Labor Market Tightness, Recruitment and Search Behavior

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Abstract

We examine the effects of labor market tightness on firms' recruitment behavior and job seekers' activity. We use a novel dataset from an online job board with high-frequency information on over 5 million vacancy postings and 1.26 million job seekers between 2012 and 2017. We construct two measures of tightness: one, from job seekers' perspective, based on the rate at which applicants start and stop searching for jobs and another, from employers' point of view, based on mean application flows. We find that job seekers submit more applications when markets are tight, apply to postings offering higher wages, and focus their search on a narrower set of skill requirements, job function categories, and locations. Meanwhile, employers are more likely to post wages when markets are slack and, conditional on posting a wage, offered wages rise with tightness. The share of postings for independent contractors (instead of employees) increases with slack. We then study changes in search activity with the arrival of information using the 7-day window around regional unemployment announcements. Employers increase postings after a high-unemployment announcement, and the share of postings offering an explicit wage also increases. Job seekers browse more job postings, but submit a similar number of applications, allocating them across a wider set of job titles and locations.

JEL Codes: J30, J60, M55

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1 Introduction

In the standard Diamond, Mortensen and Pissarides (DMP) model, the ratio of vacancies to unemployment determines the rate at which workers flow out of unemployment and the length of time it takes employers to fill a vacancy. Job seekers' and employers' expectations about the likelihood of a successful search reflect the available information on the relevant labor market's tightness. Optimal search and bargaining strategies accordingly vary with tightness.

In this paper, we examine employers' and applicants' responses to labor market tightness fluctuations across various margins. We use a novel dataset that allows us to track over 57,000 firms that post more than 7 million vacancies to an online job board over a 5-year period, as well as the 125 million applications they receive. Using mean daily application flows across Metropolitan Statistical Areas (MSA) and within narrowly defined skill requirement categories, we estimate the elasticity of postings with respect to tightness. We also analyze whether application flows affect employers' propensity to post wages or bargain with individual workers over pay. Further, we examine whether job seekers spread or narrow their search, geographically and across skill requirements, in response to changes in local labor market tightness. Finally, we use the high-frequency tracking of vacancy postings and applications in our data to study whether employers or job seekers update their priors about labor market conditions using the Bureau of Labor Statistics local unemployment rates announcements.

Our analysis is related to the literature studying the empirical and cyclical properties of job search and recruiting. On the job seeker side, Mukoyama, Patterson and Şahin (2018) find that search intensity by non-employed workers is higher during recessions. Kudlyak, Lkhagvasuren and Sysuyev (2013) find that job seekers apply to jobs below their qualifications as job duration increases. Faberman and Kudlyak (2019) find a negative correlation between search intensity, measured by weekly applications, and search duration. Faberman et al. (2020) document heterogeneous search behavior and efficiency between employed and unemployed workers in the US. Employed workers submit fewer applications but receive more offers. Consistent with job-ladder models, search intensity among the employed declines with their current wage. In Chile, Banfi, Choi and Villena-Roldán (2019) find that employed workers apply to higher wage jobs as tenure increases and simultaneously are more flexible about occupational requirements and geographical distance. Meanwhile, unemployed workers apply to jobs with lower wages and that are more misaligned in both qualification requirements and geographical location as search duration increases.

Others have analyzed the empirical and business cycle properties of employers' search strategies. Davis, Faberman and Haltiwanger (2013) find that growing establishments fill their vacancies faster and provide a measure of employers' efforts to fill vacancies. Kaas and Kircher (2015) develop a model with firm-specific matching rates determined by their endogenous choice of posted wages and number of vacancies. Employers can also affect their job-filling rate by modifying their requirements. Several papers have documented that firms become more selective during downturns, leading to higher rejection rates and lower aggregate matching efficiency (Nakamura (2008), Hershbein and Kahn (2018), Gavazza, Mongey and Violante (2018), Modestino, Shoag and Ballance (2020), Acharya and Wee (2020), Lochner et al. (2021).) Modestino, Shoag and Ballance (2016) further finds that skill requirements declined as county unemployment rates recovered after the Great Recession. Baert et al. (2015) use fictitious job applications in Belgium and find that employers are less likely to discriminate in occupations where vacancies are harder to fill.

We make two contributions to this literature. First, we systematically exploit employer-posting-applications matched data to study slack. Hall and Schulhofer-Wohl (2017) show that outflow rates from unemployment for various search duration categories and job filling rates across industries co-move with a single, underlying measure of tightness. Using detailed applicant activity to measure the rate at which job seekers flow out of search, we aim to provide a more comprehensive measure of tightness that includes both on the job search as well as unemployed applicants. Second, we describe various margins that employers and job seekers use to adjust their search strategies including the number and frequency of applications, the type of postings targeted by job seekers, and on the employers' side, the skill set requirements, the type of contracts offered, and the choice of wage setting mechanism.

Our paper is also related to the literature examining information frictions in labor markets. Canonical models of job search assume employers and job seekers have complete information about crucial determinants of the value of participating in labor market search. In these models, costly search prevents all job seekers and firms with open vacancies from finding each other. Meeting a counterpart in the labor market occurs with a probability that varies with labor market tightness. Importantly, job seekers know their job finding probability and firms know the probability of filling a vacancy. Given this information, and a distribution of known or expected match productivity and duration, job seekers and potential employers decide how much effort to exert into searching and which matches to form. However, these assumptions about the information available to labor market participants have important effects on their behavior and macroeconomic outcomes.

Previous papers have studied imperfect information in the labor market. Banerjee and Sequeira (2020) focus on information frictions on the workers' side and argue that heterogeneity in knowledge regarding job prospects across locations can lead to occupational and spatial mismatch. Cardoso, Loviglio and Piemontese (2016) use survey data measurements on workers' perceptions about the unemployment rate. They find that individuals who believe the unemployment rate is higher than it actually is feel more uncertain about keeping their job and have lower reservation wages. Bassi and Nansamba (2020) use a field experiment to examine the effect of providing employers' with information about workers' skills. Conlon et al. (2018) analyze the effect of job seekers expectations on their labor market behavior and outcomes.

Overall, previous findings point to the importance of incorporating information frictions as a distinct feature from costly search. Not only is it costly to meet and screen for counterparts in the labor market. When deciding whether to participate or not, firms and workers do not have complete information about the odds of meeting or the expected quality of the match.

To this existing literature, we make two empirical contributions: first, we examine the impact of the arrival of information on both the employer and the job seeker side. As highlighted by Angeletos and Lian (2016), job seekers' and firms' expectations are interdependent. For firms, periods of high unemployment are indicative of high job-filling probabilities but can also be informative about low future demand. Meanwhile, for job seekers, high unemployment rates are informative of competitive labor markets, lowering reservation wages, quit rates, and consumption. The interaction of both agents' responses to "information shocks" determines aggregate outcomes. Second, by using high-frequency and high-volume data on firms' posting behavior and job seekers applications, we can examine the dynamic effect of information arrival on search behavior.

The paper is structured as follows. In the next section, we list the data and provide some descriptive statistics for our main samples of interest. Section 3 explains our method for calculating labor market tightness from job seekers perspective. We also replicate measures of labor market tightness from employers' perspective following Davis and Samaniego de la Parra (2020) and show how the two series compare to MSA-level tightness measures based on the Jobs Openings and Labor Turnover Survey (JOLTS). Section 4 presents the empirical results analyzing job seekers' and employers' responses to labor market tightness. Section 5 discusses how salient unemployment announcements affect firm and job seekers' decisions. Section 6 concludes.

2 Data

2.1 DHI Vacancy and Application Flows

Our analyses rely on the DHI Vacancy and Application Flows database constructed by Davis and Samaniego de la Parra (2020) (the DHI data, henceforth). DHI Group, Inc. operates online job boards where employers advertise job openings and job seekers can post their resumes and submit applications to available postings. The raw data comes from the Dice.com platform which specializes on postings for technology professionals, finance, and other high-skilled professional business services.

On the recruiter-side, the DHI data include cross-sectional[1] information on industry, location, number of employees, ownership structure, and whether the company is recruiting for themselves or on behalf of another employer. For each job posting, the data include information on the location where the job takes place, an extended job title description, contract terms[2] and wage, if explicitly offered.[3] We observe the exact date-time stamp when the posting first became available to receive applications and when it was permanently re-

[1]This information is not updated through time. It is our understanding that the data reflects employers' characteristics at the time the first job posting is advertised on Dice.com

[2]Contract terms determine whether the job is full-time or part-time, and whether the individual is hired as an employee or as an independent contractor.

[3]17% of postings include an explicit wage or wage range.

moved. Companies can decide to deactivate any posting, stopping the flow of applications, and then re-activate it at any point. For each date, the DHI data tracks the exact number of seconds each posting was active on the platform, the number of views it received, and its daily applications. It also allows second-by-second tracking of each job seekers' activity on the platform. We observe the IP address from which they submit each application, their work authorization status, and a self-reported job title.[4,5]

We focus on job postings for US-based employment. This excludes work that is exclusively remote, but includes postings that allow for telecommuting as long as a location is specified for the job. To identify these postings, we first clean and standardize the location information as reported in the DHI data.[6] We then use Google's Geocoding API to match the resulting set of locations to standardized job cities, counties, and states in the US. For any remaining job postings that could not be matched to a city through geocoding, we look for the closest name using Zillow's neighborhood dataset and various online city-county crosswalks. We manually match the remaining locations. Finally, we identify the MSA associated to each job posting using the NBER's MSA-county crosswalk[7] and only keep job postings with locations that can be matched to a county in the US. [8]

Our final recruiter-side sample includes 20,292 distinct employers[9] with over 6 million job postings located across 384 unique Metropolitan Statistical Areas. Figure 1 shows the distribution of employers and postings across MSAs for an average month between 2012 and 2017.

[4]The applicants' job title could reflect their current, most recent, or desired position.

[5]For more information on the DHI data, see Davis and Samaniego de la Parra (2020) and its accompanying data dictionary Davis and Samaniego de la Parra (2019).

[6]This included excluding job postings missing location information; those where the location information included variations of the words "unspecified", "remote", "anywhere" or "at home"; removing all punctuation and special characters in job locations; homogeneizing acronym use; and replacing all capital letters with lowercase letters.

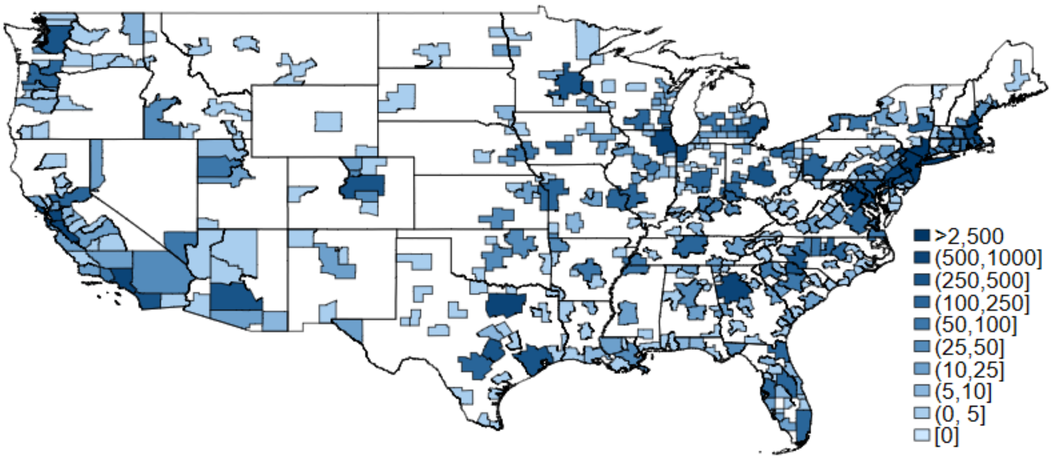
[7]We use the 2015 crosswalk available at the NBER's Public Use Data Archive.

[8]We include only employers with at least one posting that was active for no more than 30 days. This last restriction on the sample is meant to exclude employers that use a single vacancy posting for more than one job and for continuing recruitment needs. See Davis and Samaniego de la Parra (2020) for additional details on "standard" job postings.

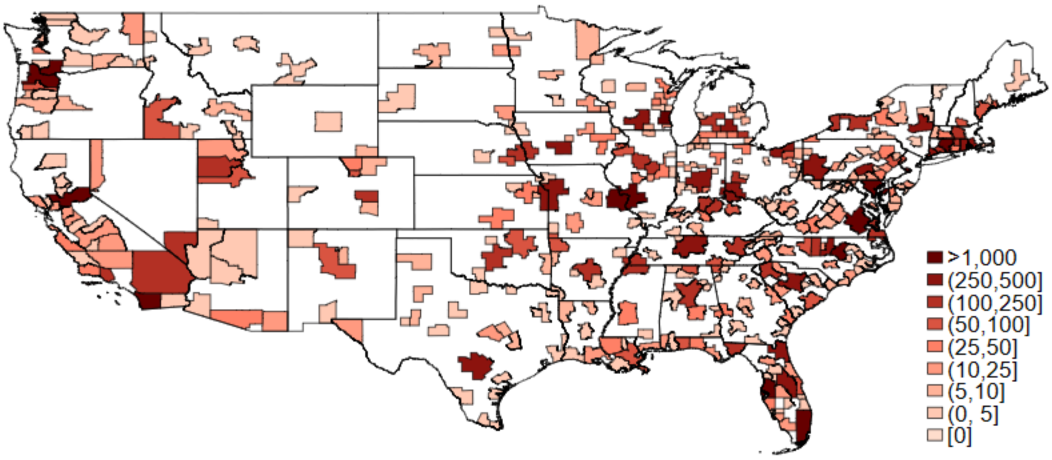
[9]The DHI data uniquely identifies employer-side accounts. However, a company can have multiple accounts with DHI (for example, different establishments or departments). To uniquely identify employers, we use Google's JSON API and fuzzy matching to identify all of a company's accounts with DHI based on the company's name and location associated with the account.

Figure 1: Mean Active Employers and US-based Job Postings 2012 - 2017

(a) Employers



(b) Job Postings



The average employer is active in 10 MSAs and has 19 active postings on an average recruiting month.[10] We are interested in analyzing both the intensive margin of recruiting as well as the extensive margin (i.e. whether an employer decides to have an active job posting in a given labor market or not). Therefore, we construct a balanced employer-MSA monthly panel. We identify an employer's first recruiting date as the day of its first job posting on the platform. We assume an employer's recruitment spell ends after a 3-

[10] i.e. a month when the employer has at least one posting active for at least one day in the month.

month period of inactivity (i.e. zero active job postings) by all of its accounts.[11] We further assume that during a recruitment spell, the employer is active at all MSAs where it ever has a job posting.[12] Table 1 provides additional descriptive statistics for employers and postings during active recruitment spells.

Table 1: DHI Employers: Descriptive Statistics

Variable	Mean per Employer-Month	(s.e.)
Postings	18.8	(36.8)
Views per Vacancy	176.5	(192.5)
Applications per Vacancy	13.9	(29.6)
Posting Duration	11.4	(8.1)
Active MSAs	10.0	(8.7)
W2 Contracts (%)	67.1	(44.5)
Wage Posting Vacancies (%)	16.1	34.7
Wage/Hour (USD$)	59.93	(79.78)
Wage/Year (USD$)	86,493.35	(25,497.50)
No. of Employers	20,292	

These statistics refer to the average per employer across months when they are actively recruiting as defined above. We exclude the first and last year of the sample to ensure we are measuring complete recruitment spells. Therefore, these statistics refer to the period between January 2013 and December 2016.

On the applicant side, we include all individuals applying from within the US, and who submit at least one application to a US-based job posting. We use IP addresses to determine applicants' locations.[13] We cannot observe whether a match is formed after a job seeker

[11]For example, consider employer A who first post and then removes a job on December 2012. The same employer then posts a different job on February 2013 and removes it on March 2013. If the employer then does not post another job between March 2013 and June 2013, employer A is considered as actively recruiting between December 2012 and March 2013. It is inactive until the next job posting by any of its accounts.

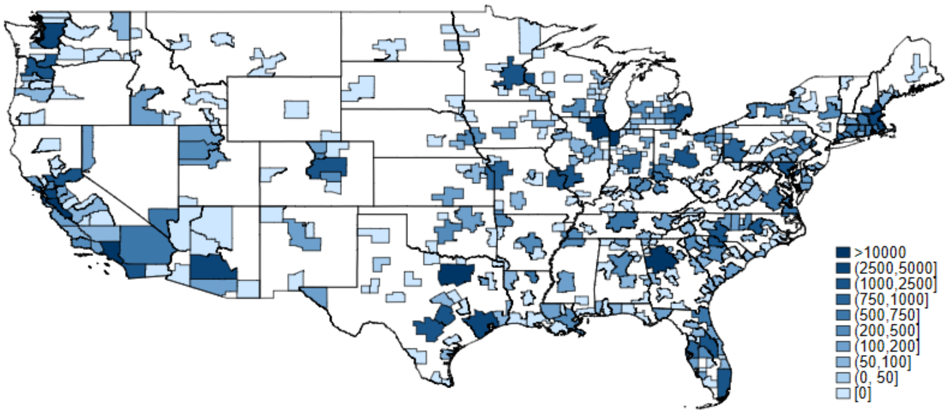
[12]For example, consider employer B who posts a job in MSA 1 on March 2013 and then removes it on June 2013. The same employer then posts a job in MSA 2 on July 2015 and removes it on August 2015. Employer B is considered as active at both MSA 1 and MSA 2 between March 2013 and June 2013, and then again between July and August 2015.

[13]It is important to note that IP addresses vary through time. Since we use a crosswalk from Jan.-Feb. 2020 between IP-addresses and GPS coordinates, job seekers' location may be incorrectly assigned if an IP address is associated to a different set of coordinates across time. The fact that we observe few changes in

applies to a posting, nor can we determine whether an individual looks for work through other channels. Instead, for each job seeker, we equate the day of their first application on the platform with the start of their job search. We assume an individual job search stops after submitting an application that is followed by a period of inactivity of 3 months or more. We define a search spell as the length of time between applications where the interval between each application is less than 3 months.

Figure 2: Mean Active Job Seekers and US-based Applications 2012 - 2017

(a) Active Job Seekers



(b) Applications

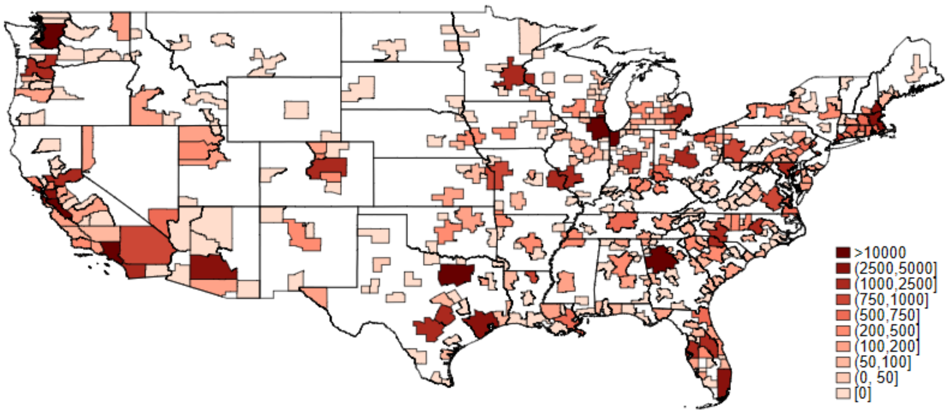


Figure 2 shows the distribution of job seekers and applications across MSAs for an

location for a single applicant indicates that the magnitude of this issue is small.

average month between 2012 and 2017. The median MSA has 155 active job seekers submitting 171 applications on an average month. During an average search spell, job seekers submit 8 applications to postings across 3 different MSAs, including their own residence.[14]

2.2 Bureau of Labor Statistics Local Area Unemployment Press Releases

The Local Area Unemployment Statistics (LAUS) program at the U.S. Bureau of Labor Statistics (BLS) produces monthly estimates of the total employment and unemployment for each of the 389 metropolitan areas in the United States. Each month's numbers are published on a scheduled date and accompanied with a press release listing the areas with the highest and lowest unemployment rates in the country and summarizing year-on-year changes. Historical estimates from the LAUS program are revised annually "new population controls from the Census Bureau, updated input data, and reestimation."[15] Since we are interested in employers' and job seekers' reactions to the arrival of information embedded in BLS's announcements, we scrape archived press releases from the LAUS program. Using these press releases, we construct a balanced panel of un-revised MSA level unemployment rate announcements.

We focus on employers' and job seekers' activity on the DHI platform on the 7-day window surrounding each of the LAUS program's monthly press releases between February 2012 and November 2017. We consider an employer (job seeker) as being active around the 7-day window if the date of the BLS announcement is between a recruitment (job search) spell, as defined in the previous section.

Two things are worth highlighting about the BLS press releases. First, the information on the press release has a one month lag, that is, September's press release contains information about August's labor market conditions. Second, the dates of the announcements are known well in advance: the BLS publishes the schedule for all its monthly press releases on its website. These aspects are important because a) employers and job seekers

[14]We refer to a job seekers MSA of residence as the MSA from where they submit applications.

[15]https://www.bls.gov/lau/launews1.htm

know when to expect the announcement and b) the information is not forward looking. However, we argue that it may still convey information useful to update expectations on job finding and job filling rates.[16]

3 Tightness and Search Behavior

In the standard search and matching framework, the number of hires is determined by a function of the ratio of vacancies to job-seekers in a market (i.e. the labor market tightness). Tightness then determines the job finding rate for job seekers and the vacancy filling rate for employers. We measure tightness from job seekers' perspective using the share of applicants in month t whose search spell ends in month $t + 1$. While we cannot observe matches, we assume that workers have not found a job and continue to search if they apply to at least one job within a 3-month window of the prior application. Job seekers whose search spell ends (i.e. who do not submit additional applications) are considered as outflows from job search.

It is important to note that the underlying concept of our measure of tightness from the job seekers' perspective differs substantially from the job finding rate in a standard DMP model. For example, Hall and Schulhofer-Wohl (2017) measure tightness using the outflow rate from unemployment. Abraham, Haltiwanger and Rendell (2020) highlight the importance of using a broader definition of job seekers to measure labor market tightness. Since the universe of job seekers on the DHI platform includes both employed and unemployed individuals, our measure is closer to an outflow rate from search. We, however, cannot distinguish outflows from the DHI platform from search stops through other channels or from job matching.

Figure 3 compares our measure of labor market tightness from the job seeker perspective (panel b) to the vacancies-to-unemployment ratio calculated using MSA-level JOLTS

[16] Consider, for example, a model as inGonzalez and Shi (2010) or Buyukbaşaran (2020) where job seekers are heterogeneous and have incomplete information about their matching probability. In these models, failure to find a match conveys information about workers' type. In a more general setting with aggregate shocks, workers' experience on the labor market is less informative about their type during a downturn. Therefore, we would expect high unemployment rate announcements to be associated with a lower correlation between unemployment duration and discouraged job seekers. We develop this argument in more detail in section 5.

data (panel a). The levels are, of course, different, but the series have simultaneous drops and trend upwards in the largest 18 MSA's specially starting mid-2014. The correlation coefficient ranges from 0.61 to 0.83 between 2012 and 2017. Moreover, the rank order is preserved for the 5 MSA's with the highest recorded levels of tightness and the 5 MSA's with the lowest values using either measure.

Figure 3: Labor Market Tightness at 18 largest MSAs: Job Seekers' Perspective

(a) JOLTS V to U ratio

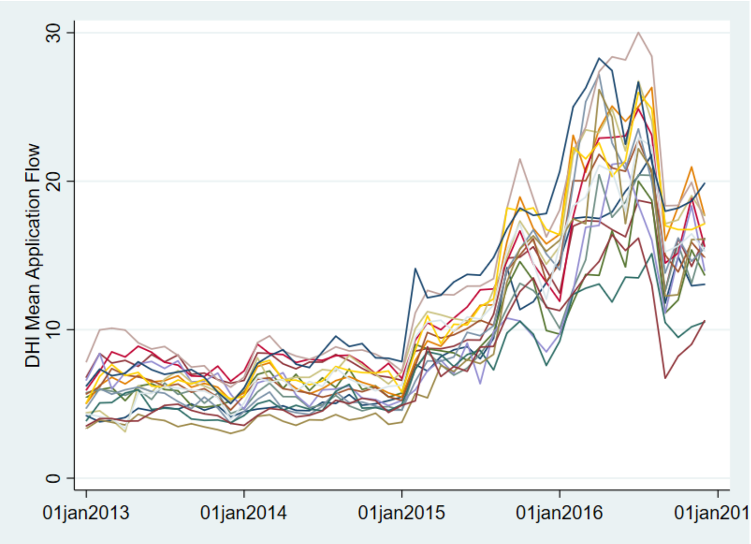
(b) DHI Outflow Rates

From the employers' perspective, we follow Davis and Samaniego de la Parra (2020) and measure anticipated tightness using mean applications per posting. We group postings into categories based on the MSA of employment, denoted as m, and advertised skill requirements, s, and estimate anticipated labor market tightness for each category mXs. In this sense, employers who post a vacancy in a location-skill group with a high level of mean daily applications face a slack labor market while those that require workers with skills in low supply in a certain location face a tight labor market.

Figure 4 plots mean application per vacancy posting in each of the major metropolitan statistical areas. As with our measure of labor market tightness from the job seekers' perspective, mean application flows in each MSA are highly correlated with JOLTS-based vacancy-to-unemployment ratios. The correlation coefficient between the two time series ranges from 0.6, for the area encompassing Minneapolis-St. Paul-Bloomington, MN-WI, to to 0.92, for Dallas-Fort Worth-Arlington, TX.

Figure 4: Labor Market Tightness at 18 largest MSAs: Employers' Perspective

(a) DHI Mean Application Flows per Posting



4 Labor Market Tightness and Search Behavior

4.1 Job Seeker Behavior

In this section, we analyze the effects of labor market tightness on job seeker behavior. In particular, we examine whether, and through which channels, job seekers broaden their search efforts when labor markets are slack. We consider changes in the number and frequency of applications, as well as changes in the type of jobs targeted by applicants. We characterize job types based on skill requirements, distance from job seeker residence, posting age at the time of application, and wage levels.

Let $Y_{i,m,t}$ denote a search criterion by job seeker i, searching from location m in period t. We consider the following 6 search behaviors for applicants: the number of applications submitted, share of applications to postings with wage information, median wage (conditional on applying to postings with wage information), median posting age, number of applications to postings with requirements different from those posted by applicant, and number of applications outside MSA of residence. $X_{m,t}$ includes the natural log of GDP and commercial property vacancy rates, λ_i, γ_m and ι_t are applicant, MSA, and calendar time fixed effects, respectively. We cluster standard errors at the reported skillXMSA level.[17]

$$Y_{i,m,t} = \beta_0 + \beta_1 search\_outflow\_rate_{m,t} + X'_{m,t}\delta + \lambda_i + \gamma_m + \iota_t + \epsilon_{i,m,t} \tag{1}$$

Table 2: Job Seekers' Outflow Rates and Applicant Search Behavior (2013-2016)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Mean	Coeff. (β_1)	std. err.	No. Obs.	R2
Natural Logarithm					
Applications	8.33	0.006***	(0.002)	5,790,776	0.608
Mean Wage/Hour	62.66	0.002	(0.002)	1,506,099	0.590
SD(Wage/Hour)	32.82	0.008	(0.006)	617,751	0.564
Mean Wage/Year	84,128.40	0.006**	(0.002)	431,327	0.693
SD(Wage/Year)	12,442.4	-0.012	(0.009)	98,886	0.662
Mean Posting Age	23.68	-0.006***	(0.002)	5,780,917	0.403
Mean Seconds Elapsed b/w Applications	17,626.62	0.018***	(0.003)	5,156,576	0.395
Share of Applications					
Wage Posting Jobs	1.49	0.057	(0.069)	5,790,776	0.348
Employee (W2) Contract Jobs	4.67	-0.141*	(0.075)	5,790,776	0.489
Distinct Job Functions	2.36	-0.154**	(0.063)	5,790,776	0.512
Distinct Skill Requirements	2.04	-0.215***	(0.069)	5,790,776	0.504
Distinct MSAs	2.94	-0.183***	(0.059)	5,790,776	0.493
Mean Outflow Rate	3.285				
SD(Outflow Rate)	(0.837)				

Notes: All regressions include individual, MSA, and year-month fixed effects. We report two-way clustered standard errors using the applicant's reported skill category and MSA as clusters.

Table 2 shows the estimated coefficients. Each row depicts a different outcome variable.

[17]Reported skills include 59 skill categories and an "other" group for all other categories. The underlying assumption for this two-way cluster is that errors could be serially correlated at the labor market level, where a market is defined by the applicants' skill set and their location.

The last row presents the unconditional mean and standard deviation for the main regressor of interest $search\_outflow\_rate_{m,t}$. Column (1) shows the mean for the dependent variable in each row. The average applicant submits 8 applications during each search spell. On average, 18% of the postings targeted by applicants offer an explicit wage. Conditional on applying to postings with a wage offer, the mean wage is \$62 for jobs with hourly contracts and \$84,128 for postings with annual salaries. The average job seeker on the DHI platform targets job postings with 2.36 distinct job functions and 2 skill requirements specified in the postings' job title. Job seekers apply to postings in 2.9 different MSAs in an average month. Column (2) shows the coefficient of interest, β_1, estimated using equation 1. This coefficient reflects the change in each dependent variable associated with a 1 percentage point increase in outflow rate from search activity on the DHI platform. A 1 percentage point increase in our measure of tightness is associated with a 0.6% increase in average monthly applications submitted and a 0.6% increase in the offered wage of postings, conditional on applying to a job that offers an explicit wage. Moreover, job seekers apply to a smaller set of job functions and skill requirements. Their search also narrows geographically: a 1 percentage point increase in the outflow rate from DHI search is associated with an 18% decline in the number of MSAs to which job seekers send applications.

4.2 Recruitment Effects

When posting a vacancy on the DHI platform, employers choose the type of contract to offer (full-time vs. part-time, as a W2 employee or an independent contractor), the set of skills to require, and whether to post an hourly wage or annual salary. If a wage is posted, the employer also determines whether to post a single value or a range. All of these decisions potentially affect the number and type of job seekers they can attract. Moreover, employers can also choose how many vacancies to post, how to distribute their skill requirements across postings, and for how long to receive applications (i.e. posting duration.) In this section, we look at how employers respond along these various margins to changes in labor market tightness.

We follow Davis and Samaniego de la Parra (2020) and use the average application flow per posting to measure slackness. We define slack for each MSA-skill category as:

$$slack_{m \times s \times t} = \frac{A_{m,s,t}}{V_{m,s,t}} \qquad \forall t \tag{2}$$

where $A_{m,s,t}$ is the total number of applications received by job postings located in MSA m that require skill s in month t, and $V_{m,s,t}$ is the total number of vacancy postings in the MSA-skill-month.

The intuition behind using mean application flows to proxy for labor market slackness is simple. In times when the supply of job seekers in a given location-skill category is plentiful, the average vacancy posting receives more applications.[18] This measure, however, is not appropriate for MSA-skill groups with very few postings. Therefore, we focus on categories with at least 100 vacancy postings and at least 25 active employers on each month from January 2013 to December 2016.

We use the specification in equation 3 to estimate the effects of labor market slack on employers' recruitment strategies. We include employer (λ_j), MSA-time ($\gamma_{m \times t}$)and skill requirements-time ($\iota_{s \times t}$) fixed effects to control for unobserved employer characteristics and shifts over time across locations or in the portfolio of skill requirements. Through these controls, we seek to alleviate concerns of shifts in the composition of job seekers and vacancy postings in the DHI platform across time that affect our measure of slackness.

$$Y_{j,m,s,t} = \beta_0 + \beta_1 ln\left(slack_{m,s,t}\right) + \lambda_j + \gamma_{m \times t} + \iota_{s \times t} + \epsilon_{j,m,s,t} \tag{3}$$

Column (1) in Table 3 shows the unconditional mean for the recruitment margin listed in each row. The average employer has 2.9 active postings across various MSA-skill categories. Each of these postings lists, on average, 1.2 different skill requirements. Requirements differ across postings with 3.7 distinct skills mentioned on average for each employer. The average employer offers an explicit wage in 16% of its active postings, and 2 out of 3 postings is for a W2 employee contract (as opposed to independent contractors). Conditional on offering an hourly contract, the mean wage posted is USD$59.93 while the

[18]After controlling for employer fixed effects, and time dummies for each MSA and skill requirement, a 1 percent increase in our measure of slack is associated with an 18 percent increase in the number of views per posting.

mean annual salary is $86,493.35.

We separately estimate β_1 in equation 3 for different recruitment decisions as dependent variables. Column (2) presents the estimated coefficients. This coefficient reflects the percent or percentage point change in each dependent variable associated with a 1 percent increase in slackness. Contrary to the predictions in a standard DMP model, we find that the number of vacancy postings increases with tightness[19] (an elasticity of 21%) while posting duration decreases. Extending a posting duration may substitute for posting additional vacancies if a single posting can attract suitable applicants for more than one opening.

Table 3: Recruitment Behavior and Labor Market Tightness (2013-2016)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Mean	Coeff. (β_1)	std. err.	No. Obs.	R2
Natural Logarithm					
Active Postings	2.86	-0.210***	(0.020)	79,301	0.351
Mean Posting Duration	11.41	0.072***	(0.011)	79,301	0.362
Total Skills Required (across postings)	3.73	0.187***	(0.058)	79,301	0.767
Mean Skill Requirements (within posting)	1.21	-0.047***	(0.003)	79,301	0.133
Share of Active Postings					
W2 Contract	67.11	-3.302***	(0.343)	79,301	0.485
Wage Posting	16.04	0.887*	(0.467)	79,301	0.467
Natural Logarithm - Conditional on Wage Posting					
Mean Wage/Hour	59.93	-0.085*	(0.043)	8,093	0.575
Mean Wage/Year	86,493.35	-0.184***	(0.047)	1,129	0.465
SD(Wage/Hour)	17.58	0.133	(0.251)	804	0.646
SD(Wage/Year)	17,737.27	-0.099	(0.737)	252	0.475
Mean Daily Applications	11.05				
SD(Daily Applications)	(9.54)				

Notes: All regressions include employer, MSA-year-month and skill-year-month fixed effects. We report clustered standard errors using the first skill requirement mentioned in the postings' job title and MSA as separate clusters.

We find evidence consistent with a re-allocation of skill requirements across postings.

[19]Mean application flows per posting is our measure of slackness. We refer to tightness as $-1 \times slack$.

When markets are slack, employers' reduce the number of skills listed on any one posting but increase the number of distinct skills required across their active postings. This is consistent with employers posting more specialized vacancies when labor market tightness declines. The share of postings for independent contractors (non-W2 contracts) increases by 3.3 percentage points with a 1 percent increase in slack.

A 1 percent increase in slack is associated with close to a 1 percentage point increase in the share of postings in which an employer offers an explicit wage. Conditional on making a wage offer, the elasticity of annual wages to slack is -0.18% and for hourly wages it is -0.09%.

These findings provide evidence of job seekers' and employers' adjustments in their search behavior with changes in the gap between available vacancies and potential workers. An increase in job finding rates, measured by the outflow rate from search on the DHI platform, has a very small effect on total applications submitted (0.6% for a 1 percentage point increase in outflow rate). Instead, job seekers respond to increases in tightness by concentrating their applications towards a single MSA, and to a less diverse set of job functions and skill requirements. In this sense, applicants narrow their search when markets are tight. Meanwhile, employers adjust their ads towards more specialized jobs (fewer skills required per job posting but more distinct skills mentioned across their listings) with a higher share of explicit wage offers. Offered wages decline with slack but we find no change in the wage dispersion across postings.

5 Unemployment Rate Announcements and Search Behavior

Standard models of search assume employers and job seekers have complete information about their matching rate. In such a setting, we would not expect press releases about the state of the labor market in a prior period to have a direct effect on job search or recruitment strategies. Allowing for incomplete information, however, can introduce an effect for unemployment rate announcements on search behavior. Consider, for example, a model as in Gonzalez and Shi (2010) where workers learn about their job finding prospects based on the repeated outcomes of their search. In this environment, adding information about the aggregate state of the labor market can attenuate or exacerbate such a learning process. Success (failure) to find a match is more informative about the workers' ability when markets are slack (tight). From an employer's perspective, information about the prior month's unemployment rate can affect their expectations about future demand[20]. The information can also lead to adjusting job filling rate expectations.

In this section, our goal is to analyze the impact of regional unemployment announcements on employer and job seeker behavior. We rely on BLS's monthly press releases which publish data about the prior month's unemployment rate for each MSA in the US. These announcements are scheduled in advance and the data is not concurrent. However, in a setting with incomplete information, precise information about the prior month's state of the labor market can lead to firms and job seekers adjusting their tightness priors. We examine whether their responses to BLS press releases are consistent with such an updating.

On the employer side, our analyses include the effects on the probability of posting a vacancy, the probability of removing an existing vacancy, the probability of reallocating an existing vacancy to a different location, the total number of vacancies posted, the mean vacancy posting duration, the share of vacancies with explicit wage offers (i.e. wage posting vacancies), the natural log of the wage for wage-posting vacancies, and the number of skills required by the vacancy posting. On the job seeker side, we focus on the probability of applying for a vacancy posting, the daily number of submitted applications, and the geographical and occupational "dispersion" in applications.

For each MSA-month, we classify the 7-day window after a BLS announcement (inclusive of the day of the announcement) as the *After = 1* period and the 7 days before the announcement as the *After = 0* period. For each employer that has at least one active posting[21] during the 7-day window around a BLS announcement, we measure each of their decision margins (number of postings, probability of posting, etc.) separately in each of these windows each month. We want to focus on the effect of unemployment an-

[20]Garmaise, Levi and Lustig (2020) estimate a 2%, persistent decline in discretionary spending after a high unemployment rate announcement.

[21]We consider a posting to be "active" if it is visible to job seekers at any point and for any positive duration during the 7-day window around the announcement.

nouncements on employers' expectations about the labor market. However, a high (low) unemployment can also be indicative of low (high) demand. To remove the latter effect, we focus on employers with a non-local customer base.[22] Our final sample includes 31,182 employers. Our job seeker sample includes close to 3 million individuals who submitted at least one application within the 7-day window around a BLS announcement.

Following Garmaise, Levi and Lustig (2020), we focus on "salient" (i.e. x-month maximums and minimums where x is equal to 3, 6 or 12). These announcements are "likely to attract particular attention from consumers for behavioral reasons."[23] They are also more likely to be picked up by local media and therefore reach a larger share of labor market participants.

5.1 Job Seekers

Let $A_{i,m,t}$ denote a decision margin for job seeker i, submitting applications from MSA m on period t, where each t denotes a 7-day window before of after a BLS announcement. Equation 4 displays our baseline specification. We use the inverse hyperbolic sine transformation for our dependent variables because our data is constructed as a balanced panel around the announcement and thus it includes periods with no activity by the job seeker. ζ_i, δ_s, ι_t, and dow_t are job seeker, state, week, and day of the week[24] fixed effects, respectively.

Our main coefficients of interest, $\beta_{a,h}$ and $\beta_{a,l}$, respectively describe the impact of an X-month maximum and minimum on job seekers' search behavior in the 7-day window after unemployment announcement relative to their activity in the pre-announcement period. We control for the current and lagged unemployment rate in the MSA, and the unemployment rate in the state.[25] In this sense, $\beta_{a,h}$ and $\beta_{a,l}$ capture the effect of a salient announcement

[22]We categorize an employer as having a "non-local" customer base or demand if their clients are located in a different state as the job posting. To identify the location of their clients, we first manually categorized 2,000 randomly selected employers based on their websites' descriptions of their services and clients. Then, we scrapped all the companies' websites, tokenized their contents, and use the content from the manually categorized websites to train a machine learning algorithm to categorize the rest.

[23]Direct quote from Garmaise, Levi and Lustig (2020).

[24]This refers to day of the week when the announcement is made. Davis and Samaniego de la Parra (2019) note that applications rise early during the week and are much lower during weekends.

[25]Most MSAs are contained within a single state. For those MSAs whose boundaries expand over more than one state, we assign the MSA to the state where most of the MSAs population is concentrated.

net of the impact of the unemployment level. This specification relies on an event study around the local unemployment announcement date for each job seeker-month. We compare deviations in the average search activity (broadly defined) of job seekers located at MSAs that experience an X-month maximum or minimum against the deviations exhibited by those who do not have a salient announcement. We double cluster all standard errors using applicants' location and their first self-reported skill.

$$\begin{aligned} &sinh^{-1}\left(A_{i,m,t}\right) = \beta_a After_t + \beta_h High_{m,t} + \beta_l Low_{m,t} \\ &+ \beta_{a,h} After_t \times High_{m,t} + \beta_{a,l} After_t \times Low_{m,t} \\ &+ \gamma_1 u\_rate_{m,t} + \gamma_2 u\_rate_{m,t-1} + \gamma_3 u\_rate_{s,t} + dow_t + \delta_s + \iota_t + \zeta_i + \epsilon_{i,m,t} \end{aligned} \tag{4}$$

Table 4: Job Seekers' Response to Salient Regional Unemployment Announcements

Dependent Variable (Inv. Hyperbolic Sine); 6-Mth High					
	(1)	(2)	(3)	(4)	(5)
	Mean Views	Applications			
	per Posting	Total	To a Different MSA	Distinct MSAs	Distinct Job Functions
High	0.002*	-0.008	0.068**	0.017**	0.039***
AfterXHigh	0.035**	-0.000	0.050***	0.022**	0.016***
Low	-0.001	-0.004	-0.084**	-0.005*	0.011
AfterXLow	0.004**	0.001	-0.070**	0.001	0.006
Job Seekers	2,999,498				
Observations	7,198,795				

Table 4 shows the estimated coefficients. Each column presents a different dependent variable. In the 7-day window after a salient announcement of either high or low unemployment, the average job posting receives more views than before the announcement. The effect is almost an order of magnitude larger (3.5% vs. 0.4%) when the announcement is a 6-month high than when it is a 6 month low. While the number of applications submitted does not significantly change, we find evidence consistent with job seekers re-allocating their applications in various ways.

First, applicants are more likely to apply to job postings within their own MSA when the unemployment rate is at a 6-month low. The effect is exacerbated after the BLS's press release. Overall, relative to periods with non-salient announcements, the number of applications submitted to "outside-of-own-MSA" job postings declines by 1.5% (-0.084+-0.07). Analogously, the number of applications to other MSAs increases after a 6-month high announcement. This is consistent with job seekers updating their expectations on job finding rates in their location and seeking areas with less market slack.

Second, job seekers spread their applications across more MSAs and more diverse job functions after a high unemployment rate announcement. On average, job seekers submit applications to job postings located in 2.9 different MSAs (their own location and two "out-of-own-MSA".)[26] On the week prior to a 6-month high announcement, the number of distinct MSAs that job seekers apply to increases by 1.7% and an additional 2.2% on the week after the announcement. Job seekers broaden their search across job titles, too. The number of distinct job functions that job seekers apply for increases by 1.6% after a 6-month high announcement. We do not find evidence of a change in the set of job functions targeted by applicants after a 6-month high unemployment rate. It is important to note that the applicant pool using the DHI platform likely over-represents on-the-job search. This perhaps explains the asymmetric effect of 6-month high versus 6-month low announcements.

5.2 Employers

We estimate an analogous specification for employers, examining their decision to post and remove vacancies around the 7-day window around a BLS press release. We also examine employers' propensity to post explicit wages. Table 5 shows the estimated coefficients.

Consistent with the prediction in a standard search model, employers post more vacancies when the unemployment rate is high. During the week before a 6-month high announcement, the number of new vacancies is 1.4% higher relative to non-salient announcement periods. On the week after the announcement, new vacancy postings increase by an additional 3.7%. Meanwhile, around a low unemployment rate announcement, vacancy postings decline although the magnitude is much smaller. It is important to note that

[26] See Table 2 for unconditional means on applicants' search behavior.

the sample for this analysis includes only companies with non-local customer base who are therefore less affected by the potential negative impact of high unemployment on consumer demand.

Table 5: Employers' Response to Salient Regional Unemployment Announcements

Dependent Variable (Inv. Hyperbolic Sine); 6-Mth High				
	(1)	(2)	(3)	(4)
	Vacancy Postings			Wage Posting
	New	Removed	Active	(% of active postings)
High	0.014***	-0.010***	0.021*	0.040***
After X High	0.037***	-0.020***	0.011	0.006**
Low	-0.009*	-0.001***	-0.009	-0.022**
After X Low	-0.001*	0.002***	0.001	-0.003**
No. of Employers	31,182			
No. of Observations	161,299,219			

On average, employers offer an explicit wage for 16% of their vacancy postings. The week before the BLS publishes a press release announcing a 6-month high unemployment rate for the MSA where the job is to take place, the share of postings in the location that offer a wage increases by 4 percentage points. The week after the announcement the share increases by an additional 0.6 percentage points. The opposite happens when the announcement is for a 6-month low, although the magnitude of the effect is halved. We conclude that employers favor wage posting when the unemployment rate is high, and wage bargaining when it is low.

6 Conclusions

In standard theoretical models, the ratio of vacancies to unemployment provides a sufficient statistic for the job finding and the job filling rate. In practice, these rates deviate from their model-predicted counterparts. We construct a new measure of tightness based on the outflow rate from search using data from an online job board with over 1 million users on the job search side and over 30,000 companies on the hiring side. We show that our measure co-moves with the JOLTS based tightness measure. Unlike JOLTS based estimates, our measure includes all job seekers using the platform regardless of their current employment status and therefore is closer to the theoretical construct of tightness. Moreover, we can calculate it for various categories defined by skill requirements, job titles, and location.

We use this new measure to examine how job seekers' search behavior adjusts with tightness. We find evidence consistent with individuals diversifying their search, that is applying to a wider set of job functions, skill requirements and locations, when markets are slack. Applicants target postings offering higher wages when markets are tight.

On the employer side, we use mean applications per posting as our measure of labor market slack. Employers post more jobs for independent contractors, and fewer for W2 employees, when market are slack. We also find a positive correlation between the number of skills listed on any one posting and labor market tightness. However, the number of distinct skills required across an employers' active postings declines in tight labor market. This is consistent with employers posting more specialized vacancies when labor market tightness declines. When tightness rises, the share of postings that offers an explicit wage declines.

Finally, we study employers' and job seekers' search behavior around the 7-day week of salient regional unemployment rate announcements. We find evidence consistent with the BLS monthly press releases containing information that leads to companies and applicants to updated their priors on tightness. During the weeks around a high-unemployment rate announcement, job seekers broaden their search both geographically and in terms of job description, and target job postings outside their own location. Employers post more vacancies and are more likely to offer an explicit wage at MSAs where the unemployment rate is announced to be at a 6-month high.

These various findings suggest that both employers and job seekers respond to labor market tightness using a variety of margins. Recruitment and job search is not limited to posting vacancies or investing time finding a suitable job. Instead, employers adjust the contract terms and job characteristics in their postings. Similarly, job seekers re-allocate their applications resulting in a positive correlation between labor market tightness and the scope of their search.

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