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

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Abstract

This article analyzes the phenomenon of firm-driven labor market search—or outbound recruiting—where recruiters are increasingly "hunting for talent" rather than passively relying on workers to search for and apply to job vacancies. Our research methodology leverages three approaches. We first develop a labor market model that incorporates firm-driven search and then derive the equilibrium conditions under which firms use outbound recruiting and study its effect on hiring strategy, performance, and worker outcomes. We then test our model's predictions using two data sources representing worker outcomes and firm choices. First, data from a nationality representative survey of 13,000 US workers shows that the percentage of workers hired through recruiting has increased from 4.2% in 1991 to 17.8% in 2020. This share is larger for higher-skilled workers, those with online profiles on LinkedIn, and those employed in high-technology hubs (e.g., Silicon Valley). We complement this analysis with data on the near universe of online job postings from 2010 to 2020. Here, we find that firms, especially those that need high-skilled workers, are hiring more recruiters with significant skill in scouring the internet for passive candidates. Indeed, demand for such recruiters has tripled over the past decade. A key implication of our model and findings is that outbound recruiting is most beneficial for firms that have higher skill demands, and at the margin, may shift firms to seek out higher skilled workers.

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1 Introduction

A firm's performance relies on finding, hiring, and retaining talented workers (Coff and Kryscynski, 2011; Cowgill and Perkowski, 2021). However, much of the existing research on human capital strategy assumes that firms rely on workers to find them rather than the other way around. This framework, in which workers primarily drive search, is embedded in theoretical models of labor markets (e.g., Jovanovic, 1979; Mortensen and Vishwanath, 1994) as well as in extensive empirical work on firms' hiring decisions and human resource capabilities (Bertrand and Mullainathan, 2004; Fernandez and Sosa, 2005; Burbano, 2016). 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; Wolthoff, 2018).

Increasingly, however, two trends may have re-shaped how firms hire. First, digitization and the internet have enabled firms to take a more active role in finding talent—via access to vast databases of up-to-date worker profiles (Autor, 2001; Finlay and Coverdill, 2007; Coverdill and Finlay, 2017; Elfenbein and Sterling, 2018). Such data has the potential to reduce the costs of finding workers, especially those not actively searching. In addition, the literature has documented a decrease in on-the-job training and a corresponding rise in demand for high-skill workers (Cappelli, 2012, 2015). The rising demand for externally sourced labor *and* the lower cost of finding passive candidates has likely changed how often firms actively search for workers. Yet, because prior research has largely assumed workers search for jobs, there remains a considerable gap in our understanding of how widespread this practice is, which workers and firms are most likely to participate, and the impact of firm-driven search on labor markets and firm outcomes.[1]

[1]A notable exception is the research on executive search. Indeed, recent research on the market for executives has looked at topics ranging from how firms search for executives with particular skills (Hansen

Currently, our understanding of firm-driven "outbound" recruiting rests almost entirely on indirect inferences and relatively ad hoc labor market models.[2] For example, a Federal Reserve report 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). Similarly, in a new survey of job search behavior of both employed and unemployed workers, Faberman et al. (2020) find that around 22 percent of the employed report searching for work on the job in the prior four weeks. Finally, Coverdill and Finlay (2017) along with Cappelli (2019) argue from both rich case studies and qualitative data that firms increasingly prefer to hire "passive candidates" and scour online databases (e.g., LinkedIn) for people to poach.

This paper sheds a more systematic light on how firms hunt for talent by developing a formal model of labor markets that incorporates outbound recruiting and by testing our model's predictions on two macro-level data sets. Our model extends the canonical Diamond (1982) labor market model to incorporate the two major labor market trends that prior research links to hunting for talent: the rising demand by firms for pre-trained high-skilled workers and the increasing ease of searching for passive candidates online (Coverdill and Finlay, 2017). Specifically, in our model, a firm decides (1) how much to invest in recruiting capabilities given the benefits of hiring hard-to-find higher-skilled labor and (2) the cost to the firm of simply waiting for hard-to-find talent to apply on their own relative to the cost of developing recruiting capabilities. Our model shows that (1) firms will engage in more outbound recruiting when the cost of searching

et al., 2021) to how gender bias emerges in executive hiring pipelines (Fernandez-Mateo and Fernandez, 2016). However, given that the market for CEOs is but a fraction of the total labor market, it remains unknown whether firm-driven search is merely an artifact of markets for executives or an increasingly prevalent hiring mode.

[2]Indeed, in their book on headhunting and technology Coverdill and Finlay (2017) note that "Estimates of the number of headhunters, firms, placements, and use by client companies have always been in short supply and flimsy, as solid sources like the Bureau of Labor Statistics pay no attention to headhunting."

drops, (2) that this increase will be higher for firms that demand higher-skilled workers, and (3) that investments in cheaper outbound recruiting will lead firms to shift their labor demand towards higher-skilled talent. Beyond serving as a helpful framework for future studies, our model highlights that "hunting for talent" is not only a consequence of skill hungry firms looking for new ways to hire talent, but that easier "hunting" may also lead firms to shift their labor demand towards higher-skilled workers and so shape the labor market itself.

We take our model's predictions to data using two different macro-level data sources. The first data set is a new nationally representative survey of U.S. workers that allows us to directly measure the percentage of the labor force that has been "hunted" as against hired through worker-driven applications or network-type referrals. We show that nearly 18 percent of all employed workers in the U.S. in January 2020 were hired into their present company by the outbound recruiting effort of their employer, either directly or through a headhunter. In 1991, the only year we have comparable data from the General Social Survey, this figure was 4.2%. This increase has come at the expense of direct worker-driven applications and not from a reduction in network referrals, which we find have held steady at 33%, similar to the estimated rate of referrals going back to the 1970s (Granovetter, 1973, 1995; Burks et al., 2015). Consistent with our model, this rate is greatest for workers who use LinkedIn and work in higher-skilled professions. While there is meaningful regional, firm, and demographic variation, we find that firm-driven search is much more prevalent in all subgroups of our data than in the past. While over 25 percent of Silicon Valley workers are hired through outbound recruiting, we find that a healthy 15 percent of workers in Sacramento are too. Finally, we also see some evidence for a gender gap in outbound search with 18.9 percent of men landed their current position by being recruited, against 16 percent of women.[3]

[3] We also find that the percentages we find in our January 2020 survey remain consistent after the COVID-

Our second data set covers the near universe of U.S. online job postings from 2010 through 2020 from Burning Glass Technologies (BGT) (Hershbein and Kahn, 2018; Deming and Kahn, 2018). We use the BGT data in two ways. First, we use it to show that firms increasingly demand HR professionals who can hunt for talent, with the percentage of HR jobs requiring recruiting skills jumping from 33% in 2010 to almost 50% by the end of 2020. Similarly, in 2010 only 2% of HR jobs listed social media (e.g., LinkedIn, GitHub) as a skill, but by 2020 that figure had quintupled to 10% of all HR jobs. Consistent with our model, as the cost of searching has dropped due to the advent of platforms like LinkedIn, we see firms investing more in their recruiting capabilities.

To further test our model's second and third predictions—that firms that demand higher-skilled workers will be more likely to hunt for talent *and* that hunting for talent shifts a firm's skill demands upward—we again leverage the BGT data aggregated to a firm-level panel. Specifically, we focus on growth-focused firms for which we can adequately measure a firm's time-varying skill and recruiting demand and because identifying, hiring, and managing talent is critical for these fast-growing organizations (Chatterji et al., 2019; Kim, 2020). Consistent with our second prediction, we find growth-focused firms that initially demand higher-skilled workers are significantly more likely to post for a recruiter in the future. To check our third prediction, we use event-study models to show that once a firm decides to invest in recruiting, they discontinuously shift their future labor demand from lower- to higher-skilled workers. Overall, our findings show that hunting primarily alleviates search and matching frictions for higher-skilled firms and workers.

Our model and findings hold several important implications for research on human

19 pandemic, which took hold in the U.S. only months after our survey. In a supplementary survey run in September of 2020, we find that 16.09% of workers had been recruited and that this figure jumped to 18.85% for workers who switched jobs during the pandemic.

capital strategy and labor markets. 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 are essential in an environment where competitors are actively recruiting a firm's workers. Second, our findings also highlight the importance of recruiters as crucial intermediaries between firms and workers (Finlay and Coverdill, 2007; Cowgill and Perkowski, 2021). A key implication of our model and findings is that outbound recruiting is most beneficial for firms that have higher skill demands, and at the margin, may shift firms to seek out higher skilled workers. 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 (Fernandez-Mateo and Fernandez, 2016). Indeed, a growing literature on the labor market frictions introduced by recruiters is emerging (Cowgill and Perkowski, 2021; Kim, 2020). Our findings provide novel and crucial macro-level empirical evidence of their increasing importance. Third, we also contribute to the literature on "search and matching" in the labor market. In particular, we add to the recent literature on firms' recruiting practices (Baydur, 2017; Wolthoff, 2018) 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 in our model.

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 this paper's scope, we believe they would be important avenues for future research.

2 A theory of firm-driven labor market search

2.1 Technological change, skills, and firm-driven search

In the American labor market, two trends—increasingly heterogeneous skill demands and the decreasing costs of searching for workers—have reshaped the calculus of how firms hire. On the one hand, recent literature has documented a decrease in on-the-job training and a rise in demand for high-skill workers (Cappelli, 2012, 2015). This shift has several consequences for the human capital strategy of firms. First, firms may substitute lower-skilled candidates whom they train 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.

Simultaneously, the Internet has changed both the cost of screening incoming candidate applications and finding potential candidates, or *hunting* for talent (Autor, 2001). While online job boards have been around for several decades, in recent years, many more workers have gotten access to the Internet and created online profiles that showcase their skills and experience. Indeed, over 163 million Americans use LinkedIn, a prominent online career platform that allows workers to post profiles and apply for jobs.[4] Beyond lowering the cost of finding workers these online profiles make firm-driven search possible. Indeed, Coverdill and Finlay (2017) give an illustrative example of a headhunter who conducted "a highly specialized LinkedIn search that probably could not have been accomplished, let alone quickly, through traditional networks or phone sourcing." Thus we expect that the mass digitization of the labor market has reduced the cost of finding workers, especially those not actively looking for a job. Our framework, outlined below, incorporates these two factors—skills and outbound search costs—into the classical Diamond-Mortensen-Pissarides (DMP) framework (Diamond, 1982; Mortensen, 1982; Pissarides, 1985).

2.1.1 A model of firm search and labor market matching

Our model of firm-driven search builds on the standard Diamond-Mortensen-Pissarides (DMP) framework (Diamond, 1982; Mortensen, 1982; Pissarides, 1985) of labor market matching. We introduce two innovations to the standard model: (1) we relax the assumption that workers have homogenous skills and (2) we allow firms to invest in outbound search in addition to posting a job opening. Below we outline the standard model upon which we develop our theory of outbound search.

Our model considers an economy that firms and workers populate. In this economy, both workers and firms maximize their expected discounted lifetime utilities, which correspond to Bellman equations, specified in Section A1.2. In the model, time is discrete, and the discount factor for future wages is β. At any given time, workers are either employed or unemployed. In the standard DMP model *only* unemployed workers

[4] https://www.linkedin.com

search for jobs. If a worker cannot find a job, she will receive unemployment benefits z, exogenously specified.

In this framework, the population of workers L consumes everything they earn. We model firms as units of production. At any point in time, a firm can be active or inactive. A firm is active when matched to a worker, and together they produce units of output. When inactive, firms post vacancies to find workers. Active firms face an exogenous probability of closure, leading to job destruction, of δ_i, and so this parameter determines the flow of workers to unemployment. An inactive firm can post job vacancies and start its activity in any period by hiring workers. Firms incur the fixed cost of opening a vacancy, γ_i.

A matching function determines the flow into employment, where once firms post vacancies they are filled through a matching function denoted as $m(U, V)$ that depends on U, the total unemployed workers, and V, the total number of vacancies[5]. In this model, there exists a single unemployment and vacancy rates —respectively, u and v— facing all firms and workers, such that $U = uL$ and $V = vL$. Given these parameters we can write the rate at which a vacancy is filled as the ratio of matches to vacancies $\frac{m(uL,vL)}{vL} = m(\frac{1}{\theta}, 1)$ with $\theta = \frac{U}{V} = \frac{u}{v}$. As in Mortensen and Pissarides (1994), we assume vacancies fill according to a random Poisson process, with $m(.,.)$ represented as a Poisson arrival rate. Importantly, in the standard model, the rate at which vacancies fill is not influenced by the firm's actions—the matching function is exogenous, and firms wait for a match. As the ratio of vacancies to unemployment ($\theta = v/u$) increases, so does time for a match and the costs for firms. After a match in each period, the worker's wage is set through a Nash bargaining process.

The standard DMP-model described above is the primary analytical framework used in labor economics to shed light on unemployment dynamics, business cycles,

[5] The DMP model assumes the matching function has constant returns to scale.

worker turnover, and wage inequality. We adapt this model to account for more firm-level heterogeneity and agency in searching for workers. Specifically, we augment the model by introducing heterogeneity in terms of worker skill, each firm's skill demand, and allowing firms to choose how much they invest in outbound recruiting versus simply waiting for applications to roll in (Acemoglu, 1999; Shi, 2002; Lindenlaub and Postel-Vinay, 2016; Lise and Postel-Vinay, 2020).

2.2 A labor market with heterogeneous skills and firm-driven search

We depart from the Diamond-Mortensen-Pissarides (DMP) framework described above and introduce two novel elements. First, we assume firms demand heterogeneous skills x_i, and face workers with a distribution of skills in the population.

Second, firms can choose other hiring mechanisms to fill their vacancies; they can decide how much of their hiring is through inbound applications versus outbound recruiting. We employ an approach similar to Baydur (2017), in that we augment the DMP framework by adding a stage between vacancy posting and wage bargaining. In our model, the three stages are: (1) Firms post vacancies; (2) Firms decide how to fill vacancies either through inbound or outbound recruiting; (3) A firm-worker match is realized and Nash bargaining for wages unfolds, leading to an equilibrium.

In our updated model, each firm i demands a specific number of skills x_i. The firm is born with production technology, and the firm must hire workers to produce an output of Y_i according to their skill-specific production function $Y_i = A_i F(N_i, X_i)$. A is a technology parameter, N_i is the number of workers hired by the firm, and X_i their corresponding skill level, with $i \in [0, x^{max}]$, where x^{max} corresponds to the highest number of skills a worker can possess. We assume that workers who have a high number of skills accumulate skills below their position in the distribution. Thus, if a firm requires a specific skill level X_i, it will need to hire a worker with at least that skill level or higher, where the distribution is $1 - P(X_i) = p(X_i)$. We will henceforth set output per employee as $y_i = A_i f(x_i)$, where $y_i = Y_i/N_i$ and $x_i = X_i/N_i$. To produce, firms need to find workers with at least the number of skills required by their production function.

On the other side of the labor market, workers have an immutable skill level x_i, with which they are born. There is a continuum of workers in the economy, each corresponding to a skill level, represented by the number of skills x_i. Each number of skills has a total labor force L_i. The distribution of skills is $p(x_i) = e^{-x_i}$. At any time, a worker is either employed or unemployed. An employed worker receives a wage w_i, obtained as a result of Nash bargaining, as developed in Appendix A1.

Finally, we introduce the option that firms can choose between 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. We denote h_i as the intensity of outbound recruiting chosen by firm i.

In the model, firms incur costs when engaging in both types of recruiting. The firm must incur the fixed cost of opening a vacancy as in DMP, γ_i, which is common for inbound and outbound recruiting. We add two new cost parameters to our model, ρ_i and σ_i. If the firm requires many skills, it must be selective about which talent to attract. As a result, a firm cannot simply be matched with the first arrival. Therefore, the firm must pay a variable cost of reviewing incoming applications, $\rho_i \in [0, 1]$ to ensure it will hire the right talent. 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 in the model can be considered the recruiter's time spent searching for suitable candidates, both online and offline. The advantage of engaging in outbound recruiting is that the firm can directly target workers with their required skill level, whereas the screening cost ρ_i does not alter the distribution of skills faced by firms.

2.3 How workers and firms are matched

Building on the assumptions above, in stage one, firms start by posting vacancies for skill level $i \in [0, x^{max}]$, V_i, knowing they will receive applications from unemployed workers as a result. These vacancies fill according to a random Poisson process, where unemployed workers U_i looking for a job can match to a vacancy according to this Poisson process. This matching process models random contacts between the two sides of the labor market and 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 that varies based on the number of skills required. We assume that $m(.,.)$ is concave, increasing in both its arguments, exhibits constant returns to scale, and $m(U_i, 0) = m(0, V_i) = 0$ as in the standard DMP framework.

The matching function 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 $q(\theta)$, which is defied as the ratio of the number of matches to vacancies:

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

In Equation 1 $\theta_i \equiv v_i / u_i$ 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 as in Mortensen and Pissarides (1994). Due to the constant returns to scale assumption of the matching process $m(.,.)$, we can derive the last equality in equation (1). Given that all firms and employees within the skill requirement i face the same vacancy and unemployment rates, we can represent the rate of arrival of matches as a one-argument function $q(\theta)$.

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 longer firms must spend to find their desired candidate, increasing time to match. Simultaneously, $\theta_i q(\theta_i)$ is the Poisson arrival rate of matches for each unemployed worker[6].

As seen in our model, the matching technology described cannot discriminate between different skill levels. The arrival rate of $q(\theta_i)$ guarantees a match; however, not necessarily a fast or the right match for all firms. The higher the skill level required by the firm, the less likely it is to find the right match by solely relying on inbound applications. We model this by positing that when firms rely on inbound applications, the likelihood of a right match becomes $p(x_i)q(\theta_i)$. That is, the firm faces a shrinking likelihood of obtaining the right match by waiting for inbound applications to its vacancy postings. Conversely, if the firm invests in outbound recruiting, it can bypass the arrival rate of unemployed workers altogether. In doing so, the firm explicitly targets the talent it wants to hire by incurring a cost of "hunting", σ_i.

[6] $\theta_i q(\theta_i) = \frac{m(u_i L_i, v_i L_i)}{u_i L_i} = m(1, \theta_i)$

2.4 When do firms hunt for talent? Equilibrium and Comparative statics

Given the structure described above, workers and firms each optimize expected utilities. In the case of workers, they must decide whether to search for a job that will pay a wage w_i or remain unemployed and collect unemployment benefits z. In the firm's case, it must decide whether to post a vacancy and, conditional on posting, whether it should invest in an outbound search. These decisions, in turn, shift and are shifted by the equilibrium wage paid to workers by firms with different skill demands and to workers with different skills. In the Appendix, we show that worker and firm expected utilities can be characterized as Bellman equations, which let us derive our model's key equilibrium parameters via the intersection of labor demand and supply and the Beveridge curve steady-state condition on unemployment. Formal derivations and proofs are developed in Appendix A1. Using these labor market equilibrium conditions, we can derive a simple close-form expression for the firm's maximized profit function π_i^* in equilibrium:

$$\underbrace{\pi_i^*}_{\text{Max profit}} = \underbrace{A_i x_i^{\alpha}}_{\text{Revenue}} - \underbrace{w_i^*}_{\text{Wage}} - \underbrace{(1-h_i)\rho_i}_{\text{Cost of inbound search}} - \underbrace{h_i\sigma_i}_{\text{Cost of outbound search}} - \underbrace{\frac{\gamma_i(\beta+\delta_i)}{((1-h_i)p(x_i)+h_i)q(\theta_i)}}_{\text{Cost of unfilled vacancy}} \tag{2}$$

Given this profit function, a few patterns become clear regardless of the mode of hiring chosen by the firm. Namely, when there is an increase in the cost of an open vacancy γ_i, the likelihood of job destruction δ_i, or the discount factor β—profits decrease. Crucially, this translates into the value of vacancies going down. To maintain equilibrium, this implies that firms will post fewer vacancies for each unemployed worker.

More consequentially, we note that the actual cost of outbound recruiting (σ_i)

determines how profitable it is for firms to switch hiring modes. If the cost of finding skilled workers decreases (e.g., there is a shock that increases the availability of online worker profiles), the value of outbound recruiting increases.

Proposition 1 *The firm's intensity of outbound recruiting (h_i) increases as the exogenous cost of outbound search (σ_i) decreases.*

Proof. We first compute the F.O.C. for outbound recruiting intensity, and then we take the partial derivative of the F.O.C. with respect to the cost of outbound recruiting, σ_i.

$$\frac{\partial \pi_i}{\partial h_i} = \rho_i - \sigma_i - \underbrace{\frac{-\gamma_i \overbrace{(1-p(x_i))}^{<0} q(\theta_i)}{[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2}}_{>0} < 0 if \rho_i > \sigma_i$$

$$\partial \frac{\left(\frac{\partial \pi_i}{\partial x_i}\right)}{\partial \sigma_i} = -1 < 0$$

We want to assess how the optimal decision of investment in outbound recruiting (h_i) changes with the cost of outbound recruiting (σ_i). In our model, h_i is the firm's decision variable, so we start taking the derivative of profits with respect to h_i — the first order condition. Note that the optimal wage w_i^* is locked in every period as a result of Nash bargaining, so bargained wages do not respond contemporaneously to changes in outbound recruiting h_i. Next, we take the second order derivative with respect to outbound recruiting cost, which reveals the optimal response of outbound recruiting to changes in its cost. As shown in the proof, as the cost σ_i increases, the firm adjusts its outbound recruiting level h_i downwards.

Second, we highlight the importance of skill requirements. Our model proposes that, all else equal, the firm will choose how much to invest in outbound recruiting to conduct its hiring objectives based on its demanded level of skill. We show that a firm requiring a higher number of skills will adjust its outbound intensity upward, such that the share of positions hired through outbound recruiting increases.

Proposition 2 *As the firm requires higher skills (x_i) the optimal choice of outbound recruiting intensity (h_i^*) increases, provided the cost of hunting is lower than the cost of screening incoming applications.*

Proof. We will use the implicit function theorem to evaluate the sign of $\frac{dh_i}{dx_i}$.

$$\frac{dh_i}{dx_i} = -\frac{\frac{\partial \pi_i}{\partial x_i}}{\frac{\partial \pi_i}{\partial h_i}}$$

The partial derivatives of π_i with respect for h_i and x_i are:

$$\frac{\partial \pi_i}{\partial x_i} = \underbrace{A_i(1-\alpha)x_i^{(\alpha-1)}}_{>0} - \underbrace{\frac{\gamma_i \overbrace{p'(x_i)}^{>0} q(\theta_i)(1-h_i)}{[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2}}_{>0} > 0$$

$$\frac{\partial \pi_i}{\partial h_i} < 0$$

We are interested in how demand for skills x_i affects the optimal level of outbound recruiting h_i; that is, $\frac{dh_i}{dx_i}$. We use the implicit function theorem to evaluate this derivative, since it allows us to derive the effect of two decision variables on each other with their relationship determined by the optimal profit function as described in Equation (2). We find that $\frac{dh_i}{dx_i} > 0$ when $\rho_i > \sigma_i$; if the cost of hunting is lower than the cost of reviewing applications, higher skill requirements imply higher level of outbound recruiting.

Lastly, we note that, once the firm has decided to invest in outbound recruiting, it will require a higher skill level from its employees.

Proposition 3 *The higher the outbound recruiting intensity (h_i) for a firm, the higher the optimal skill level (x_i) required in their vacancies.*

$$\partial\frac{\left(\frac{\partial \pi_i}{\partial x_i}\right)}{\partial h_i} = -\gamma_i \underbrace{p'(x_i)}_{<0} q(\theta_i)[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2 - \frac{\gamma_i \overbrace{p'(x_i)}^{<0} q(\theta_i)(1-h_i)2((1-h_i)p(x_i)+h_i)q(\theta_i)\overbrace{(-p(x_i)+1)}^{>0}}{[(1-h_i)p(x_i)+h_i]^4 q(\theta_i)^4}$$

In the last proposition, we evaluate how firms adapt their higher skill demand when changing outbound recruiting levels. We take the first-order condition of profit with respect to skill demand x_i, and use the result to evaluate the derivative with respect to outbound recruiting h_i. We find that the result is positive, meaning firms adjust their skill demand upwards after increasing outbound recruiting. The intuition here would be that, after making the investment to outbound recruiting, the new matching technology increases the value of higher skilled workers.

3 Data and methods

Our empirical approach in this article is descriptive and analyzes two primary data sets, one of which is new for this article. We use the predictions from our model presented in the prior section to guide our analysis.

First, we conducted a nationally representative survey of American workers to understand the use of outbound recruiting in the US labor market. These data allow us to estimate national-level facts about the prevalence of this practice and build 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. This data allows us to document changes in the demand for recruiters and test what sorts of firms are most likely to invest in these capabilities.

3.1 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. We specified a sample size that would provide us a margin of error of ±1%. The collected survey responses are then weighted to reflect the population figures in the Current Population Survey (CPS) conducted by the US Census Bureau.[7]

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 employed Americans were initially hired by 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

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

- 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 allowed us 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 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*. Again, 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).

3.2 Job postings 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 of U.S. job postings from 2010 through 2020 and are described in more detail by Deming and Kahn (2018). The raw job descriptions are cleaned and structured by BGT.

We structure this data in two ways. First, we leverage the fact that the data provider assigns each job a SOC code; we identify all postings classified as "Human Resources" roles. Using these 3,672,630 HR job postings from 2010 through 2020, we create a year-month level data set to measure how H.R. skill demands have changed over the last decade. Precisely, we measure two critical aspects of H.R. skill. First, we measure if the H.R. positions are focused on recruiting or headhunting. To do so, we check if the raw text of the job title includes the words "recruit," "talent," or "candidate sourcing." We classify such jobs as recruiting-focused. Second, we check the job's skills requirements and classify the job as recruiting-focused if the skill list includes the same words. We also measure whether the H.R. position requires social media skillsby checking if BGT classifies the job requiring the use of social media platofrms (e.g. LinkedIn, Facebook, Twitter, ...) or lists "social media" as a general skill. This second measure allows us to check if firms increasingly demand H.R. professionals who can use platforms like LinkedIn, GitHub, and Twitter to hunt for talent.

The second way we use the BGT data leverages the fact that most job postings list the employer name allowing us to build a firm-level data set. With this data, we study which firms are more likely to invest in recruiting and whether investments in recruiting change the sorts of workers a firm demands in the future. Appendix A2 describes how we use fuzzy matching to create employer I.D.s within cities. However, using the BGT data to analyze firm-level behavior presents two challenges. First, job postings reveal the firm's demand for talent and not the firm's current stock of human capital. This limitation is a concern because a firm could have posted for and hired a recruiter in 2008, but since our panel starts in 2010,[8] we would classify it as having not invested in recruiting capabilities. The second challenge is that many firms hire

[8]The BGT data includes a handful of observations from 2007. However, we exclude this early data because it captures much less of the U.S. labor market and BGT is missing postings from 2008 and 2009.

only one or two workers, rely on more informal H.R. processes, and rarely hire. These firms are likely to seek talent without writing and posting a formal job ad, so the skills these firms demand will be poorly measured in the BGT data.

To overcome these challenges, we focus on "growth-focused" firms in the BGT data where we can best measure the history of job and skill demand within the firm. First, to overcome the fact that firms hire before the BGT panel started in 2010, we limit our data to firms whose first posting is in January 2016 or later. For these firms, we know they had not been posting for jobs for at least six years beforehand. This lack of hiring may be because the firms are new startups or are older firms that only focused on growing their labor force in 2016 or later. In either case, these firms will be less likely to have hired a recruiter right before our panel begins. Second, we limit our sample to firms that have posted at least 20 job postings. This restriction helps us exclude firms that do not write up formal job descriptions or only hire once or twice and thus are very unlikely to ever try and hire a full-time recruiter.

We then use this sample of "growing" firms to build a firm-month level panel data set that runs through 2020. Specifically, each firm that meets the two criteria above enters our firm-month panel as soon as the firm has posted 20 job postings. For example, a firm that first posted for a job in June 2015 and had its 20th posting in October 2016 would enter our panel in October 2016. For this October 2016 cohort, we would have a balanced panel running through 2020. However, our overall panel is not balanced as different cohorts are observed for different numbers of months. Our first cohort is from January 2016 and runs for 60 months. Our final cohort from December 2018 runs for 25 months. We do not include "entering" firms in 2019 or later to have at least two years of posting data. The result across all our cohorts is a data set with 1,222,338 firm-month observations from 34,157 firms.

For each firm month, we construct two key variables. First, in each month, we mark whether the firm has "Posted for a recruiter?" yet. For firms that posted for a recruiter in their first 20 postings, this variable will always be 1. For firms that never try and hire a recruiter, this variable will be zero. Appendix Figure A5 shows the the percentage of firms by cohort year that have posted for a recruiter overtime. Roughly 10% of firms post for a recruiter in their first 20 postings, with the recruiting rate converging to roughly 30% after about two years.

Our second core variable measures whether the firm demands higher- or lower-skilled workers. To measure the firm's skill demand, we exploit the fact that BGT parses job postings for skill requirements (Hershbein and Kahn, 2018). For example, in our sample of growth-focused firms in the BGT data, the online engagement platform Pendo posted job ads for an "Account Executive." The Account Executive job posting listed 12 different skills: *prospective clients, research, business-to-business, sales, product sales, technical assistance, software as a service (SaaS), customer contact, product management, business development, contract negotiation, salesforce.* BGT derives these skills from the raw job posting text, maps these skills maps them to an ontology similar to O*NET codes, and sanitizes skills to remove duplicates and fix spelling errors. For our analysis, we simply sum the number of skills listed in the job posting according to BGT. We find the average job lists 6.06 skills for our sample of firms with a standard deviation of 7.51 skills. We then aggregate the job level skills and calculate a simple average of the number of skills across all postings to estimate the firm's skill demand that month. In months where the firm does not post any jobs, we set the value of this variable to 0. Appendix Figure A4B shows the average number of skills at the posting level and at the firm-month level.

Beyond these two key variables, we also created a variable for the total number of jobs a firm posts in a month and data on the MSA the firm operates in and the firm's industry (NAICS3). These latter two measures are often missing, so analyses relying on our MSA or industry measures rely on a smaller sample of firms for which we have this information.

4 Results

4.1 The rise of recruited workers and recruiting professionals

4.1.1 Evidence of firm-driven search from a nationally representative worker survey

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 the other 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 asked 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 total US sample found and applied for the role themselves, and existing employees referred another 34.6% of workers.

[Table 1 about here.]

How does this compare to past estimates of hiring sources? As noted earlier in the paper, prior work studying how workers get jobs has an overwhelming focus on how workers apply to job openings (e.g., Pissarides, 1985) or how existing employees use their social networks to hire through referrals (e.g., Fernandez and Weinberg, 1997).

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

As such, surveys of U.S. workers have rarely explicitly asked workers whether they were recruited, either by a headhunting firm or their employer (Carrillo-Tudela et al., 2015). That said, in the 1991 wave, the General Social Survey[10] included the following question: "There are many ways people hear about jobs – such as from ads, employment agencies, or from other people. Could you tell me how you found out about work at your present employer? Please tell me all the ways that you found out about this job." Respondents could select "From a recruiter for this employer." We find that 4.87% of workers indicated they had been recruited.

A potential concern with the GSS number is that the unemployment rate in 1991 was approximately 6%; the rate was 3.6% in December 2019. Perhaps the increase in recruiting is simply cyclical and not a secular trend over the last few decades? While we lack definitive data to rule out this alternative, we also conducted a new survey of 1,175 U.S. workers in September 2020. Due to the COVID-19 pandemic, which hit the U.S. in March of 2020, the unemployment rate spiked to 14.8% in April of 2020, and while it dropped, by September 2020, the rate was still 7.8%. Despite this higher unemployment rate, our September 2020 survey indicates that 16.09% of workers were hired through firm-driven search. Further, among those that switched jobs after the beginning of the pandemic, the outbound recruiting figure was 18.85%. The increased prevalence of recruiting does not appear to be an artifact of the tight pre-pandemic labor market.

This increase in recruiting is not only temporally robust but appears across the U.S., though the increase is strongest in labor markets with stronger (technological) skill demand. We over-sampled workers in five U.S. MSAs (Rochester, Denver, Sacramento, Portland, and Miami) to test for geographic variation. We selected these regions randomly within the 2019 unemployment-rate quintiles. We over-sampled three major

[10]https://gssdataexplorer.norc.org/variables/1282/vshow

technology hubs in the United States (San Jose, San Francisco, and New York City). We present these results in Table 2. As shown in the table, all regions recruit at rates higher than the 1991 rate of 4.87%. That said, there are differences in outbound recruiting by region. In San Jose—the home of Silicon Valley— 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 ($z = 3.7$, $p \leq .01$).

[Table 2 about here.]

Another notable pattern in Table 2 is the overall stability of referrals, at approximately 33 to 34%, with little variability across regions. Instead, 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.

Consistent with the idea that digital platforms have played a role in lowering the costs of firm-driven search, we find that workers who used LinkedIn are more likely to have been recruited. The largest online professional network, LinkedIn allows workers to create online career profiles and share information about their education, experience, and skill while building connections to other workers. LinkedIn then sells access to these workers-especially data on workers with particular skills and experiences-to firms and recruiters hunting for talent. Consistent with the idea that online platforms enable firm-driven search in Table 3 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 3 about here.]

Appendix A3 presents a number of additional results from our survey. In short, we find male workers are more likely to have been recruited than female workers, we find little in the way of a race gap, and that STEM workers are the most likely to have been recruited.

4.1.2 Evidence of firm-driven search from job postings

Our model suggests that the increase in recruiting is the result of firms investing in outbound recruiting capabilities. A consequence of these investments is that the demand by firms for HR professionals with headhunting and recruiting skills should have increased. Even for firms without the resources to hire a dedicated headhunter, if online platforms have lowered the cost to find the talent, we should expect the demand for HR professionals who can use these social platforms to grow. Figure 1 tests these predictions.

Figure 1A shows the percentage of HR job postings in the complete BGT data that are either explicitly titled as looking for a recruiter or list recruiting as a skill in the job posting. In 2010 roughly 33% of HR jobs involved recruiting; by the end of 2020, almost 50% of HR jobs involved recruiting. While the increasing demand for HR professionals with recruiting skills appears linear over this period, there is a steep drop in early 2020 due to the onset of the COVID-19 pandemic in the United States. However, with the shift to remote work and the opening of the US economy, we see that the percentage of HR jobs that focus on recruiting has more than rebounded to the pre-pandemic trend.

This increase is robust. Appendix Figure A1 shows the percentage of job postings in the BGT data classified as HR roles has been roughly constant at about 1.4%, with a steep drop to around 1% post-covid. While the percentage of HR-focused recruiting has bounced back to pre-pandemic trends, the BGT data suggests firms were still hiring fewer HR professionals through the end of 2020. Appendix Figures A2 and A3 show that the increase in demand for recruiting skills holds when we focus on just listed skills or job titles. HR roles in 2020 are more outbound focused than they were in 2010.

[Figure 1 about here.]

Echoing Table 3, which showed that workers active on LinkedIn are more likely to be recruited, we show in Figure 1B that firms are increasingly looking for HR professionals with social media skills. In 2010, 2% of HR jobs listed "social media" (e.g., LinkedIn, Github, ...) as a skill; by the end of 2020, over 10%. Again, we see a dip due to the COVID-19 pandemic, but one that ends after six months.

Overall, our nationally representative worker survey and our analysis of job postings show that recruiting is much more prevalent in the US labor market than in the past three decades. By way of contrast, the percentage of workers hired through referrals appears to have barely budged over the last half-century and appears constant across labor markets. Consistent with the idea that digitization has allowed recruiters to identify workers more efficiently and at a lower cost, we find that LinkedIn users are more likely to be recruited. Firms increasingly seek out HR professionals who can use social media, presumably to hunt for talent.

4.2 High skill firms are more likely to hire recruiters

Beyond a rise in outbound recruiting, a key prediction of our labor-market model is that firms with higher skill requirements will be more likely to invest in firm-driven search. Since workers with more skills are harder to find, outbound search allows firms that rely on skilled talent to increase the odds they find a worker who meets their skill needs.

We test this prediction using our sample of growth-focused firms. To do so, we calculate the average skill requirement for the firm's first 20 postings. For each of these 34,157 firms, we then calculate if the firm subsequently posts for a recruiter. Figure 2 presents a binned scatter plot of whether the firm tries to hire a recruiter against the average number of skills the firm demands in its first 20 postings for firms in the 2016 cohort. We find a strong positive relationship. A firm that demands five skills on average goes on to post for a recruiter 40% of the time, whereas a firm that demands 15 skills goes on to post for a recruiter nearly 80% of the time.

[Figure 2 about here.]

Table 4 presents linear probability models of whether the firm posts for a recruiter on the average skill count for the firm's first twenty posts. These models include growth-focused firms from all cohorts. They include fixed effects for each cohort to account for the fact that firms that enter our data in January 2016 are at risk of hiring a recruiter for a much more extended period than firms that enter in December of 2018. Model 1 presents the model with no additional controls and reveals that when firms demand one additional skill, on average, their probability of hiring a recruiter increases by 4.1%.

In Model 2, we include MSA fixed effects to test if this skill-recruiting relationship is driven by the firm's skill demand or the fact firms in hot high-skilled labor markets might need to hire a recruiter regardless of the firm's skill demand. We find little evidence that the labor market is what matters. Similarly, in Model 3, we include Industry fixed effects and again find little evidence that these differences explain the skill-recruiting relationship.

Finally, in Model 4, we include MSA-Industry fixed effects. This model tests if firms operating in the same MSA and the same industry are more likely to post for a recruiter when they demand higher-skilled workers. The coefficient shrinks ever so slightly to 3.7%. Differences across labor markets or industries do not appear to explain our results. Instead, and consistent with our model, it appears that firms that demand harder-to-find high-skilled workers are more likely to try to hire someone who can help them hunt for talent themselves.

[Table 4 about here.]

4.3 Firms that invest in recruiting choose to search for higher-skilled workers

The third prediction from our model is that when firms decide to invest in outbound recruiting, they will also be more likely to raise their skill requirements. To test if investments in recruiting lead firms to up their skill requirements we leverage the fact that *when* a firm posts for a recruiter differs across firms within the same cohort. Some firms post in a matter of months, and others take a year or two. While we cannot observe whether the firm ultimately hires a recruiter, nor is this variation likely exogenous, it allows us to construct event-study type models to check if when a firm decides to move to outbound recruiting if it also makes a meaningful shift towards higher-skilled workers.

Figure 3 shows event-study lead-lag plots for six firm cohorts that post for a recruiter at some point during our panel. The y-axis is the average number of skills a firm lists in its job posting in a month (excluding HR posts). The x-axis is the number of months before and after the firm posts its first post for a recruiter. We split the data by cohorts because we observe some cohorts for more months than others and to better ensure our "control" firms will have similar growth trajectories. Put differently, within each cohort we have a canonical staggered difference-in-differences design.

[Figure 3 about here.]

For each cohort presented in Figure 3 we see a marked and sudden jump in the average number of skills the firm demands in the month after it decides to post for a recruiter. The increase is substantial, roughly six additional skills when the average job in our sample lists 6.06 skills. While there is a decrease in the skill demand over time, even after 18 months, firms are looking for high-skilled workers. The sudden jump suggests that it is not the recruiter that is having the effect—who is unlikely to start within a month of a job posting—but instead firms deciding to both invest in recruiting and at the same time move towards a higher-skilled workforce. This finding is consistent with the predictions of our model.

While Figure 3 shows a clear shift in the firm's skill demand, a potential concern is that the pattern is simply driven by firms posting more jobs in more months. Since months without a job posting are coded as zeroes, it might well be that the shift is in the firm's demand for labor, not its demand for higher-skilled workers. To address this alternative in Figure 4 we plot the average number of postings per month relative to the first month the firm posts for a recruiter. Unlike Figure 3, there is no clear jump in the month after posting. Instead, it appears that until the firm decides to hire a recruiter, a firm is increasingly likely to post for other roles. Further, once they post for a recruiter, the number of postings remains essentially flat. As shown in Appendix Figures A6 and A7, the results in Figure 3 and 4 hold with when we estimate the event-study models using Sun and Abraham's (2020) correction to address staggered roll out bias. The most notable difference between the corrected and uncorrected estimates is that the standard errors are wider after 18 months. There is also a more pronounced drop for the January and June 2019 cohorts. This drop may result from the onset of the pandemic in early 2020, which impacted hiring by firms in these cohorts. No matter, in both sets of plot we find a distinct increase in a firm's skills demand after posting but no such increase in the number of jobs it posts.

[Figure 4 about here.]

To further confirm that our results reflect a shift in the demand for high-skilled workers and not merely increases in overall demand, Table 5 presents regression estimates of the average number of skills on whether the firm has posted for a recruiter. Model 1 includes cohort and year-month fixed effects. Model 2 adds firm fixed effects and is the standard two-way fixed effects model, with its benefits and biases. Models 3 and 4 replicate Models 1 and 2 but drop all months where the firm has zero job postings to isolate the effect on the intensive "number of skills margin" against the extensive "did the firm post?" margin. The results are consistent with the findings in Figures 3 and 4. Once firms decide to invest in recruiting, they increase the skills they demand in other roles.

[Table 5 about here.]

5 Discussion and Conclusion

We theorize that the reduced cost of finding workers due to the emergence of digital labor market platforms (e.g., LinkedIn) (Elfenbein and Sterling, 2018) combined with the preference for hiring high-skilled workers externally (Cappelli, 2012) has led to the prevalence of firm-driven search in the economy. We formalize these ideas using a generalization of the classical Diamond-Mortensen-Pissarides (DMP) framework that incorporates heterogeneous skills and firm agency in the use of outbound recruiting. Our model generates several predictions about which workers and firms are most likely to be impacted by these shifts.

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. 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).

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 labor, are increasingly developing capabilities to better hunt for talent. These changes are reflected in four core 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. Third, we see that this demand is concentrated in firms requiring high-skilled workers. Finally, firms that invest in trying to hire recruiters appear to shift their skill demands upward.

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. An important implication of our model and findings is that outbound recruiting is most beneficial for firms that have higher skill demands, and at the margin, may shift firms to seek out higher skilled workers.

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 or databases firms now rely on (e.g., hired.com, online spreadsheets listing recently exited employees from significant technology firms[11]). 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-

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

driven search impacts gender, racial, and geographic inequality.

Another contribution of our research is to a 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 are becoming increasingly data-driven, likely affecting 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, provides much needed evidence on the 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. we believe that extending our model and relaxing some of its assumptions can provide new insight. By allowing for wage bargaining at the firm-worker level, our model allows for the study job polarization and wage inequality, which are essential ingredients in assessing who gains and who loses from outbound recruiting practices, both on the worker and firm sides. Our model could be extended to analyze the role of outbound recruiting in talent creation rather than simply its allocation.

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 skills (Barney, 1991)? Which firms and workers will benefit from outbound recruiting? How will this shift affect the nature of existing labor market signals, such as firm status (Bidwell et al., 2015), 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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Figure 1: The changing skill requirements for HR professionals. Panel A shows the percentage of online US HR job postings that list job recruiting as a skill or have "recruiting" as part of the job title. Panel B shows the percentage of online US HR job postings that require social media skills (e.g., LinkedIn, GitHub, Twitter). Points indicate the percentage for a given month and are scaled by the number of job postings in that month.

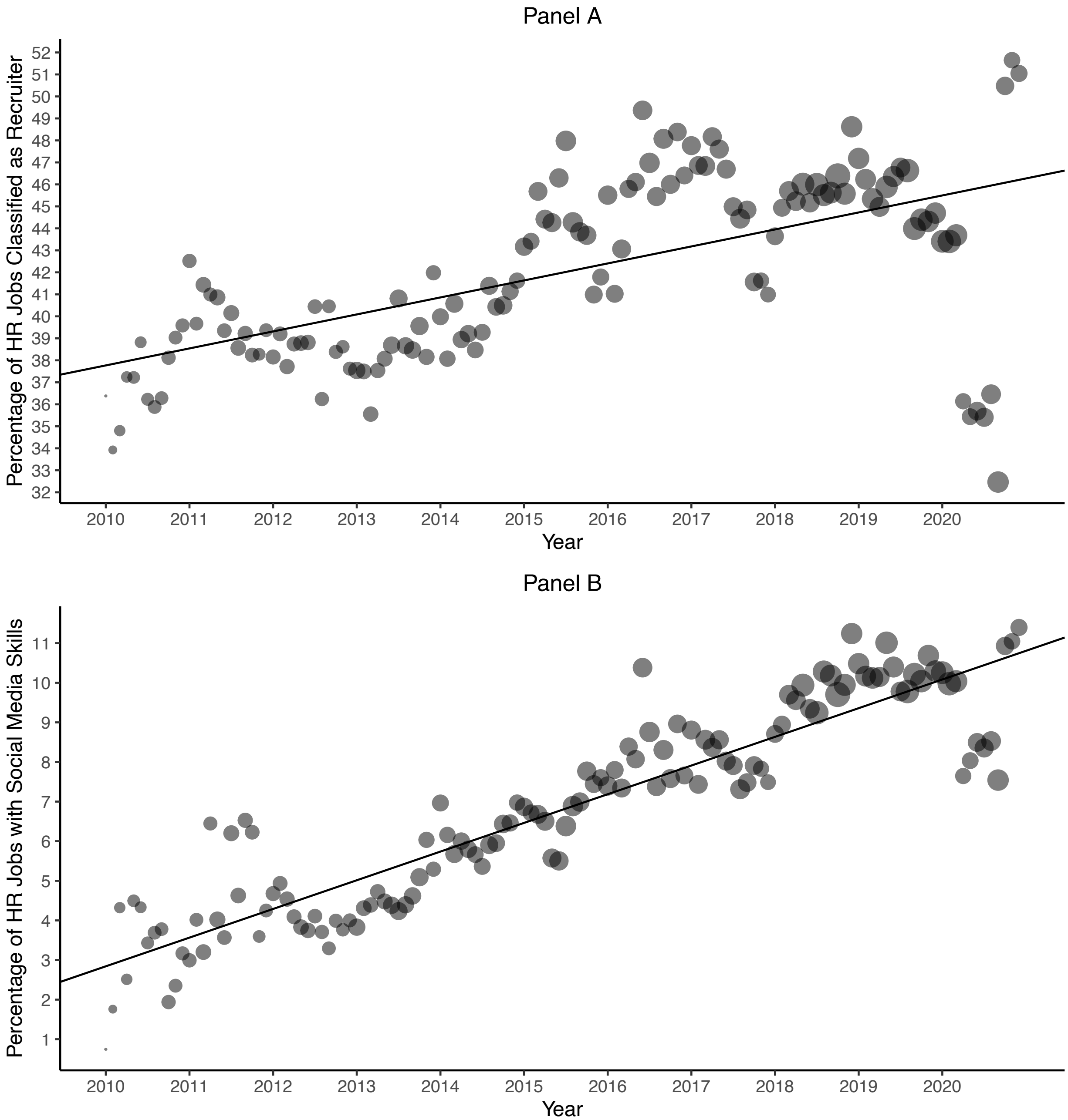

Figure 2: Binned scatter plot showing the probability a firm posts for a recruiter in in the future (y-axis) against the average number of skills the firm demands in the first 20 job postings that Burning Glass records (x-axis). This plot includes all firms that had there 20th job posting as of December 31st, 2016 and a first post no earlier than January 1st, 2015. We track whether the firm hires a recruiter in the future through December 31st, 2020.

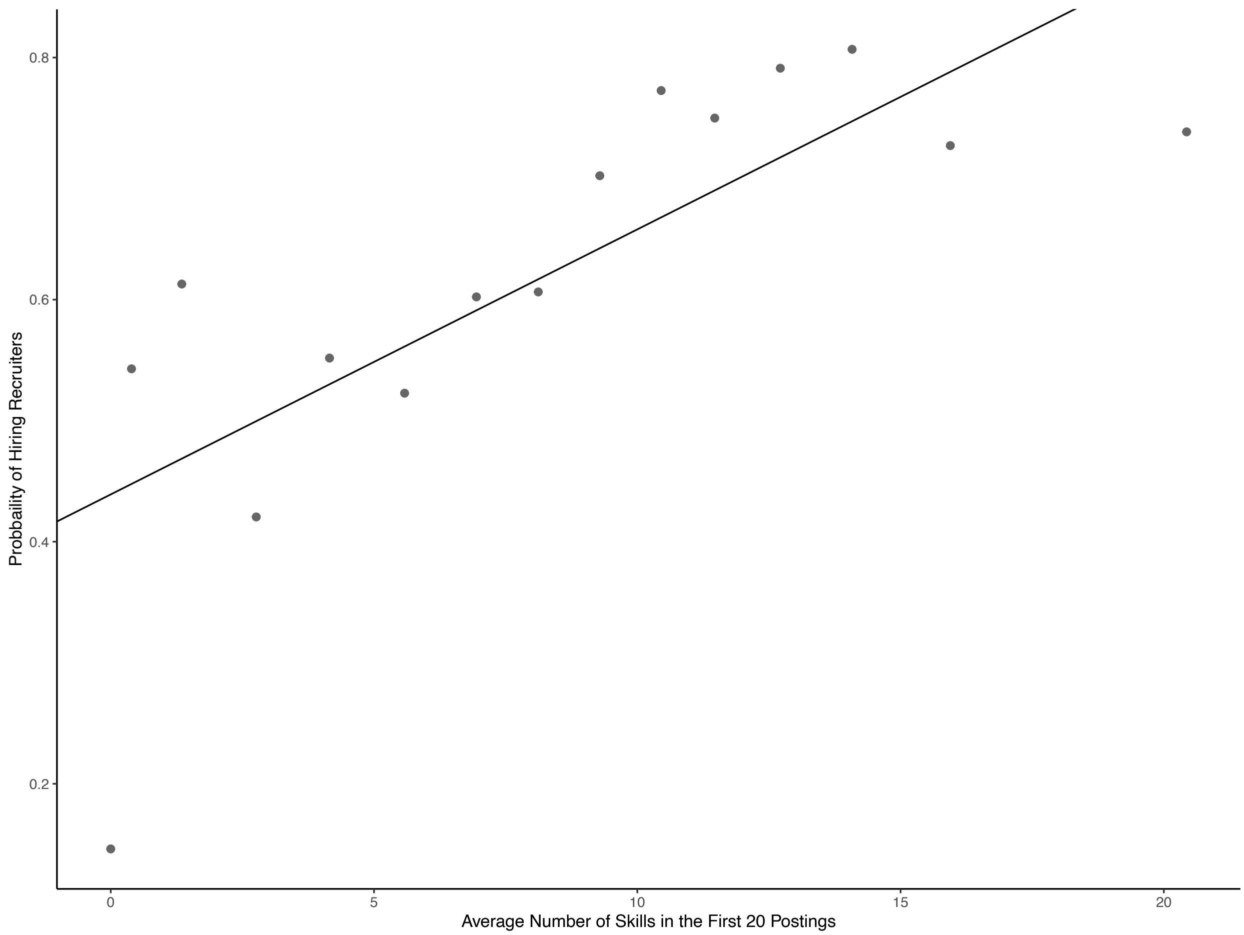

Figure 3: Event-study plots showing the firm's skill demand before and after deciding to invest in recruiting. The x-axis is month for the firm's first recruiting posting and the y-axis is the estimated effect on the average number of skills listed in job postings that month. Each plot represents a different cohort of growth-focused firms, with the results labelled "January, 2016" including firms that posted their 20th job in that month and "June, 2018" representing firms that posted their 20th job in that month. Bars are 95% confidence intervals clustered at the firm level. Recruiting jobs are excluded when calculating the dependent variable. Models include firm and time-period fixed effects.

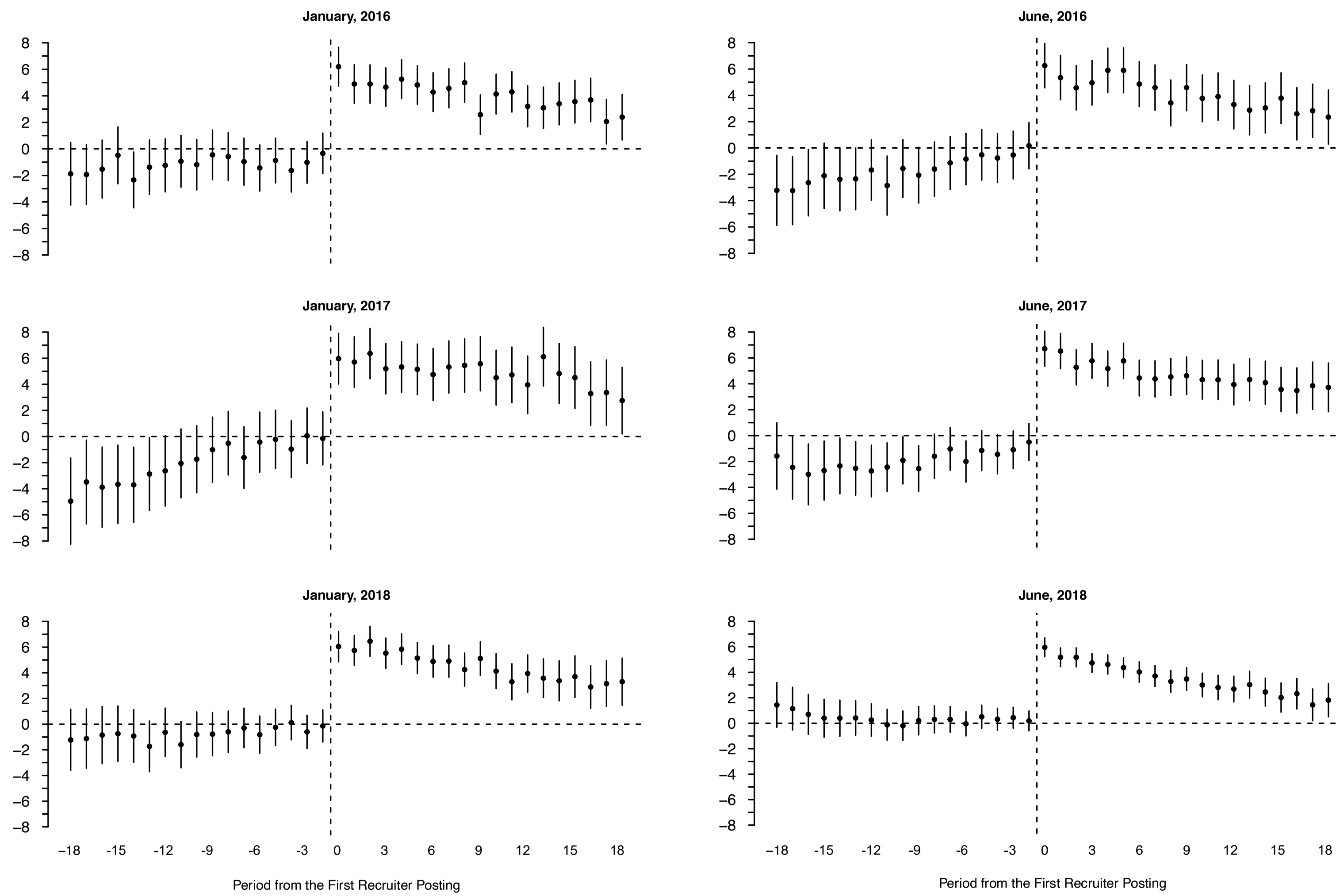

Figure 4: Event-study plots showing the firm's number of job postings before and after deciding to invest in recruiting. The x-axis is the month for the firm's first recruiting posting, and the y-axis is the estimated effect on the number of job postings. Each plot represents a different cohort of growth-focused firms, with the results labeled "January 2016" including firms that posted their 20th job in that month and "June 2018" representing firms that posted their 20th job. Bars are 95% confidence intervals clustered at the firm level. Recruiting jobs are excluded when calculating the dependent variable. Models include firm and time-period fixed effects.

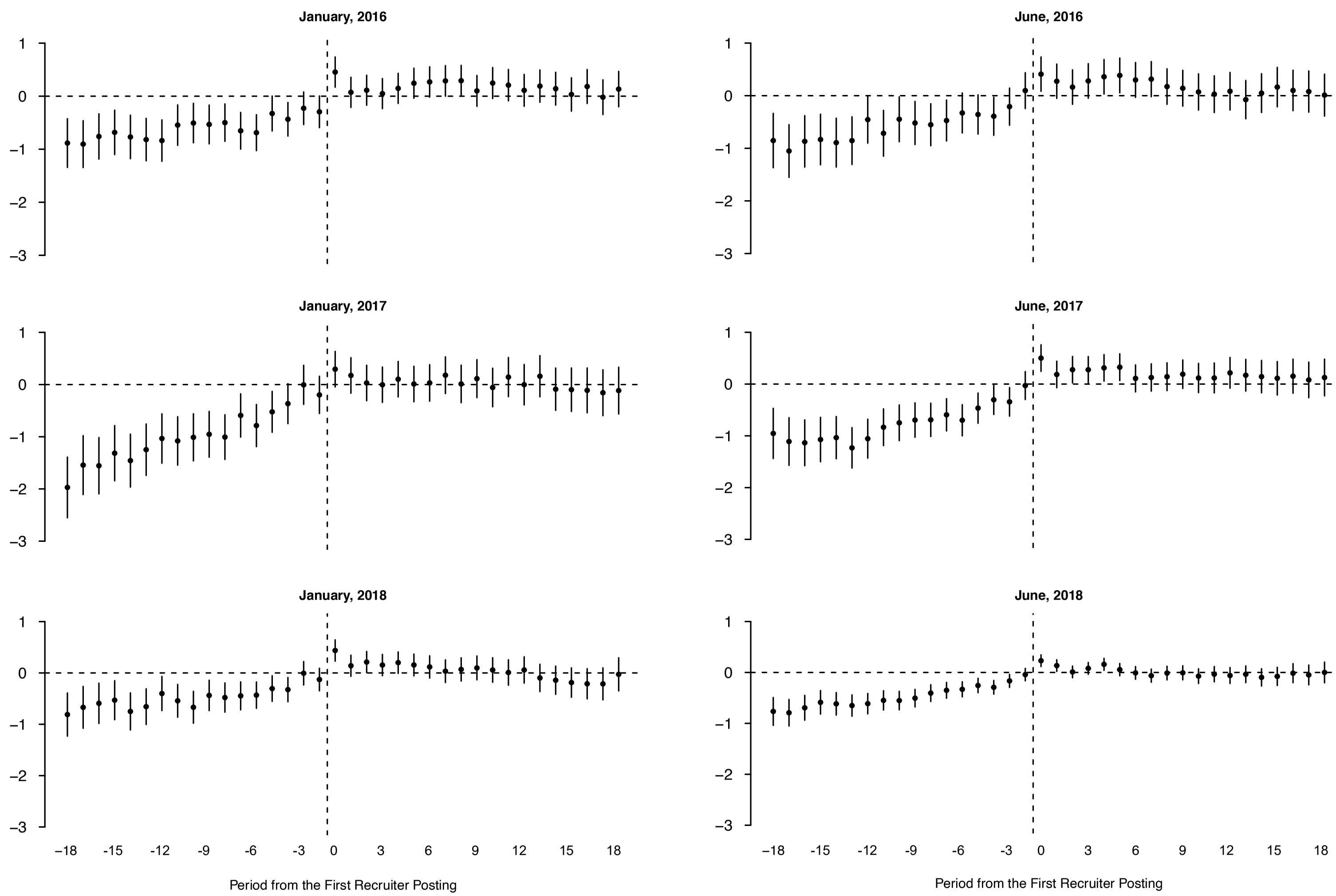

Table 1: The prevalence of different hiring mechanisms in the United States labor market in January 2020.

	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 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 3: 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 4: Cross-sectional models that regress whether a firm ever hires a recruiter on the average skill of the firm's first 20 online job postings. The data include all firms with at least 20 postings that started posting after 2015. To control for variation in how long a firm has been at risk of hiring a recruiter, all models include cohort fixed effects for the month-year the firm enters our data. Model 1 includes no further controls. Model 2 includes MSA controls, with the sample size dropping as we lack MSA information for most firms in our sample. Model 3 includes industry fixed-effects, again with the smaller sample size due to missing data. Finally, model 4 includes MSA×Industry fixed effects.

Dependent Variable:	Posts for a recruiter?			
Model:	(1)	(2)	(3)	(4)
Average skill count of the first 20 postings	0.041***	0.039***	0.040***	0.037***
	(0.0008)	(0.001)	(0.0008)	(0.001)
Fixed-effects				
Cohort	Yes	Yes	Yes	Yes
MSA		Yes		
Industry			Yes	
MSA×Industry				Yes
Fit statistics				
Observations	34,152	13,246	16,039	6,724
R^2	0.19199	0.24150	0.22076	0.46350

Robust standard-errors clustered at the firm level in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Table 5: Panel models regress the number of skills the firm demands in its job postings on its decision to invest in recruiting. The data is at the year-month-firm level for the 1,222,338 firms in our sample of growth-focused firms that have posted for at least 20 positions. All models include year-month fixed effects to account for across-firm time trends. Models 2 and 5 include firm fixed effects. Models 1 and 2 include all months, with average skills set to zero in months when the firm doesn't post at least one new job. Models 3 and 4 only only include months where the firm posts at least on job.

Dependent Variables:	Average skill count per post			
Model:	(1)	(2)	(3)	(4)
Posted for a recruiter?	6.2***	5.4***	8.8***	6.5***
	(0.12)	(0.27)	(0.08)	(0.25)
Fixed-effects				
Year-Month	Yes	Yes	Yes	Yes
Firm		Yes		Yes
Sample Restrictions				
Only months with a job posting			Yes	Yes
Fit statistics				
Observations	1,222,338	1,222,338	568,217	568,217
R^2	0.23886	0.60042	0.36598	0.77658

Robust standard-errors clustered at the firm level in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Online Appendix:
Hunting for Talent

A1 Proofs

A1.1 Parameters list

[Table A1 about here.]

Both agent types maximize their expected utilities summarized by the Bellman equations in Equation (3) and (4). The equations transform the infinitely lived agent's optimization problem into a recursive, one-period objective function. Formal derivations of Bellman equations are in Appendix A1.

A1.1.1 Worker's optimization

Let V_i^e and V_i^u denote the value being employed and unemployed with skill level $i \in [0, x^{max}]$. After a match, unemployment only occurs as a result of shock to the survival of a firm. Since δ_i is the exogenous probability of firm closure, it is also the probability of unemployment. In the employed state, agents receive a bargained wage of w_i, whereas, in unemployment, agents receive unemployment benefits z_i. The expected discounted lifetime net income of being employed corresponds to the wage earned while employed w_i, netting the likelihood of becoming unemployed and transferring to the state where they receive the unemployment payment.

$$\beta V_i^e = w_i - \delta_i (V_i^e - V_i^u) \quad \forall i \in [0, x^{max}] \tag{3}$$

Thus, the expected discounted lifetime net income of being unemployed corresponds to the unemployment benefits z_i added to the likelihood of becoming employed.

$$\beta V_i^u = z_i + [(1 - h_i) p(x_i) \theta_i q(\theta_i)](V_i^e - V_i^u) \quad \forall i \in [0, x^{max}] \tag{4}$$

Note that, in our model —and differently from the standard DMP framework— equation (3) describes the likelihood of becoming employed as $[(1-h_i)p(x_i)\theta_i q(\theta_i)]$. As described in Section 2.2, h_i is the intensity of hiring through outbound recruiting, and $h_i \in [0, 1]$. When the firm allocates resources to inbound recruiting $(1 - h_i)$, it receives a rate of matching of $p(x_i)q(\theta_i)$ as described in the previous section (and therefore workers receive a rate of matching of $p(x_i)\theta_i q(\theta_i)$).

A1.1.2 Firm's optimization

The firm's production function is $y_i = A_i f(x_i)$. We assume the firm has access to a Cobb-Douglas production technology, such that $y_l = A_l x_i^{\alpha}$. Additionally, we also assume that a worker with a higher skill level can perform the tasks of a skill requirement below hers. Firms decide what share of jobs are hired through outbound recruiting, with outbound intensity represented by h_i.

We define J_i as the value of hiring workers — the value of a "job" to the firm— and V_i as the value of posting a vacancy. The value functions for the firm are as follows:

$$\beta J_i = A_i x_i^{\alpha} - w_i - (1 - h_i)\rho_i - h_i\sigma_i - \delta_l(J_i - V_i) \tag{5}$$

The intertemporal value of a job depends on production ($A_i x_i^{\alpha}$) net of the cost filling the job (w_i, waged paid to the worker), the cost of each means of recruiting (ρ_i for inbound and σ_i for outbound) and the likelihood of firm closure with its corresponding transition to inactive state ($\delta_i(J_i - V_i)$).

$$\beta V_i = -\gamma_i + [(1 - h_i)p(x_i)q(\theta_i) + h_i q(\theta_i)](J_i - V_i) \tag{6}$$

The intertemporal value of a vacancy depends on the cost of keeping a vacancy open γ_i, net of the matching rate. This value is determined by the weighted average of the rate of inbound and outbound matches, $[(1-h_i)p(x_i)q(\theta_i)+h_i q(\theta_i)](J_i-V_i)$. Similar to the worker's case, the weights are the recruiting intensities in inbound $(1 - h_i)$ and outbound (h_i).

Appendix A1 takes the agents' optimization problems described in this section and derives the steady-state equilibrium.

A1.2 Agents' Optimization Problems: Bellman Equations

As in the standard DMP, we use the Bellman equation method to derive the intertemporal discounted lifetime income of both workers and firms. The Bellman equation transforms an infinite horizon (repeated) problem into a dynamic programming problem, for which the horizon is one period. In the case of workers, we derive the discounted lifetime income for both unemployed and employed states; similarly, we derive both discounted lifetime income for active and inactive firms. In this Appendix, we will focus on the derivation of the Bellman equation for unemployed workers, which corresponds to Equation (4). The derivation process is equivalent for the other three equations (employed workers, active firms, and inactive firms).

Unemployed Workers' lifetime income, V^u. During an infinitesimal time period dt, unemployed workers enjoy benefits z_i and may find a job. If the worker does not leave unemployment, s/he will keep earning z_i at $t + dt$. Conversely, if the worker finds a job, s/he will start earning the lifetime value of an employed worker, V^e. The probability that the unemployed worker finds a job in dt is equivalent to the probability that they get matched through inbound recruiting, $(1-h_i)p(x_i)\theta_i q(\theta_i)\cdot dt$, where h_i is the intensity of outbound recruiting —and therefore $1-h_i$ is the intensity of inbound recruiting—; $\theta_i q(\theta_i)$ is the arrival rate of a match for workers, and $p(x_i)$ the probability density of skills (shrinkage factor). For simplicity of the derivation, we will henceforth denote this probability by ϵ. Summarizing in equation form, and recalling the discount rate β, we have:

$$\underbrace{V^u(t)}_{\text{value of unemployment at time } t} = z_i(t)dt + \frac{1}{1+\beta dt}[\underbrace{\epsilon dt}_{\text{prob finding job}} V^e(t+dt) + \overbrace{(1-\epsilon dt)}^{\text{prob staying unemployed}} V^u(t+dt)]$$

Developing further:

$$\begin{aligned}(1+\beta dt)V^u(t) =& (1+\beta dt)z_i(t) + \epsilon dt V^e(t+dt) + (1-\epsilon dt)V^u(t+dt)\\ \beta V^u(t)dt =& z_i(t)dt + \beta z_i(t)dt^2 + \epsilon dt[V^e(t+dt) - V^u(t+dt)] + V^u(t+dt) - V^u(t)\\ \beta V^u(t) =& z_i(t) + \beta z_i(t)dt + \epsilon[V^e(t+dt) - V^u(t+dt)] + \frac{V^u(t+dt) - V^u(t)}{dt}\end{aligned}$$

Now, we take the limit as $dt \longrightarrow 0$:

$$\beta V^u(t) = z_i(t) + \epsilon[V^e(t) - V^u(t)] + \dot{V^u}(t)$$

with $\dot{V^u}(t) = \frac{dV^u(t)}{dt} = \lim_{dt\to 0}\frac{V^u(t+dt)-V^u(t)}{dt}$. We know that, in steady-state, $\dot{V^u}(t) = 0$, $V^e(t) = V^e$ and $V^u(t) = V^u$. The lifetime discounted worker income is therefore:

$$\begin{aligned}\beta V^u =& z_i + \epsilon[V^e - V^u]\\ \beta V^u =& z_i + [(1-h_i)\theta_i q(\theta_i)][V^e - V^u]\end{aligned}$$

which is Equation (4).

A1.3 Equilibrium Derivation

In this section we derive the conditions for steady-state equilibrium, based on the optimization of the agent's objective functions described in Section **??**. In the standard DMP model, equilibrium is derived from three conditions: (i) labor demand, (ii) labor supply, and (iii) Beveridge curve, which determines unemployment.

Free-entry condition and labor demand. In steady-state and because of free entry, firms post vacancies until $V_i \equiv 0$. As a result, Equations (5) and (**??**) become:

$$q(\theta_i) = \frac{\gamma_i(\beta + \delta_i)}{((1-h_i)p(x_i) + h_i)(A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i - h_i\sigma_i)} \quad \forall i \in [0, x^{max}] \quad (7)$$

Equation (7) represents the downward sloping labor demand curve in the (θ_i, w_i) space. The derivation of the labor demand curve can be found in Appendix A1 .

$$\begin{aligned} \beta J_i =& A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i - h_i\sigma_i - \delta_i(J_i - 0) \Leftrightarrow \\ (\beta + \gamma_i)J_i =& A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i - h_i\sigma_i \end{aligned}$$

$$\begin{aligned} 0 =& -\gamma_i + [(1-h_i)p(x_i) + h_i]q(\theta_i)(J_i - 0) \Leftrightarrow \\ J_i =& \frac{\gamma_i}{[(1-h_i)p(x_i) + h_i]q(\theta_i)} \end{aligned}$$

which together —equating J_i— become Equation (7), representing labor demand:

$$q(\theta_i) = \frac{\gamma_i(\beta + \delta_i)}{((1-h_i)p(x_i) + h_i)(A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i - h_i\sigma_i)} \quad \forall i \in [0, x^{max}]$$

Nash bargaining and labor supply. As explained in Section **??**, agents negotiate wages each period. Wage is determined by the maximization of total surplus per Equation (8):

$$\max_{\{w_i\}} \quad (V^e - V^u)^{\mu}(J_i - V_i)^{1-\mu}$$

F.O.C.

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

Note that $\frac{\partial V^u}{\partial w_i} = 0$ because wages are negotiated period to period. Rearranging Equations (3) and (5), we get:

$$V^e = \frac{w_i + \delta V^u}{\beta + \delta_i}$$
$$J_i = \frac{A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i q(\theta_i) - h_i \sigma_i q(\theta_i)}{\beta + \delta_i}$$

Replacing these in the F.O.C.:

$$\frac{\mu}{1-\mu}\frac{1}{\beta+\delta_i}\frac{A_i x_i^{\alpha} - w_i - (1-h_i)\rho_i q(\theta_i) - h_i \sigma_i q(\theta_i)}{\beta + \delta_i} + (V^e - V^u)\left(-\frac{1}{\beta+\delta_i}\right) = 0 \Leftrightarrow$$
$$(V^e - V^u) = \frac{\mu}{1-\mu}\frac{\gamma_i}{q(\theta_i)[(1-h_i)p(x_i) + h_i]} \tag{8}$$

Equation (8) defines a relationship between wages w_i and labor market tightness θ_i. Subtracting Equation (3) from (4) we get:

$$(V_l^e - V_l^u) = \frac{w_i - z_i}{\beta + \delta_i + [(1-h_i)p(x_i) + h_i]\theta_i q(\theta_i)}$$

Finally, plugging this result into Equation (8):

$$\begin{aligned}
\frac{w_i - z_i}{\beta + \delta_i + [(1-h_i)p(x_i) + h_i]\theta_i q(\theta_i)} &= \frac{\mu}{1-\mu}\frac{\gamma_i}{q(\theta_i)[(1-h_i)p(x_i) + h_i]} \Leftrightarrow \\
w_i &= z_i + \frac{\mu}{(1-\mu)}\frac{\gamma_i(\beta + \delta_i + ((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i))}{((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i))}
\end{aligned}$$

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

$$\begin{aligned}
((1-h_i)p(x_i) + h_i)(A_i x_i - w_i - (1-h_i)\rho_i - h_i\sigma_i)q(\theta_i) &= \gamma_i(\beta + \delta_i) \\
((1-h_i)p(x_i) + h_i)\left(A_i x_i - z_i - \frac{\mu}{1-\mu}\frac{\gamma_i(\beta + \delta_i + ((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i))}{((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i)})\right)q(\theta_i &= \gamma_i(\beta + \delta_1) \\
(1-\mu)\left(A_i x_i - z_i - \mu\gamma_i\frac{\beta + \delta_i + (1-h_i)p(x_i) + h_i}{(1-h_i)p(x_i) + h_i}\right) &= \frac{\gamma_i(\beta + \delta_i)}{q(\theta_i)((1-h_i)p(x_i) + h_i)}
\end{aligned}$$

Unemployment steady-state. unemployment steady-state is:

$$u_i^* = \frac{\delta_i}{\delta_i + [(1-h_i)p(x_i) + h_i]\theta_i q(\theta_i)}$$

Proposition 4 *The labor market equilibrium is characterized by the following equations:*

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

$$q(\theta_i) = \frac{\gamma_i(\beta + \delta_i)}{((1-h_i)p(x_i) + h_i)(A_i x_i^\alpha - w_i - (1-h_i)\rho_i - h_i\sigma_i)}$$

2. *Labor supply:*

$$w_i = z_i + \frac{\mu}{(1-\mu)}\frac{\gamma_i(\beta + \delta_i + ((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i))}{((1-h_i)p(x_i) + h_i)\theta_i q(\theta_i))}$$

3. Beveridge curve:

$$u_i^* = \frac{\delta_i}{\delta_i + [(1-h_i)p(x_i) + h_i]\theta_i q(\theta_i)}$$

A1.4 Comparative Statics

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.

$$\pi_i^* = A_i x_i^\alpha - w_i - (1-h_i)\rho_i - h_i\sigma_i - \frac{\gamma_i(\beta+\delta_i)}{((1-h_i)p(x_i)+h_i)q(\theta_i)}$$

Proposition 1. The higher the cost of finding candidates, the lower the optimal choice of outbound recruiting intensity h_i.

Proof. We first compute the F.O.C. for outbound recruiting intensity, and then we take the partial derivative of the F.O.C. with respect to the cost of outbound recruiting, σ_i.

$$\frac{\partial \pi_i}{\partial h_i} = \rho_i - \sigma_i - \underbrace{\frac{-\gamma_i \overbrace{(1-p(x_i))}^{<0} q(\theta_i)}{[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2}}_{>0} < 0 if \rho_i > \sigma_i$$

$$\partial \frac{\left(\frac{\partial \pi_i}{\partial x_i}\right)}{\partial \sigma_i} = -1 < 0$$

Proposition 2. The higher the skill level required by the firm, the higher the optimal choice of outbound recruiting intensity, h_i^*, provided the cost of hunting is lower than the cost of screening incoming applications.

Proof. We will use the implicit function theorem to evaluate the sign of $\frac{dh_i}{dx_i}$.

$$\frac{dh_i}{dx_i} = -\frac{\frac{\partial \pi_i}{\partial x_i}}{\frac{\partial \pi_i}{\partial h_i}}$$

The partial derivatives of π_i with respect for h_i and x_i are:

$$\frac{\partial \pi_i}{\partial x_i} = \underbrace{A_i(1-\alpha)x_i^{(\alpha-1)}}_{>0} - \underbrace{\frac{\gamma_i \overbrace{p'(x_i)}^{>0} q(\theta_i)(1-h_i)}{[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2}}_{>0} > 0$$

$$\frac{\partial \pi_i}{\partial h_i} < 0$$

As a result, we find that $\frac{dh_i}{dx_i} > 0$ when $\rho_i > \sigma_i$; if the cost of hunting is lower than the cost of reviewing applications, higher skill requirements imply higher level of outbound recruiting.

Proposition 3. The higher the outbound recruiting intensity, the higher the optimal skill level x_i required by the firm.

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

$$\partial \frac{\left(\frac{\partial \pi_i}{\partial x_i}\right)}{\partial h_i} = -\gamma_i \underbrace{p'(x_i)}_{<0} q(\theta_i)[(1-h_i)p(x_i)+h_i]^2 q(\theta_i)^2 -$$
$$\frac{\gamma_i \overbrace{p'(x_i)}^{<0} q(\theta_i)(1-h_i)2((1-h_i)p(x_i)+h_i)q(\theta_i) \overbrace{(-p(x_i)+1)}^{>0}}{[(1-h_i)p(x_i)+h_i]^4 q(\theta_i)^4}$$

A2 Fuzzy matching job postings to create firm-level job posting data

A3 Additional Survey Results

Here we report additional breakdowns of the percentage of the American workforce that was hired through recruiting by education, occupation, firm size, and demographics.

A3.1 Education

Table A2 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 A2 about here.]

A3.2 Occupation

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 A3 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 A3 about here.]

A3.2.1 Firm Size

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 A4, we see workers hired through outbound recruiting are more likely to work in small rather than large firms. Table A4 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 A4 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.

A3.3 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 A5, 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 A5 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 A6, 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 A6 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 A7 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 A7 about here.]

Corroborating this evidence, in Table A8, 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 A8 about here.]

A4 Fuzzy matching firm names in the BGT data

Company names in the Burning Glass dataset are not standardized across the dataset. Multiple iterations of the same company name are present in the data. In order to standardize these names, we performed fuzzy matching. Each company name in the dataset was first cleaned by expanding common abbreviations, setting all tokens to lower case, and removing punctuation in order to achieve consistency. Once the company names were cleaned, each name was compared to all other names that began with the same letter. A string distance measures were used to compare each pair of names. We used the Python package FuzzyWuzzy (https://github.com/seatgeek/fuzzywuzzy) to calculate the Levenshtein distance similarity ratio between the two cleaned strings.

A similarity ratio was calculated for each pair of names under three different settings. First, a score was computed using the standardization described above. Second, a score was computed after removing common words from the cleaned names that may produce false positives when matching, such as "incorporated". Third, a score was computed after removing all words from the names that appear in an English dictionary. Many company names feature family names or invented words that can be decisive when fuzzy matching, such as Xerox. Along with similarity scores, booleans for matching sectors and NAICS codes were also generated.

After each pair of company names is compared, a heuristically-chosen threshold was used to decide if a pair of names was a match. At least one of the three Levenshtein distance similarity ratios needed to be above 90. The first and second ratios were required to be at least 80 (we did not require the third ratio, computed once dictionary words were removed, to be above a certain threshold, since many company names had no words that were not present in the dictionary). The sectors of the two companies were also not allowed to be mismatched (an explicit match was not required due to missingness in the data). Finally, under these constraints, if the third ratio was 100 or not applicable (in the case that one or both of the names had no non-dictionary words), the pair of names would be considered a match.

A5 Additional Job Posting Results

Here we report additional analysis of our job posting data. See the body of the paper for discussion of these figures and tables.

[Figure A1 about here.]

[Figure A2 about here.]

[Figure A3 about here.]

[Figure A4 about here.]

[Figure A5 about here.]

[Figure A6 about here.]

[Figure A7 about here.]

Figure A1: Percentage of online US job postings classified as HR roles by BGT.

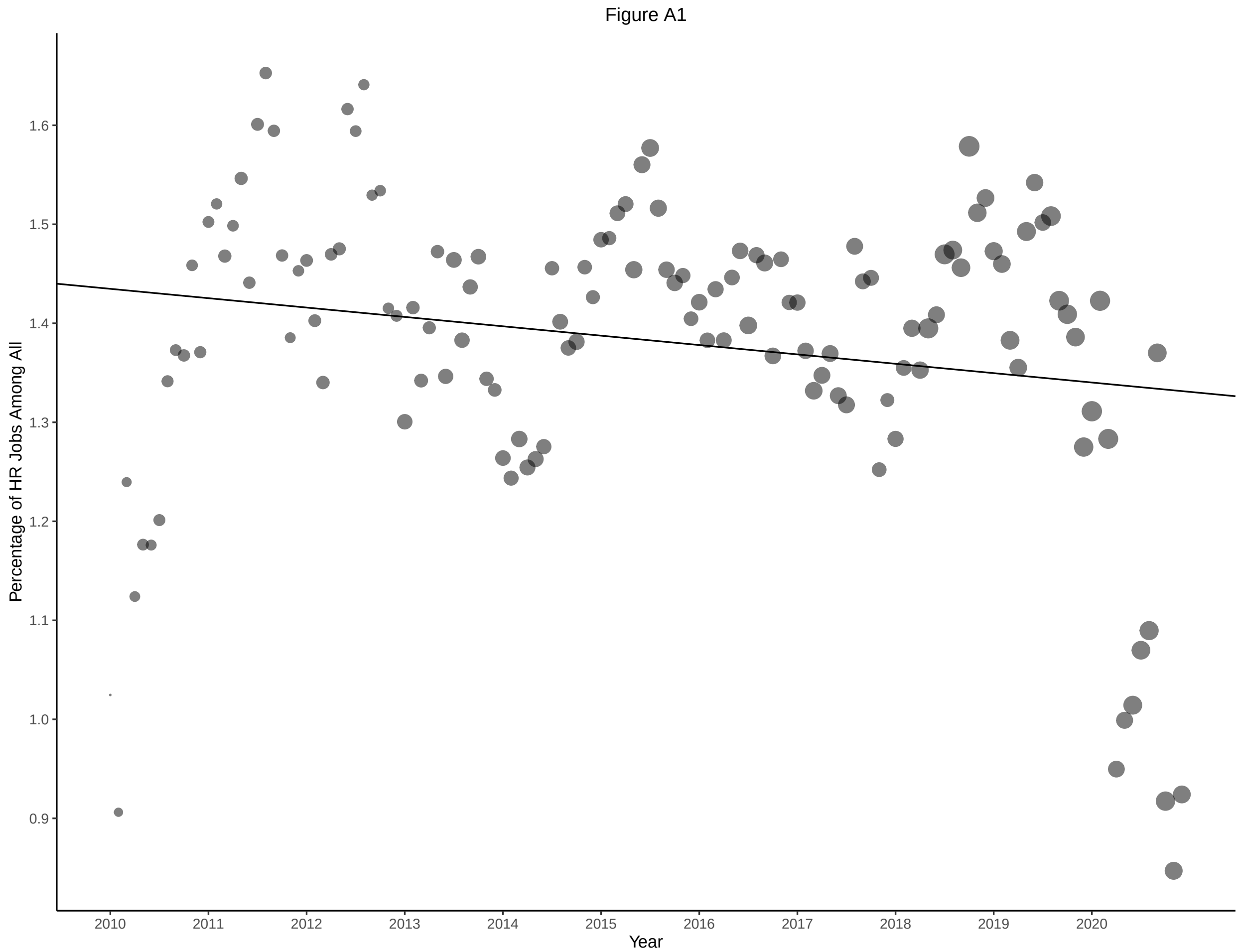

Figure A2: Percentage of online US HR job postings that list recruiting as a skill.

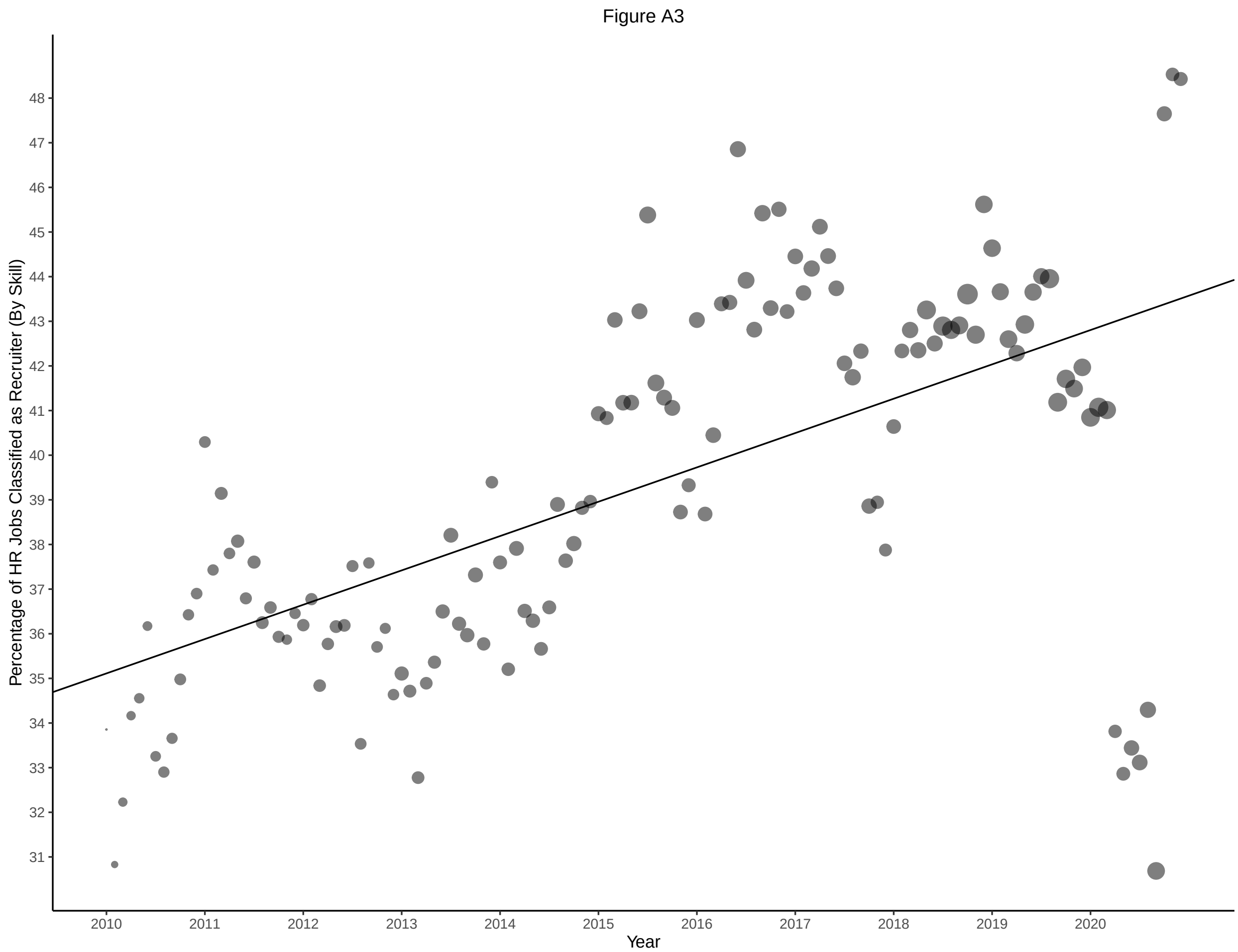

Figure A3: Percentage of online US HR job postings that have recruiting as part of the job title.

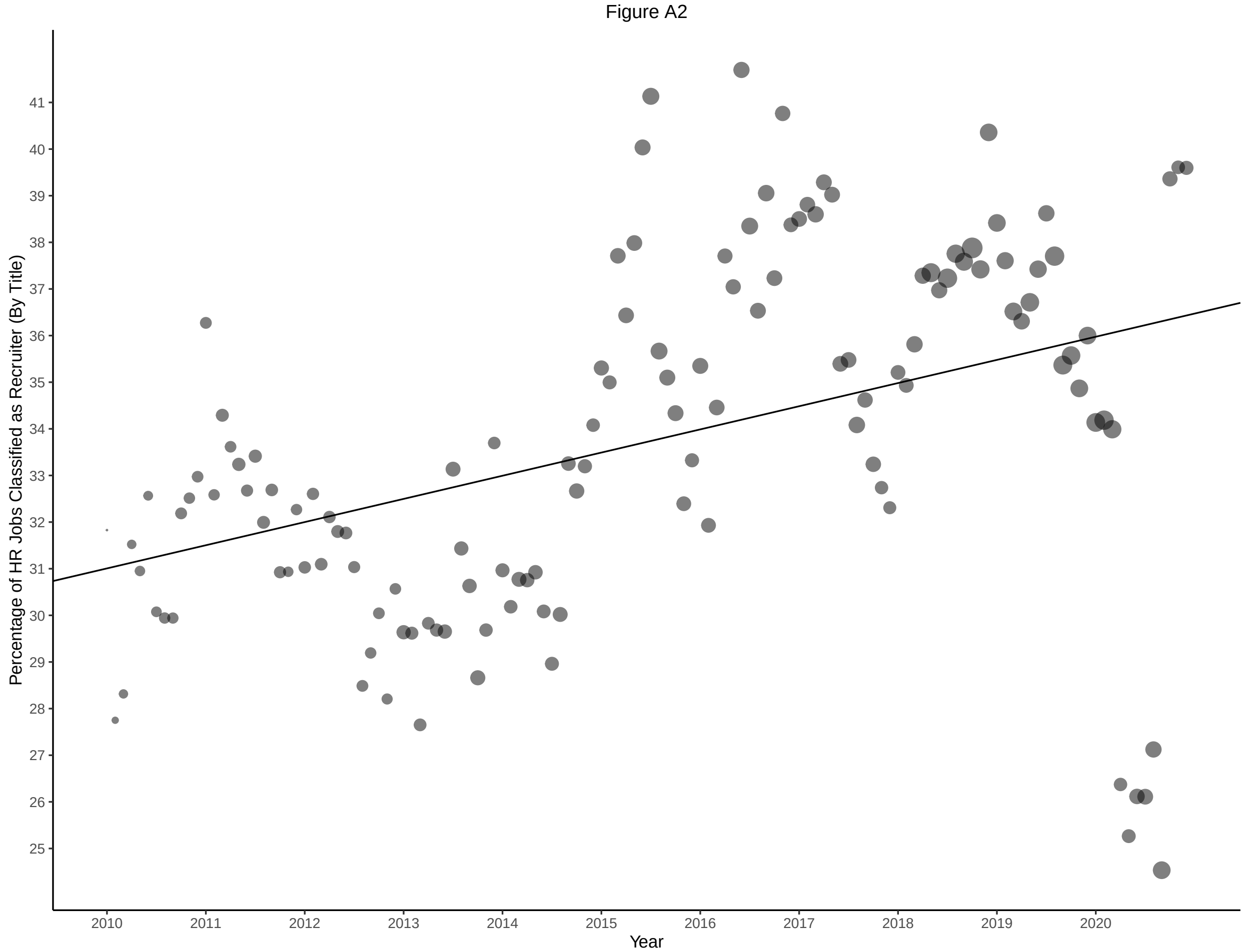

Figure A4: The distribution of the number of skills per job. The graph on the left shows the average number of skills per month for firms that posted at least one job in a month. The graph on the right shows the distribution of the number of skills listed for individual jobs in our data. Both graphs reveal that skill requirements vary dramatically across both job descriptions and aggregated firm-months.

Figure A5

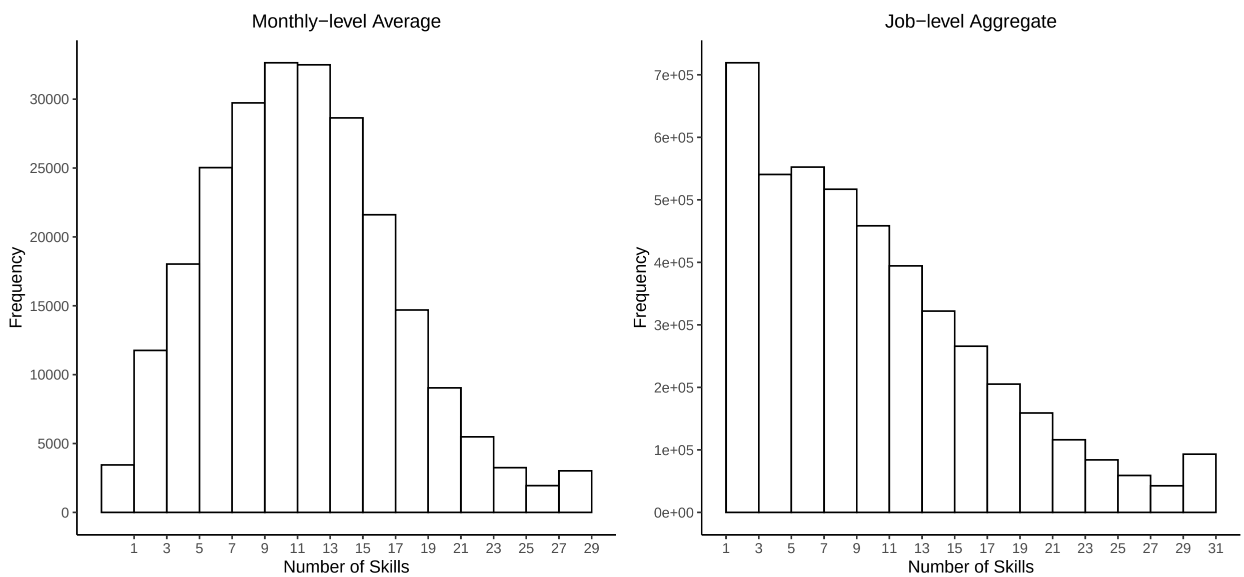

Figure A5: This graph aggregates our year-month cohorts into annual cohorts to show the percentage of firms, by year when they first enter our data, that have posted for a recruiter. The graph reveals that roughly 10% of firms had already posted for a recruiter in their first 20 postings. By the end of our panel just under 30% of firms, irrespective of which cohort they are apart of, had posted for a recrtuiter.

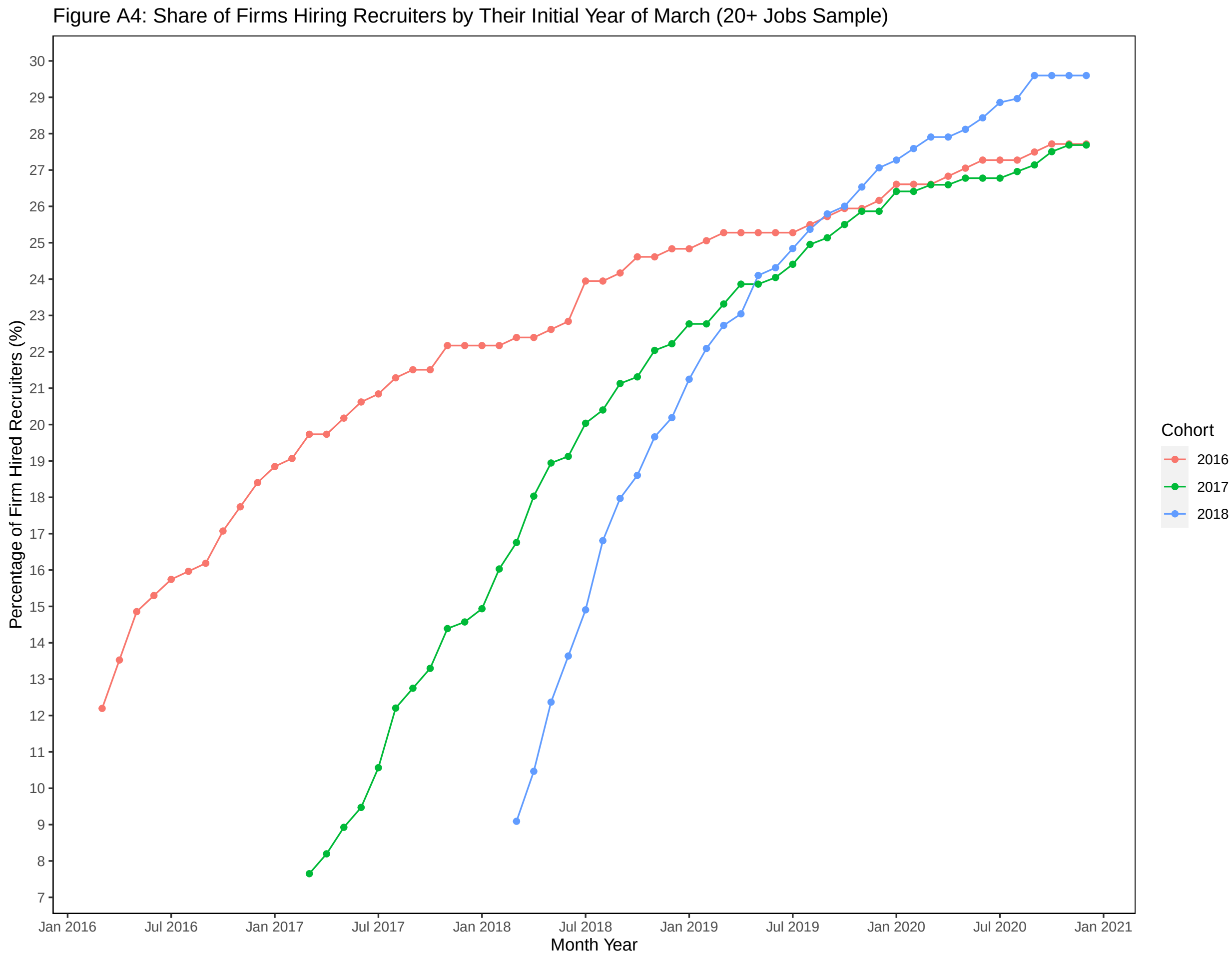

Figure A6: Sun and Abraham staggered roll out adjusted event-study plots showing the firm's skill demand before and after deciding to invest in recruiting. The x-axis is month for the firm's first recruiting posting and the y-axis is estimated effect on the average number of skills demanded for that month. Each plot represents a different cohort of growth-focused firms, with the results labelled "January, 2016" including firms that posted their 20th job in that month and "June, 2018" representing firms that posted their 20th job in that month. Bars are 95% confidence intervals. Recruiting jobs are excluded when calculating the dependent variable.

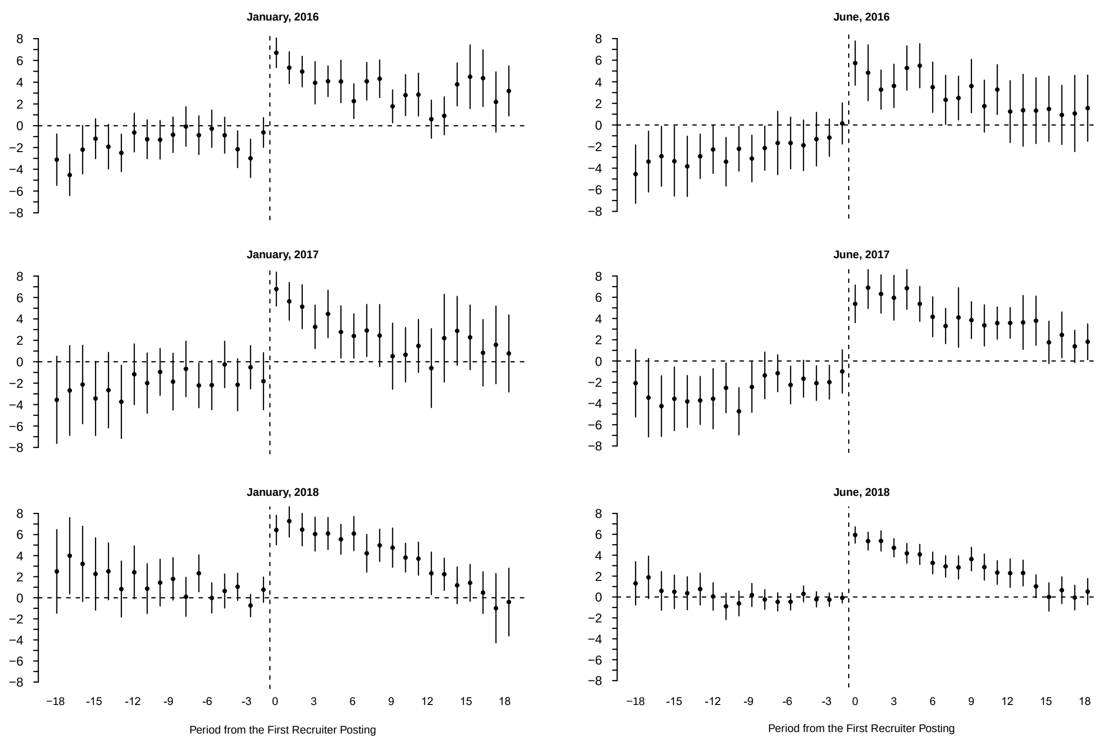

Figure A7: Sun and Abraham staggered roll out adjusted event-study plots showing the firm's number of job postings before after deciding to invest in recruiting. The x-axis is month for the firm's first recruiting posting and the y-axis is estimated effect on the number of job postings. Each plot represents a different cohort of growth-focused firms, with the results labelled "January, 2016" including firms that posted their 20th job in that month and "June, 2018" representing firms that posted their 20th job in that month. Bars are 95% confidence intervals. Recruiting jobs are excluded when calculating the dependent variable.

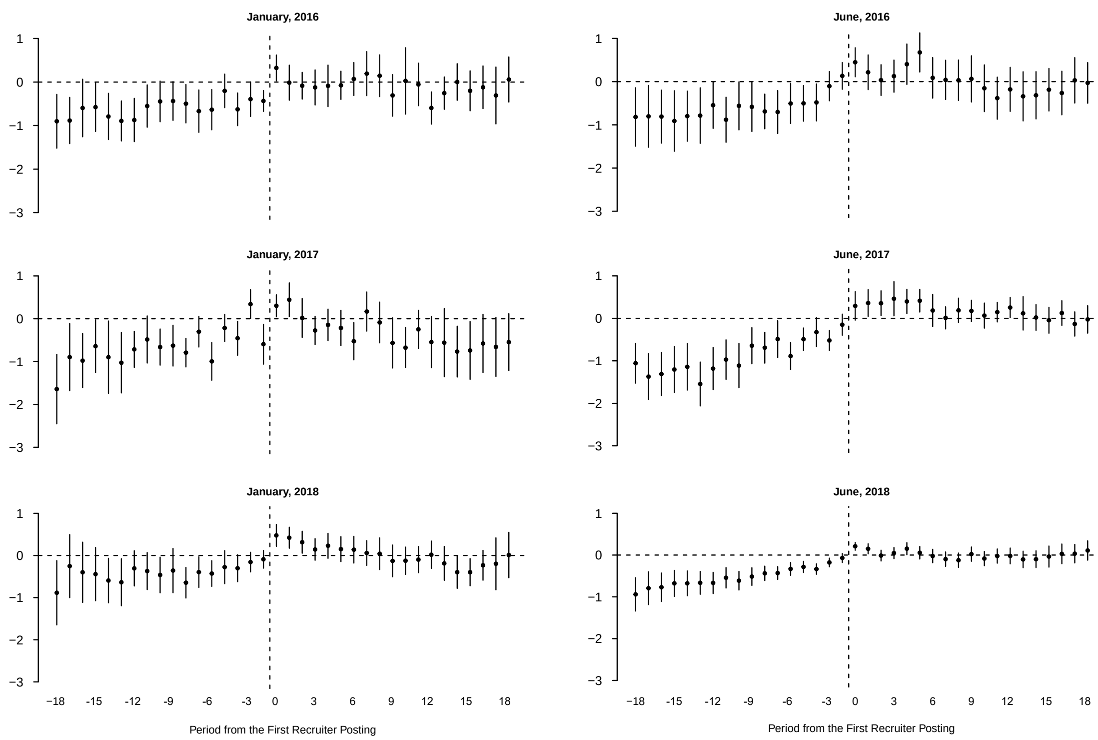

Table A1: Model parameters. Description.

Parameter	**Description**
β	Discount factor
z	Unemployment benefits
L	Total population of workers, both employed and unemployed
U and u	Total number of unemployed workers and unemployment rate
V and v	Total number of vacancies posted and vacancy rate
δ	Exogenous probability pf firm closure and job destruction
γ	Exogenous cost of keeping and open vacancy
$m(.,.)$	Matching function
θ	Thickness of the labor market, $\theta = v/u$
x	Number of skills, with distribution $p(x)$
Y and y	Total output and output per worker
A	Firm's technology
α	Cobb-Douglas production function parameter
ρ	Inbound recruiting cost
σ	Outbound recruiting cost
$q(\theta)$	Rate of occurrence of a match
h	Outbound recruiting intensity
$1-h$	Inbound recruiting intensity
μ	Nash bargaining weights

Table A2: 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 A3: 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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