Recruiting Intensity, Hires, and Vacancies: Evidence from Firm-Level Data*

Eliza Forsythe, University of Illinois, Urbana-Champaign†

Russell Weinstein, University of Illinois, Urbana-Champaign‡

February 11, 2022

Abstract

We investigate employer recruiting behavior, using detailed firm-level data from a national survey of employers hiring recent college graduates. We show employers adjust recruiting effort, hiring standards, and compensation with the business cycle, beliefs about tightness, and their own hiring plans. We then show that firms expending greater recruiting effort hire more individuals per vacancy. The results suggest that when firms want to increase hires they adjust vacancies and recruiting intensity per vacancy. If true more broadly in the labor market, it may help explain the breakdown in the standard matching function during the Great Recession. For the firms in our sample, the difference in firm vacancy yields between 2011 and 2015 would have more than doubled if recruiting effort had been constant. Finally, we estimate that our measure of recruiting effort can explain 61% of the elasticity of the vacancy yield with respect to hires in our data.

*We are grateful to seminar participants at the LERA@ASSA Meetings and the University of Illinois, and to our discussant Jason Faberman, for helpful comments. We thank Ed Koc at NACE for assistance with the data. We thank Anahid Bauer, Juan Muñoz, Noelia Romero, and Yuhao Yang for excellent research assistance. A previous version of this paper circulated with the title "Recruiting Intensity Over the Business Cycle".

†School of Labor and Employment Relations and the Department of Economics; eforsyth@illinois.edu

‡School of Labor and Employment Relations and the Department of Economics; weinst@illinois.edu

1 Introduction

In the aftermath of the Great Recession, the core relationship between vacancies, unemployment, and hires broke down (Elsby, Michaels, & Ratner, 2015). Despite many job seekers per vacancy, the hiring rate did not increase as much as standard theory would predict, suggesting a disruption in the process of matching job seekers to open positions. Using establishment-level hiring and vacancy data, Davis, Faberman, and Haltiwanger (2013) presented novel cross-sectional evidence that when firms increase hires, they also fill a greater proportion of their vacancies. This stands in marked contrast to the standard matching model's prediction that hires are proportional to vacancies, conditional on market tightness. Their result suggests that when firms want to increase hires they adjust vacancies, but conditional on vacancies they also adjust along other dimensions, such as recruiting intensity, to increase hires.

If firms decrease recruiting intensity per vacancy during recessions, this implies standard matching models using vacancies as an input will overestimate the number of hires in recessions. Davis et al. (2013) found indirect evidence that firms reduced recruiting intensity during and after the Great Recession, and show this behavior can partially explain the slow recovery from the recession.

Given the breakdown in the standard matching function, and following Davis et al. (2013), a growing literature focuses on the role of employer recruiting intensity, and its relationship to aggregate outcomes. Several papers, including Davis et al. (2013), have constructed measures of recruiting intensity using micro-level data on hires and vacancies. However, there is limited evidence using firm-level data directly measuring the use of specific recruiting strategies, how and when firms adjust these strategies, and their impact on the firm's hires.

We use 2006-2016 firm-level recruiting, vacancies, and hires data for 250 mostly large U.S. employers recruiting new college graduates. Our objective is to understand the extent to which firms use recruiting intensity per vacancy, in addition to vacancies, to meet their hiring goals. We do so in two ways. First, we study how employers adjust recruiting effort, compensation, and screening selectivity in response to the business cycle, perceived labor market tightness, and hiring objectives. This importantly documents whether firms adjust recruiting behavior when there are changes in their own demand or in the labor market. Second, we investigate whether employers fill more of their vacancies when they increase their recruiting, conditional on market tightness. This would be consistent with firms adjusting hires in this market not only by adjusting vacancies, but additionally through recruiting intensity per vacancy.

Our data richly describe a particular labor market: large firms recruiting recent college

graduates. Despite the importance of this market, it remains a largely unexplored area of research.[1] We believe that this focus is valuable for several reasons. First, the focus in our data on very large firms allows us to study a segment of the labor market in which roughly 50% of U.S. workers are employed. Nearly 90% of our sample consists of firms with more than 500 employees, and firms with over 500 employees employed over 50% of U.S. workers in 2016 (Statistics of U.S. Business, 2018). Further, the firms in our sample employ roughly 2.5% of the United States labor force.[2]

Second, the labor market for new college graduates represents labor market entry for a large number of individuals.[3] In addition, college campuses present an opportunity to recruit and hire these new entrants in a structured and directed search. Reflecting this market's value to employers, many firms have departments whose main focus is university relations and recruiting. This is true for roughly 75% of firms in our sample.[4] Further, on average approximately 55% of full-time entry-level professional hires by firms in our sample were new college graduates.[5]

This market is also particularly consequential for workers. It is well documented that individuals graduating college during recessions experience long-run earnings losses (Kahn, 2010; Oreopoulos, Von Wachter, & Heisz, 2012). Studying recruiting and hiring in this specific market allows us to provide evidence on the channels through which these effects may occur. In addition, evidence shows recessions' persistent effects are importantly explained by starting one's career at a lower quality employer (Oreopoulos et al., 2012).[6] By showing the specific ways in which large firms adjust recruiting, we provide insights into which workers may be most affected by reductions in labor demand.

A key contribution of our paper derives from the richness of our data, which allows us to study various ways in which employers can adjust recruiting intensity, including compensation generosity, search effort, and screening selectivity.[7] More generous compensation may

[1] Weinstein (2018), Weinstein (2022), and Weinstein (2021) study the firm's choice of which campuses to target for recruiting using data from up to 70 prestigious finance, consulting, and Fortune 250 firms. Oyer and Schaefer (2016) study the relationship between law schools and law firms. Rivera (2011) and Rivera (2012) study screening and hiring at professional services firms recruiting on campus, using interviews and observation of a hiring committee. Kuhnen and Oyer (2016), Kuhnen (2011), and Laschever and Weinstein (2020) study job search and hiring in the market for professional master's degree students.

[2] We calculate this using the binned firm size distribution in Table 1 and use the 2016 Statistics of U.S. Business (2018) data to calculate the average firm size within each bin.

[3] In 2006-2007, U.S. colleges and universities awarded over 3 million degrees (U.S. Department of Education, National Center for Education Statistics, 2012).

[4] Among firms in our sample from 2011-2013; this information was not collected post-2013.

[5] This is for hires over 2011-2016. In each year, firms report the percent of full-time entry-level professional hires who were new college graduates.

[6] Several other papers show the importance of initial matches. See Oyer (2006), Liu, Salvanes, and Sorensen (2016), and Arellano-Bover (2020).

[7] These aspects of recruiting intensity are similar to the taxonomy offered in Carrillo-Tudela, Gartner,

encourage applicants to apply to and accept positions, increasing vacancy yields. Search effort encompasses recruiter time and financial investments in recruiting activities. These activities may make the firm more visible or attractive, implying potentially more applicants, greater acceptance likelihood, and thus higher vacancy yields. Finally, if employers are very selective in recruiting and screening applicants, this effectively decreases the size of the applicant pool and the intensity with which the firm is recruiting, reducing the vacancy yield. We have multiple detailed measures of employer effort and standards, allowing us to construct indices of this recruiting behavior.

We find that recruiting methods are responsive to the business cycle, perceived labor market tightness, and hiring objectives. Employers increase recruiting effort and compensation generosity when they plan to hire more individuals and decrease along these dimensions when they plan to hire fewer, conditional on beliefs about labor market tightness. This provides important initial evidence that in this market when employers want to increase hires they adjust on dimensions other than vacancies, which the standard matching model does not incorporate. Employers also increase recruiting effort and compensation generosity with their beliefs about market tightness. Further, we show employers reduced recruiting effort and compensation generosity in the early years of the Great Recession, and increased recruiting through the recovery. We also see adjustments in recruiting selectivity, though our evidence is only suggestive given lower levels of precision.

Together, this evidence is consistent with employers decreasing recruiting intensity to decrease hires, and this being more prevalent during recessionary periods. If employers decrease recruiting effort and compensation conditional on posted vacancies, and this has an effect on hires, this would lead the standard matching model to overpredict hires in this market during the Great Recession.

We investigate this by testing whether adjustments in recruiting are correlated with the proportion of the firm's vacancies that are filled (e.g. the vacancy yield). If adjustments in recruiting are simply scaling with vacancies, then the proportion of vacancies filled would remain unchanged. However, if firms are adjusting recruiting per vacancy, then recruiting adjustments would affect the likelihood of filling vacancies, with implications for total hires in this market. We find that a one standard deviation decrease in the recruiting effort index is associated with a 3.7% decrease in the firm's vacancy yield, conditional on labor market tightness. We also see that within firms, increases in recruiting effort are associated with increases in vacancy yield, using a specification with firm fixed effects. Given that we do

and Kaas (2020). Gavazza, Mongey, and Violante (2018) also suggest firm recruiting decisions can make the firm more visible, more attractive, or allow the firm to screen more candidates per unit of time. Davis et al. (2013) also identify similar dimensions of recruiting intensity.

not have purely exogenous differences in recruiting effort, we are careful about attributing causality. However, these results are consistent with firm recruiting behavior affecting vacancy yields in this market.

To the extent that our estimate is causal, it implies the percentage difference in the average firm-level vacancy yield in our sample between 2010-2011 and 2014-2015 would have more than doubled (from 1.1% to 2.3%), if recruiting effort had been constant. To quantify the importance of recruiting intensity, Davis et al. (2013) focus on the elasticity of the firm's vacancy yield with respect to hires, the novel result suggesting firms adjust recruiting in addition to vacancies. Although Davis et al. (2013) do not have data on firm recruiting behavior, they propose a decomposition method to estimate the residual of the elasticity, arguing this is likely driven by recruiting intensity. Adapting their decomposition method for our setting, we find that our measure of recruiting effort can account for 61% of the overall elasticity of the vacancy yield with respect to hires in our sample.

Our results are consistent with the Davis et al. (2013) hypothesis that when employers are less interested in hiring they adjust vacancies and recruiting intensity per vacancy, dampening hires relative to what would be expected based on vacancies. We believe that documenting these relationships using firm-level recruiting data makes an important contribution to the literature. While we find a strong relationship between recruiting effort and vacancy yields, our other measures of recruiting intensity (compensation generosity and our recruiting standards index) do not have a statistically significant relationship with vacancy yields. Thus, in our setting, recruiting effort is the main lever that employers adjust to influence the vacancy yield.

Our evidence is also informative about which types of workers may be most adversely affected when employer demand is lower. Firms adjust hires by adjusting effort, including career fairs, travel, and technology. This suggests that some students will be particularly likely to lose access to large firms, and it will be the students at universities where the firm stops attending the career fairs, and the farther universities. These may also be students with fewer networks to large firms. Weinstein (2021) finds that graduates of less selective universities are more adversely impacted by graduating during the Great Recession, and employers were more likely to stop recruiting at their less selective, smaller, and farther target campuses during the Great Recession. Further, when hires are lower recruiting standards are higher, suggesting that students most adversely affected by a reduction in firm demand may be lower GPA students, those from two-year colleges, and those with less relevant experience.

There is a growing theoretical literature on how recruiting intensity enriches standard search and matching models.[8] The micro-level evidence on recruitment behavior is primarily

[8] Wolthoff (2017) develops a search model to study employer recruiting decisions; calibrating the model

an older literature that has experienced a resurgence. Several recent papers have found changes in the content of firms' job postings with market tightness (Hershbein & Kahn, 2018; Sasser Modestino, Shoag, & Ballance, 2016, in press; Ma & Samaniego de la Parra, 2021).[9]

Two recent papers study recruiting intensity using German data for a representative sample of establishments (Carrillo-Tudela et al., 2020; Lochner, Merkl, Stüber, & Gürtzgen, 2021), and we see our paper as complementary for several reasons. While their data contain detailed measures of vacancies and employment, the recruiting data are from surveys asking only about recruiting for the firm's most recent hire. As we will discuss, we see our comprehensive recruiting data as one of our contributions. Carrillo-Tudela et al. (2020) find that labor markets in which firms on average used more search methods and relaxed hiring standards have higher labor-market-level vacancy yields. At the employer level, they show relationships between recruiting intensity and the number of hires relative to employment, though they do not show the relationship between firm-level recruiting and firm-level vacancy yield. Lochner et al. (2021) show employers expend less recruiting effort during periods of high unemployment.[10]

We make three important contributions to this literature. We provide the first evidence of the relationship between firm-level recruiting measures and firm-level vacancy yields, helping to show firms use recruiting intensity, separately from vacancies, to affect hires. Second, we show this and also show that firms adjust recruiting with their hiring plans, beliefs about labor market tightness, and the business cycle, using many detailed measures of firm-level recruiting effort, such as the number of career fairs or days between interview and offer. Other data sources typically have fewer, and coarser, measures of effort, such as the number of search methods used (Roper, 1988; Carrillo-Tudela et al., 2020; Lochner et al., 2021) or number of hours spent on search (Barron, Bishop, & Dunkelberg, 1985). Third, we richly describe recruiting and hiring behavior for large firms recruiting new college graduates in the U.S. – a large and consequential labor market.

shows employer hiring standards increase during recessions while recruiting intensity decreases. Gavazza et al. (2018) show that under equilibrium random search with recruiting intensity, employers meet hiring goals by adjusting recruiting intensity. Leduc and Liu (2020) estimate a dynamic stochastic general equilibrium model and show employers adjust both recruiting intensity and the number of vacancies. Mongey and Violante (2019) develop a method to derive aggregate recruiting intensity from aggregate data.

[9] Weinstein (2022) finds that firms adjust recruiting when opening new offices, and they start to recruit at nearby universities. Somewhat paradoxically, Faberman and Menzio (2018) find that higher wages are associated with longer vacancy duration, likely because higher wages are associated with stricter standards and tighter markets.

[10] Lochner et al. (2021) also document a 'u-shaped' relationship between recruiting intensity measures and employment growth. They argue that high-turnover in shrinking establishments can explain high recruiting effort for these employers.

Our evidence suggests procyclical recruiting intensity serves to dampen the forces of the standard matching function over the business cycle in the market for new graduates. If the large employers in our sample behave similarly when they hire beyond the entry-level college market, our results may hold more generally and explain the slow recovery of aggregate hires after the Great Recession.

2 Data

We use data from two firm-level surveys from the National Association of Colleges and Employers (NACE), an organization focusing on the development and employment of college-educated individuals. Its members include over 8000 college career services professionals from over 2000 colleges and universities in the United States, and over 3000 university relations and recruiting professionals from over 900 employers. To provide information to its members and other interested groups, NACE conducts multiple surveys of its members each year. We use data from the Recruiting Benchmarks (2008-2016) and Job Outlook (2006-2016) surveys to study recruiting intensity. Both of these surveys are sent to members who recruit new college graduates for entry-level jobs at their employer.

The Recruiting Benchmarks survey is administered each year between May and July. The survey focuses on the firm's recruiting activity over the past academic year. The Job Outlook survey is administered each year between August and September, and recruiting professionals describe hiring plans for the coming academic year, as well as hiring outcomes in the past academic year.

These surveys richly describe these firms' recruiting, vacancy posting, and hiring behavior in the market for recent college graduates. We will analyze whether the evidence is consistent with these firms adjusting recruiting when they want to adjust the number of hires of recent graduates. Given the nature of our data, we will not be able to address whether firms reallocate recruiting effort away from recent graduates and towards experienced hires or non-college graduates as their demand changes.

To analyze the relationship between hiring plans, beliefs about market tightness, and recruiting intensity, we use multiple waves of the Job Outlook survey. We call this our forward-looking sample. To analyze the relationship between recruiting intensity and vacancy yield, we merge the two surveys. The Job Outlook survey has information on hires and vacancies in the past year, while the Recruiting Benchmarks survey has information on recruiting activity that year. We call this merged dataset our backward-looking sample.

We first create a consistent name variable, in order to include firm fixed effects and to merge the surveys. Employer names in the data are not standardized over time or across

surveys. We take a fairly conservative approach in creating this consistent measure. We benefit from a NACE ID given to the specific person filling out the survey.

We group companies for which the names are almost identical or there is a reason to think they are the same (i.e. a documented name change), and there is at least one instance in which they share the same ID, state, region, and industry. We separate companies for which the employer names and IDs were the same, but location and industry were different. This raises the possibility the individual is reporting based on a different unit or division. We also separate companies for which there was more than one ID for that company responding to the same survey in the same year, as this also suggests these individuals were reporting for different divisions within the company within the year. Other than these changes, we use the reported names.[11]

Table 1 shows firm characteristics for our two main samples. The backward-looking sample has 405 observations, from 269 different firms. Roughly 34% of the observations are from manufacturing firms, 11% from Finance and Insurance, and over 21% from professional and technical services.[12] Given this last category is quite diverse, ranging from accounting and advertising to engineering services, we split this two-digit NAICS code into four-digit codes. The data predominantly consist of very large firms. Approximately 25% of observations are from firms with more than 20,000 employees, 38% from firms with more than 10,000 employees, and 89% are from firms with more than 500 employees. While firms with over 500 employees comprise a small percentage of all firms in the U.S., in 2016 they employed over 50% of workers in the economy (Statistics of U.S. Business, 2018).[13] Sample composition is very similar for the forward-looking sample (column 2), which contains 709 observations from 250 firms. The forward-looking sample is restricted to firms with at least two observations so we can include firm fixed effects. We also present additional summary statistics on the distribution of years in the sample (Figure A.1), and number of observations per firm (Table A.1).[14]

[11] In our backward-looking regression sample, 88% of firms have the same ID associated with all observations of the firm. Further, 97% of the firms in our sample would not be matched to a different "parent" firm if we did not separate firms for the reasons given above. In the forward-looking sample, these numbers are 56% and 98%, respectively.

[12] Industries are defined using two-digit NAICS codes, based on the six-digit NAICS codes in the data.

[13] In 2016, roughly .3% of U.S. firms had over 500 employees (Statistics of U.S. Business, 2018).

[14] In Appendix Table A.2, we compare the NACE sample industry distribution to the distribution of all firms, and of large firms, from the Census Enterprise Statistics Program. The NACE sample is more similar to the distribution of large firms, however unsurprising given the NACE focus on recruiting recent college graduates, manufacturing, and professional, scientific, and technical services are over-represented, while retail industries, and the residual set of industries are under-represented. Among the residual set of industries, roughly 20% of large firms are in health care and social assistance based on the Census Enterprise Statistics, while the NACE share is under 1%. This likely reflects that a large fraction of this industry's employment is health care practitioners and health care support occupations (e.g., home health aides and

Table 1: Employer Characteristics

% by Industry:	Backward-Looking Sample	Forward-Looking Sample
Manufacturing	0.34	0.34
Finance & Insurance	0.11	0.11
Mgmt, Sci., and Tech. Consulting	0.08	0.06
Retail	0.07	0.06
Construction	0.05	0.06
Architectural and Engineering Services	0.03	0.05
All Other	0.31	0.33
% by Company Size (# Employees):		
$>$ 10,000	0.38	0.34
5,001-10,000	0.14	0.14
2,501-5,000	0.16	0.13
1,001-2,500	0.14	0.13
501-1,000	0.07	0.10
$\leq$ 500	0.11	0.16
Firms	269	250
Observations	405	709

Notes: Column 1 presents summary statistics for the backward-looking regression sample and Column 2 presents summary statistics for the forward-looking sample. The forward-looking sample is restricted to firms with at least two observations. The size categories slightly differ in the two surveys. The largest category in the forward-looking sample is $>$ 10000, whereas in the backward-looking sample we use data from the Recruiting Benchmarks survey in which there are separate categories for 10001-20000 and $>$ 20000. For the purposes of this table, we combine the two largest categories for the backward-looking sample.

The two surveys contain a variety of questions about recruiting behavior. Due to differences between the two surveys, we construct two sets of recruiting measures: the Job Outlook Survey asks detailed questions about plans for the coming year, which we label 'Forward-Looking' measures. The Recruiting Benchmark instead asks questions about recruiting activities in the past year, which we identify as 'Backward-Looking' measures.

Forward-Looking Measures

The Job Outlook survey includes several questions about recruiting plans in the coming year, however not all questions are asked each year. To maximize the sample, we use five key questions in which employers are asked about changes in their recruiting effort for the upcoming year: (1) Do you plan to increase career fairs? (2) Do you plan to travel more for recruiting? (3) Do you plan to use more technology in recruiting? (4) Do you plan to use more social networks in recruiting? (5) Do you plan to change your branding in recruiting?[15]

Table 2: Summary Statistics: Forward-Looking Measures

In Coming Year's Recruiting	Mean	SD
Plan Increase Hires	0.44	0.50
Plan Decrease Hires	0.15	0.36
Believe Labor Market is Tight	0.84	0.36
Recruiting Effort		
Forward-Looking Effort Index	0.00	1
More Career Fairs	0.30	0.46
More Travel	0.18	0.38
Change Brand	0.33	0.47
More Technology	0.51	0.50
More Social Networks	0.48	0.50
Recruiting Standards		
Plan to Hire Associate's Degree Graduate	.16	.37
Plan to Hire Int'l Students for U.S. Jobs	.28	.45
Compensation Generosity		
Planned % Incr. In Offered Starting Salary (Real)	0.24	2.85
Plan to Offer Bonus	0.51	0.50

Notes: The Forward-Looking Index ranges from -1.2 to 2.3. The Percent change in real salary ranges from -2.2 to 23.20. Sample Size for the main forward-looking sample is 709. Sample size is smaller (460) for the percent change in real starting salary. Similarly for the signing bonus, where the sample is 669 due to missing values.

nursing assistants), which likely describes relatively few new college graduates from four-year universities.

[15]Branding refers to the employer's brand on campus, which might be developed through a variety of techniques, including the materials, the events, and the relationships through which the firm advertises their vacancies.

To reduce the dimensionality of the recruiting effort variables, we perform principal component analysis and keep the component with the largest eigenvalue. We then normalize this measure to have mean zero and standard deviation one, and refer to it as the Forward-Looking Recruiting Effort Index. Our analysis is limited to data collected in 2011 to 2016, which refers to hiring plans in the 2011-2012 through the 2016-2017 academic years. Table 3 shows how each binary variable is weighted in the index before standardization. As expected each of these variables has positive loadings, making it intuitive to interpret this as a recruiting effort index.

Table 3: Forward-Looking Recruiting Effort Index

In Coming Year's Recruiting	Eigenvector
More Career Fairs	0.48
More Travel	0.47
More Social Networks	0.46
More Technology	0.41
Change Brand	0.40
Eigenvalue	1.74
Fraction of Variance	34.8%
Number of Firms	250
Number of Observations	709

Notes: Eigenvectors associated with the first principal component of these variables.

We investigate two additional variables that capture compensation generosity: the real percent increase in starting salary that firms plan to offer, and an indicator for whether the firm plans on offering a signing bonus.[16] In addition, we have two measures of screening and hiring selectivity: whether the firm plans to hire international students for U.S. jobs, and whether the firm plans to hire individuals with an associate's degree. While these do not necessarily imply lowering hiring standards, they do imply the firm is considering a broader group of applicants, and this expands the applicant pool. Summary statistics of all variables are reported in Table 2, restricted to the firms with more than one observation in the sample, as our analysis will include firm fixed effects.

[16]The survey instrument asks firms for the planned percent increase in starting salaries, in which firms could respond with any number, including a negative number. The data show the values for this variable are greater than or equal to zero with a mass at zero, along with missing values. Based on this, we do not see the variable as censored, but instead, using the terminology of Wooldridge (2002), we treat this as a corner solution outcome in which a value of zero is truly zero. In this setting, estimating a linear model is more justified than in a setting where a value of zero may not be the true value. Appendix Table A.5 shows results using the planned real log signing bonus offer.

Backward-Looking Recruiting Measures

The second set of recruiting measures are based on realized recruiting activities in the prior year. Most of these are derived from the Recruiting Benchmark Survey, though several are from the Job Outlook Survey. We call these measures backward-looking to distinguish from the forward-looking recruiting plans from Section 2.1.

We use principal component analysis to construct indices for recruiting effort and hiring standards, and in addition will use an indicator for offering signing bonuses to measure compensation generosity.

Our index of recruiting effort is constructed using four variables that describe employer actions during the recruiting process. These include an indicator for whether the firm participates in on-campus recruiting, the number of career fairs attended, the elapsed time between interviewing a candidate and making an offer (or notifying that an offer will not be extended), and the amount of time candidates are given to decide on an offer.

Intuitively, participating in on-campus recruiting, attending more career fairs, and making offers more expediently can be seen as increases in recruiting effort.[17] Conditional on labor market tightness, extending the offer acceptance deadline decreases the likelihood that applicants reject the offer in anticipation of future offers from other firms. While extending the deadline may increase the likelihood the applicant receives another offer, the firm would also have the opportunity to match these alternative offers. While the firm is waiting, they also may continue their recruiting process in case the offer is ultimately rejected. As a result, we interpret longer deadlines as consistent with greater effort and as another benefit to the applicant.[18]

Our index of recruiting standards is constructed using three measures: whether the firm screens on GPA, whether the firm recruited from universities other than four year public or not-for-profit (for example, whether they recruit at two-year colleges, for-profit universities, and online universities), and whether the firm prefers candidates with relevant experience when hiring a new college graduate for an entry-level position. Other choices were preference for any experience, regardless of relevance; and experience does not factor into the decision when hiring a new college graduate.[19]

[17]It is possible that longer intervals between the interview and offer may reflect more effort in screening applicants, rather than a lack of expedience. We would expect this to be more likely if we used vacancy duration (as suggested by Van Ours and Ridder (1993)), rather than time between interview and offer, as much screening has already taken place before the interview. We also see a negative eigenvector on this variable in the effort index, and a positive eigenvector on career fairs attended, consistent with this reflecting expedience.

[18]We show in Table A.11 that our main results are robust to excluding this component from the effort index.

[19]In each year respondents are asked about the types of universities targeted, specifically in the previous

Table 4: Summary Statistics: Backward-Looking Measures

Variable	Mean	SD
Hires Last Year	188	627
Vacancies Last Year	201	690
Recruiting Effort		
Participate in On-Campus Recruiting	0.84	0.37
Days from Interview to Offer	23	20
Days from Offer to Deadline	15	13
Career Fairs Attended	37	48
Recruiting Standards		
Screen on GPA	0.75	0.43
Recruited from non-Four Yr. Public/NFP Univ.	0.17	0.37
Prefer Relevant Experience	0.68	0.47
Compensation Generosity		
Gave Signing Bonus	0.54	0.50

If firms are adjusting standards to increase the likelihood of filling the vacancy, we would expect them to be less likely to screen on GPA, more likely to recruit from a wider range of universities, and less likely to prefer relevant experience. This would widen the pool of applicants.[20] Finally, our measure of compensation generosity is whether the firm offered a signing bonus last year.

We note these surveys have many other variables that capture recruiting intensity, but we do not use them as they are asked inconsistently over time. Further for some of these questions the response rate is low. These additional variables include number of HR staff involved in university recruiting, total recruiting budget, and whether the firm is using video interviewing, online advertising, or pre-employment assessment tests.

Our measures of hires and vacancies are both backward looking, and come from the Job Outlook survey. In August-September of each year, respondents are asked how many college graduates their organization hired during the previous academic year for full-time entry-level positions. In the same survey, respondents are also asked how many positions were available

year's recruiting (in the Recruiting Benchmark survey). However, the questions about GPA screening and preferences for experience are worded more generally, and are asked in the Job Outlook survey. For example, respondents are asked "Do you screen college candidates by GPA?" in August to September of each year. We assume the answer to this question is relevant for recruiting in the previous year, as the current year's recruiting has likely not yet begun. However, we acknowledge this may introduce noise into the standards measure.

[20] If firms do not screen before selecting interviewees, they may end up interviewing low match-quality applicants who are unlikely to accept an offer, even if the firm was willing to make one. If the firm has a fixed number of interview slots, then despite the larger applicant pool because of the lack of screening, the vacancy yield may be lower. But the firm could avoid this by increasing the interview rate among the applicant pool. If applicants observe the firm's screening standards, high quality applicants may only apply to firms with high standards, which could also affect the vacancy yield.

for graduates in the previous academic year, and we use this as our measure of vacancies. In Section 3.3 we discuss the differences in these measures relative to JOLTS measures of hires and vacancies, and the implications of these differences for our results.[21]

All of our analysis using the backward-looking sample, including the construction of the index using principal components, restrict to observations for which the ratio of hires to vacancies is not more than 2.5.[22] We use alternative sample restrictions for robustness, as we will discuss.

We construct the indices using the observations that are not missing values for any of the variables in any of the indices, and that are in our main regression sample. As we will be taking logs of the recruiting effort and standards index, and it has mean zero, we first shift the mean by ten, and then take the log. We then standardize, so the log index is mean zero and standard deviation one, to make the results easier to interpret. Results are similar when shifting the mean of the index by five or shifting the mean by 15, instead of by ten.

Table 5: Backward-Looking Recruiting Effort Index

	Eigenvector
On-Campus Recruiting	0.684
Days from Offer to Deadline	0.5191
Career Fairs Attended	0.4448
Days from Interview to Offer	-0.2547
Eigenvalue	1.24
Fraction of Variance	30.9%
Number of Firms	269
Number of Observations	405

Notes: Eigenvectors associated with the first principal component of these variables.

Table 4 shows summary statistics for the recruiting measures, as well as hires and vacancies.[23]

[21]The Job Outlook survey also asks about positions available in the coming academic year, which could be an alternative measure of vacancies. However, using a forward-looking measure of vacancies and a backward-looking measure of hires from the Job Outlook survey would require merging employer observations across consecutive years to calculate the vacancy yield. This would be even more demanding on an already small sample.

[22]This is the 98.6th percentile of the backward-looking sample with nonmissing hires, vacancies, and career fairs data. Career fairs are one of our measures of recruiting, as well as a variable in the principal components analysis. Dropping instead the 99th percentile and above would imply keeping an additional two observations for which the ratio is 5 and 6.9. Given these are so much larger than 2.5, they appear closer to outliers and so we exclude those as well. We drop observations at the first percentile and below of the hires to vacancies ratio (roughly .27). We discuss several additional refinements in the appendix.

[23]Appendix Figure A.3 shows the distribution of hires per vacancy in the backward-looking regression sample.

Table 5 shows the eigenvectors for the first principal component from our analysis of effort variables. This component quite intuitively measures recruiting effort. It has positive loading on whether the firm participates in on-campus recruiting, negative loading on the time between interview and offer, positive loading on career fairs attended, and on time to offer deadline. This component explains roughly 31% of the overall variance.

Table 6: Backward-Looking Recruiting Standards Index

	Eigenvector
Screen on GPA	0.6315
Prefer Relevant Experience	0.5532
Recruit from non-Four Yr. Public/NFP	-0.5434
Eigenvalue	1.19
Fraction of Variance	39.7%
Number of Firms	269
Number of Observations	405

Notes: Eigenvectors associated with the first principal component of these variables.

Table 6 shows the eigenvectors for the first component from our analysis of the recruiting standards variables. This component quite intuitively measures standards. There are positive loadings on GPA screening, preference for experience, and negative loading on recruiting at a wider range of universities. Thus, a more positive value of this index is associated with higher recruiting standards and less intensity. This component explains roughly 40% of the overall variance.

3 Recruiting Intensity, Hiring Plans, Hires, and Beliefs about Tightness

To analyze the effect of recruiting intensity on the vacancy yield, we begin by introducing some simple notation. Consider the following basic matching relationship from the standard Diamond-Mortensen-Pissarides (DMP) search and matching model:

$$f_t \equiv \mu(v_t, u_t)$$

where f_t is the fill rate, and is determined by the matching function μ and the two arguments: aggregate vacancies (v_t) and job seekers (u_t) at time t. This yields total hires for employer e

$$h_{et} = f_t v_{et} \tag{1}$$

Thus, the number of workers a firm hires depends on two factors: how many vacancies the firm posts and aggregate labor market statistics (v_t and u_t).

In this classic framework, all firms face the same job filling rate f_t, thus the only way an employer can increase the number of hires is to increase the number of vacancies. To enrich this model, we follow Davis et al. (2013), by allowing firms to take actions to influence the likelihood that a vacancy is filled. For instance, the firm can advertise the vacancy in more places, change the skill requirements to be less selective, or increase the wage. Thus, if a firm wants to increase the number of hires, it can increase the number of job postings as well as increase recruiting intensity.

Formally, we can generalize this framework by defining $q(v_{et}, x_{et})$ to be the effective vacancies posted by employer e. This is a function of the number of vacancies, as well as other recruiting actions (x_{et}) that can be taken by the employer to influence the number of hires. In particular, we will focus on three dimensions of recruiting intensity: effort ($x_{f_{et}}$), hiring standards ($x_{s_{et}}$), and compensation generosity ($x_{c_{et}}$). Thus, we can write

$$h_{et} = \tilde{f}_t q(v_{et}, x_{f_{et}}, x_{s_{et}}, x_{c_{et}}) \tag{2}$$

where $\tilde{f}_t$ now depends on effective vacancies.

Equation 2 shows two things. First, the number of hires continues to depend on the aggregate state of the labor market ($\tilde{f}_t$). Holding vacancies and recruiting intensity fixed, if the labor market is tight, the aggregate fill rate will fall, and thus hires will fall. Second, conditional on labor market tightness, increases in vacancies or to any of the three dimensions of recruiting intensity will lead to an increase in hires. Thus, if an employer has a targeted number of hires, the employer can adjust recruiting intensity and vacancies to reach that target, given aggregate labor market tightness. This also suggests that a decline in vacancies may under-predict the decline in hires, if employers also reduce recruiting intensity per vacancy.

In this section we investigate how firms adjust recruiting intensity in conjunction with the firm's hiring plans, as well as with their beliefs about labor market tightness. Similar to the previous literature, we also show the relationship between recruiting intensity and realized hires. In addition, we investigate whether firms changed their recruiting intensity during the Great Recession, though our data are more limited in this time period. In doing so, we provide direct evidence of whether firms are operating along the margin of recruiting intensity, which has only recently begun to receive considerable attention in the literature, and with limited direct evidence.

Recruiting, Hiring Plans, and Beliefs about Market Tightness

We begin by examining how recruiting activities change in response to changes in planned hiring and beliefs about the labor market. This allows us to look in detail at the micro-level decision-making process underlying cyclical hiring behavior. In particular, we can consider an employer who has a targeted number of hires for the coming recruiting season. Given equation 2 and their beliefs about $\tilde{f}_t$ in the coming year, they choose how many vacancies to post and how much to invest in various dimensions of recruiting intensity. In this section, we provide evidence that employers adjust their planned recruiting behavior when they intend to increase or decrease hires in the coming year, or when they believe the labor market will become more or less slack.

In the Job Outlook survey, respondents are asked about their hiring intentions for the coming year. To measure hiring plans, we use a question in which respondents are asked if they plan to increase, decrease, or maintain hiring in the coming year. To measure beliefs about labor market tightness, we use a question in which respondents are asked to rate the labor market for new graduates in their industry in the coming year. If they rate the labor market as good, very good, or excellent, we define this as a belief that the firm will face a tight labor market in the coming year. If they rate the labor market as poor or fair, we define this as a belief that the labor market will be slack in the coming year. We combine these with our forward-looking measures of recruiting effort, standards, and compensation generosity, also derived from the Job Outlook Survey and described in Section 2.1.

To measure the relationship between recruiting intensity, hiring plans, and beliefs about market tightness, we estimate Equation 3, where t indicates year and e indicates firm. We include firm fixed effects (Ω_e), and thus we measure how recruiting intensity changes with changes in the firm's hiring plans or beliefs. We restrict our analysis to firms with at least two observations, and cluster standard errors at the firm level. Note that we do not include year fixed effects in these specifications, instead using beliefs about labor market tightness to control for tightness. Year fixed effects may also capture trends in recruiting variables that are not related to tightness, but related to technology for example. In Appendix Table A.4 we show results are similar with the inclusion of year fixed effects.

$$\begin{aligned}\text{Recruiting Measure}_{et} &= \beta_0 + \beta_1 \text{Plan Increase Hires}_{et} + \beta_2 \text{Believe LM Will Be Tight}_{et} \\ &+ \Omega_e + \epsilon_{et} \end{aligned} \tag{3}$$

Table 7 shows the results from estimating Equation 3 for the three different dependent variables. In Panel A, we focus on the Forward-Looking Recruiting Effort Index. Here we

Table 7: Relationship Between Hiring Plans, Beliefs, and Recruiting

	(1)	(2)	(3)	(4)
Panel A: Forward-Looking Recruiting Effort Index				
Plan Increase Hires	0.413***		0.378***	0.784***
	(0.090)		(0.089)	(0.229)
Believe Labor Market will be Tight		0.408***	0.325***	0.464***
		(0.122)	(0.114)	(0.137)
Interaction Term				-0.459*
				(0.255)
Firms	250	250	250	250
Observations	709	709	709	709
R-squared	0.513	0.499	0.521	0.524
Panel B: Planned % Increase in Offered Starting Salary (Real)				
Plan Increase Hires	1.072***		1.008**	0.584
	(0.410)		(0.411)	(0.529)
Believe Labor Market will be Tight		0.838***	0.594**	0.431
		(0.296)	(0.295)	(0.399)
Interaction Term				0.485
				(0.790)
Firms	146	146	146	146
Observations	376	376	376	376
R-squared	0.424	0.410	0.427	0.428
Panel C: Plan to Offer Signing Bonus				
Plan Increase Hires	0.029		0.022	-0.079
	(0.042)		(0.042)	(0.124)
Believe Labor Market will be Tight		0.069	0.064	0.029
		(0.069)	(0.068)	(0.084)
Interaction Term				0.114
				(0.130)
Firms	238	238	238	238
Observations	669	669	669	669
R-squared	0.571	0.572	0.572	0.573

Notes: All regressions include firm fixed effects. Coefficients from estimates of Equation 3. Standard errors clustered at the firm level, $***p < 0.01, **p < 0.05, *p < 0.1$. Firms measures the number of non-singleton firms in the sample.

see that when employers plan to increase hiring relative to the prior year, they increase recruiting effort by 0.41 standard deviations (column 1). Recall the standard DMP search and matching model assumes that employers can only increase hires by adjusting vacancies. This result provides direct evidence that employers adjust on additional margins when they want to increase hiring.

Next, we show that when employers that believe the labor market will be tight they plan to increase recruiting intensity by 0.41 standard deviations, relative to when they believe the market will be slack (column 2). However, this could be due to the fact that employers expand hiring when the labor market is tight. Thus, we want to know whether employers that plan to increase hiring put forth more recruiting effort after accounting for their beliefs about labor market tightness. Conditional on the employer's beliefs about tightness, when they plan to increase hiring they increase recruiting effort an additional .38 standard deviations (column 3). This provides important evidence that when employers want to increase hires they also adjust their recruiting effort.

Finally, in Column 4, we show this result is robust to the fully saturated model with an interaction term, and the coefficient on Plan Increase Hires grows to 0.78. The negative interaction indicates that the increase in recruiting effort when firms plan to increase hires is smaller when firms believe the market is tight. This could indicate decreasing returns to scale in recruiting effort.[24] Thus, hiring plans and beliefs about tightness are capturing different features of a firm's recruiting behavior.

Although our recruiting effort measures are very detailed, they measure total recruiting effort, rather than effort per position. This raises the possibility that employers may be holding effort per vacancy constant. In the next section, we test whether these increases in recruiting effort are associated with increases in effort per vacancy by looking at the relationship with the vacancy yield. We next turn to recruiting measures that are truly per-position: starting salary increases and signing bonuses.

In Panel B of Table 7 we focus on the reported percent change in real starting salary that employers plan to offer. In Column (1) we see that plans to increase hiring are associated with planning a 1.1 percentage point larger increase in real starting salary offer, relative to years in which the firm is not increasing hires.[25] In Column (3) we show a similar result (1 percentage point) even after controlling for beliefs about market tightness. The fully saturated model in Column (4) yields a similar point estimate for the difference in starting salary increase when firms plan to increase hires, conditional on beliefs that the market is

[24] We also have relatively few observations for firms that plan to increase hires despite believing the labor market is slack (30 observations, or roughly 4%), thus the negative interaction term could also reflect noise in the estimate of the coefficient on Plan Increase Hires. See Appendix Table A.3.

[25] The mean planned real percent increase in starting salary is -.8% when firms are not increasing hires.

tight. In addition, we find that planned increases in offered starting salaries are larger when employers believe the market is tight (Column 2), even after controlling for hiring plans (Column 3).

Finally, In Panel C of Table 7 we focus on an indicator for whether the employer plans to offer a signing bonus. The sample size is smaller than panel A due to missing data. While confidence intervals are large and the point estimates are not significant, the estimates are suggestive that employers may be more likely to offer bonuses when they plan to increase hires.[26]

In Appendix Table A.6, we show the corresponding results for plans to decrease hiring and beliefs that the labor market will be slack. Point estimates are consistent, showing that employers decrease recruiting effort and compensation generosity when they want to decrease hiring or if they believe that the labor market is slack. In Appendix Table A.7 we show additional results for selectivity. These are underpowered but suggestive that firms decrease selectivity when planning to increase hires and when they believe the labor market is tight, namely by planning to hire associate's degree graduates or international students for U.S. jobs.

Thus, consistent with Equation 2, employers are not limited to adjusting vacancies in order to adjust hiring and respond to changes in beliefs about labor market tightness. Instead employers also adjust recruiting effort and compensation generosity. Employers reduce recruiting effort and compensation generosity when they believe the labor market to be slack and increase recruiting effort and compensation generosity when they believe the labor market to be tight. In Appendix Figure A.4, we show that these beliefs track with the state of the aggregate labor market, with beliefs about tightness falling to a nadir in 2010 and improving thereafter. Thus, our results about recruiting behavior, hiring plans, and beliefs provide evidence consistent with Davis et al. (2013), that recruiting intensity fell during the Great Recession as employers wanted to decrease hires, and these adjustments resulted in a breakdown of the standard matching function. We investigate the time series dimension of recruiting behavior more directly below.

Although we have shown how employers adjust recruiting behavior, the data used in this section do not include information on the number of vacancies. In Section 4 we use the backward-looking sample, which is a merged dataset that contains vacancy posting, allowing us to directly estimate Equation 2. This allows us to test whether these adjustments in recruiting effort and compensation generosity influence the number of hires per vacancy, which has important aggregate implications for the performance of the standard matching

[26] In Appendix Table A.5, we show further suggestive evidence that employers increase the bonus size when they believe the labor market will be tight.

function.

Recruiting Intensity over the Business Cycle

In the previous section, we showed that recruiting plans vary based on beliefs about labor market tightness. In this section we focus on how recruiting measures varied over the Great Recession and subsequent recovery. Although the surveys are available for the 2006-2007 academic year (Job Outlook) or the 2007-2008 academic year (Recruiting Benchmarks), the questionnaires change over time. Thus we can only track a limited set of recruiting measures before the Great Recession. In addition, the data during the recession and pre-recession years do not contain data on vacancies or hiring plans.

In Figure 1, we illustrate how several dimensions of recruiting behavior change over time. Each figure is based on estimating a regression with firm fixed effects, and restricting to firms that have data for 2007-2008. Thus, the coefficient in each year can be interpreted as the average change in recruiting over time within employers, relative to 2007-2008. We have limited power here given we are studying effects by year over an already small sample, but given the novelty of the data and the importance of the question we nonetheless find these results informative with the appropriate caveats.

In panel A, we examine plans for the percent increase in real starting salary offers for the coming year. Relative to the planned increase in real starting salary offers in 2007-2008, the planned increase reached its lowest level in 2009-2010. In this year, the planned increase was 2.4 percentage points lower than in 2007-2008. The increase remained substantially below the 2007-2008 salary increase level through 2012-2013. In panel B, we measure the firm's plan to use signing bonuses. Here we see that relative to 2007-2008, the likelihood of planning to offer a signing bonus fell to its lowest level in 2010-2011. In that year firms were 24 percentage points less likely to plan to offer a signing bonus compared with 2007-2008, statistically significant at the 5% level. Signing bonus intentions then increased in magnitude relative to this lowest point.

In panel C, we show that, relative to the 2007-2008 academic year, the number of career fairs attended fell roughly 33% in 2010-2011. As the economy recovered, firms again increased the career fairs they attended. By 2013-2014, we cannot rule out that career fairs had returned to their 2007-2008 levels.[27] In panel D, we show the use of internet advertising also fell over 10 percentage points in 2009-2010, relative to 2007-2008, and then increased in magnitude during the recovery.

[27]While it is possible this could reflect changes in the total number of career fairs in the country, rather than employer recruiting intensity, we think this is unlikely given that universities often hold career fairs at similar times each year (Fall and Spring) as part of the structured campus recruiting process.

Figure 1: Recruiting over the Great Recession

(a) Planned % Increase in Offered Salary (Real)

(b) Plan to Offer a Signing Bonus

(c) Career Fairs Attended

(d) Internet Advertising

Notes: All figures include firm-fixed effects, and restrict to firms with data for 2007-2008. Standard errors are clustered at the firm level. Plots show 95% confidence intervals. Year corresponds to the Spring semester of the academic year (i.e. 2007 refers to the 2006-2007 academic year). Number of career fairs is missing in 2010.

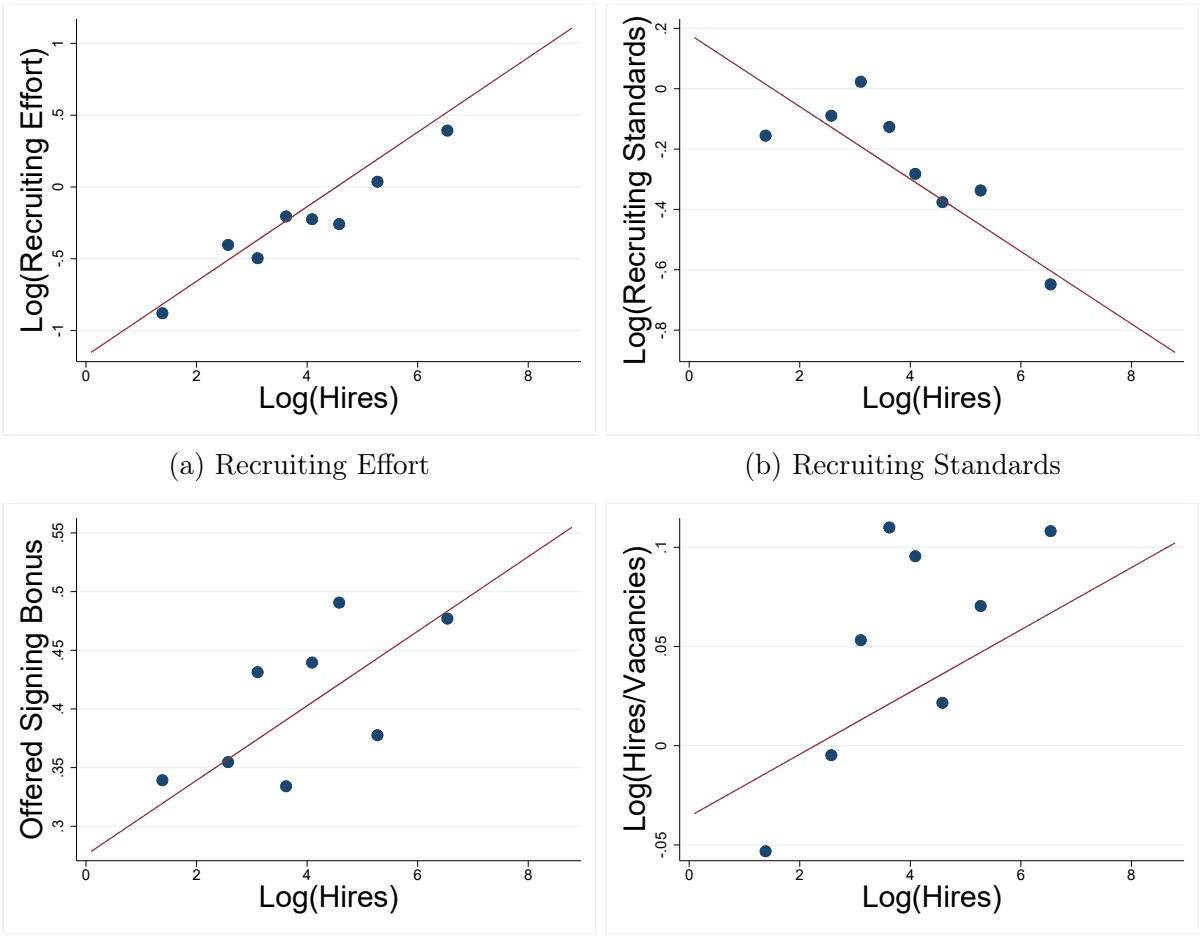
Across a range of measures, we find that recruiting intensity fell during the Great Recession and slowly recovered. Thus, while we cannot directly measure how employers jointly adjusted hiring, vacancies, and recruiting intensity during the Great Recession period, these results are consistent with the result from the previous section that recruiting effort fell when employers believed the labor market to be slack and when their hiring plans changed.

Recruiting Intensity and Hires

We have shown that firms adjust recruiting effort and compensation generosity if they plan to hire more individuals in the coming year. We are able to implement these tests

using the survey question on hiring plans, which is not available in many datasets. In this section we present results from the related test of whether realized hires are correlated with realized recruiting measures, using the backward-looking sample. Using realized hires, rather than hiring plans, allows us to analyze the relationship with realized recruiting measures. These measures are in levels rather than in changes relative to the previous year, facilitating analysis across all years in the data. Further, using realized hires allows us to more directly connect to the novel result in Davis et al. (2013), that firms fill more of their vacancies when they hire more individuals.

Figure 2: Hires, Recruiting, and the Vacancy Yield



(a) Recruiting Effort

(b) Recruiting Standards

(c) Offered Signing Bonus

(d) Vacancy Yield

Notes: Figures show the results of binscatter regressions, including industry, firm size group, and year fixed effects.

In Figure 2 we divide observations into bins based on log(hires). Controlling for industry, firm size group, and year, when firms hire more individuals they have higher recruiting

effort, lower standards, and are more likely to offer a signing bonus. Columns one through three of Table 8 show these relationships by estimating linear regressions. We also see similar relationships when including firm fixed effects, even though the sample size falls substantially (Appendix Figure A.6, Appendix Table A.9).

This relationship between hires and recruiting may simply indicate that recruiting is scaling with vacancies. In the next section we analyze variation in the vacancy yield coming from variation in recruiting, which would suggest adjustments in recruiting over and above adjustments in vacancies.

Finally, there is a positive relationship between hires and firm-level vacancy yield (Figure 2 and column five of Table 8), consistent with Davis et al. (2013). The elasticity of the vacancy yield with respect to hires is .016, though the confidence interval includes zero. Within firms, the elasticity of the vacancy yield with respect to hires is .1, and statistically significant at the 1% level (Appendix Figure A.6 and column 3 of Appendix Table A.9). When firms increase hires they are not simply increasing vacancies proportionally, as the standard theory would predict. Some other change leads them to also fill more of their vacancies, and the evidence here suggests that may be recruiting intensity.

We note that these elasticities are substantially smaller than the elasticity of .82 in Davis et al. (2013). This could be for several reasons. First, Davis et al. (2013) calculate the elasticity of the vacancy yield with respect to the hiring rate (hires relative to employment), while we calculate the elasticity of the vacancy yield with respect to hires, conditional on employment size bins, many of which are quite large. It is possible that conditional on these size bins, observations with the largest percentage increase in hires have smaller percentage increases in hires relative to employment. Given that recruiting intensity should be highest for employers that are trying to grow relative to employment, this would lead to a downward bias on the elasticity. Differences in employment should be much smaller within firms than within size bins, and so this bias should be reduced with firm fixed effects. Indeed, we do find this leads to a much larger elasticity in our data.

Second, there are important differences in the reporting of vacancies and hires in our data relative to Davis et al. (2013) that could lead to differences in the vacancy yield, and the elasticity. In Davis et al. (2013), the vacancy yield is constructed by dividing hires in month t by vacancies reported at the end of month $t-1$. This may inflate the vacancy yield for two reasons, as discussed by the authors. First, hires in month t may be the result of vacancies posted in month t that were not posted in month $t-1$. While the authors show that this time aggregation concern does not completely drive their result, they do show evidence that the vacancy yield will be upward biased at growing establishments due to this issue, thus leading to an upward bias in the elasticity.

Second, the authors show evidence suggesting that hires in their data occur even if there was no vacancy posted. These hires should not contribute to the vacancy yield, since they are not resulting from vacancies, and thus the vacancy yield will be upward biased. If this is especially common at growing establishments, this will also lead to a larger estimated elasticity. As Davis et al. (2013) suggest, this may be especially common in some sectors recruiting for certain types of occupations, where hiring takes place in such a fashion where measured vacancies are less common (e.g. a hiring hall for construction workers).

In our data, the vacancy yield is likely to be closer to one for several reasons. First, recruiting for entry-level hires among soon-to-be college graduates is often a very formalized process, organized through the employer's division of university recruiting, that starts at the beginning of the academic year. It is much more likely that hires through this process are mediated through the available positions reported by the employer. It is less likely that these employers will report hires, without reporting an available position associated with that hire. This will decrease the amount by which the vacancy yield will move above one, and thus the estimated elasticity may be much smaller.

Second, the vacancy yield is constructed by using vacancies reported for a given graduating class for the last year, and hires of new college graduates reported in the last year, both reported in the same survey. This implies elasticities will not be upward biased due to time aggregation issues, as the measures of hires and vacancies refer specifically to new graduates in the past year. In other words, vacancies in our setting expire at the end of the year, and so none of the hires can correspond to a previous year's vacancies. Recall bias may also lead firms to report vacancies very similar to hires in our data.

Indeed, the mean vacancy yield in our data is much closer to one (.95), and the standard deviation in our data is also relatively small (.23). In Davis et al. (2013) the mean vacancy yield is 1.3, and growing establishments have vacancy yields that range from one to roughly seven. Thus, if the upward bias in the vacancy yield in Davis et al. (2013) is especially large among growing establishments, for which they provide some evidence, the elasticity of the vacancy yield with respect to hires will also be inflated.

In addition, our sample is skewed toward larger firms and industries with larger establishments, which tend to have lower vacancy yields.[28] According to Statistics of US Businesses Census data from 2012, the average establishment size was 16.3. In contrast, if we reweight the SUSB data to match the NACE firm size and industry distribution, the average establishment size for our sample is 100. Further, for manufacturing firms (which comprise 1/3 of

[28] A greater share of hires may be mediated through vacancies at larger firms, where the hiring process is more formal. The average vacancy yield for the very large establishments in the Davis et al. (2013) data is much smaller than for the smaller establishments.

our sample), the average establishment size is 202, using the firm size distribution from the NACE data. In Appendix Table A.12, we calculate the vacancy yield by establishment size using JOLTS data. The average yield for establishments of size 10-49 is 1.28. However, the vacancy yield falls dramatically for larger establishments, falling to 1.15 for establishments with 50-249 employees, and falling below 1 for establishments with 250 employees or larger. Thus, our smaller vacancy yields are consistent with a sample that is comprised of larger establishments.

4 Do Recruiting Adjustments Influence Vacancy Yields?

We have shown that when firms increase hires, and hiring plans, they also increase recruiting effort and compensation generosity. In this section we directly test whether these increases are associated with increases in the firm's vacancy yield (the proportion of vacancies that are filled). If adjustments in recruiting simply reflected adjustments in vacancies, the vacancy yield would be unchanged. At an aggregate level, we can observe vacancies and hiring but not recruiting intensity, thus it is important to document whether recruiting behavior leads to changes in the vacancy yield.

To analyze the effect of recruiting on the vacancy yield, we return to the notation from Section 3. In order to estimate Equation 2, we must choose a particular functional form. Following Davis et al. (2013), we allow for economies of scale in vacancies and recruiting. Thus, we can write effective vacancies as follows:

$$q(v_{et}, x_{et}) \equiv v_{et}^{\gamma} x_{f_{et}}^{\delta_f} x_{s_{et}}^{\delta_s} x_{c_{et}}^{\delta_c}$$

where γ and each δ_i govern the economies of scale in vacancies and recruiting, respectively.

Rewriting equation (1) to allow hires to depend on effective vacancies, rather than vacancies, we can rewrite the employer's job filling rate, or vacancy yield, f_{et} as follows:

$$f_{et} = \frac{h_{et}}{v_{et}} = \frac{\tilde{f}_t v_{et}^{\gamma} x_{f_{et}}^{\delta_f} x_{s_{et}}^{\delta_s} x_{c_{et}}^{\delta_c}}{v_{et}}$$

where $\tilde{f}_t$ depends on all employers' effective vacancies.

We can then express this in logs:

$$lnf_{et} = ln\tilde{f}_t + (\gamma - 1)lnv_{et} + \delta_f lnx_{f_{et}} + \delta_s lnx_{s_{et}} + \delta_c lnx_{c_{et}} \tag{4}$$

We can then estimate Equation 4 directly as follows:

$$ln\frac{h_{et}}{v_{et}} = \beta_0 + \beta_1 lnv_{et} + \beta_f lnx_{f_{et}} + \beta_s lnx_{s_{et}} + \beta_c lnx_{c_{et}} + \Gamma_t + \epsilon_{et} \tag{5}$$

where Γ_t are year fixed effects, which absorb the aggregate fill rate $\tilde{f}_t$. Because there may be systematic differences in recruiting, hires, and vacancies across industry and firm size, we additionally include industry and firm size class fixed effects. For robustness, we include firm fixed effects, which decreases the sample size due to a more limited number of firms responding to both surveys in multiple years. From Equation 5, the economies of scale in vacancies is $\gamma = 1 + \hat{\beta}_1$, and the economies of scale with respect to each component of recruiting intensity is the $\hat{\beta}_i$ on each respective $x_{i_{et}}$.

We analyze the relationship between recruiting and vacancy yields by estimating Equation 5, using the backward-looking sample, comprised of the merged Recruiting Benchmark-Job Outlook survey data and our measures of recruiting defined in Section 2.2. We include all principal components of the effort and standards variables in the estimation of Equation 5. While the components for a given set of variables are uncorrelated with each other by definition, they may be correlated with vacancies and the fill rate, affecting the coefficient on ln(vacancies), and thus also the coefficients on the recruiting indices.

Table 8 column 6 shows that conditional on ln(vacancies), firm size, industry, and year, a one standard deviation increase in the recruiting effort index is associated with approximately a 3.7% increase in the vacancy yield.[29] Offering a signing bonus is not associated with a statistically significant difference in the vacancy yield. Increasing the recruiting standards index is not associated with a difference in the vacancy yield that is statistically significant from zero, although it is positive in magnitude. A positive coefficient on standards is not consistent with the intuition that higher standards should reduce the yield. However, this index may be correlated with some unobservable variable that is positively correlated with yield.[30] Below we discuss several alternative specifications to address variables that may bias the results.

Interestingly, increasing vacancies is associated with a decrease in the vacancy yield, conditional on recruiting, industry, size bin, and year. However, if we were to interpret this as reflecting the extent of returns to scale in vacancies, the deviation from constant returns

[29] Dropping the six singleton observations in this regression does not yield meaningful differences in the standard errors, and none of the significance thresholds for the presented coefficients in Table 8 change. The coefficient is also significant at the 5% level when standard errors are calculated based on 400 bootstrap replications, to account for the fact that the principal components are generated regressors. Appendix Figure A.7 shows the relationship between our recruiting variables and vacancy yield less parametrically.

[30] Another potential explanation is that when standards are lower, higher quality applicants are less likely to apply, and so firms make fewer offers.

Table 8: Relationship Between Vacancies, Recruiting, and Vacancy Yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Effort	Standards	Bonus	ln(Vacancies)	ln(H/V)	ln(H/V)	ln(H/V)
ln(Hires)	0.260***	-0.120***	0.0318	0.984***	0.0157		
	(0.0405)	(0.0455)	(0.0238)	(0.0133)	(0.0133)		
ln(Vacancies)						-0.0461***	-0.0383**
						(0.0165)	(0.0185)
Recruiting Effort,						0.0371**	0.0418*
standardized						(0.0160)	(0.0227)
Recruiting Standards,						0.0253	0.0246
standardized						(0.0192)	(0.0215)
Offered Signing Bonus						-0.00702	0.0208
						(0.0242)	(0.0334)
Firms	269	269	269	269	269	269	269
Observations	405	405	405	405	405	405	405
R-squared	0.328	0.227	0.139	0.977	0.110	0.156	0.377
Industry FE	Y	Y	Y	Y	Y	Y	N
Size FE	Y	Y	Y	Y	Y	Y	N
Year FE	Y	Y	Y	Y	Y	Y	N
Ind-Year FE	N	N	N	N	N	N	Y
Size-Year FE	N	N	N	N	N	N	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Standard errors clustered at the firm level. Recruiting Effort is the first principal component based on principal components analysis and four variables describing employer recruiting effort. Recruiting Standards is the first principal component based on principal components analysis and three variables describing employer recruiting standards. For both Recruiting Effort and Recruiting Standards, we add 10 to the first principal component, take the log, and then standardize so it has mean zero and standard deviation of one. Columns 6 and 7 additionally include the log of the other components (after adding 10) from the effort and standards analysis. There are 25 industry categories, seven firm size categories, and indicators for six years (2010-2011 through 2015-2016).

to scale is not large. Given that the employer size bins are large, the vacancies variable may be additionally capturing employer size, and as we have already discussed vacancy yields in JOLTS are smaller for larger employers.[31]

Using our estimates in column 6, we present a simple back-of-the-envelope calculation to understand how lower levels of recruiting during the recession may have affected the vacancy yield for the firms in our sample. Among the firms in our sample, average recruiting effort was

[31] We note that Davis et al. (2013) find evidence of mild increasing returns to scale in vacancies, although as the authors acknowledge there is more to be learned from micro-level data. In particular Davis et al. (2013) estimate returns to scale in vacancies without a control for firm-level recruiting intensity. Davis et al. (2013) use employment as an instrument for vacancies to address endogeneity and measurement error. We do not proceed similarly because we do not have a measure of employment other than our size bins, and employment may be correlated with vacancy yield for reasons other than its relationship with vacancies, thus not satisfying the exclusion restriction.

higher in 2014-2015 relative to 2010-2011 by roughly .33 standard deviations. We multiply this difference in recruiting effort by .0371, our estimated impact of recruiting effort on the vacancy yield in Table 8 column 6. This difference yields a 1.2% increase in the vacancy yield. Average vacancy yields in 2010-2011 were 1.1% higher for the firms in our sample than in 2014-2015. Thus, if recruiting effort had been the same in 2010-2011 as it was in 2014-2015, the percentage difference in average vacancy yield between these years would have more than doubled (from 1.1% to 2.3%). Lower recruiting effort by these firms during the recession kept vacancy yields for these firms lower than would be expected if recruiting intensity was constant over the business cycle.[32]

Additionally, we find that our measure of recruiting effort and our estimates in Table 8 explain roughly 61% of the elasticity of the vacancy yield with respect to hires in our data. To do so, we adjust the decomposition of the elasticity used in Davis et al. (2013) to incorporate our recruiting measures. In particular, we differentiate equation 4 with respect to the total number of hires, which allows us to calculate the elasticity using the coefficient estimates from Table 8. More details are provided in the online appendix. Recruiting intensity can play an important aggregate role even if there is no elasticity of the vacancy yield with respect to hires. Similarly, there are other reasons this elasticity may exist other than recruiting intensity, for example if the firms that are increasing hires are experiencing firm-specific increases in match efficiency, for reasons other than firm actions, such as decreases in geographic or skills mismatch for that firm. However, this exercise represents another way in which to identify how recruiting intensity contributes to labor market relationships.

Robustness

Column 7 shows the coefficient on the effort index is slightly larger in magnitude when including industry-year and firm size-year fixed effects to allow for market tightness to vary by industry and firm size. The coefficients on standards and signing bonus are still not statistically distinct from zero. Our preferred estimates are those in column 6 given the small sample, and that column 7 adds 145 fixed effects.

These results provide important evidence that when firms increase their recruiting effort this is associated with increases in their vacancy yield. Because we condition on vacancies, it

[32]We compare 2010-2011 to 2014-2015 because our sample size drops substantially in 2015-2016 (from 71 in 2014-2015 to 49 in 2015-2016). Our estimate from Table 8 implies that if recruiting effort had been the same in 2010-2011 as it was in 2015-2016, the percentage difference in the vacancy yield between these years would have increased by 1 percentage point, which is similar in level terms to the comparison to 2014-2015. This similarity is because recruiting effort was similar in 2014-2015 and 2015-2016. However, this increase in the vacancy yield if recruiting in 2010-2011 had been at 2015-2016 levels implies a smaller relative increase in the percentage difference in the average vacancy yield between these years (14%), given there was a greater difference in the vacancy yield (7.2%) between 2010-2011 and 2015-2016.

also implies an increase in hires. These results are consistent with employers using channels other than vacancies, namely recruiting effort, to increase hires.

Conditional on vacancies, industry, and size, firms with higher recruiting effort may differ systematically in ways that are correlated with the vacancy yield, such as management quality. This omitted variables bias may explain the coefficient on effort, rather than adjustments in firm effort affecting the vacancy yield. To address this concern, we estimate a specification with firm fixed effects, implying identification is not driven by differences across firms. The identification assumption is that when there are recruiting changes within a firm, there are not other firm-specific changes that would affect its vacancy yield, controlling for average changes in vacancy yield in other firms that year.

Including firm fixed effects nearly halves the sample size, but still yields a sample with 81 firms observed at least twice, and 33 firms observed at least three times (Appendix Table A.9). We see that increasing recruiting effort by one standard deviation is associated with an 11.7% increase in the vacancy yield ($p \leq .05$), larger than the effect in Table 8 with industry and size fixed effects. The coefficients on the standards index and offering a signing bonus continue to be statistically insignificant from zero.

Using the sample and estimates from this specification to implement our back-of-the-envelope calculation implies the percentage difference in the average vacancy yield between 2010-2011 and 2014-2015 would have nearly tripled (from 2.7% to 7.6%) if recruiting in 2010-2011 was the same as in 2014-2015. The elasticity of the vacancy yield with respect to hires is much larger when including firm fixed effects, and the contribution of recruiting effort is smaller but still substantial, explaining roughly 18%. The confidence intervals on our estimates also suggest recruiting effort could explain a much greater proportion of the elasticity, including the roughly 60% we found using our main specification above.

Appendix Table A.9 shows that including industry-year fixed effects along with firm fixed effects yields similar results.[33] Appendix Table A.10 shows the relationship between effort and the vacancy yield nearly doubles when using career fairs as our main measure of recruiting effort, rather than the effort index. Appendix Table A.10 shows our results are robust to our definition of outliers for the vacancy yield variable.[34]

Together, the results in this section show that increases in recruiting effort are associated with increases in the vacancy yield. This provides important evidence that when firms want

[33]Given that we already have a smaller sample due to the firm fixed effects, we use the eleven supersectors defined by the Bureau of Labor Statistics instead of the two-digit NAICS codes to define industry in those specifications.

[34]The coefficients on the effort index and on the indicator for offering a signing bonus increase substantially when including the observations with vacancy yield above 2.5. This further motivates us to focus on specifications excluding those observations.

to adjust hires, they are not simply adjusting vacancies, but also the intensity with which they are recruiting for the vacancy.

5 Conclusions and Implications for 2021 Graduates

During and after the Great Recession, hires fell more than predicted by standard matching functions, given the number of vacancies and unemployed. A growing literature has developed attempting to explain this puzzle. Motivated by a novel finding that growing firms fill more of their vacancies, Davis et al. (2013) provide indirect evidence that employers adjust recruiting intensity in addition to vacancies, and that declining recruiting intensity was responsible for the slow recovery.

Using unique firm-level data, we provide evidence that large firms recruiting new college graduates adjust recruiting, in addition to vacancies, to meet their hiring needs. First, we show that firms adjust recruiting effort, hiring standards, and compensation generosity in response to the business cycle, beliefs about labor market tightness, and hiring plans. We then show that firms which expend greater effort in recruiting have higher vacancy yields. Our estimates imply that the percentage difference in the average firm-level vacancy yield between 2010-2011 and 2014-2015 would have more than doubled for the firms in our sample, if recruiting effort had been constant, rather than so much lower in 2010-2011. Further, our measure of recruiting effort explains 61% of the elasticity of the vacancy yield with respect to hires in our data. These results make important contributions to the growing literature on recruiting intensity, because of the richness of our recruiting data as well as our novel results showing a relationship between firm-level recruiting and firm-level vacancy yield.

Together, our results show firms adjust recruiting when they want to increase hires. Further, we show these adjustments are in addition to the adjustments in vacancies, as they are associated with changes in the vacancy yield. Our data focus on very large firms recruiting recent college graduates. We believe that richly describing this large and consequential labor market is an additional contribution of our paper.

If the relationships we identify apply more widely across employers, or across job types within large employers, this would help to explain why hires fell more than standard theory would have predicted during and after the Great Recession. This is important for policymakers, who may infer that the breakdown between hiring and vacancies is due to structural mismatch between job seekers and employers. Instead, if employers reduce recruiting intensity, measured vacancies will over-estimate labor demand during downturns. This also has implications for matching models. As Davis et al. (2013) note, based on Pissarides (2000), incorporating recruiting intensity into the standard model is not enough to account for these

findings, suggesting other adjustments to the building blocks of the standard model are necessary.

By studying how employers adjust recruiting when they have lower demand, we also provide insights into which types of workers will be most affected. Our results suggest that when large firms have lower demand, the students who lose access will be those at universities where the firm stops attending the career fairs, those at farther universities, lower GPA students, those from two-year colleges, and those with less relevant experience. These may also be students who are already at risk of adverse impacts.

In April 2020, the Covid-19 pandemic led to a rapid economic collapse in the United States. Job postings in particular dropped dramatically and remained depressed into November 2020 (Forsythe, Kahn, Lange, & Wiczer, 2020). The 2021 NACE Job Outlook Survey provides some indicators that this decline also affected the market for recent college graduates (National Association of Colleges and Employers, 2021). First, 31% of employers planned to decrease hiring in 2020-2021, compared with a rate of 15% between 2012 and 2017. Second, 65% of employers believed the labor market would be fair or poor for new college graduates, which is larger than at the lowest point of the Great Recession (2010) when 61% of employers believed the labor market to be fair or poor.[35] We show that both measures are correlated with decreased recruiting effort and compensation generosity at the firm-level. As an initial indicator that recruiting intensity declined, only 42% of employers planned to increase starting salary offers in 2020-2021 (compared with over 60% in the previous 3 years).[36] We show that one of the ways in which firms decrease hires is through decreasing recruiting effort, conditional on vacancies. Thus, it is quite likely that 2021 graduates will face a sharp decline in hiring, that will be above and beyond what is predicted based on the decline in the number of vacancies.

Research on past recessions has shown that cuts in hiring fall disproportionately on young workers (Forsythe, 2022), and graduating during recessions can lead to long-term earnings losses (Kahn, 2010; Oreopoulos et al., 2012). Graduates in 2020 and 2021 are poised to suffer a similar fate, and deserve particular attention from policy makers.

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[35] From 2007 to 2017, 21% of employers believed the labor market would be fair or poor for new college graduates.

[36] Over 80% of recruiters have indicated they plan to do at least some recruiting online in 2020-2021, which may indicate a decline in recruiting intensity.

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Appendix: For Online Publication

Data Notes

The hires and vacancies data are particularly noisy in the survey, thus required cleaning. Beginning in 2013, NACE began asking employers to report hires separately for domestic and international positions, but vacancies and unfilled vacancies are ambiguous as to whether respondents should report the total number of vacancies or just vacancies for US positions. In this case, we used the sum of all hires for the hiring variable, unless the number of vacancies less unfilled vacancies was exactly equal to domestic hires, in which case we presume that the respondent is only considering domestic hires. One observation in our sample reported approximately 75 hires in the U.S., and we code this as 75 hires.

In some cases, when asked to report the average signing bonus, employers report a range. In those instances we use the midpoint of the range. Before the year 2016, respondents were asked to give the number of days between interview and offer, and between offer and offer deadline. In 2016, respondents were asked to choose from the following groups: less than one week, one week, two weeks, three weeks, one month, and more than one month. To make this consistent with the earlier years, we imputed 3.5 days for less than one week, 7 days for one week, 14 days for two weeks, 21 days for three weeks, and 30 days for one month. For more than one month, we replaced this variable with the mean number of days for respondents in prior years who reported more than 30 days.

A How Much of the Variation in Vacancy Yields Can be Explained by Recruiting Intensity?

We follow the decomposition in Davis et al. (2013) of the elasticity of the vacancy yield with respect to hires. We then show how much of the elasticity can be accounted for by each of our three dimensions of recruiting intensity.

In particular, we return to Equation 4 and differentiate with respect to the total number of hires.[37]

$$\frac{dlnf_{et}}{dlnh_{et}} = \frac{dln\tilde{f}_t}{dlnh_{et}} + (\gamma - 1)\frac{dlnv_{et}}{dlnh_{et}} + \delta_f \frac{dlnx_{f_{et}}}{dlnh_{et}} + \delta_s \frac{dlnx_{s_{et}}}{dlnh_{et}} + \delta_c \frac{dlnx_{c_{et}}}{dlnh_{et}} \tag{6}$$

[37] There are two key differences in this expression compared with the comparable expression in Davis et al. (2013). First, since college recruiting happens over a standard annual cycle, we are not concerned with aggregation bias so do not translate the problem into the daily analog. Second, Davis et al. (2013) differentiate with respect to hires per employment, while we differentiate with respect to total hires given that our survey data provide only bins of firm size. We also emphasize that the vacancy yield may vary with total hires, rather than only hires per employment, though as we discuss in the paper differentiating with respect to hires could lead to a downward bias in the elasticity.

Table 8 shows our estimates of the elasticity of our recruiting measures and vacancies with respect to hires, using the same regression we use to estimate the elasticity of the vacancy yield with respect to hires. Table 8 also shows our estimates of the $\hat{\delta}_i$. Using these estimates, we can calculate each dimension's contribution to the elasticity of the fill rate with respect to hires, as specified in equation (6). Note that there are similarities between this decomposition and a Oaxaca-Blinder decomposition.[38]

Using our estimates from Table 8, we find that our recruiting effort measure explains roughly 61% of the elasticity of the vacancy yield with respect to hires in our data. We focus only on the contribution of the recruiting effort measure, since the other measures did not have statistically significant effects on the vacancy yield.[39]

Thus, while we are able to capture some of the variation in the elasticity of vacancy yields with respect to hiring in our data, some remains unexplained. This could be due to changes in recruiting intensity that are outside the scope of the survey. Perhaps most notably, our only measure of compensation generosity when looking at vacancy yields is whether the firm offers a signing bonus, and we do not observe actual starting salaries. This may be an important dimension on which firms adjust in order to increase hires. Alternatively, as we state in the paper, firms that are increasing hires may also be those that are experiencing firm-specific changes in match efficiency for reasons other than firm actions, for example decreases in skill or geographic mismatch for that firm. Nonetheless, we are able to say that our measures of recruiting effort can explain substantially more of the elasticity than our measures of selectivity or compensation generosity.

[38] In our case, the vacancy yield increases with hires partly because when firms want to increase hires they recruit more intensely. To obtain the contribution of this channel, we multiply the elasticity of recruiting measures with respect to hires by the impact of the recruiting measure on the vacancy yield, controlling for other measures.

[39] Using the results from the specification with firm fixed effects (Table A.9), the elasticity of the vacancy yield with respect to hires is much larger, and the contribution of recruiting effort is smaller but still substantial, explaining roughly 18%. The confidence intervals on the estimates do not allow us to rule out that recruiting effort explains a much greater fraction of the elasticity, including the 60% we find based on our principal results.

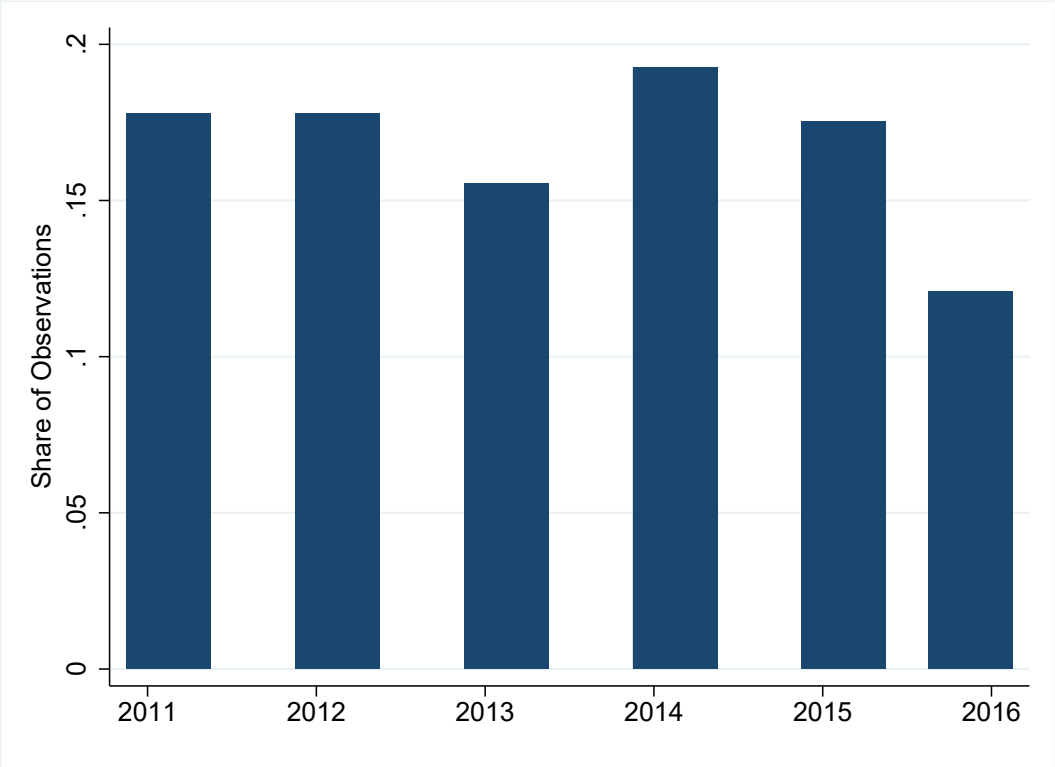


Figure A.1: Distribution of Observations in the Backward-Looking Regression Sample

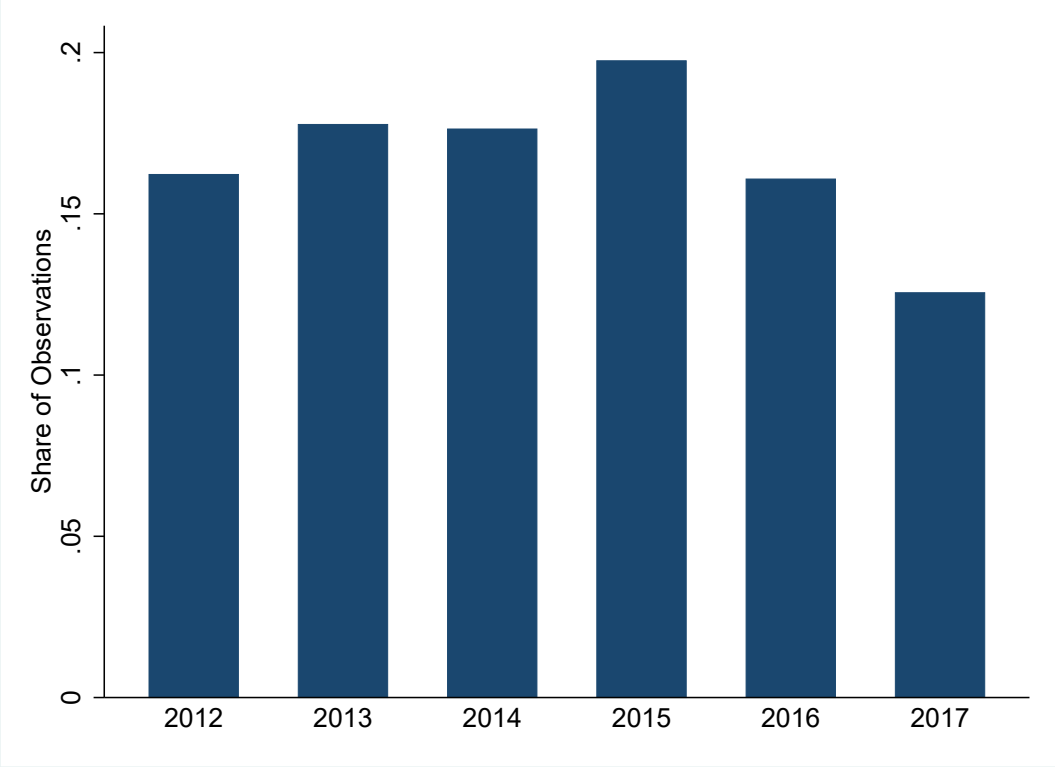


Figure A.2: Distribution of Observations in the Forward-Looking Regression Sample

Table A.1: Observations per firm

	Number of Firms	
Number of observations per firm	Backward-Looking Sample	Forward-Looking Sample
1	188	0
2	48	130
3	17	66
4	12	30
5	2	13
6	2	11
	269	250

Notes: Table shows the number of observations per firm in the backward-looking sample and the forward-looking sample. Note the forward-looking sample restricts to firms with at least two observations.

Table A.2: Industry Distribution: NACE vs. All U.S. Firms

NACE Industry Name	NAICS Sector	NACE Share	Share Census ESP 5000+	Share Census ESP All Firms
Construction	23	0.05	0.01	0.11
Manufacturing	31-33	0.34	0.16	0.04
Retail	44-45	0.07	0.13	0.12
Finance & Insurance	52	0.11	0.08	0.05
Prof., Sci., and Tech. Services	54	0.21	0.06	0.14
All Other		0.22	0.56	0.54

Notes: This table compares the NACE industry distribution with data from the 2012 Census Enterprise Statistics Program (ESP). Share Census ESP 5000+ refers to the industry distribution among firms that have at least 5000 employees. In Table 1, in the interest of space, we showed only two subsectors of NAICS code 54 (Management, Scientific, and Technical Consulting, and Architectural and Engineering Services). Here in order to compare to the Census Enterprise Statistics data, we add in the other subsectors of NAICS code 54.

Table A.3: Firm Hiring Plans by Beliefs About Market Tightness

Hiring Plans:	Believe Slack Market	Believe Tight Market
Decrease	24	81
Maintain	57	232
Increase	30	285

Notes: Table shows the number of observations in each cell, restricted to the regression sample. This reflects 709 observations over 250 unique firms.

Figure A.3: Distribution of Hires per Vacancy in the Backward-Looking Regression Sample

Table A.4: Relationship between Hiring, Beliefs, and Recruiting, Including Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Forward-Looking Effort Index		Plan Bonus		% Change in Real Salary	
Plan Inc. Hires	0.400***	0.359***	0.022	0.018	1.008**	1.000**
	(0.093)	(0.088)	(0.042)	(0.042)	(0.411)	(0.388)
Believe Tight	0.339***	0.469***	0.064	0.048	0.594**	0.417
	(0.118)	(0.119)	(0.068)	(0.073)	(0.295)	(0.339)
Observations	709	709	669	669	376	376
R-squared	0.519	0.541	0.572	0.577	0.427	0.458
Plan Dec. Hires	-0.243**	-0.266**	0.014	0.074	-0.579*	-0.315
	(0.107)	(0.117)	(0.072)	(0.079)	(0.316)	(0.342)
Believe Slack	-0.390***	-0.514***	-0.070	-0.059	-0.734**	-0.644*
	(0.118)	(0.117)	(0.069)	(0.073)	(0.290)	(0.333)
Observations	709	709	669	669	376	376
R-squared	0.503	0.529	0.572	0.578	0.413	0.442
Year FE	No	Yes	No	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regressions are similar to Table 7, but additionally include year fixed effects. Standard errors clustered at the firm level. See text and Table 7 for details.

Figure A.4: Share of firms who report the state of the labor market is good, very good, or excellent. Blue line includes all firms surveyed, red line includes all firms in the main forward-looking regression sample. Year corresponds to the year of the Spring semester (i.e. 2010 refers to 2009-2010 academic year).

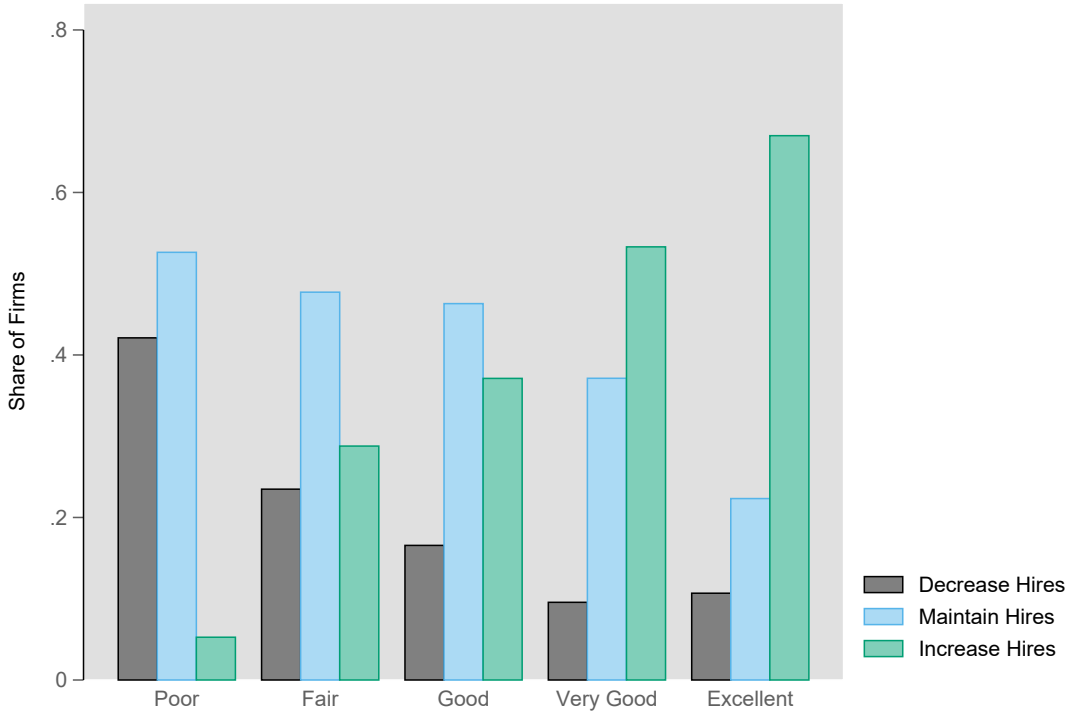


Figure A.5: Share of firms who plan to decrease, maintain, or increase hiring by beliefs about the state of the labor market. Note: Observations are restricted to the regression sample.

Table A.5: Relationship Between Hiring Plans, Beliefs, and Planned Real Log Signing Bonus

	(1)	(2)	(3)	(4)
Plan Increase Hires	-0.014		-0.040	0.541***
	(0.076)		(0.078)	(0.203)
Believe Labor Market will be Tight		0.179	0.192	0.286*
		(0.130)	(0.137)	(0.151)
Interaction Term				-0.605***
				(0.220)
Firms	74	74	74	74
Observations	189	189	189	189
R-squared	0.725	0.729	0.729	0.735
Plan Decrease Hires	-0.038		-0.023	0.116
	(0.147)		(0.137)	(0.130)
Believe Labor Market will be Slack		-0.179	-0.176	-0.019
		(0.130)	(0.123)	(0.076)
Interaction Term				-1.006**
				(0.483)
Firms	74	74	74	74
Observations	189	189	189	189
R-squared	0.725	0.729	0.729	0.746

Notes: All regressions include firm fixed effects. Coefficients from estimates of Equation 3. Standard errors clustered at the firm level, $***p < 0.01, **p < 0.05, *p < 0.1$. Firms measures the number of non-singleton firms in the sample. The real signing bonus ranges from 0 to $25,518. The sample is restricted to employers who report that they will offer signing bonuses.

Table A.6: Relationship between Plans to Decrease Hiring, Beliefs, and Recruiting

	(1)	(2)	(3)	(4)
Panel A: Forward-Looking Recruiting Effort Index				
Plan Decrease Hires	-0.265**		-0.238**	-0.250*
	(0.108)		(0.107)	(0.129)
Believe Labor Market will be Slack		-0.408***	-0.389***	-0.400***
		(0.122)	(0.118)	(0.127)
Interaction Term				0.062
				(0.259)
Firms	250	250	250	250
Observations	709	709	709	709
R-squared	0.493	0.499	0.504	0.504
Panel B: Planned % Increase in Offered Starting Salary (Real)				
Plan Decrease Hires	-0.682**		-0.579*	-0.487
	(0.320)		(0.316)	(0.394)
Believe Labor Market will be Slack		-0.838***	-0.734**	-0.666**
		(0.296)	(0.290)	(0.309)
Interaction Term				-0.393
				(0.627)
Firms	146	146	146	146
Observations	376	376	376	376
R-squared	0.409	0.410	0.413	0.413
Panel C: Plan to Offer Signing Bonus				
Plan Decrease Hires	0.010		0.014	-0.010
	(0.072)		(0.072)	(0.084)
Believe Labor Market will be Slack		-0.069	-0.070	-0.093
		(0.069)	(0.069)	(0.071)
Interaction Term				0.134
				(0.156)
Firms	238	238	238	238
Observations	669	669	669	669
R-squared	0.571	0.572	0.572	0.573

Notes: All regressions include firm fixed effects. Coefficients from estimates of Equation 3. Standard errors clustered at the firm level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firms measures the number of non-singleton firms in the sample.

Table A.7: Recruiting Selectivity, Hiring Plans, and Beliefs about Tightness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Planning to Hire Associate's Degree Holders?						
Plan Increase Hires	0.041		0.041	0.031	0.184**	0.174**
	(0.026)		(0.026)	(0.027)	(0.082)	(0.082)
Believe Tight		0.008	-0.001	0.007	0.048	0.054
		(0.049)	(0.050)	(0.050)	(0.058)	(0.059)
Interaction Term					-0.162*	-0.161*
			(0.043)	(0.043)	(0.088)	(0.087)
R-squared	0.668	0.667	0.668	0.673	0.671	0.676
Panel B: Planning to Hire International Students?						
Plan Increase Hires	0.030		0.022	0.020	-0.053	-0.049
	(0.033)		(0.033)	(0.032)	(0.085)	(0.087)
Believe Tight		0.079*	0.074*	0.068	0.048	0.045
		(0.041)	(0.042)	(0.044)	(0.050)	(0.051)
Interaction Term					0.086	0.078
					(0.088)	(0.090)
R-squared	0.665	0.667	0.667	0.668	0.667	0.669
Firms	250	250	250	250	250	250
Observations	709	709	709	709	709	709
Year FE?	No	No	No	Yes	No	Yes

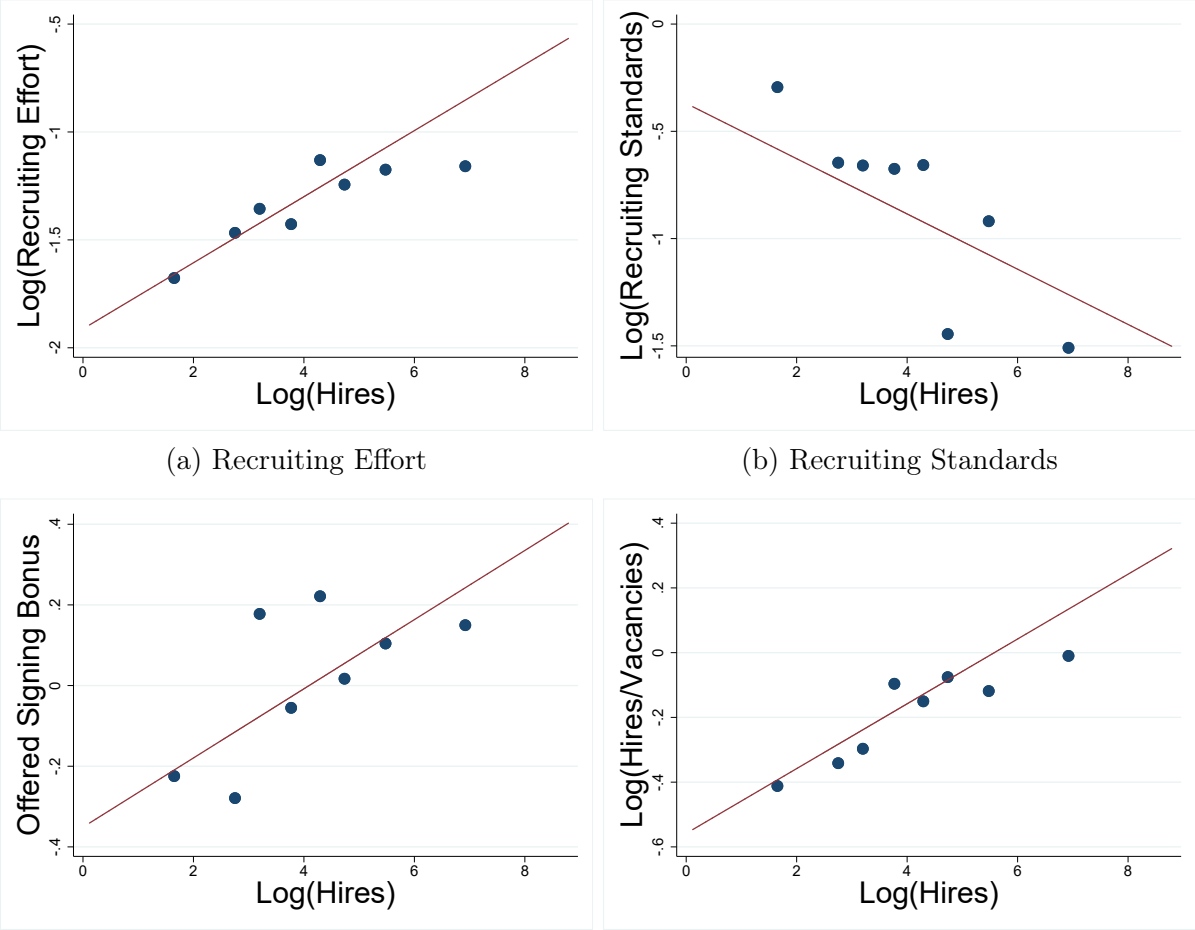
Notes: Coefficients from estimates of Equation 3. Standard errors clustered at the firm level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firms measures the number of non-singleton firms in the sample.

Table A.8: Beliefs About the State of the Labor Market for New Graduates

	(1)	(2)	(3)
	Forward-Looking Recruiting Effort Index	% Change in Real Salary	Real Log Bonus
Fair	0.035	2.063***	-0.440**
	(0.181)	(0.534)	(0.197)
Good	0.367*	2.478***	-0.212
	(0.195)	(0.606)	(0.143)
Very Good	0.522**	2.987***	-0.195
	(0.210)	(0.590)	(0.149)
Excellent	0.657***	4.186***	-0.284
	(0.216)	(1.101)	(0.202)
Firms	250	146	74
Observations	709	376	189
R-squared	0.502	0.431	0.732

Notes: All regressions include firm fixed effects. Coefficients from regressing the dependent variable on beliefs about the state of the labor market for new college graduates disaggregated into five categories, with 'poor' omitted. Standard errors clustered at the firm level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firms measures the number of non-singleton firms in the sample.

Figure A.6: Hires, Recruiting, and the Vacancy Yield, Including Firm Fixed Effects



(a) Recruiting Effort

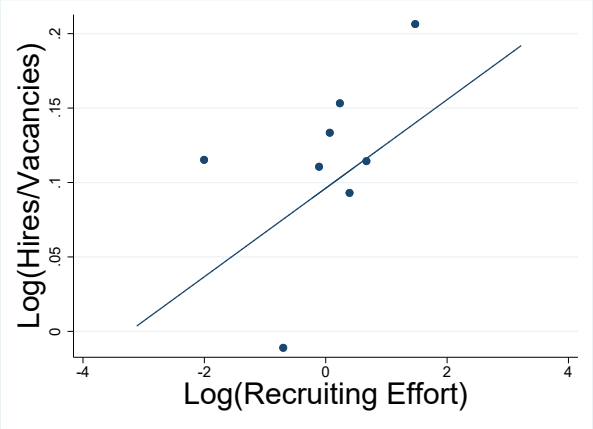
(b) Recruiting Standards

(c) Offered Signing Bonus

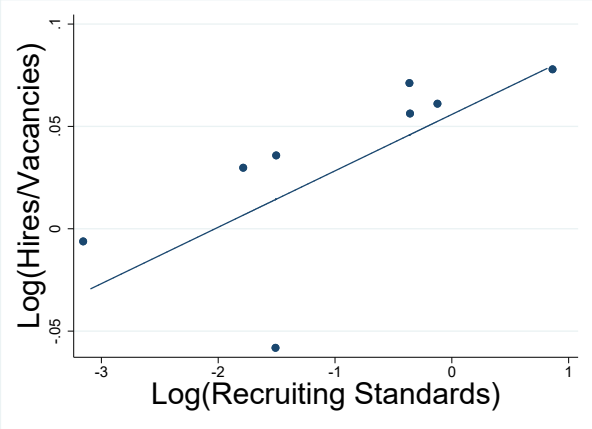
(d) Vacancy Yield

Notes: Figures show the results of binscatter regressions, including firm fixed effects and year fixed effects.

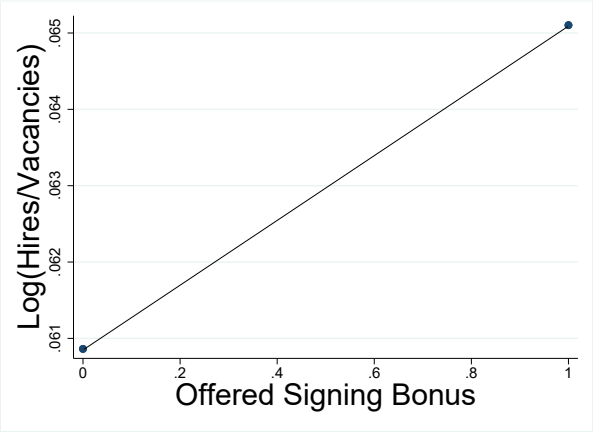
Figure A.7: Recruiting and Firm-Level Vacancy Yield



(a) Effort Index



(b) Standards Index



(c) Offered Signing Bonus

Notes: All figures include controls for ln(vacancies), industry fixed effects, firm size fixed effects, and year fixed effects.

Table A.9: Relationship Between Vacancies, Recruiting, and Vacancy Yield, Including Firm Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Effort	Standards	Bonus	ln(Vacancies)	ln(H/V)	ln(H/V)	ln(H/V)
ln(Hires)	0.153**	-0.129	0.0858	0.900***	0.100***		
	(0.0690)	(0.117)	(0.0592)	(0.0317)	(0.0317)		
ln(Vacancies)						-0.0100	-0.0376
						(0.0391)	(0.0468)
Recruiting Effort,						0.117**	0.115**
standardized						(0.0464)	(0.0465)
Recruiting Standards,						0.0314	-0.0161
standardized						(0.0336)	(0.0273)
Offered Signing Bonus						-0.0332	-0.0243
						(0.0418)	(0.0437)
Firms	81	81	81	81	81	81	77
Observations	217	217	217	217	217	217	201
R-squared	0.828	0.731	0.630	0.991	0.594	0.619	0.706
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	N
Industry-Year FE	N	N	N	N	N	N	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Standard errors clustered at the firm level. Regressions are similar to Table 8, but include firm fixed effects. The number of observations falls in column 7 due to the inclusion of industry-year fixed effects, which increases the number of singleton observations that are the only observation in their industry-year cell. See text and Table 8 for details.

Table A.10: Relationship Between Vacancies, Recruiting, and Vacancy Yield, Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(H/V)	ln(H/V)	ln(H/V)	ln(H/V)	ln(H/V)	ln(Fairs)
ln(Vacancies)	-0.0547**	-0.0649***	-0.0868***	-0.124***	-0.0545***	
	(0.0220)	(0.0216)	(0.0261)	(0.0372)	(0.0188)	
Recruiting Effort,	0.0348**	0.0353**	0.0492**	0.0734***		
standardized	(0.0169)	(0.0175)	(0.0209)	(0.0279)		
Recruiting Standards,	0.0385*	0.0305	0.0206	-0.00101	0.0103	
standardized	(0.0214)	(0.0217)	(0.0245)	(0.0312)	(0.0152)	
Offered Signing Bonus	0.0336	0.0311	0.0711*	0.101**	-0.0139	
	(0.0332)	(0.0338)	(0.0387)	(0.0440)	(0.0231)	
ln(Career Fairs),					0.0664**	
standardized					(0.0275)	
ln(Hires)						0.447***
						(0.0313)
Firms	264	270	273	274	266	266
Observations	397	409	414	416	396	396
R-squared	0.225	0.228	0.207	0.204	0.137	0.687
Included values of H/V	$\leq$ 1.3	$\leq$ 2.29	$\leq$ 7.5	All	.28$\leq$H/V$\leq$2.5	.28$\leq$H/V$\leq$2.5
(percentiles)	(95th)	(98th)	(99th)	(All)	(1st to 98.6th)	(1st to 98.6th)
Industry FE	Y	Y	Y	Y	Y	Y
Size FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Standard errors clustered at the firm level. Recruiting Effort and Standards in columns 1 through 4 are calculated as described in Table 8 and in the text, but only on the regression sample specific to each column. Percentiles are relative to the sample of observations with nonmissing values of ln(career fairs), industry, size, ln(vacancies), and ln(hires). The sample in column (5) uses the same sample restrictions and same indices as the main specification in Table 8 but some observations are dropped because they have a value of zero for career fairs. We standardize the log career fairs variable so it has mean zero and standard deviation of one among the observations in the main regression sample in Table 8. See Table 8 and text for details.

Table A.11: Relationship Between Vacancies, Recruiting, and Vacancy Yield, Recruiting Effort Index without Time to Deadline

	(1)	(2)	(3)
	Effort	ln(H/V)	ln(H/V)
ln(Hires)	0.289***		
	(0.0429)		
ln(Vacancies)		-0.0450***	-0.0352*
		(0.0164)	(0.0182)
Recruiting Effort,		0.0396**	0.0406*
standardized		(0.0161)	(0.0218)
Recruiting Standards,		0.0259	0.0248
standardized		(0.0192)	(0.0215)
Offered Signing Bonus		-0.00822	0.0185
		(0.0242)	(0.0332)
Firms	269	269	269
Observations	405	405	405
R-squared	0.383	0.152	0.371
Industry FE	Y	Y	N
Size FE	Y	Y	N
Year FE	Y	Y	N
Ind-Year FE	N	N	Y
Size-Year FE	N	N	Y

Notes: Table is analogous to Table 8 but constructs the recruiting effort index without number of days between offer and deadline. See Table 8 for details.

Table A.12: JOLTS Vacancy Yield by Establishment Size

Establishment Size	Vacancy Yield
1-9	1.26
10-49	1.28
50-249	1.15
250-999	0.96
1000-4999	0.70
5000+	0.46

Notes: Vacancy yield constructed using JOLTS data from 2011 to 2016, with monthly hires divided by the prior month's openings.