Cappelli, 2015; Bidwell, 2011).

Workers are characterized by a type of skill X_i, with $i \in \{l, h\}$. We assume workers are born with a certain immutable skill and that the labor force of type h is relatively scarcer, without loss of generality. Specifically, the share of high-skill workers in the economy is p, with $p << 1 - p$. At any time period, a worker is either employed or unemployed. An employed worker receives a wage w_i, obtained as a result of Nash bargaining, as illustrated in Section 3.4. We assume that employed workers do not search for a job, but they can be invited to switch to a new firm. An unemployed worker can search for a job; if s/he cannot find one, s/he will receive unemployment benefits z_i. Workers consume everything they earn.

Firms are units of production; at any point in time, the firm is either active or inactive. The firm is born with production technology, and it does not change. The firm must hire workers to produce an output of Y_i according to the sector-specific production function. In the low-skill sector, firms exhibit the production function $Y_l = A_l \alpha_l F(X_i, N_i)$. A is a technology parameter, α_l is a sector-specific skill complementarity parameter, and N_i is the number of workers hired by the firm, which can be both types $i \in \{l, h\}$; that is, a low-skill sector firm need not hire a specific type of worker to deploy in production. Conversely, a high-skill sector firm needs high-skill workers. Therefore, their production function is $Y_h = A_h \alpha_h F(X_h, N_h)$. We will henceforth use output per employee as $y_i = A_i \alpha_i f(x_i)$, where $y_i = Y_i/N_i$ and $x_i = X_i/N_i$.

Active firms face an exogenous probability of closure, leading to job destruction, of δ_i. An inactive firm can start its activity in any period by hiring workers.

In this model, we introduce the possibility of firms choosing two different hiring mechanisms to acquire talent. Specifically, the firm can decide to hire workers by posting a job and waiting for applicants to arrive — as in the traditional DMP framework — or to use its resources to engage in "hunting" for talent; that is, finding candidates and actively inviting them to participate in the selection process. We will call these two hiring mechanisms, inbound and outbound recruiting.

Firms will face costs when engaging in both types of recruiting. First, the firm must incur the fixed cost of opening a vacancy, γ_i, which is common to both inbound and outbound recruiting. Second, if the firm is selective about which talent to attract —such as in the high-skill sector— it must pay a variable cost of reviewing incoming applications, $\rho_i \in [0, 1]$. Lastly, if the firm chooses to do outbound recruiting, it will face the additional cost of searching for candidates, $\sigma_i \in [0, 1]$. The variable cost of outbound recruiting can be thought of as the recruiter's time searching for suitable candidates, both online and offline.

3.2 Matching Technology

Firms start by posting vacancies in sector $i \in \{l, h\}$, V_i, knowing they will receive applications from unemployed workers as a result. Vacancies can be filled according to a random Poisson process; as well, unemployed workers U_i looking for a job can find one according to a Poisson random process. This process is governed by contacts between the two sides of the labor market, whose number is determined by the function $m(U_i, V_i) = m(u_i L_i, v_i L_i)$, where u_i is the unemployment rate and v_i is the vacancy rate. We assume that $m(.)$ is concave, increasing in both its arguments, exhibits constant returns to scale, and $m(U_i, 0) = m(0, V_i) = 0$.

The matching technology described implies that the number of job contacts will be equivalent to the number of job matches; the only mediating factor is time to match. The rate at which a firm can fill a vacancy is, therefore:

$$q(\theta_i) = \frac{m(u_i L_i, v_i L_i)}{v_i L_i} = m\Big(\frac{1}{\theta_i}, 1\Big) \tag{1}$$

where $\theta_i \equiv v_i / u_i$ is labor market tightness —the ratio of vacancies to unemployment— and $q(\theta_i)$ is the Poisson arrival rate of matches for each posted vacancy. The arrival rate of matches per vacancy can be verified as a non-increasing function in theta, $q'(\theta_i) \leq 0$. This means that the higher the labor market tightness, the firms must spend more time screening and increasing time to match. Simultaneously, $\theta_i q(\theta_i)$ is the Poisson arrival rate of matches for each unemployed worker[2].

Note that the matching technology described cannot discriminate between a low-skill or high-skill worker type. Therefore, the arrival rate of $q(\theta_i)$ guarantees a match, not necessarily the right match for high-skill sector firms. As described above, we assume that both skill types X_i with $i \in \{l, h\}$ can perform equally in the low-skill

[2] $\theta_i q(\theta_i) = m(1, \theta_i)$

sector — a high-skill type is deployed in the low-skill sector as if they were a low-skill type. Therefore, low-skill sector firms do not have a worker screening problem; they are bound simply by the Poisson process matching described above.

Conversely, high-skill sector firms can only deploy talent that is high-skill[3]. However, when the high-skill firm posts a vacancy, it cannot know which type of worker it will be matched according to $q(\theta_h)$. As such, it's production function is actually:

$$y_h = p[(\mathbb{1}_{\{x=x_h\}})A_h \alpha_h f(x_h)] \tag{2}$$

Equation (2) shows that the high-skill sector firm, when relying solely on inbound recruiting without screening, will deploy high-skill production with a probability p. Recall that $p << 1-p$, which means that the waiting time through the Poisson arrival rate for matches $q(\theta_i)$ increases in the high-skills sector to more than double.

The matching process for outbound recruiting changes with the intervention of the firm. Instead of facing the same Poisson random process that governs the rate at which unemployed workers are matched with a vacancy, the firm can expand the pool of potential candidates by tapping into employed workers. To do so, the firm must pay $\sigma_i \in [0,1]$ to reach an already employed candidate to fill its vacancy. There is a direct relationship between the resources committed to outbound recruiting and the share of employed workers they can consider, and consequently, the rate of matching. As a result of the process of outbound recruiting, the Poisson process for matching is now:

$$q(\tilde{\theta}) = q\left(\theta \times \frac{u_i}{u_i + (1-\sigma_i)(1-u_i)}\right) = q\left(\frac{v_i}{u_i + (1-\sigma_i)(1-u_i)}\right) \tag{3}$$

where $\tilde{\theta}$ is the modified labor market tightness when the firm uses outbound recruiting.

[3]Here, we assume the most extreme case of low-skill workers not being able to work at the high-skill sector. This restriction can be relaxed into a probabilistic model of talent deployment. We believe our approach makes the model more tractable, without compromising on its intuition and conclusions.

If the cost of outbound recruiting is very high, $\sigma_i \rightarrow 1$, then $q(\tilde{\theta}) \rightarrow q(\theta)$. As costs of outbound recruiting decrease, the firm can tap into a larger pool of employed workers $(1 - u_i)$.

3.3 Agents' Optimization Problems

Worker's optimization. Let V_i^e and V_i^u denote the expected discounted lifetime net income of being employed and unemployed in each sector $i \in \{l, h\}$, respectively. The value of being employed corresponds to the wage earned while employed, netting the likelihood of becoming unemployed.

$$\beta V_i^e = w_i - \delta_i (V_i^e - V_i^u) \quad \forall i \in \{l, h\} \tag{4}$$

The value of being unemployed corresponds to the unemployment benefits added to the likelihood of becoming employed.

$$\beta V_i^u = z_i + \theta_i q(\theta_i)(V_i^e - V_i^u) \quad \forall i \in \{l, h\} \tag{5}$$

Low-skill sector firm's optimization. The low-skill sector firm's production function is, as defined above, $y_l = A_l \alpha_l f(x_i)$. We assume the firm has access to a Cobb-Douglas production technology, such that $y_l = A_l \alpha_l x_i^{\epsilon}$. Additionally, we also assume that high-skill and low-skill workers perform equally in the low-skill firm. As a consequence, the low-skill sector firm will always choose inbound recruiting. Since there is no added value in production from hiring a high-skill worker specifically, incurring in the cost of finding high-skill workers does not make sense for low-skill firms. Moreover, the speed of finding a match only increases as a result of outbound recruiting if the firm is searching for a particular skill. Since this is not the case for them, low-skill firms do better by allowing the matching process to unfold as in the DMP framework.

We define J_l as the value of hiring workers — the value of a "job" to the firm— and V_l as the value of posting a vacancy. The value functions for the low-skill sector firm are as follows:

$$\beta J_l = A_l \alpha_l x_i^{\epsilon} - w_l - \delta_l (J_l - V_l) \quad \forall i \in \{l, h\} \tag{6}$$

The intertemporal value of a job depends on production ($A_l \alpha_l x_i^{\epsilon}$) net of the cost of filling the job (w_l) and the likelihood of job destruction ($\delta_l (J_l - V_l)$).

$$\beta V_l = -\gamma_l + q(\theta_l)(J_l - V_l) \tag{7}$$

The intertemporal value of a vacancy depends on the cost of keeping a vacancy open γ_l, net of the rate of matching, $q(\theta_l)(J_l - V_l)$.

High-skill sector firm's optimization. Let J_h^k and V_h^k denote the value of filling and posting a vacancy, respectively, in either of two hiring choices: $k \in \{I, O\}$, where I stands for inbound recruiting and O stands for outbound recruiting. The cost of recruitment for firms in the high-skill sector will vary according to the hiring mechanism. In the case of inbound recruiting, since the firm can only produce with high-skill workers, the firm's costs consist of keeping a vacancy open (γ_h) and the cost of reviewing each application (ρ_h) in order to screen for high-skill. In the case of outbound recruiting, the firm will face the additional cost of finding candidates rather than waiting for applications to come in (σ_h).

We start by defining the intertemporal value functions for the high-skill sector when using inbound recruiting. The structure is similar to that in Equations (6) and (7), with the difference that high-skill firms face the screening cost ρ_h, since only matches with high-skill workers will allow them to fill their job.

$$\beta J_h^I = A_h \alpha_h x_h^{\epsilon} - w_h - \rho_h q(\theta_h) - \delta_h (J_h^I - V_h^I) \tag{8}$$

$$\beta V_h^I = -\gamma_h + pq(\theta_h)(J_h^I - V_h^I) \tag{9}$$

Note that, in the high-skill sector, firms fill their vacancy at a lower rate than in the low-skill sector $pq(\theta_h) < q(\theta_l)$ due to their skill-specific search.

If the high-skill firm engages in outbound recruiting, their intertemporal value functions are:

$$\beta J_h^O = A_h \alpha_h x_h^{\epsilon} - w_h - \sigma_h q(\tilde{\theta_h}) - \delta_h (J_h^O - V_h^O) \tag{10}$$

$$\beta V_h^O = -\gamma_h + \tilde{\theta}_h q(\tilde{\theta_h})(J_h^O - V_h^O) \tag{11}$$

3.4 Equilibrium Characterization

Low-skill sector equilibrium. Low-skill sector firms behave as in the traditional DMP framework; therefore, equilibrium unfolds in the same way[4]. In steady-state and because of free entry, firms post vacancies until $V_l \equiv 0$; this implies that:

$$q(\theta_l) = \frac{(\beta + \delta_l)\gamma_l}{A_l \alpha_l x_i - w_l} \quad \forall i \in \{l, h\} \tag{12}$$

Equation (12) represents the downward sloping labor demand curve in the (θ_l, w_l) space. As for the labor supply, at each period, total surplus is subject to Nash-bargaining between firms and workers. Thereby, wage in each sector i is determined

[4]See Appendix A for a full derivation of the equilibrium outcomes.

by the following optimization problem:

$$\max_{\{w_i\}} \quad (V_i^e - V_i^u)^{\mu}(J_i - V_i)^{1-\mu} \quad \forall i \in \{l, h\} \tag{13}$$

where μ is the weight attributed to workers' surplus. The derivation of first-order conditions can be found in Appendix A. In equilibrium, the low-skill sector labor supply is characterized by:

$$w_l = (1-\mu)z_l + \mu(A_l \alpha_l x_i^{\epsilon} + \gamma_l \theta_l) \tag{14}$$

Equation (14) defines a positive relationship between wages and labor market tightness in the space (θ_l, w_l).

In equilibrium, labor demand must equal labor supply. Equating Equations (12) and (14) yields the following equilibrium condition[5] for the low-skill sector:

$$(1-\mu)(A_l \alpha_l x_i - z_l) = \frac{\gamma_l}{q(\theta_l^*)}[\delta_l + \beta + \mu \theta_l^* q(\theta_l^*)] \tag{15}$$

The unique θ_l^* is then plugged into Equation (14) to derive the unique w_l^*.

Having established the optimal wage and labor market tightness, we now present the unemployment determination equation. The unemployment rate is determined by the difference between two flows — the flow of workers into unemployment, $\delta_l(1-u_l)L_l$, and the flow of unemployed workers into new jobs, $\theta_l q(\theta_l) u_l L_l$.

$$\dot{u}_l = \delta_l(1-u_l) - \theta_l q(\theta_l) u_l \tag{16}$$

Note that, in steady-state, inflows must equal outflows into unemployment, $\dot{u}_l = 0$. Therefore, unemployment is determined by the following equation, known as the

[5] Derivations can be found in Appendix A.

Beveridge curve:

$$u_l^* = \frac{\delta_l}{\delta_l + \theta_l q(\theta_l)} \tag{17}$$

Proposition 1 *The low-skill labor market equilibrium is characterized by the following equations:*

1. *Free-entry condition/labor demand:*

$$q(\theta_l) = \frac{(\beta + \delta_l)\gamma_l}{A_l \alpha_l x_i - w_l}$$

2. *Labor supply:*

$$w_l = (1 - \mu) z_l + \mu (A_l \alpha_l x_i \epsilon + \gamma_l \theta_l)$$

3. *Beveridge curve:*

$$u_l^* = \frac{\delta_l}{\delta_l + \theta_l q(\theta_l)}$$

Proof. See Appendix A.

High-skill sector equilibrium. High-skill sector firms face a different matching technology, as well as different costs of hiring. Similarly to the low-skill sector, in steady-state firms will post vacancies until $V_h^k \equiv 0$ with $k \in \{I, O\}$, which results in the following inbound and outbound labor demand functions:

$$(\beta + \delta_h)\gamma_h = pq(\theta_h)[A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h)] \tag{18}$$

$$(\beta + \delta_h)\gamma_h = q(\tilde{\theta_h})[A_h \alpha_h x_h^\epsilon - w_h - \sigma_h q(\tilde{\theta_h})] \tag{19}$$

Both curves for the inbound and outbound recruiting choices available to high-skill sector firms highlight more inelastic labor demand curves. The presence of both *screening* and *hunting* costs create a buffer between the market conditions and firm's labor demand.

Similarly to the low-skill sector, wages are Nash bargained at each period, with maximization problems analogous to Equation (13) for the high-skill sector. Labor supply for each type of recruitment —inbound and outbound— is characterized by the following equations[6]:

$$w_h^I = (1-\mu)z_h + \mu\left(A_h\alpha_h x_h^\epsilon - \rho_h q(\theta_h) - \frac{\gamma_h\theta_h}{p}\right) \tag{20}$$

$$w_h^O = (1-\mu)z_h + \mu(A_h\alpha_h x_h^\epsilon - \sigma_h q(\tilde{\theta_h}) - \gamma_h\tilde{\theta_h}) \tag{21}$$

The intersections of labor demand and supply with each recruitment mechanism lead to the following wages in equilibrium:

$$(1-\mu)(A_h\alpha_h x_h^\epsilon - z_h - \rho_h q(\theta_h^*)) = \frac{\gamma_h}{pq(\theta_h^*)}[\beta + \delta_h + \frac{\mu}{p}\theta_h^* q(\theta_h^*)] \tag{22}$$

$$(1-\mu)(A_h\alpha_h x_h^\epsilon - z_h - \sigma_h q(\tilde{\theta_h^*})) = \frac{\gamma_h}{q(\tilde{\theta_h^*})}[\beta + \delta_h + \mu\tilde{\theta_h^*} q(\tilde{\theta_h^*})] \tag{23}$$

Finally, we solve for equilibrium unemployment. As in the low-skill sector, flows into labor must equal flows out of labor in the high-skill sector, both under inbound or outbound recruiting. In steady-state, $\dot{u_h} = 0$ and therefore we have:

$$u_{h,I}^* = \frac{\delta_h}{\delta_h + p\theta_h q(\theta_h)} \tag{24}$$

$$u_{h,O}^* = \frac{\delta_h}{\delta_h + \tilde{\theta_h} q(\tilde{\theta_h})} \tag{25}$$

Note that, as the cost of outbound recruiting σ_h decreases, the equilibrium unemployment rate under outbound recruiting $u_{h,O}^*$ also decreases relative to the inbound recruiting counterpart $u_{h,I}^*$, suggesting there may be a welfare improving mechanism when some firms switch to outbound recruiting.

[6] Derivations can be found in Appendix A.

Proposition 2 *The high-skill labor market equilibrium is characterized by the following equations:*

1. *Free-entry condition/labor demand with inbound recruiting:*

$$(\beta + \delta_h)\gamma_h = pq(\theta_h)[A_h \alpha_h x_h^{\epsilon} - w_h - \rho_h q(\theta_h)]$$

Free-entry condition/labor demand with outbound recruiting:

$$(\beta + \delta_h)\gamma_h = q(\tilde{\theta_h})[A_h \alpha_h x_h^{\epsilon} - w_h - \sigma_h q(\tilde{\theta_h})]$$

2. *Labor supply:*

$$w_h^I = (1-\mu)z_h + \mu\left(A_h \alpha_h x_h^{\epsilon} - \rho_h q(\theta_h) - \frac{\gamma_h \theta_h}{p}\right)$$

$$w_h^O = (1-\mu)z_h + \mu(A_h \alpha_h x_h^{\epsilon} - \sigma_h q(\tilde{\theta_h}) - \gamma_h \tilde{\theta_h})$$

3. *Beveridge curve:*

$$u_{h,I}^* = \frac{\delta_h}{\delta_h + p\theta_h q(\theta_h)}$$

$$u_{h,O}^* = \frac{\delta_h}{\delta_h + \tilde{\theta_h} q(\tilde{\theta_h})}$$

Proof. See Appendix A.

3.5 Comparative Statics and Predictions

Using the labor market equilibrium conditions derived in Section 3.4, we discuss comparative statics of the model to establish testable predictions that we use in our empirical analysis. We will focus our comparative statics analysis on the high-skill sector, since that is the sector in which the share of workers p is binding.

In steady-state equilibrium, under free entry, firms make zero profits π_h^k both with inbound and outbound recruiting:

$$\pi_h^I = A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h) - \frac{(\beta + \delta_h)\gamma_h}{pq(\theta_h)} = 0 \tag{26}$$

$$\pi_h^O = A_h \alpha_h x_h^\epsilon - w_h - \sigma_h q(\tilde{\theta_h}) - \frac{(\beta + \delta_h)\gamma_h}{q(\tilde{\theta_h})} = 0 \tag{27}$$

A few patterns emerge[7] regardless of whether the firm chooses to recruit via inbound or outbound mechanisms. When there is an increase in the cost of an open vacancy γ_h, the likelihood of job destruction δ_h, or the discount factor β, both profits under inbound and outbound recruiting decrease. Simultaneously, this translates into value of vacancies going down. To maintain equilibrium, this implies that firms will post less vacancies for each unemployed worker in the high-skill sector. However, these shifts will not affect firm's decision to use inbound or outbound recruiting.

Conversely, other parameters govern the balance in profitability between engaging in inbound or outbound recruiting.

Proposition 3 *The more binding the skill requirement for the firm (lower share of high-skill workers, p), the more likely it will engage in outbound recruiting.*

Proof. See Appendix A.

First, we highlight the importance of skill requirements. Since high-skill sector firms require high-skill workers specifically, the share of high-skill workers in the economy p is crucial to determine the rate at which high-skills sector firms can be matched to the appropriate worker. As such, a change in p shifts how profitable it is to switch to outbound recruiting.

[7] Derivations for comparative statics referred to in this Section can be found in Appendix A.

Proposition 4 *The higher the the cost of screening applicants (ρ_h), the more likely a firm with high-skill requirements is to choose outbound recruiting.*

Proof. See Appendix A.

Second, we focus on the cost of screening applications ρ_h for firms who recruit inbound. For some firms, the cost of screening may be higher because they are looking for a very specific profile, or because the adverse selection inherent in waiting for an unemployed person to apply is especially costly for them (e.g., a high-tech firm whose sector is constantly changing and stepping out of employment may imply an erosion of skills). In such cases, outbound recruiting becomes comparatively a better option.

Proposition 5 *The lower the cost of finding skilled workers (σ_h), the more likely a firm with high-skill requirements is to choose outbound recruiting.*

Proof. See Appendix A.

Lastly, we note that the actual cost of outbound recruiting (σ_h) determines how profitably it is for firms to switch hiring modes. If the cost of finding skilled workers decreases (e.g., there is a shock availability of high-skill workers' profiles online), J_h^O increases. Thus, to re-establish equilibrium, wages will adjust upward.

In summary, we predict that firms will engage more in outbound recruiting when (a) they face more binding skill requirements; (b) they face higher costs of screening applications; or (c) they have access to a lower cost of finding workers outside their applicant pool (lower cost of "hunting") and, as a result, high-skill workers will be paid higher wages.

Since we find that firms that face more binding skill requirements are more likely to choose to hire talent through outbound recruiting, we expect a higher prevalence of outbound recruiting for high-skill workers. Moreover, if a higher cost of screening applicants increases the optimally of outbound recruiting, we should observe that workers in densely populated areas, or located in regions with high concentration of high-skill workers, exhibit a higher likelihood of being "hunted". Lastly, based on our predictions regarding the cost of outbound recruiting, we expect workers employed in sectors of the economy

In the next two sections, we present two pieces of data —one derived from a worker-level survey on modes of hiring, another representing firm-level demand for recruiting skills— that together present suggestive evidence of the mechanisms predicted in this section.

4 Empirical Methodology

Our empirical approach in this article is descriptive and consists of analyzing two primary data sets, one of which is new for this article. We use our theoretical framework to guide our predictions of data patterns.

First, we conducted a nationally representative survey of American workers to understand the prevalence of outbound recruiting firms in the US labor market. These data allow us to provide national-level facts about the prevalence of this practice and insights into how it varies by workers and workplace characteristics. Second, we analyze a large sample of American firms and their job postings over the past decade. We focus on understanding firms' characteristics that best predict the degree to which they invest in capabilities that enable firm-driven labor market search– namely, recruiters who find, vet, and hire passive candidates. We describe these data below.

4.1 Survey of American Workers

To conduct our survey of American workers, we contracted with CivicScience, a major polling company based in the United States. CivicScience has an on-demand sample of over 85 million Americans over 18 years old. After specifying a sample size that would provide us a margin of error of ±1% survey responses from sub-samples are then re-weighted to reflect the population figures in the Current Population Survey (CPS) conducted by the US Census Bureau.[8]

For our study, we surveyed a nationally representative sample of 18 to 65-year-old men and women, broadly representing the United States' working-age population. Our total sample consists of 13,680 responses to a question to understand how an employed American was initially hired into their present company. Specifically, we asked: 'Which of the following options best describes how you first got hired by your present employer?' Employed respondents had five options from which they could choose the one that *best* represented their situation.

- I found a job posting and applied for the role
- I was referred to this employer by an existing employee
- A recruiter from this employer reached out to me and invited me to apply
- A headhunting firm reached out to me and invited me to apply
- I reached out to a headhunting firm

In addition to responses to our question of interest, the CivicScience platform provided us with the ability to cross-tabulate our question's results with other questions asked of the sample. For our study, these additional questions broadly fall into five categories: (1) education, occupation, and income; (2) workers' technology use; (3) firm size; (4) geography; (5) demographic characteristics. For our analysis, we create one dependent variable—the proportion of respondents who state that the best

[8] A a complete description of the firm's methodology can be found here: https://civicscience.com/white-paper-assessing-our-methodology/.

description of how they were hired into their present firm was (a)'A recruiter from this employer reached out to me and invited me to apply' or (b)'A headhunting firm reached out to me and invited me to apply.' We call this variable *Outbound recruiting*. The cross-tabulations are reweighted using CPS weights to match the observable demographics of our sample to that of the American population (e.g., Deville, Särndal and Sautory, 1993; Kolenikov, 2014). For regional estimates, estimates are reweighted to reflect MSA-specific weights. Such reweighting techniques are commonly used in the strategy literature by scholars conducting sample surveys (e.g., Bennett and Chatterji, 2017; Starr, Prescott and Bishara, 2019) .

4.2 Hiring by US-based firms

To shed further insight into the firm-level investments in outbound recruiting, we complement our worker survey with data covering the near universe of online job postings from Burning Glass Technologies (BGT). Our data include tens-of-millions U.S. job postings from 2010 through 2018 and are described in more detail by Deming and Kahn (2018). The raw job descriptions are cleaned and structured by BGT. The data provider assigns each job a SOC title; with these, we identify all postings classified as "Human Resources" roles. We aggregate this data into firm-year observations for the firm-level analysis, with 200,279 total firms in our sample.

Our analysis asks three broad questions of these data: (1) how has the demand for recruiters changed over time; (2) what types of skills do firms want in recruiters; and (3) what is the relationship between the kinds of skills firms require and level of their demand for recruiters? For the latter, we estimate firm-year regressions evaluating the probability that a firm posts a recruiter job as a function of the share of non-recruiting postings that require different types of skills, including cognitive, social, character, managerial, as well as technical. In these models, we include a variety of controls, including controls for the total number of non-HR postings and fixed-effects for year, industry, MSA, and firm.

5 Results

5.1 Survey of American Workers

We begin our analysis by estimating the overall prevalence of outbound recruiting in the United States labor market. We present these results in Table 1. This table provides insight into how widespread this practice is relative to mechanisms through which firms find and recruit workers.[9] Overall, we find that 17.8% of workers are hired through a firm-driven search process—i.e., a recruiter at the employer (12.5%) or contracted headhunter (5.3%) reached out to them and asking them to apply. Our survey also provides insight into the prevalence of other modes of hiring as well. Nearly 43.9% of workers in the full US sample found and applied for the role themselves, and existing employees referred to another 34.6% of workers.

To ensure that our results are robust to contextual factors affecting the entire economy, such as the COVID-19 pandemic, we conducted a new survey in September, 2020. With this sample, we find that our results are quite similar. Overall, we find with a nationally representative sample of 1,175 workers that overall 16.09% of workers are hired through firm-driven search, and among those that switched jobs after the beginning of the pandemic, that number is 18.85%.

[Table 1 about here.]

[9]The margin of error for these estimates is ±1%.

While these broad statistics suggest that firm-driven search is quite prevalent in the United States, these baseline statistics mask significant heterogeneity. Results vary considerably depending on firm and worker characteristics as well as geographic region.

5.1.1 Education, occupation and income

Research shows that educational attainment and labor market outcomes are positively related—educated, and higher-skilled workers are in higher demand. Moreover, our model suggests that higher skill requirements will induce a higher prevalence of firms' outbound recruiting behavior. As a result, we should expect a link between attainment and how workers are hired, i.e., through inbound or outbound channels, especially if there is intense competition between firms for certain types of high-skilled, knowledge-intensive talent. As competition for such labor increases, firms should invest more in finding capable workers and be more likely to recruit them directly.

Table 2 provides a cross-tabulation of educational attainment and the hiring mode. We see that the prevalence of outbound recruiting increases with education level. The largest difference is between those without college degrees (16.0%) and those with graduate or professional degrees (20.8%), a statistically significant difference of 4.8% ($z = 3.17$ and $p \leq .01$). However, a meaningful and statistically significant difference exists between those with some college, an associate's or a bachelor's degree, and those with graduate degrees with both differences being significant at $p \leq .01$. These results suggest that highly educated workers, i.e., those with graduate and professional degrees, are more likely to be hired through firm-driven recruitment processes.

It is interesting to note how outbound recruiting trades-off with the two other significant hiring modes across education levels. As the education level increases, the rate of outbound recruiting increases, but the rate of referrals also decrease—from

42.64% for those with high school degrees or less to 30.08% for those with graduate or professional degrees. A complementary change can also be seen in the increase in outbound recruiting as education levels increase.

[Table 2 about here.]

Corroborating this evidence, in Table 3, we find that the higher end of the income distribution in the labor market is where outbound recruiting is concentrated. We see that the probability of this practice for those earning less than $50,000 is 14.6%. In contrast, the proportion is considerably higher for those making over a hundred thousand dollars at 20.3%—a difference of 5.7%. This difference is statistically significant at conventional levels ($z = 5.54$, $p \leq .01$).

[Table 3 about here.]

Some of the variation observed may be driven by occupation-level heterogeneity. While our data do not have a specific measure of a surveyed person's occupation, we know the broad specialization for their undergraduate major for college-educated workers. Table 4 suggests that there may be considerable differences in the prevalence of this practice based on whether individuals have specialized in STEM (20.8%), Health & Medicine (19.4%), and business (20.1%) versus social science (16.4%) or education (15.2%). Comparing the first three categories (20.27%) to the latter two (16.3%) we find a statistically significant difference of 3.9% ($z = 3.515$, $p \leq .01$).

[Table 4 about here.]

5.1.2 Use of LinkedIn

Our model predicts that, if the costs of outbound recruiting decrease, high-skill sector firms will use it more. One of the most significant enabling factors for firms aiming to search for candidates is the growth of online networks and job search platforms. Perhaps the most significant of these has been LinkedIn, where individuals can create online career profiles and share information about their education, experience, skill, and build a database of the connections to other workers. In Table 5 we see that LinkedIn users are significantly more likely to have been actively recruited by a firm (21.1%) versus non-users (15.5%), a difference of 5.6% that is statistically significant ($z = 3.88$, $p \leq .01$). What does this shift to outbound recruiting substitute for? The largest difference in behavior appears in the use of direct applications to jobs with LinkedIn users at 40.15% and non-Users at 44.01% ($z = 2.06$, $p \leq .05$).

[Table 5 about here.]

Though descriptive, this finding supports our paper's central premise that technology has enabled firms to engage in active search for candidates. Together, our results suggest that not only has technology-enabled this type of firm behavior, but it has impacted workers differently. Specifically, high-skilled workers in high-income jobs are more likely to experience firms reaching out to them with new job opportunities.

5.1.3 Firm characteristics

Our worker-level survey allows us to gain considerable insight into *who* are the likely targets of firm-driven search. However, a perhaps equally important question is: which firms are most likely to leverage this hiring mechanism? According to our model's predictions, we expect firms with a higher screening cost to engage more in outbound recruiting. These can be small, less established firms. In Table 6, we see workers hired through outbound recruiting are more likely to work in small rather than large firms. Table 6 shows that workers in small firms (with fewer than 100 employees) have a 22.1% likelihood of being recruited through this method versus 14.4% for those in large firms (more than 5000+ employees), this difference of 7.6% is statistically significant ($z = 3.01$, $p \leq .01$).

[Table 6 about here.]

While not statistically different, small and medium-sized firms also appear to rely more heavily on recruiting workers through referrals than large firms, with referral percentages at 39.79% and 39.13% versus 35.81%.

The increased use of outbound recruiting by small firms suggests a possible strategy to find and compete for high-quality workers in tight labor markets.

5.1.4 Demographic characteristics

Next, we examine whether the prevalence of outbound recruiting varies based on workers' demographic characteristics, namely their age, race or ethnicity, gender, and geographic location. In Table 7, we find no difference between different age cohorts and the extent to which they are hired in this way. The rate of firm-driven search appears comparable across age cohorts. Though the percentage difference between 18-24 years old and 25-29, as well as 35-44 years, is most substantial, these differences are not statistically significant ($p > .1$).

However, there appears to be a correlation between age and referral hiring. The rate of referrals for 18-24 years old is 30.96% whereas the rate is 37.3% for aged between 55-64, a difference of 6.44% ($z = 2.968$, $p \leq .01$). Several mechanisms, both supply and demand-driven, could lead to this outcome. On the worker side, individuals' professional networks may grow as they gain experience, and thus, these networks may be more consequential for hiring as workers age. From the demand side, workers with experience may have to use networks to communicate their more complex skills to employers. These factors may lead older workers to use network hiring more.

[Table 7 about here.]

There is a large body of research examining the role of gender in the labor market. Much of this research finds that women are disadvantaged in job search and career outcomes as well. Our findings on gender, presented in Table 8, finds evidence of a gender difference of 2.9% in the likelihood of firm-driven search—women at 16.0% and men at 18.9% ($z = 4.35$, $p \leq .01$). What is also notable is that women are less likely to be referred than men, 32.55% versus 35.98%, a difference that is also significant ($z = 4.11$, $p \leq .01$). This pattern suggests that women are significantly more likely to rely on applying to jobs than men. The need to rely on this formal channel may profoundly affect the ability to find work in certain types of firms or be hired into certain jobs that may be more remunerative.

[Table 8 about here.]

Finally, research also suggests differences across racial and ethnic groups in labor market outcomes. Namely, research has suggested the minority applicants— primarily Hispanic and African American—are disadvantaged in the labor market. Table 9 presents our results, examining the relationship between race/ethnicity and hiring mechanism. While Hispanic and Latino workers have a slightly lower likelihood of being recruited through outbound recruiting relative to Whites (16.6% vs. 17.2%), this difference is not statistically significant. However, we find some evidence that African American applicants are more likely to be recruited in this manner (19.6%), though this difference is only significant at the p $\leq$ .1 level. Although we cannot say for sure, this higher rate for African Americans may be due to firms using a proactive approach to recruit a more diverse workforce.

We also find some evidence of an increased likelihood of outbound recruiting for Asian workers (19.6%), but this difference is suggestive, though not statistically significant. Given our data, we are unable to determine whether there are considerable racial differences in this mechanism. One possibility is that firms use this mode to compensate for biases in other sources of recruiting.

However, these findings are interesting because African Americans have considerably lower rates of referrals than Whites and Hispanic workers (30.57% vs. 35.68% and 35.96%). These differences are statistically significant at p $\leq$ .01 and p $\leq$ .01, respectively. These statistics correspond to prior work that suggests a lower likelihood of references among African American workers (e.g., Smith, 2005).

[Table 9 about here.]

5.1.5 Geography

Finally, to examine whether the use of this practice varies by geographic region, we over-sampled workers in five US MSAs (Rochester, Denver, Sacramento, Portland, and Miami). We selected these regions randomly within 2019 unemployment-rate quintiles. We over-sampled three major technology hubs in the United States (San Jose, San Francisco, and New York City). We present these results in table 10. As can be seen in the table, there are differences in outbound recruiting by region. Perhaps the greatest outlier in San Jose, California, the home of Silicon Valley, with the highest concentration of technology workers and firms globally. In San Jose, 25.4% of workers are hired through outbound recruiting. In contrast, only 14.5% of workers in Rochester are. Comparing these two extremes represents a difference of 10.9% which is statistically different ($z = 3.7$, $p \leq .01$). Additional analysis suggests that this may be more due to the workforce's composition than unemployment rates.

[Table 10 about here.]

What is also notable about the pattern of results in Table 10 is the overall stability of referrals, at approximately 33 to 34%, with little variability across regions. On the other hand, it appears that firm-driven search substitutes for worker-driven search. As the percentage of firm-driven search increases, we see a corresponding and significant decrease in individuals responding that they 'found a job posting and applied for the role.' For instance, this percentage is 46.5 in Rochester, but 37.4% in San Jose. However, both MSAs have a comparable level of referrals at 34.5% and 33.2%, respectively.

5.2 Hiring by US-Based Firms

We now turn to our analysis of firm-level investment in outbound recruiting using data on job postings from Burning Glass Technologies (BGT). The different modes of recruitment, *inbound* versus *outbound*, require different capabilities from firms. Suppose more workers are actively searched for by firms today than in the past. In that case, we anticipate three trends in this data: (1) there will be an increasing demand for recruiters, (2) skill requirements will be increasingly digital, and (3) firms that depend on high-skilled workers will hire more of these recruiters, in line with our model's predictions.

5.2.1 Increasing demand for recruiters

To answer the first question, we analyze the BGT data on monthly online job postings from 2010 through 2018 in the United States, focusing on the relative importance of recruiting skills and jobs relative to the HR category as a whole. We search the job title for the word "recruiter" and tag these positions as recruiting roles within these HR postings. Figure 1 shows the percentage of job postings by month that are classified as HR roles (top) and that are recruiting roles (bottom). We scale the points by the number of job postings in the month. For general HR jobs, we see little in the way of an upward or downward trend, with a little more than 1 in 100 postings overall for HR professionals. However, for recruiting roles, we see a steady upward trend from about 0.2% to under 0.5%. There appears to be an increasing demand for recruiters corresponding to our expectations.[10]

[Figure 1 about here.]

In figure 2, we adjust our graphs to account for changes in the composition of data providers that make up the BGT data. We plot the percentage of recruiting jobs relative to the number of HR jobs to account for data heterogeneity across years as per prior literature (e.g., Deming and Kahn, 2018). As in Figure 1, we again see a steady upward climb. For example, in 2010, roughly 20% of HR postings were recruiting roles. By 2018 this share was just over 30%. Consistent with our survey results, it appears U.S. firms are increasingly relying on recruiters to find talent proactively.

[Figure 2 about here.]

5.2.2 Recruiter skills

We examine whether this shift is due to a mere change in job titles or an actual change in the skills required by firms in the recruiting role. If differences were to come from job titles, this pattern could indicate a broader trend of the changing composition of

[10] That said, Figure 1 also shows big jumps in the data series in 2014 and 207, with the percentage of both HR and recruiting jobs dropping and then bouncing back. This “jitter” is most likely an artifact of the data collection process. BGT’s underlying data sources vary over time, and when certain providers come onto the BGT platform or leave, there can be jumps in the relative composition of postings. Prior work has addressed this issue by looking at trends within a job category since shifts in the composition of HR jobs are less likely to occur than changes in the relative percentage of HR versus engineering roles.

labor demand. To explore this possibility, we use data from BGT on each job's listed skill requirements. BGT tags each job description with a vector of skills listed on the resume and produces structured skill requirements for a given job posting, ranging from "Python" to "Negotiations." The top left panel in Figure 3 plots the percentage of HR jobs that list "recruiting" as a skill.[11] Again, we see an upward trend from just over 25% to just over 40%. These changes suggest an increase in the demand for specific-skills related to the recruiting function rather than general HR skill.

[Figure 3 about here.]

To further understand the shift towards recruiting, the remaining three panels in Figure 3 show the percentage of HR jobs that require social media skills ("SOCIAL MEDIA", "LINKEDIN", "FACEBOOK", or "GITHUB"), knowledge of applicant tracking systems ("TALEO", "BRASSRING", "ICIMS", "JOBVITE", or "ATS"), and onboarding ("ONBOARDING"). We find strong upwards trends for all three. Firms increasingly show a preference for hiring recruiters who can spot talent using social media, who can log those workers into applicant tracking systems, and then onboard those hires into the company. Further, in Figure 4 we show that the "SALES" and "COMMUNICATION" skills show no strong trends upwards within HR postings, nor does the total number of skills required in an HR job, which has hovered near nine since 2010. These findings complement the evidence we present in the previous section, painting a consistent picture of rising firm-driven search.

[Figure 4 about here.]

[11]Specifically, we classify any of BGT's skills that have the phrases "RECRUITING", "RECRUITMENT", "CANDIDATE SOURCING", or "TALENT" as recruiting skills.

5.2.3 Employee skills and the demand for recruiters

Which firms are increasing their demand for recruiters? To answer this question, we aggregate our BGT data into firm-year observations. Just over 60% of postings list a firm name in the BGT data. We find these firm names through a cleaning and fuzzy matching process to generate unique firm identifiers. In each year, we then calculate the logged-plus-one count for the number of recruiter postings along with an indicator for whether a firm posted an opening for a recruiter. For all non-recruiting postings during the year, we calculate the firm's skill mix. We build on Deming and Kahn (2018) and create a count for each type of skill in a firms' postings. Skills are bucketed into the following ten categories: Cognitive, Social, Character[12], Writing, Customer Service, Project Management, People Management, Financial, Computer, and Software. For example, if a firm posts ten engineering jobs, five of which require the skill "Python," one that requires "SQL," and one that requires "Python" and "SQL" and we say the firm has a count of 7 software jobs. We then log-plus-one these counts.

Using these data, we run panel regressions where the dependent variable is how many or whether the firm posts a recruiter opening. The independent variables are the skill mix counts. Since our data spans thousands of firms and multiple years, we can include firm and year fixed effects to account for time-invariant firm heterogeneity and time-varying macro-trends. When the dependent variable is log-counts, our model is log-log so that estimates can be interpreted as elasticities. When our dependent variable is a binary indicator, estimates represent the percentage point increase in recruiter demand for a 1% increase in the skill.

Table 11 displays the estimates from our regressions. Model 1 only includes fixed effects for the year and the number of non-HR postings by the firm. These controls

[12]For example, "ENERGETIC" or "ORGANIZED."

allow us to interpret the coefficients in Table 11 as the impact of skill mix for firms holding their level of labor demand constant. We also cluster our standard errors at the Firm, MSA, and Industry levels. Consistent with our survey results that those with business and STEM skills are more likely to be recruited, we find that firms that demand project management skills, computer skills, and software skills are most likely to post for recruiters. For each skill, a 10% increase in the number of postings featuring the skill results in roughly 1% more recruiter postings. We also find that personal character positively affects, though the coefficient is approximately half as large.

None of the other coefficients are consistently significant across our models. Model 2 adds industry fixed effects using three-digit NAICS codes, and Model 3 further adds MSA fixed effects. The effect size on project management and software/computer skills remain mostly unchanged. It does not appear that differences in recruiting intensity can be explained by simple industry differences or differences in the local labor market conditions. Model 4 includes firm-level fixed effects to account for time-invariant observed and unobserved firm differences. The association between technological and management skill and hiring for outbound recruiting holds, though magnitudes for the computer/software skills drop by roughly one-third. Finally, in Model 5, we replace our logged dependent variable with a dummy for whether the firm posts for a recruiter or not to assess robustness. We find similar patterns to Columns 1-4; firms with greater demand for managerial and technical talent are more likely to have a recruiter. In this model, a 1% increase in these skills leads a firm to look for a recruiter 2-4 percentage points more often. In our regression sample, 13.9% of firm-years include posting for a recruiter. This suggests that a firm which "digitizes" its workforce from 10% software-focused to 50% would roughly double its likelihood of posting for a recruiter.

Overall, our findings suggest that there has been an increase in demand for recruiting work. This work increasingly involves online tools like social media and applicant tracking systems. The firms driving this increase are those hunting high-skilled talent. They are also in line with our survey findings, and together suggest that high-skilled managerial and technical occupations are more likely to be subject to outbound recruitment practices.

[Table 11 about here.]

6 Discussion and Conclusion

What impact has the digitization of the labor market had on the firm-driven search for talent? Recent work has highlighted the growing role of large platforms that now shape the hiring strategies of firms (Elfenbein and Sterling, 2018). We theorize that the digitization of the labor market, combined with a preference for hiring high-skilled workers versus training them in-house (Cappelli, 2012), has increased outbound recruiting by firms. Using two novel data sources, a nationally representative survey of over 13,000 American workers, and a large sample of over 80 percent job postings in the American economy, we provide new facts on the prevalence of this practice, which firms are more likely to engage in it, and which occupations and demographics are more likely to be its target.

We propose a two-sector labor market model to illustrate the firm's choice of recruiting modes and its consequence for equilibrium levels of employment and wages. In this model, we analyze the inbound versus outbound recruiting decision due to three dimensions: cost of screening, cost of hunting, and firms' skill requirements.

We find that nearly 18 percent of all employed workers in the US were hired into their present company by their employer's outbound recruiting effort, either directly or through labor market intermediaries such as a headhunter. The share of hiring driven by outbound recruiting is greatest among higher-income workers, at 20.3 percent, and those with STEM and business degrees, at 20 percent, which is consistent with our model's predictions. Moreover, there is considerable regional variation. Over a quarter of Silicon Valley workers are hired in this manner, whereas only 14.5 percent of those in Rochester are. Moreover, this channel appears primarily to substitute for worker-driven search (i.e., individuals applying to jobs without contact with the firm). Referral hiring, for the most part, seems, on the whole, to be relatively stable as a mechanism through which firms hire—at approximately 33-34 percent, which is consistent with prior estimates from past decades (Granovetter, 1995). Finally, we find evidence that workers at smaller firms are more likely to be recruited by firm-driven search. This finding is consistent with the theory that smaller firms must actively hunt for talent to compete for knowledge-workers.

We complement our worker-level survey results by analyzing a large sample of job postings in the US economy over the past decade. We find that firms, especially those relying on high-skilled technical and managerial labor, are increasingly developing capabilities to better hunt for talent. These changes are reflected in three broad findings. First, we see an overall increase in firms hiring recruiters as a share of total HR personnel. Second, we observe a growing demand for social media and digital skills among recruiters. Finally, we see that this demand is concentrated in firms requiring high-skilled workers with technical and social skills.

Our article informs three research agendas at the intersection of strategy, human capital, and digitization. First, research on firms' human capital strategy has focused on how firms can invest in complementary capabilities that turn their talent into a competitive advantage (Coff, 1997; Coff and Kryscynski, 2011). Our findings highlight that firms must also invest in capabilities that allow them to hunt for talent and keep them from being hunted. We also highlight the interplay between the cost and benefit of recruiting modes. This analysis will enable us to view firms that do not engage in outbound recruiting as behaving rationally. While wages may be a useful lever in attracting talent, non-pecuniary incentives may increasingly play an essential role in retaining high-value workers who may be actively monitored and recruited by competitors.

Second, much of the literature on the hiring interface focuses on firm decision-making in the context of worker-driven search (e.g., Bertrand and Mullainathan, 2004; Pager, Bonikowski and Western, 2009) and network recruiting (Fernandez, Castilla and Moore, 2000; Rubineau and Fernandez, 2013; Fernandez and Sosa, 2005). While these two hiring mechanisms do indeed account for a large share of how firms hire, firm-driven search and its growing prevalence among high-skilled workers suggests several questions for both job seekers and firms. For job seekers, the job search may increasingly be less about finding and applying for jobs but being an effective *passive* candidate. This change may require workers to develop find-able, signal-laden profiles that firms can discover. It may also require the ability to find and join the specialty hiring platforms, and databases firms now rely on (e.g., hired.com, online spreadsheets listing recently exited employees from major tech firms[13]). For firms, a key challenge may be developing the capabilities to find hidden gems, not on the radar of other companies. Even when workers are plentiful firm-led search may allow companies to cheaply sift through the multitudes to find the most promising workers. From both the worker and the firm's perspective, these questions raise important considerations for how firm-driven search impacts gender, racial, and geographic inequality. Another contribution of our research is to the growing literature on the digitization of the economy and its impact on firm-behavior (e.g., Brynjolfsson and McElheran, 2016). This literature argues that firms

[13] https://news.crunchbase.com/news/looking-at-spreadsheets-as-a-solution-to-layoffs/

are becoming increasingly data-driven, which is likely to affect how firms organize themselves to compete. We show evidence consistent with this theory: the growing ubiquity of data about workers has forced firms to invest in capabilities to exploit this information. In turn, this change in how firms hire has reshaped the outcomes of workers.

While we believe our proposed model, together with our empirical analyses, offer a meaningful set of new findings about the growing and likely impactful phenomenon of firm-driven search, our approach is not without limits. Our empirical results derive from a survey and observational data, which fundamentally limit our ability to make causal claims or concretely identify mechanisms. However, our results paint a consistent story and provide new insights into the prevalence of different hiring mechanisms and heterogeneity across the economy. Nevertheless, we see our study as the first step towards further research on what we identify as a growing and important phenomenon, with broad implications for our understanding of labor market outcomes and human capital strategy.

Moving forward, the continued growth of platforms that give firms access to detailed information about workers both outside and inside the organization will raise important questions for scholars and practitioners. How should firms design capabilities that allow them to find and assess worker capabilities (Barney, 1991)? How will this shift affect the nature of existing labor market signals, such as firm status (Bidwell et al., 2015; Rider and Tan, 2014), education (Spence, 1973), or experience (Ferguson and Hasan, 2013), and what impact will this have on the individual worker and the labor market as a whole? Finally, how will the broadening reach of this phenomenon affect workers beyond those in high-skilled occupations or economic hubs such as Silicon Valley or New York and the global talent pool? Addressing these questions, among others, will guide future research and practice.

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A Proofs

A.1 Low-skill sector: equilibrium derivation

The steady-state labor market equilibrium in the low-skill sector (θ_l, w_l, u_l) is such that, given $m(u_l L_l, v_l L_l)$, all workers and firms maximize their respective objective functions as described in Section 3.3. The three parameters are obtained via the intersection of labor demand and supply, as well as the Beveridge curve steady-state condition on unemployment.

Free-entry condition and labor demand. In steady-state and because of free entry, firms post vacancies until $V_l \equiv 0$. As a result, Equations (6) and (7) become:

$$\beta J_l = A_l \alpha_l x_i^{\epsilon} - w_l - \delta_l (J_l - 0) \Leftrightarrow$$

$$(\beta + \gamma_l) J_l = A_l \alpha_l x_i^{\epsilon}$$

$$0 = -\gamma_l + q(\theta_l)(J_l - 0) \Leftrightarrow q(\theta_l) J_l = \gamma_l$$

which together become Equation (12), representing labor demand:

$$q(\theta_l) = \frac{(\beta + \delta_l)\gamma_l}{A_l \alpha_l x_i^{\epsilon} - w_l} \quad \forall i \in \{l, h\}$$

Nash bargaining and labor supply. As explained in Section 3.4, agents negotiate wages each period. Wage is determined by the maximization of total surplus per Equation (13):

$$\max_{\{w_l\}} \quad (V_l^e - V_l^u)^{\mu} (J_l - V_l)^{1-\mu}$$

F.O.C.

$$\frac{\partial(.)}{\partial w_l} = 0 \Leftrightarrow \mu(V_l^e - V_l^u)^{\mu-1}\Big(\frac{\partial V_l^e}{\partial w_l} - \frac{\partial V_l^u}{\partial w_l}\Big)(J_l - V_l)^{1-\mu} + (V_l^e - V_l^u)^{\mu}(1-\mu)(J_l - V_l)^{-\mu}$$
$$\Big(\frac{\partial J_l}{\partial w_l} - \frac{\partial V_l}{\partial w_l}\Big) = 0 \Leftrightarrow$$
$$[V_l \equiv 0] \Leftrightarrow \mu(V_l^e - V_l^u)^{\mu-1}\Big(\frac{\partial V_l^e}{\partial w_l} - \frac{\partial V_l^u}{\partial w_l}\Big)J_l^{1-\mu} + (V_l^e - V_l^u)^{\mu}(1-\mu)J_l^{-\mu}\Big(\frac{\partial J_l}{\partial w_l}\Big) = 0 \Leftrightarrow$$

$$[\div J_l^{-\mu}] \Leftrightarrow \mu(V_l^e - V_l^u)^{\mu-1}\Big(\frac{\partial V_l^e}{\partial w_l} - \frac{\partial V_l^u}{\partial w_l}\Big)J_l + (V_l^e - V_l^u)^{\mu}(1-\mu)\Big(\frac{\partial J_l}{\partial w_l}\Big) = 0 \Leftrightarrow$$

$$[\div(V_l^e - V_l^u)^{\mu-1}] \Leftrightarrow \mu\Big(\frac{\partial V_l^e}{\partial w_l} - \frac{\partial V_l^u}{\partial w_l}\Big)J_l + (V_l^e - V_l^u)(1-\mu)\Big(\frac{\partial J_l}{\partial w_l}\Big) = 0 \Leftrightarrow$$

$$[\div(1-\mu)] \Leftrightarrow \frac{\mu}{1-\mu}\Big(\frac{\partial V_l^e}{\partial w_l} - \frac{\partial V_l^u}{\partial w_l}\Big)J_l + (V_l^e - V_l^u)\Big(\frac{\partial J_l}{\partial w_l}\Big) = 0 \Leftrightarrow$$

$$\Big[\frac{\partial V_l^u}{\partial w_l} = 0\Big] \Leftrightarrow \frac{\mu}{1-\mu}\Big(\frac{\partial V_l^e}{\partial w_l}\Big)J_l + V_l^e\Big(\frac{\partial J_l}{\partial w_l}\Big) = 0$$

Note that $\frac{\partial V_l^u}{\partial w_l} = 0$ because wages are negotiated period to period. Rearranging Equations (4) and (6), we get:

$$V_l^e = \frac{w_l + \delta V_l^u}{\beta + \delta_l}$$
$$J_l = \frac{A_l \alpha_l x_i^{\epsilon} - w_l}{\beta + \delta_l}$$

Replacing these in the F.O.C.:

$$\frac{\mu}{1-\mu}\frac{1}{\beta+\delta_l}\frac{A_l\alpha_l x_i^{\epsilon}-w_l}{\beta+\delta_l}+(V_l^e-V_l^u)\left(-\frac{1}{\beta+\delta_l}\right)=0\Leftrightarrow (V_l^e-V_l^u)=\frac{\mu}{1-\mu}\frac{\gamma_l}{q(\theta_l)} \tag{28}$$

Equation (28) defines a relationship between wages w_l and labor market tightness θ_l. Subtracting Equation (4) from (5) we get:

$$(V_l^e-V_l^u)=\frac{w_l-z_l}{\beta+\delta_l+\theta_l q(\theta_l)}$$

Finally, plugging this result into Equation (28):

$$\frac{w_l-z_l}{\beta+\delta_l+\theta_l q(\theta_l)}=\frac{\mu}{1-\mu}\frac{\gamma_l}{q(\theta_l)}\Leftrightarrow w_l=(1-\mu)z_l+\mu(A_l\alpha_l x_i^{\epsilon}+\gamma_l\theta_l)$$

which corresponds to labor supply. In equilibrium, wages w_l will be derived from the intersection of labor supply and demand, resulting in the following:

$$\begin{aligned}
(A_l\alpha_l x_i^{\epsilon}-w_l)q(\theta_l) =&(\beta+\delta_l)\gamma_l\Leftrightarrow\\
A_l\alpha_l x_i^{\epsilon}q(\theta_l)-(1-\mu)z_l q(\theta_l))-\mu A_l\alpha_l x_i^{\epsilon}q(\theta_l)-\mu\gamma_l\theta_l q(\theta_l) =&\gamma_l(\beta+\delta_l)\Leftrightarrow\\
(1-\mu)(A_l\alpha_l x_i^{\epsilon}-z_l)q(\theta_l)=\gamma_l[(\beta+\delta_l)+\mu\theta_l q(\theta_l)]&\Leftrightarrow\\
(1-\mu)(A_l\alpha_l x_i^{\epsilon}-z_l) =&\frac{\gamma_l}{q(\theta_l^*)[\beta+\delta_l+\mu\theta_l^* q(\theta_l^*)]}
\end{aligned}$$

Unemployment steady-state. As developed in Equations (16) and (17), unemployment steady-state is:

$$u_l^*=\frac{\delta_l}{\delta_l+\theta_l q(\theta_l)}$$

A.2 High-skill sector: equilibrium derivation

The high-skill sector equilibrium mechanism differs from the low-skill sector since firms can choose between inbound and outbound recruiting. We derive the equilibrium allocations in either case, and finish by describing when the firm chooses one recruiting mode versus the other, given parameters.

The steady-state labor market equilibrium in the high-skill sector $(\theta_h^k, w_h^k, u_h^k)$ with $k \in \{I, O\}$ is such that, given $m(u_h^k L_h^k, v_h^k L_h^k)$, all workers and firms maximize their respective objective functions as described in Section 3.3. The three parameters are obtained via the intersection of labor demand and supply, as well as the Beveridge curve steady-state condition on unemployment.

Free-entry condition and labor demand. In steady-state and because of free entry, firms post vacancies until $V_h^k \equiv 0$. As a result, Equations (8) and (9) become:

Inbound recruiting.

$$\begin{aligned} \beta J_h^I =& A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h) - \delta_h (J_h^I - 0) \Leftrightarrow J_h^I = \frac{A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h)}{\beta + \delta_h} \\ 0 =& -\gamma_h + pq(\theta_h)(J_h^I - 0) \Leftrightarrow J_h^I = \frac{\gamma_h}{pq(\theta_h)} \end{aligned}$$

which together become Equation (18), representing labor demand:

$$(\beta + \delta_h)\gamma_h = pq(\theta_h)[A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h)]$$

Outbound recruiting.

$$
\begin{aligned}
\beta J_h^O =& A_h \alpha_h x_h^\epsilon - w_h \sigma_h q(\tilde{\theta_h}) - \delta_h (J_h^O - 0) \Leftrightarrow J_h^O = \frac{A_h \alpha_h x_h^\epsilon - w_h - \sigma_h q(\tilde{\theta_h})}{(\beta + \delta_h)} \\
0 =& - \gamma_h + \tilde{\theta_h} q(\tilde{\theta_h})(J_h^O - 0) \Leftrightarrow J_h^O = \frac{\gamma_h}{q(\tilde{\theta_h})}
\end{aligned}
$$

which together become Equation (19), representing labor demand:

$$
(\beta + \delta_h)\gamma_h = q(\tilde{\theta_h}))[A_h \alpha_h x_h^\epsilon - w_h - \sigma_h q(\tilde{\theta_h})]
$$

Nash bargaining and labor supply. As explained in Section 3.4, agents negotiate wages each period. Wage is determined by the maximization of total surplus:

$$
\max_{\{w_l\}} \quad (V_l^e - V_l^u)^\mu (J_h^k - V_h^k)^{1-\mu}
$$

The derivation of $F.O.C.$ unfolds similarly to $\frac{\partial(.)}{\partial w_l}$, yielding:

$$
\frac{\mu}{1-\mu}\left(\frac{\partial V_l^e}{\partial w_l}\right) J_h^k + V_l^e \left(\frac{\partial J_h^k}{\partial w_l}\right) = 0
$$

Inbound recruiting.

Rearranging Equations (4) and (18) and replacing them in the $F.O.C.$ yields:

$$
\begin{aligned}
\frac{w_h - z_h}{\beta + \delta_h + \theta_h q(\theta_h)} =& \frac{\mu}{1-\mu} \frac{\gamma_h}{pq(\theta_h)} \Leftrightarrow pq(\theta_h)(1-\mu) w_h = pq(\theta_h)(1-\mu) z_h + \mu \gamma_h (\beta + \delta_h) + \mu \gamma_h \theta_h q(\theta_h) \\
\Leftrightarrow w_h^I =& (1-\mu) z_h + \mu \left(A_h \alpha_h x_h^\epsilon - \rho_h q(\theta_h) - \frac{\gamma_h \theta_h}{p} \right)
\end{aligned}
$$

Outbound recruiting.

Rearranging Equations (4) and (19) and replacing them in the $F.O.C.$ yields:

$$w_h^{)} =(1-\mu)z_h + \mu(A_h\alpha_h x_h^{\epsilon} - \sigma_h q(\tilde{\theta_h}) - \mu\gamma_h\tilde{\theta_h})$$

In equilibrium, wages w_h^k will be determined by the intersection of labor supply and demand, as follows:

Inbound recruiting.

$$(\beta+\delta_h)\gamma_h = pq(\theta_h)[A_h\alpha_h x_h^{\epsilon} - w_h - \rho_h q(\theta_h)] \Leftrightarrow$$

$$(\beta+\delta_h)\gamma_h = pq(\theta_h)[A_h\alpha_h x_h^{\epsilon} - \underbrace{(1-\mu)z_h - \mu(A_h\alpha_h x_h^{\epsilon} - \rho_h q(\theta_h) - p^{-1}\gamma_h\theta_h) - \rho_h q(\theta_h)}_{Eq.(20)} \Leftrightarrow$$

$$(\beta+\delta_h)\gamma_h = y_h pq(\theta_h) - (1-\mu)z_h pq(\theta_h) -_h pq(\theta_h) + \mu\rho_h q(\theta_h)pq(\theta_h) + \mu p^{-1}\gamma_h\theta_h q(\theta_h) - p\rho_h q(\theta_h)^2 \Leftrightarrow$$

$$(1-\mu)(y_h - z_h - \rho_h q(\theta_h^*)) = \frac{\gamma_h}{q(\theta_h^*)}[\beta+\delta_h+\frac{\mu}{p}\theta_h^* q(\theta_h^*)]$$

where $y_h = A_h\alpha_h x_h^{\epsilon}$.

Outbound recruiting.

$$(1-\mu)(y_h - z_h - \sigma_h q(\tilde{\theta_h^*})) = \frac{\gamma_h}{q(\tilde{\theta_h^*})}[\beta+\delta_h+\mu\tilde{\theta_h^*}q(\tilde{\theta_h^*})]$$

Unemployment steady-state. As developed in Equations (24) and (25), unemployment at steady-state is:

$$u_h, I^* = \frac{\delta_h}{\delta_h + \theta_h q(\theta_h)}$$
$$u_h, O^* = \frac{\delta_h}{\delta_h + \tilde{\theta}_h q(\tilde{\theta_h})}$$

A.3 Comparative Statics: inbound versus outbound recruiting

Profits with inbound recruiting. In steady-state equilibrium, under free entry, firms make zero profits π_h^k both in both inbound and outbound recruiting.

$$\pi_h^I = A_h \alpha_h x_h^\epsilon - w_h - \rho_h q(\theta_h) - \frac{(\beta + \delta_h)\gamma_h}{pq(\theta_h)} = 0$$
$$\pi_h^O = A_h \alpha_h x_h^\epsilon - w_h - \sigma_h q(\tilde{\theta_h}) - \frac{(\beta + \delta_h)\gamma_h}{q(\tilde{\theta}_h)} = 0$$

Proposition 3. The more binding the skill requirement for the firm —lower share of high-skill workers, p—, the more likely it will engage in outbound recruiting.

Proof. Note that only inbound recruiting profits are directly affected by the share of high-skill workers in the economy:

$$\frac{\partial \pi_h^I}{\partial p} = \frac{(\beta + \delta_h)\gamma_h q(\theta_h)}{[pq(\theta_h)]^2} > 0$$

The more binding (lower p) the skill requirement for the firm, the lower the profit they can derive from filling a vacancy through applications, rendering the outbound option preferable.

Proposition 4. The higher the the cost of screening applicants (ρ_h), the more likely a firm with high-skill requirements is to choose outbound recruiting.

Proof. Firms who use inbound recruiting must spend resources to screen candidates (ρ_h):

$$\frac{\partial \pi_h^I}{\partial \rho_h} = -q(\theta_h) < 0$$

The higher the screening costs of incoming applications, the lower the profit they can derive from filling a vacancy through applications, rendering the outbound option preferable.

Proposition 5. The lower the cost of finding skilled workers (σ_h), the more likely a firm with high-skill requirements is to choose outbound recruiting.

Proof. The cost of finding skilled workers (σ_h) is only relevant for firms who engage in outbound recruiting:

$$\frac{\partial \pi_h^O}{\partial \sigma_h} = -\sigma_h < 0$$

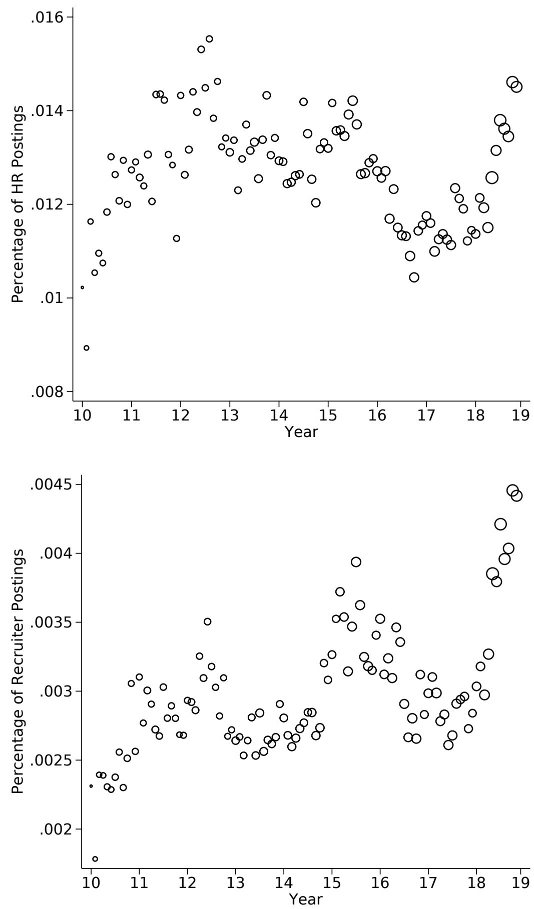

Figure 1: The top panel shows the percent of all postings classified as HR jobs each month. The bottom panel the percent of all postings that are classified as recruiting roles. Points are scaled by the number of job postings in the month.

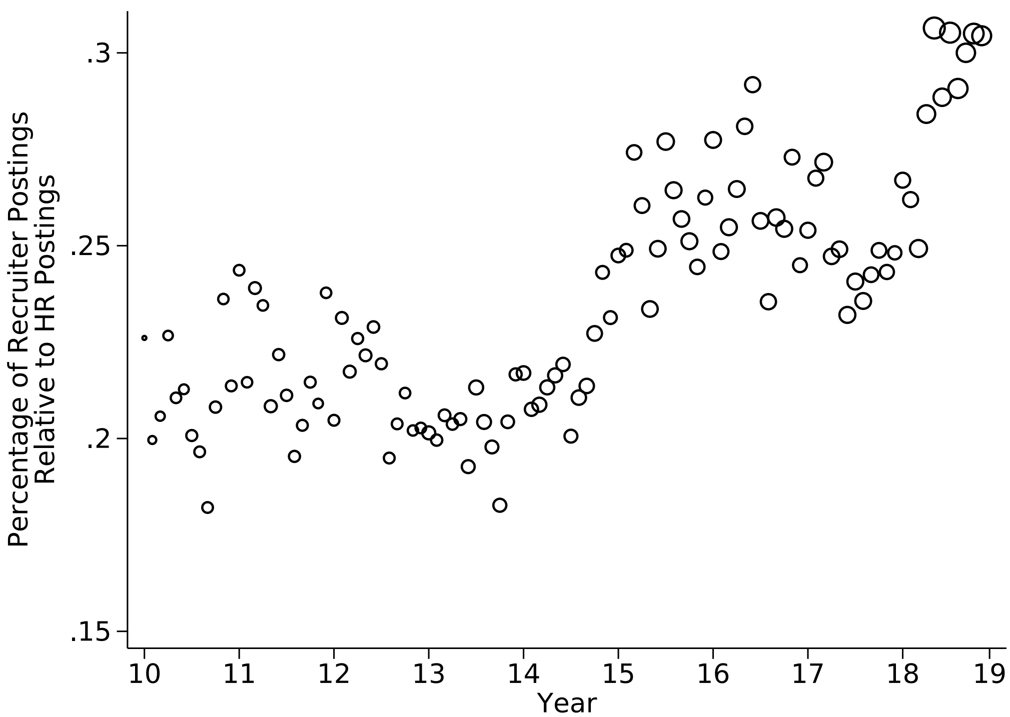

Figure 2: The percent of HR posts where the job title is classified as focused on recruiting. Points are scaled by the number of job postings in the month.

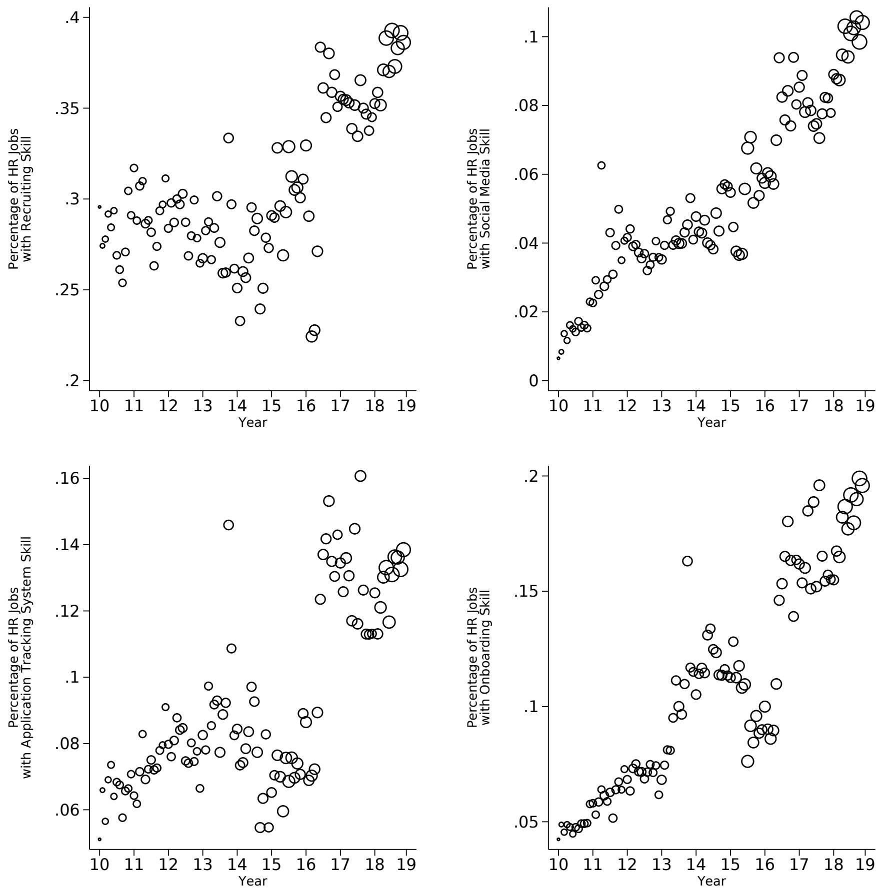

Figure 3: The percent of HR posts that list recruiting as a skill (top left), that list social media as a skill (top right), that list applicant tracking systems as a skill (bottom left), and onboarding as a skill (bottom right). Points are scaled by the number of job postings in the month.

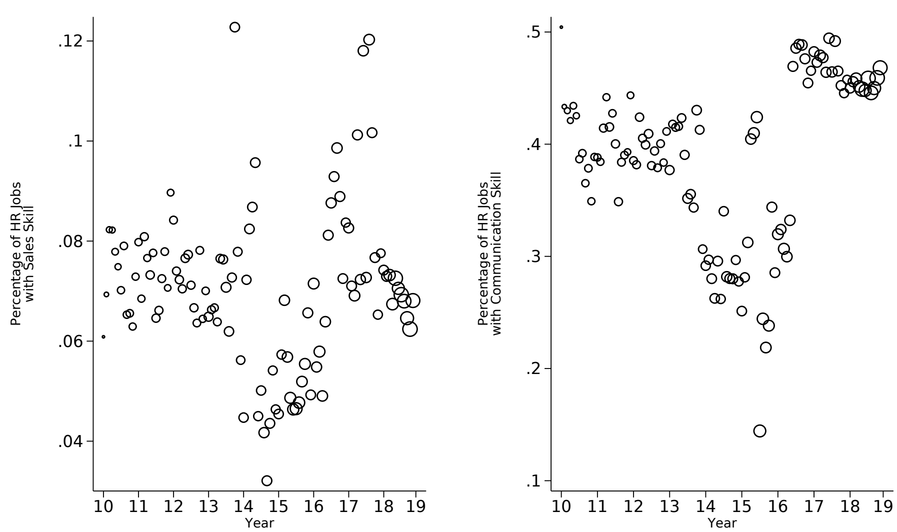

Figure 4: The percent of HR posts that list sales as a skill (left) and the percent that list communication as a skill (right). Points are scaled by the number of job postings in the month.

Table 1: The prevalence of different hiring mechanisms in the United States labor market in January 2020.

	USA (N)	(%)
I found and applied for the role	6,003	43.9%
Referred by existing employee	4,732	34.6%
Recruiter invited me to apply	1,711	12.5%
Headhunting firm invited me to apply	725	5.3%
I reached out to a headhunting firm	497	3.6%
Firm driven search (%)	2,436	**17.8%**
Total	13,668	**100.0%**

Table 2: The prevalence of different hiring mechanisms in the United States labor market based on education level.

	HS or less	Some college, no degree	Bachelor's or assoc. degree	Graduate/Prof degree
I found and applied for the role	403	1,023	2,059	806
Referred by existing employee	449	935	1,472	531
Recruiter invited me to apply	134	302	531	245
Headhunting firm invited me to apply	34	108	245	122
I reached out to a headhunting firm	33	91	157	61
Firm driven search (%)	**16.0%**	**16.7%**	**17.4%**	**20.8%**
Total	1,053	2,459	4,464	1,765

Table 3: The prevalence of different hiring mechanisms in the United States labor market based on income level.

	Under \$50,000	\$50,000-\$100,000	\$100,000+
I found and applied for the role	1,006	1,624	1,781
Referred by existing employee	671	1,249	1,627
Recruiter invited me to apply	220	426	615
Headhunting firm invited me to apply	80	153	290
I reached out to a headhunting firm	78	125	138
Firm driven search (%)	**14.6%**	**16.2%**	**20.3%**
Total	2,055	3,577	4,451

Table 4: The prevalence of different hiring mechanisms in the United States labor market based on specialization.

	STEM	Health & medicine	Business	Social sciences Arts & humanities	Education
I found and applied for the role	559	185	652	816	89
Referred by existing employee	387	136	512	561	68
Recruiter invited me to apply	171	65	207	202	19
Headhunting firm invited me to apply	87	16	103	81	10
I reached out to a headhunting firm	39	16	67	63	5
Firm driven search (%)	20.8%	19.4%	20.1%	16.4%	15.2%
Total	1,243	418	1,541	1,723	191

Table 5: The prevalence of different hiring mechanisms in the United States labor market based on use of LinkedIn.

	Users	Non-Users
I found and applied for the role	483	728
Referred by existing employee	426	621
Recruiter invited me to apply	164	205
Headhunting firm invited me to apply	90	51
I reached out to a headhunting firm	40	49
Firm driven search (%)	21.1%	15.5%
Total	1,203	1,654

Table 6: The prevalence of different hiring mechanisms in the United States labor market based on estimated number of employees at current employer.

	Large (5,000+ employees)	Midsize (100 - 4,999 employees)	Small (less than 100 employees)
I found and applied for the role	207	215	163
Referred by existing employee	159	198	191
Recruiter invited me to apply	48	54	78
Headhunting firm invited me to apply	16	26	28
I reached out to a headhunting firm	14	13	20
Firm driven search (%)	14.4%	15.8%	22.1%
Total	444	506	480

Table 7: The prevalence of different hiring mechanisms in the United States labor market based on respondent age.

	18 - 24	25 - 29	30 - 34	35 - 44	45 - 54	55 - 64
I found and applied for the role	356	439	507	1,354	2,753	589
Referred by existing employee	239	261	328	995	2,383	527
Recruiter invited me to apply	99	117	109	410	790	181
Headhunting firm invited me to apply	32	52	72	171	328	68
I reached out to a headhunting firm	46	42	51	92	217	48
Firm driven search (%)	17.0%	18.6%	17.0%	19.2%	17.3%	17.6%
Total	772	911	1,067	3,022	6,471	1,413

Table 8: The prevalence of different hiring mechanisms in the United States labor market based on respondent gender.

	Male	Female
I found and applied for the role	3,472	2,536
Referred by existing employee	3,000	1,738
Recruiter invited me to apply	1,114	597
Headhunting firm invited me to apply	466	259
I reached out to a headhunting firm	287	210
Firm driven search (%)	18.9%	16.0%
Total	8,339	5,340

Table 9: The prevalence of different hiring mechanisms in the United States labor market based on respondent's race and ethnicity.

	White or Caucasian	Hispanic or Latino	Black	Asian or Pacific Islander	Other
I found and applied for the role	3,454	362	333	150	414
Referred by existing employee	2,812	301	221	107	276
Recruiter invited me to apply	961	94	98	44	110
Headhunting firm invited me to apply	395	45	44	21	59
I reached out to a headhunting firm	259	35	27	9	36
Firm driven search (%)	17.2%	16.6%	19.6%	19.6%	18.9%
Total	7,881	837	723	331	895

Table 10: The prevalence of different hiring mechanisms in the United States labor market in January 2020, MSA-level results.

	Rochest.	Denv.	Sacram.	NYC	Portl.	San Fran.	Miami	San Jose
I found and applied for the role	175.0	246.4	216.7	333.7	199.6	305.4	214.5	146.4
%	46.5%	47.6%	46.9%	43.7%	43.3%	41.6%	43.7%	37.4%
Referred by existing employee	129.8	173.7	150.0	265.8	150.6	256.7	163.5	129.9
%	34.5%	33.6%	32.4%	34.8%	32.6%	34.9%	33.3%	33.2%
Recruiter invited me to apply	41.4	48.6	53.5	85.1	61.3	86.5	67.4	57.6
%	11.0%	9.4%	11.6%	11.2%	13.3%	11.8%	13.7%	14.7%
Headhunting firm invited me to apply	13.1	31.8	19.1	43.3	22.9	50.6	24.5	41.8
%	3.5%	6.1%	4.1%	5.7%	5.0%	6.9%	5.0%	10.7%
I reached out to a headhunting firm	17.2	16.9	23.2	35.2	26.9	35.8	20.8	15.5
%	4.6%	3.3%	5.0%	4.6%	5.8%	4.9%	4.2%	4.0%
Total firm-driven search	54.5	80.4	72.6	128.4	84.2	137.1	91.9	99.4
%	14.5%	15.5%	15.7%	16.8%	18.3%	18.7%	18.7%	25.4%
Total response count	376.5	517.4	462.5	763.1	461.3	735.0	490.7	391.2

Table 11: What drives a firm's demand for recruiters? Here we regress whether a firm posts for recruiters on that firm's skill mix. The independent variables are logged-plus-one skill counts across all the postings by a firm in a given year. In columns (1)-(4), the dependent variable is the logged-plus-1 count of recruiter positions posted by the firm. In Column (5) the dependent variable is a binary indicator for whether the firm posts a recruiter job ad. We include fixed effects for the number of non-HR positions in all our models to account for differences due to firm scale. Relatedly, we drop all observations with fewer than 10 non-HR postings since such firms are extremely unlikely to hire a recruiter in that year. That said, our primary findings hold when including all firm-year observations or when focusing only on firm-years with 50 or more postings. All regressions are at the firm-year level, are weighted by the number of postings by the firm in a given year, and include robust standard errors clustered at the firm-MSA-industry level. '$*p < 0.01; **p < 0.001$.

	Log-recruiter postings				*Recruiter posting?*
	(1)	(2)	(3)	(4)	(5)
Log-Cognitive	-0.020	-0.019*	-0.021*	-0.005	0.005
	(0.008)	(0.007)	(0.007)	(0.004)	(0.003)
Log-Social	-0.015	-0.016	-0.017	-0.017	-0.014**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)
Log-Character	0.043**	0.045**	0.043**	0.029**	0.016**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)
Log-Writing	0.007	0.009	0.009	0.018	0.007
	(0.009)	(0.007)	(0.007)	(0.007)	(0.004)
Log-Customer Service	0.028**	0.022	0.023*	0.011	0.002
	(0.007)	(0.009)	(0.008)	(0.007)	(0.004)
Log-Project Management	0.094**	0.089**	0.090**	0.084**	0.035**
	(0.010)	(0.009)	(0.010)	(0.007)	(0.005)
Log-People Management	0.009	0.012	0.011	0.016	0.010
	(0.008)	(0.006)	(0.006)	(0.008)	(0.004)
Log-Financial	-0.039**	-0.015	-0.015	0.025**	0.010*
	(0.010)	(0.008)	(0.008)	(0.007)	(0.003)
Log-Computer	0.083**	0.072**	0.074**	0.056**	0.037**
	(0.007)	(0.006)	(0.006)	(0.007)	(0.004)
Log-Software	0.101**	0.096**	0.095**	0.058**	0.022**
	(0.009)	(0.007)	(0.007)	(0.005)	(0.003)
# Non-HR Postings FE	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs	No	Yes	Yes	Yes	Yes
MSA FEs	No	No	Yes	Yes	Yes
Firm FEs	No	No	No	Yes	Yes
Observations	500,042	500,042	500,038	396,270	396,270
Number of Firms	200,279	200,279	200,275	96,574	96,574
R^2	0.622	0.633	0.644	0.853	0.706