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

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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 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.

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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. In an influential paper, Davis, Faberman, and Haltiwanger (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 matching function governing the relationship between vacancies, unemployment and hires, and following Davis et al. (2013), a growing literature focuses on the role of employer recruiting intensity in determining aggregate hires. However, there is limited evidence using firm-level data that directly measures the use of specific recruiting strategies, how and when firms adjust these strategies, and their impact on hiring.

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 and compensation 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 recruiting intensity, conditional on market tightness, consistent with employers using recruiting intensity per vacancy to adjust hires.

Our data richly describe a particular labor market: large firms recruiting recent college graduates. Despite the importance of this market, it remains an underexplored area of research.[1] We believe that this focus is valuable for several reasons. The labor market for new college graduates is a large and consequential labor market, matching millions of young workers with their first entry-level position. Recruiting on college campuses is often quite structured, which we rely on for understanding how vacancies, recruiting behavior, and hires are determined. Employers value this market, with over 75% of firms in our sample having departments whose main focus is university relations and recruiting. This market is also

[1] Weinstein (2018), Weinstein (2022), and Weinstein (2021) study the firm's choice of which campuses to target for recruiting. Oyer and Schaefer (2016) study the relationship between law schools and law firms. Rivera (2011) and Rivera (2012) study hiring for firms recruiting on campus, using interviews and observation of a hiring committee. Kuhnen and Oyer (2016), Kuhnen (2011), and Laschever and Weinstein (2020) study the market for professional master's degree students.

extremely important for workers, with a large literature documenting the long-run effects of the initial match for college graduates.[2] Finally, our focus on large firms allows us to study a segment of the labor market in which roughly 50% of U.S. workers are employed.[3]

A key contribution of our paper derives from the richness of our data, which allows us to study various ways in which employers adjust recruiting intensity, including compensation generosity, search effort, and screening selectivity.[4] We find that employers increase recruiting effort and compensation generosity when they plan to hire more individuals, conditional on beliefs about labor market tightness. Employers also increase recruiting effort and compensation generosity when they believe the labor market will be tight. Further, we show employers reduced recruiting effort and compensation generosity in the early years of the Great Recession, and increased recruiting effort and compensation generosity through the recovery. This evidence is consistent with employers decreasing recruiting intensity to decrease hires, and this being more prevalent during recessionary periods.

We next investigate whether firm-level adjustments in recruiting behavior are correlated with the share of vacancies filled. We find that a one standard deviation decrease in recruiting effort is associated with a 3.7% decrease in the firm's vacancy yield (e.g. hires per vacancy), conditional on labor market tightness. We also see this relationship within firms. While we caution that these relationships are not necessarily causal, this is consistent with firms using recruiting intensity to adjust hires.

Treating the estimates as causal, the firm-level vacancy yield would have been 1.2% higher in 2011 if firms expended as much effort recruiting as they did in 2015. This is a nontrivial effect, and is about one-third of a standard deviation of the average vacancy yield across years.

Although the matching function between job seekers and vacancies is a fundamental tool for understanding the labor market, it is well-known that this 'black box' function is sensitive to the behavior of job seekers and employers (see Petrongolo and Pissarides (2008) for a review). While there is a well-developed literature exploring how search behavior of job seekers can influence the properties of the aggregate job finding rate,[5] the literature connecting employer behavior to job filling is more nascent. Recent theoretical papers with

[2]See Kahn (2010), Oreopoulos, Von Wachter, and Heisz (2012), Oyer (2006), Liu, Salvanes, and Sorensen (2016), and Arellano-Bover (2020).

[3]We calculate that the firms in our sample employ roughly 2.5% of the U.S. labor force, using the binned firm size distribution in Table 1 and the 2016 Statistics of U.S. Business (2018) to calculate the average firm size within each bin.

[4]These aspects of recruiting intensity are similar to the taxonomy in Carrillo-Tudela, Gartner, and Kaas (2020). Gavazza, Mongey, and Violante (2018) similarly suggest recruiting can make the firm more visible, more attractive, or allow the firm to screen more candidates per unit of time. Davis et al. (2013) identify similar dimensions.

[5]See for instance Clark et al. (1979) and Hall (2005)

calibration exercises have shown how firm decisions about recruiting intensity and vacancies influence macroeconomic dynamics, though none of these papers have firm-level data on recruiting activities over time.[6] While there is an older literature with micro-evidence on firm recruiting behavior, few papers are able to connect this to the vacancy yield or job filling rate.[7]

Our paper is most closely related to two recent papers using a representative sample of German establishments to study recruiting intensity (Carrillo-Tudela et al., 2020; Lochner, Merkl, Stüber, & Gürtzgen, 2021). We see our paper as complementary for several reasons. First, we provide novel evidence of the relationship between firm-level recruiting measures and firm-level vacancy yields, consistent with firms using recruiting intensity, separately from vacancies, to affect hires. Carrillo-Tudela et al. (2020) show this relationship at the labor-market level. Second, we show 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 do not have information on firms' labor market beliefs, and they 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 focus on different labor markets; our paper richly describes recruiting and hiring behavior for large firms recruiting new college graduates in the U.S. – a large and consequential labor market.

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. Although we caution that our results are specific to this specific segment of the labor market, to the extent that the large employers in our sample behave similarly when they hire more broadly, our results suggest recruiting behavior may have contributed to the slow recovery of aggregate hires after the Great Recession.

2 Data and Empirical Setting

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

[6]See Wolthoff (2017), Gavazza et al. (2018), Leduc and Liu (2020), and Mongey and Violante (2019).

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

over 2000 colleges and universities in the United States, and over 3000 university relations and recruiting professionals from over 900 employers. NACE conducts multiple surveys of its members each year. We use data from the Recruiting Benchmarks (2008-2016) and Job Outlook (2006-2016) surveys, both of which are sent to members who recruit new college graduates for entry-level jobs at their employer. These surveys richly describe these firms' recruiting, vacancy posting, and hiring behavior. We discuss the data briefly here and in more detail in the Data Appendix.

Hiring in the labor market for new college graduates is a highly structured process, in which employers hire on an annual time-scale. Employers typically make hiring plans for the coming cycle in the early fall, and take actions throughout the year to adjust the recruitment process. By late spring, most employers will have finalized the recruitment process and hired some number of new graduates who will join the employers over the summer.

The NACE surveys reflect this timeline, with the Job Outlook survey (administered August-September) focusing on hiring plans for the coming year and the Recruiting Benchmarks survey (administered May-July) focusing on recruiting behavior over the previous year. In addition, the Job Outlook survey collects data on hires and vacancies in the previous year. We use data from the Job Outlook survey to construct our forward-looking sample, which focuses on hiring intentions and beliefs. To measure the relationship between recruiting activity and realized hires relative to vacancies, we merge the two surveys, referring to it as our backward-looking sample. Both samples use surveys administered from 2011 through 2016.

Table 1 shows firm characteristics for the backward- and forward-looking samples. We show the summary statistics for the forward-looking sample restricting to firms with multiple observations, but show the backward-looking statistics without this restriction given the smaller size of that sample. However, imposing this restriction yields very similar similar summary statistics (Appendix Table A.6).[8] Roughly 33% of the observations are from manufacturing firms, 11% from Finance and Insurance, and over 21% from professional and technical services. Firms in our sample are large, with over 80% employing more than 500 workers. Firms of this size employ over half of all workers (Statistics of U.S. Business, 2018), even though they comprise a small percentage of firms in the U.S. We acknowledge there are potentially significant differences by firm size related to hiring and recruiting, but we see our results as informative for understanding recruiting in our important setting.

[8]We also construct the principal components indices with and without this restriction.

Table 1: Employer Characteristics

% by Industry:	Backward-Looking Sample	Forward-Looking Sample
Manufacturing	0.34	0.33
Finance & Insurance	0.11	0.11
Mgmt, Sci., and Tech. Consulting	0.08	0.07
Retail	0.07	0.06
Construction	0.05	0.06
Architectural and Engineering Services	0.03	0.04
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
≤ 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, reflecting hiring from 2012 through 2017. 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.

Forward-Looking Measures

To measure recruiting intentions for the coming year, we use five key questions: Do you plan to increase career fairs?, Do you plan to travel more for recruiting?, Do you plan to use more technology in recruiting?, Do you plan to use more social networks in recruiting?, and Do you plan to change your branding in recruiting?[9]

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. In addition 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. More details on the variable construction are discussed in the Data Appendix. Summary statistics of all variables are reported in Table 2.

Respondents are asked if they plan to increase, decrease, or maintain hiring in the coming year, which we use to measure hiring plans. In addition, respondents are asked to rate the labor market for new graduates in their industry in the coming year. We code ratings of good or better as a belief that the firm will face a tight labor market in the coming year.

Backward-Looking Measures

The second set of recruiting measures are based on realized recruiting activities in the prior year. We construct an index of recruiting effort using four variables: 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. Longer deadlines provide further opportunities for applicants to obtain other offers and negotiate, increasing the employer effort required.

Our index of recruiting selectivity is constructed using three measures: whether the firm screens on GPA, whether the firm recruited from universities other than four-year public and not-for-profit universities (for example, whether they recruit at two-year colleges, for-profit universities, and online universities), and whether the firm prefers candidates with relevant experience. These measures reflect how broad of an applicant pool the firm is willing to

[9] Branding refers to the employer's brand on campus, which might be developed by recruiting materials, events, and relationships on campus.

Table 2: Summary Statistics: Recruiting Measures

	Mean	SD
Panel A: Forward-Looking Measures		
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
Compensation Generosity		
Planned % Incr. In Offered Starting Salary (Real)	0.24	2.85
Plan to Offer Bonus	0.51	0.50
Panel B: Backward-Looking Measures		
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 Selectivity		
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

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.

consider.

We use principal component analysis to construct indices for recruiting effort and recruiting selectivity. Because the log of the recruiting index enters equation (5), we standardize the log of the index to be mean zero and standard deviation one, rather than standardizing the level. Finally, we use an indicator for whether the firm gave signing bonuses to measure compensation generosity. Panel B of Table 2 shows summary statistics for the backward-looking recruiting measures. Appendix A discusses these measures in more detail.

To measure vacancies and hires, we use retrospective data from the Job Outlook survey on how many positions were available in the previous academic year and how many college graduates were ultimately hired for full-time entry-level positions. Table 2 shows summary statistics for these variables. These measures differ somewhat from the standard measures included in the JOLTS survey, which we discuss in Appendix A.

For a few observations, the reported hires are many times larger than the reported vacancies, likely reflecting data quality. We restrict the backward-looking sample to observations in which the number of hires relative to vacancies is more than roughly .25, but no more than 2.5 (roughly the 1st and 99th percentiles). In Appendix A we discuss this restriction in more detail. For robustness we explore alternative sample restrictions.

3 Hiring Plans, Beliefs about Tightness, and Recruiting Intensity

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. We begin by introducing some notation. Consider the following basic macro-economic matching function:

$$f_t \equiv \mu(v_t, u_t) \tag{1}$$

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

$$h_{et} = f_t \times v_{et} \tag{2}$$

Thus, the number of workers a firm hires depends on two factors: how many vacancies the firm posts (v_{et}) 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 framework, 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 vacancies 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 selectivity ($x_{s_{et}}$), and compensation generosity ($x_{c_{et}}$). Thus, we can write

$$h_{et} = \tilde{f}_t q(v_{et}, x_{f_{et}}, x_{s_{et}}, x_{c_{et}}) \tag{3}$$

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

Equation 3 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 firm-level hires will fall. Second, conditional on labor market tightness, increases in vacancies or in recruiting intensity will lead to an increase in firm-level 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.

If firms adjust recruiting intensity, estimates of aggregate hiring based on a standard matching function as in Equation 1 will diverge from actual hires. For instance, if employers decrease recruiting activity per vacancy when the labor market is slack, the gap between predicted hires from the standard matching function and actual hires will vary systematically over the business cycle, similar to what we saw after the Great Recession.

We begin by examining changes in recruiting activities when firms change hiring plans or beliefs about market tightness. This allows us to look in detail at the micro-level decision-making process underlying cyclical hiring behavior. If firms are adjusting recruiting intensity in order to achieve targeted hires, Equation (3) implies we should see they adjust recruiting when they want to increase hires, conditional on their beliefs about labor market tightness. Similarly, we should see they adjust recruiting when they believe the market will be tight, conditional on their hiring plans. This adjustment counterbalances the lower aggregate fill rate, helping them to achieve their hiring target.

This leads us to estimate Equation (4), where t indicates year and e indicates firm.

$$\text{Recruiting Measure}_{et} = \beta_0 + \beta_1 \text{Plan Increase Hires}_{et} + \beta_2 \text{Plan Decrease Hires}_{et} + \beta_3 \text{Believe LM Will Be Tight}_{et} + \Omega_e + \epsilon_{et} \tag{4}$$

By including firm fixed effects (Ω_e), we measure how recruiting intensity changes with changes in the firm's hiring plans or beliefs. All variables are described in Section 2.1. The coefficients on $PlanIncreaseHires$ and $PlanDecreaseHires$ are relative to the omitted group $PlanMaintainHires$. We cluster standard errors at the firm level. Since our outcome measures the firm's recruiting strategy, the relevant measure of tightness should be the firm's belief about tightness. However, we additionally include year fixed effects to control for any changes over time in recruiting behavior unrelated to tightness, such as technology adoption or inflation in market wages.

Table 3 shows the results from estimating Equation (4) for the three different dependent variables. In Panel A, we focus on the Forward-Looking Recruiting Effort Index. When employers plan to increase hires compared to the prior year, they are more likely to plan on expending more recruiting effort relative to the prior year, compared to when they plan on maintaining hires, with a magnitude of 0.3 standard deviations when including employer and year fixed effects. This result provides direct evidence that employers adjust on additional margins when they want to increase hiring, in contrast to the standard search and matching model which implies that employers can only increase hires by adjusting vacancies.

We also see that employers increase recruiting effort by about 0.5 standard deviations when they believe the labor market will be tight. This shows that employers are responsive to perceived difficulty in hiring, and adjust recruiting effort, and not only vacancies, accordingly. Interestingly, we do not find a symmetric decrease in recruiting effort for employers that plan to decrease hires, relative to maintaining hires. However, in column 4 the magnitude is negative and the confidence intervals suggest we cannot rule out a large negative effect, and the coefficient on $PlanIncreaseHires$ is statistically different from $PlanDecreaseHires$ across specifications.

In Panel B of Table 3 we focus on the percent change in real starting salary that the employer plans to offer. We again see a robust increase in planned salary increases when employers plan to increase hires, ranging from about 0.6% in the cross-section to 1% when we include firm fixed effects. Although the coefficients on plan to decrease hires are again not statistically significant, we reject equality with the coefficient on plan to increase hires. Similarly, employers plan to increase salaries when they believe the labor market will be tight. Finally, In Panel C of Table 3 we focus on an indicator for whether the employer plans

Table 3: Relationship Between Hiring Plans, Beliefs, and Recruiting

	(1)	(2)	(3)	(4)
Panel A: Forward-Looking Recruiting Effort Index				
Plan Increase Hires	0.611***	0.594***	0.375***	0.331***
	(0.063)	(0.063)	(0.094)	(0.088)
Plan Decrease Hires	0.017	-0.017	-0.101	-0.135
	(0.077)	(0.083)	(0.110)	(0.121)
Believe Labor Market will be Tight	0.351***	0.384***	0.337***	0.462***
	(0.074)	(0.075)	(0.117)	(0.118)
Firms	657	657	250	250
Observations	1,116	1,116	709	709
R-squared	0.123	0.131	0.520	0.542
Test Plan Inc. = Plan Dec.	≤ 0.0001	≤ 0.0001	.0004	.0007
Panel B: Planned % Increase in Offered Starting Salary (Real)				
Plan Increase Hires	0.605**	0.690**	0.958**	1.003**
	(0.273)	(0.277)	(0.417)	(0.395)
Plan Decrease Hires	-0.168	-0.030	-0.263	0.017
	(0.318)	(0.310)	(0.315)	(0.353)
Believe Labor Market will be Tight	0.762***	0.610***	0.558*	0.419
	(0.226)	(0.230)	(0.296)	(0.339)
Firms	471	471	146	146
Observations	701	701	376	376
R-squared	0.021	0.041	0.428	0.458
Test Plan Inc. = Plan Dec.	.03	.04	.01	.04
Panel C: Plan to Offer a Signing Bonus				
Plan Increase Hires	0.033	0.039	0.029	0.036
	(0.034)	(0.034)	(0.042)	(0.041)
Plan Decrease Hires	0.015	0.040	0.026	0.089
	(0.049)	(0.053)	(0.073)	(0.080)
Believe Labor Market will be Tight	0.118***	0.117***	0.065	0.052
	(0.041)	(0.043)	(0.068)	(0.073)
Firms	628	628	238	238
Observations	1,059	1,059	669	669
R-squared	0.010	0.012	0.572	0.579
Test Plan Inc. = Plan Dec.	0.71	0.99	0.97	0.53
Firm FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes

Notes: Coefficients from estimates of Equation (4). Standard errors clustered at the firm level, $***p < 0.01, **p < 0.05, *p < 0.1$. For each specification, we perform a Wald test for the equality of the coefficients for plan to increase hires and plan to decrease hires, and we report the p-values.

to offer a signing bonus. We do not find clear evidence that employers use bonuses to adjust hiring.

Recruiting Intensity over the Business Cycle

In the previous section, we showed that recruiting plans vary based on beliefs about labor market tightness. In Appendix Figure A.4, we show these beliefs track with the state of the aggregate labor market, with beliefs about tightness falling to a nadir in 2010 and improving thereafter. In this section we focus on how recruiting measures varied over the Great Recession and subsequent recovery.

Although small sample sizes and changing questionnaires over time limit our analysis, in Figure 1 we illustrate within-firm changes in select recruiting variables over time, among firms that responded to the survey in 2007-2008. While we have limited power, given the novelty of the data and the importance of the question we nonetheless find these results informative with the appropriate caveats. We cannot evaluate the coefficients dynamically given we do not have full balance; however, the coefficient in each year can be interpreted as the average change in recruiting over time within employers relative to 2007-2008, given we have balance in that year.

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 was 2.4 percentage points lower in 2009-2010, when it reached its lowest level. The increase remained substantially below the 2007-2008 salary increase through 2012-2013. In panel B, we see that relative to 2007-2008, the likelihood of planning to offer a signing bonus fell to its lowest level in 2010-2011, and remained statistically significantly below 2007-2008 levels until 2013-2014. In 2010-2011 firms were 29 percentage points less likely to plan to offer a signing bonus compared with 2007-2008.

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.[10] 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.

Thus, across a range of measures, we find that recruiting intensity fell during the Great Recession and slowly recovered. These results are consistent with the result from the previous section that employers adjust recruiting effort when they believed the labor market to be

[10]This is unlikely to reflect changes in the number of career fairs that universities sponsored, given that universities often hold career fairs each Fall and Spring.

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 are restricted 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). Panels A and B are estimated using the forward-looking sample, while panels C and D are estimated using the backward-looking sample. Panel A is estimated using 426 observations from 125 firms, while Panel B is estimated using 604 observations from 165 firms. Panel C is estimated using within-firm identification from 506 observations from 143 firms, and Panel D using 554 observations from 147 firms. Number of career fairs is missing in 2010.

slack and when their hiring plans changed.

4 Do Recruiting Adjustments Influence Vacancy Yields?

We have shown that when firms increase hiring plans they also increase recruiting effort and compensation generosity. However, we were unable to measure whether the increases in recruiting effort reflect increases in recruiting intensity per vacancy. 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. Since measures of recruiting intensity are not available for the broader U.S. labor market, our ability to connect recruiting behavior to the vacancy yield provides important evidence for how this omitted variable may bias estimates of the vacancy yield based on a standard matching function.

To analyze the effect of recruiting on the vacancy yield, we return to the notation from Section 3. In order to estimate the employer's job filling rate, we must choose a particular functional form for effective vacancies from Equation 3. 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. We can then 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:

$$ln f_{et} = ln \tilde{f}_t + (\gamma - 1) ln v_{et} + \delta_f ln x_{f_{et}} + \delta_s ln x_{s_{et}} + \delta_c ln x_{c_{et}} \tag{5}$$

We can then estimate Equation 5 directly as follows:

$$ln \frac{h_{et}}{v_{et}} = \beta_0 + \beta_1 ln v_{et} + \beta_f ln x_{f_{et}} + \beta_s ln x_{s_{et}} + \beta_c ln x_{c_{et}} + \Gamma_t + \epsilon_{et} \tag{6}$$

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 bin fixed effects. We additionally estimate a specification with firm fixed effects. This addresses the concern that 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. 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 decreases the sample size due to a more limited number of firms responding to both surveys in multiple years.[11]

We estimate Equation (6), using the backward-looking sample, defined in Section 2.2. We include all principal components of the effort and selectivity variables in the estimation of Equation (6). 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 4 column 1 shows that conditional on log 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.[12] Neither the selectivity index, nor offering a signing bonus, are associated with a statistically significant difference in the vacancy yield.

Increasing vacancies is associated with a decrease in the vacancy yield, conditional on recruiting, industry, size bin, and year. Given there are only a few employer size bins, vacancies may be additionally capturing employer size. This would negatively bias the coefficient on vacancies, as vacancy yields in JOLTS are negatively correlated with employer size.[13] Consistent with this, the coefficient decreases substantially and is no longer significant when including firm fixed effects.[14]

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 (column 2). 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 without firm fixed effects. The coefficients on the selectivity index and offering a signing bonus continue to be statistically indistinguishable from zero.

[11]In equation (6) we regress $ln(h/v)$ on $ln(v)$, because we allow for economies of scale in vacancies in equation (2). If we assumed no economies of scale in vacancies ($\gamma = 1$ in equation (2)), log vacancies would not be on the right-side of equation (5) or (6). Using ln(hires) as the outcome yields the same coefficients on recruiting as in equation (6), and the coefficient on ln(v) would be $\beta_1 + 1$. As we noted, due to the recruiting timeline, vacancies and effort may not be completely jointly determined. However, even if they were jointly determined as in Gavazza et al. (2018), following the intuition in Gavazza et al. (2018) we would infer that if effort was higher conditional on vacancies then it was optimal to achieve additional hires through recruiting effort not vacancies.

[12]Appendix Figure B.1 shows the relationship between recruiting variables and vacancy yield less parametrically.

[13]See Appendix Table B.7.

[14]Davis et al. (2013) find mild increasing returns to scale in vacancies, without a control for firm-level recruiting intensity, acknowledging there is more to be learned from micro-level data. They use employment as an instrument for vacancies to address endogeneity and measurement error. We do not have an employment measure other than our size bins. Further, employment may be correlated with vacancy yield for reasons other than its relationship with vacancies, violating the exclusion restriction.

Table 4: Relationship Between Recruiting and Vacancy Yield

Y = ln(H/V)	(1)	(2)	(3)	(4)
Recruiting Effort,	0.0371**	0.117**	0.0418*	0.115**
standardized	(0.0160)	(0.0464)	(0.0227)	(0.0465)
Recruiting Selectivity,	0.0253	0.0314	0.0246	-0.0161
standardized	(0.0192)	(0.0336)	(0.0215)	(0.0273)
Offered Signing Bonus	-0.00702	-0.0332	0.0208	-0.0243
	(0.0242)	(0.0418)	(0.0334)	(0.0437)
ln(Vacancies)	-0.0461***	-0.0100	-0.0383**	-0.0376
	(0.0165)	(0.0391)	(0.0185)	(0.0468)
Firms	269	81	269	77
Observations	405	217	405	201
R-squared	0.156	0.619	0.377	0.706
Industry FE, Size FE	Y	N	N	N
Firm FE	N	Y	N	Y
Year FE	Y	Y	N	N
Ind-Year, Size-Year FE	N	N	Y	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 Selectivity is the first principal component based on principal components analysis and three variables describing employer recruiting selectivity. For both Recruiting Effort and Recruiting Selectivity, we add 10 to the first principal component, take the log, and then standardize so it has mean zero and standard deviation of one. Each column additionally includes the log of the other components (after adding 10) from the effort and selectivity analysis. There are 25 industry categories, seven firm size categories, and indicators for six years (2010-2011 through 2015-2016). However, in column 4, when including industry-year fixed effects we use the 11 supersectors defined by the Bureau of Labor Statistics due to the already smaller sample.

Robustness

We estimate a number of additional specifications for robustness. Estimating regression (6) with firm fixed effects, but excluding vacancies, the coefficient on recruiting effort is very similar (Appendix Table B.4).[15] Table B.3 shows results separating the components of the selectivity index. Table 4 columns 3 and 4 allow for market tightness to vary by industry and firm size by including industry-year and firm size-year fixed effects, which yields similar effects.[16] When using career fairs as our main measure of recruiting effort the relationship

[15]Without firm fixed effects controlling for vacancies likely captures firm size. Consistent with this, excluding vacancies without firm fixed effects yields a smaller and insignificant coefficient on effort, although the 95% confidence interval includes the effect in Table 4.

[16]We use the eleven supersectors defined by the Bureau of Labor Statistics instead of the two-digit NAICS codes to construct industry-year fixed effects when including firm fixed effects, given the smaller sample.

between effort and the vacancy yield nearly doubles (Appendix Table B.5). Appendix Table B.5 shows our results are robust to our definition of outliers for the vacancy yield variable.[17]

Counterfactuals

As we have discussed, the aggregate vacancy yield during the Great Recession was much lower than predicted by a standard matching function, motivating a renewed focus on how firms adjust recruiting intensity. One of the central contributions of our paper is that we have unique firm-level recruiting, vacancy, and hiring data, allowing us to estimate the relationship between recruiting and vacancy yield, for the firms in our sample. We use these estimates to present a simple back-of-the-envelope calculation, connecting to this puzzle. For the firms in our sample, we ask how much higher their vacancy yield during the recession would have been if they had not decreased recruiting intensity. This calculation is predicated on having identified a causal relationship between recruiting and the vacancy yield, and is based on our particular though important sample of firms. It should be interpreted with all the caveats discussed thus far.

Among the firms in our sample, average recruiting effort was 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 firm's vacancy yield, implying a 1.2% increase. Thus, if recruiting effort had been the same in 2010-2011 as it was in 2014-2015, the firm-level vacancy yield would have been higher by 1.2% on average.

It is useful to know whether the additional 1.2% in the firm-level vacancy yield is large or small relative to the overall difference in vacancy yields when macroeconomic conditions vary. For the firms in our sample, average firm-level vacancy yields in 2010-2011 were 1.1% higher relative to 2014-2015. If recruiting effort had been constant, the difference in average vacancy yield between these years would have doubled (1.1% + 1.2% vs. 1.1%). As an alternative way of assessing magnitude, the standard deviation of the average firm-level vacancy yield across the six years in the sample is 3.2 percentage points. Our back-of-the-envelope estimate is a 1.2% increase, from a mean firm-level vacancy yield of .95, implying a 1.1 percentage point increase. This suggests that if recruiting effort had been constant, average firm-level vacancy yield would have been higher by about one-third of a standard deviation of the average vacancy yield across years. Lower recruiting effort by these firms during the recession kept their vacancy yield lower than would be expected if recruiting intensity was constant over the business cycle.[18]

[17] Dropping the six singleton observations from column 1, Table 4 yields similar standard errors. The coefficient on effort in column 1, Table 4 is also significant at the 5% level when standard errors are calculated based on 400 bootstrap replications, accounting for the principal components being generated regressors.

[18] We compare 2010-2011 to 2014-2015 because our sample size drops substantially in 2015-2016 (from 71

Our results with firm fixed effects imply the firm-level vacancy yield would have been an additional 4.9% higher if effort had been the same in 2010-2011 and 2014-2015, nearly tripling the percentage difference in the average vacancy yield between 2010-2011 and 2014-2015. The effect implies that if recruiting had been constant, the firm-level vacancy yield would have increased by roughly 1.2 standard deviations of the average vacancy yield across years.

We also decompose the elasticity of the vacancy yield with respect to hires, as in (Davis et al., 2013) but using our direct measures of recruiting effort, and find our measure of recruiting effort explains roughly 61%. Details are provided in section C.

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 to adjust hires, they are not only adjusting vacancies but also the intensity with which they are recruiting for the vacancy. Our results are specific to the labor market for new college graduates. However, all employers use a variety of recruiting tools to reach applicants, and if they use them similarly to the firms in our sample, this would imply misspecification of the matching function.

5 Conclusions

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 and in response to beliefs about labor market tightness. When firms expend greater recruiting effort they fill a greater fraction of their vacancies.

Our data focus on a specialized but important labor market. If the relationships we identify apply more widely across employers, or across job types within large employers, this could help explain why hires fell more than expected given the stock of unemployed workers and vacancies during and after the Great Recession.

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 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 from economic downturns.

in 2014-2015 to 49). If recruiting effort had been the same in 2010-2011 as it was in 2015-2016, firm-level vacancy yield would similarly have increased by 1% on average.

References

Arellano-Bover, J. (2020). Career consequences of firm heterogeneity for young workers: First job and firm size. *Working Paper*.

Barron, J. M., Bishop, J., & Dunkelberg, W. C. (1985). Employer search: The interviewing and hiring of new employees. *The Review of Economics and Statistics*, *67(1)*, 43–52.

Carrillo-Tudela, C., Gartner, H., & Kaas, L. (2020). Recruitment policies, job-filling rates and matching efficiency. *CEPR Discussion Paper*, *No. DP14727*.

Clark, K. B., Summers, L. H., Holt, C. C., Hall, R. E., Baily, M. N., & Clark, K. B. (1979). Labor market dynamics and unemployment: a reconsideration. *Brookings Papers on Economic Activity*, *1979*(1), 13–72.

Davis, S. J., Faberman, R. J., & Haltiwanger, J. C. (2013). The Establishment-Level Behavior of Vacancies and Hiring. *Quarterly Journal of Economics*, 581–622.

Elsby, M. W. L., Michaels, R., & Ratner, D. (2015). The Beveridge Curve: A Survey. *Journal of Economic Literature*, *53*(3), 571–630. Retrieved from http://pubs.aeaweb.org/doi/10.1257/jel.53.3.571

Faberman, R. J., & Menzio, G. (2018). Evidence on the relationship between recruiting and the starting wage. *Labour Economics*, *50*(November 2016), 67–79.

Forsythe, E. (2022). Why don't firms hire young workers during recessions. *Economic Journal*.

Forsythe, E., Kahn, L., Lange, F., & Wiczer, D. (2020). Searching, recalls, and tightness: An interim report on the covid labor market. *NBER Working Paper*(w28083).

Gavazza, A., Mongey, S., & Violante, G. L. (2018). Aggregate recruiting intensity. *American Economic Review*, *108*(8), 2088–2127.

Hall, R. E. (2005). Job loss, job finding, and unemployment in the us economy over the past fifty years. *NBER macroeconomics annual*, *20*, 101–137.

Hershbein, B., & Kahn, L. B. (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review*, *108*(7).

Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour economics*, *17*(2), 303–316.

Kuhnen, C. M. (2011). Searching for Jobs : Evidence from MBA Graduates. *Working Paper*.

Kuhnen, C. M., & Oyer, P. (2016). Exploration for Human Capital: Evidence from the MBA Labor Market. *Journal of Labor Economics*, *34*(2).

Laschever, R., & Weinstein, R. (2020). Preference Signaling and Worker-Firm Matching: Evidence from Interview Auctions. *Working Paper*.

Leduc, S., & Liu, Z. (2020). The weak job recovery in a macro model of search and recruiting intensity. *American Economic Journal: Macroeconomics*, *12*(1), 310–43.

Liu, K., Salvanes, K. G., & Sorensen, E. O. (2016). Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession. *European Economic Review*, *84*.

Lochner, B., Merkl, C., Stüber, H., & Gürtzgen, N. (2021). Recruiting intensity and hiring practices: Cross-sectional and time-series evidence. *Labour Economics*, *68*, 101939.

Ma, K., & Samaniego de la Parra, B. (2021). Labor Market Tightness, Recruitment and Search Behavior. *Working Paper*.

Mongey, S., & Violante, G. L. (2019). Macro recruiting intensity from micro data. *NBER Working Paper*(w26231).

National Association of Colleges and Employers. (2021). *Nace job outlook 2021.*

Oreopoulos, P., Von Wachter, T., & Heisz, A. (2012). The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, *4*(1), 1–29.

Oyer, P. (2006). Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives*, *20*(3).

Oyer, P., & Schaefer, S. (2016). Firm/employee matching: an industry study of u.s. lawyers. *Industrial and Labor Relations Review*, *69*(March), 378–404.

Petrongolo, B., & Pissarides, C. A. (2008). The ins and outs of european unemployment. *American economic review*, *98*(2), 256–62.

Rivera, L. A. (2011). Ivies , extracurriculars , and exclusion : Elite employers ' use of educational credentials. *Research in Social Stratification and Mobility*, *29*, 71–90.

Rivera, L. A. (2012). Hiring as Cultural Matching: The Case of Elite Professional Service Firms. *American Sociological Review*, *77*(6), 999–1022.

Roper, S. (1988). Recruitment methods and vacancy duration. *Scottish Journal of Political Economy*, *35*(1), 51–64.

Sasser Modestino, A., Shoag, D., & Ballance, J. (2016). Downskilling: Changes in Employer Skill Requirements Over the Business Cycle. *Labour Economics*, *41*.

Sasser Modestino, A., Shoag, D., & Ballance, J. (in press). Upskilling: Do Employers Demand Greater Skill When Workers Are Plentiful. *Review of Economics and Statistics*.

Statistics of U.S. Business, U. C. B. (2018). *Number of firms, number of establishments, employment, and annual payroll, by large enterprise employment sizes for the united states, naics sectors: 2016.* https://www.census.gov/data/tables/2016/econ/susb/2016-susb-annual.html (accessed: 02.29.2022).

Van Ours, J. C., & Ridder, G. (1993). Vacancy durations: search or selection? *Oxford Bulletin of Economics and Statistics*, *55*, 187–187.

Weinstein, R. (2018). Employer Screening Costs, Recruiting Strategies, and Labor Market Outcomes: An Equilibrium Analysis of On-Campus Recruiting. *Labour Economics*, *55*.

Weinstein, R. (2021). Graduating from a Less Selective University During a Recession: Evidence from Mobility Report Cards and Employer Recruiting. *Working Paper*.

Weinstein, R. (2022). Firm Decisions and Variation Across Universities in Access to High-Wage Jobs: Evidence from Employer Recruiting. *Journal of Labor Economics*, *40(1)*.

Wolthoff, R. (2017). Applications and interviews: Firms' recruiting decisions in a frictional labour market. *Review of Economic Studies*, *85*(2), 1314–1351.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* MIT press.

Appendix: For Online Publication

The Online Appendix consists of four sections. In Appendix A, we provide additional details about the data source and variable construction. In Appendix B, we provide additional supplementary results. In Appendix C, we provide a decomposition of the elasticity of the firm-level vacancy yield with respect to hires. In Appendix D, we discuss implications for 2021 graduates.

A Data Appendix

In this section, we provide more details on the data sources and sample construction. As discussed in the main text, we use data collected by the National Association of Colleges and Employers (NACE). We construct two samples using the Job Outlook Survey and Recruiting Benchmarks Survey.

Constructing Firm Identifiers

In order to include firm fixed effects and merge across surveys, we create a consistent name variable. 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. 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.

Construction of Variables

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. 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 this 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.

Descriptive Characteristics of Firms in the Sample

In this subsection we provide more details on the characteristics of firms in the sample. In Table 1 industries are defined using two-digit NAICS codes, based on the six-digit NAICS codes in the data. Given NAICS code 54 (Professional, Scientific, and Technical Services) is quite diverse, ranging from accounting and advertising to engineering services, we split this two-digit NAICS code into four-digit codes in our regression analysis. In Table 1 we combine the two largest size categories (10001-20000 and $>$ 20000), since this separation is not available for the forward-looking sample. In the backward-looking sample, approximately 25% of observations are from firms with more than 20,000 employees, with 13% between ten and twenty thousand. We present additional summary statistics on the distribution of years in the sample (Figure A.2), and number of observations per firm (Table A.1).[19]

Not all employers who receive the survey send in a response. There are roughly 900 employer members of NACE, but the overall number of respondents per year is roughly 200-300 employers. We do not observe information about hires, vacancies, or recruiting for the firms who do not respond to the survey, and so it is difficult to document the nature of the selection into survey response. There may be selection into responding in a way that biases our main results. One specific concern would be that firms who put in high effort but had low vacancy yield were discouraged about their recruiting, and chose not to respond to the survey.

In Table A.2, we compare the forward-looking sample industry distribution for NACE firms to the distribution for all firms and for large firms, from the Census Enterprise Statistics Program. The NACE sample is more similar to the distribution of large firms, which is unsurprising given the NACE sample consists of very large firms. Relative to all large firms, manufacturing, and professional, scientific, and technical services are over-represented in the NACE sample, 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

[19]Appendix Figure A.1 shows the distribution of hires per vacancy in the backward-looking regression sample.

Figure A.1: Distribution of Hires per Vacancy in the Backward-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	407
2	48	130
3	17	66
4	12	30
5	2	13
6	2	11
Total:	269	657

Notes: Table shows the number of observations per firm in the backward-looking sample and the forward-looking sample. Note the preferred forward-looking sample restricts to firms with at least two observations, which yields 250 firms.

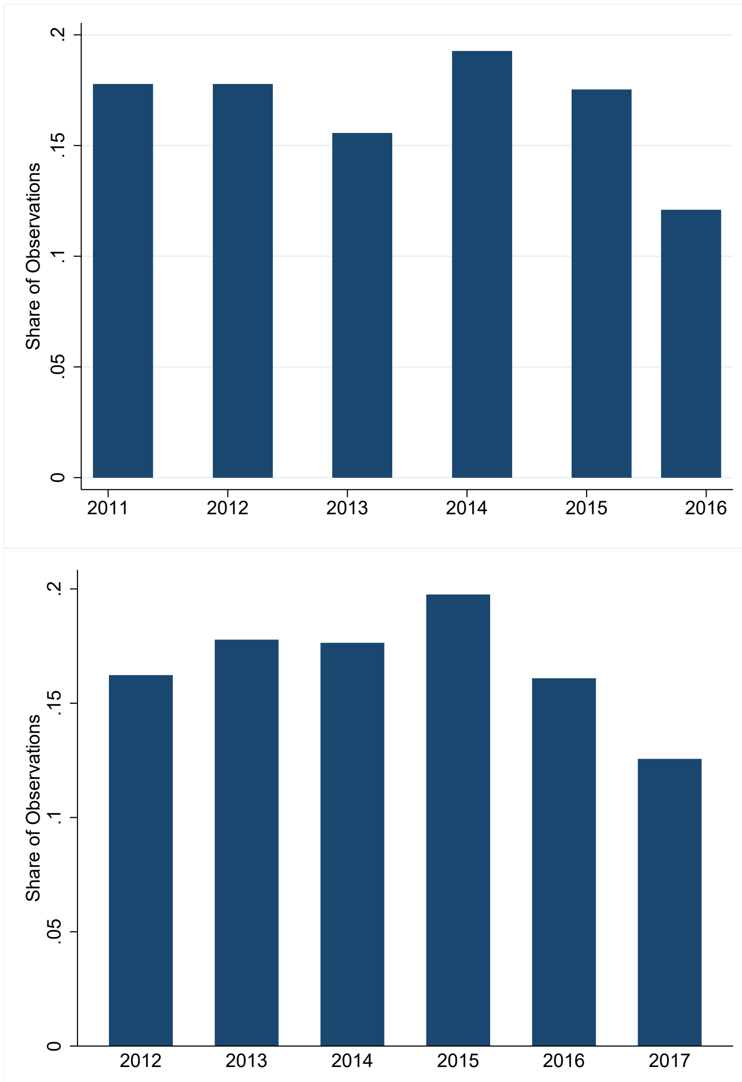


Figure A.2: Distribution of Observations in the Backward-Looking Regression Sample (top) and Forward-Looking Regression Sample (bottom). Forward-looking regression sample is restricted to firms with at least two observations.

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

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	0.06	0.01	0.11
Manufacturing	31-33	0.33	0.16	0.04
Retail	44-45	0.06	0.13	0.12
Finance & Insurance	52	0.11	0.08	0.05
Prof., Sci., and Tech. Services	54	0.20	0.06	0.14
All Other		0.23	0.56	0.54

Notes: This table compares the NACE industry distribution from the forward-looking sample 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.

Additional Details on Forward Looking Recruiting Measures

The forward-looking recruiting measures are drawn from the Job Outlook survey, and reflect hiring plans in the coming recruiting year.

Sample Construction

The sample is constructed in the following way. First, we restrict to firms with non-missing names. Second, we restrict to firms with valid answers to two key questions: whether they plan to change hires in the coming year, and how they rate the quality of the labor market in the coming year. These variables are key for the main specifications in Table 3, however as the hiring plans are only asked beginning in 2011, this limits our analysis to the 2011-2012 through the 2016-2017 academic years. We also only include firms in this sample in two years, in order to include firm fixed effects.

To estimate the results in Figure 1, we use a somewhat different sample from the forward-looking sample. We again restrict to observations with non-missing names, but include observations that do not have valid hiring plans or quality ratings of the labor market in the coming year, allowing us to examine recruiting behavior over the Great Recession. Instead those samples are restricted to firms that answered the question about salary increases (panel A) or plans to offer a signing bonus (panel B) in 2007-2008 as well as again in one subsequent year. This results in a sample of 426 observations from 125 firms for Figure 1 Panel A, and a sample of 604 observations from 165 firms for Panel B.

Recruiting Measures and Measure of Labor Market Beliefs

The Job Outlook survey includes several questions about recruiting plans in the coming year, however not all questions are asked each year. Thus, the five measures we use in the forward-looking recruiting effort index are the measures that are consistently included across years.

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.

There are several additional measures that we investigate but do not include in the main body of the paper. There is an additional measure for compensation generosity– planned real log signing bonus offer. In addition there are two measures of screening 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. We classify these variables separately from search effort, as they may additionally reflect recruiting applicants with a higher probability of accepting an offer based on their outside options. Lower outside options could be based on real or perceived productivity of applicants, discrimination, or greater hiring costs (e.g., visa sponsorship for international students). These variables are summarized in Table B.1.

In Table A.3 we show how firm hiring plans compare with beliefs about market tightness. Firms are more likely to plan to increase hiring when they believe the labor market to be tight, likely reflecting broader economic growth. This can also be seen in Figure A.3. In Figure A.4 we show how beliefs about market tightness vary by year. Consistent with the broader cycle, firms were more likely to report the market was slack in the the 2009-2010 academic year, with beliefs improving over the subsequent years.

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.

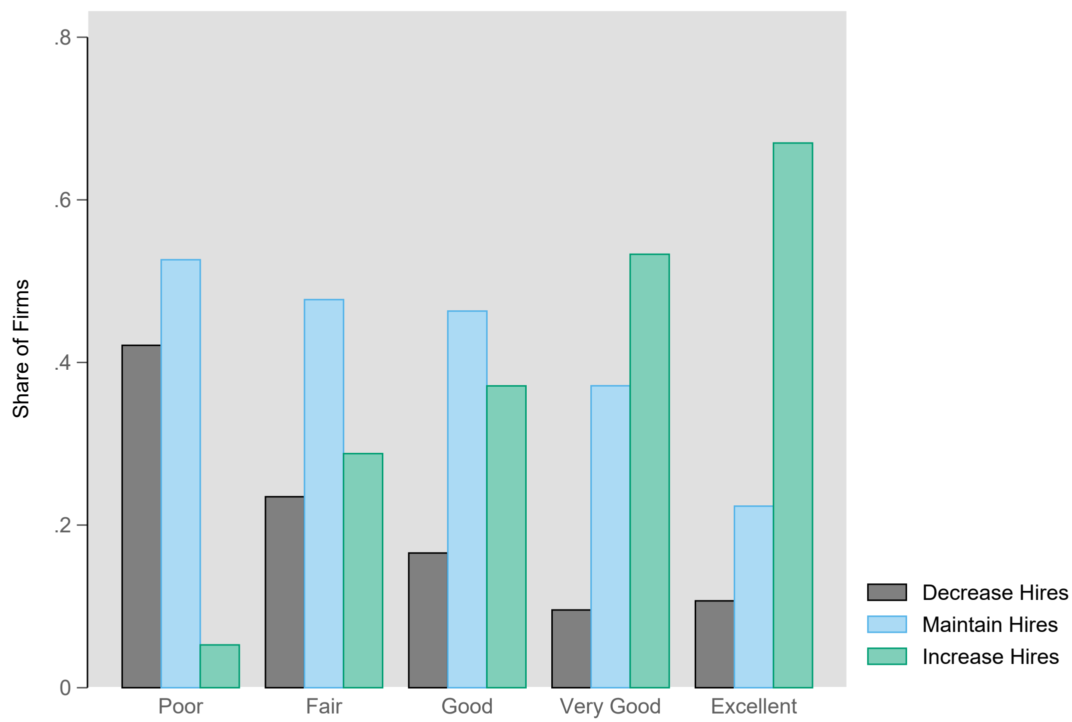


Figure A.3: Share of observations who plan to decrease, maintain, or increase hiring by beliefs about the state of the labor market. Note: Observations are restricted to the regression sample. This reflects 709 observations over 250 unique firms.

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).

Forward-Looking Recruiting Index

Table A.5 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 A.4: 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.

Table A.5: Forward-Looking Recruiting Effort Index, Sample without Restricting to Firms with Multiple Observations

In Coming Year's Recruiting	Eigenvector
More Career Fairs	0.45
More Travel	0.46
More Social Networks	0.48
More Technology	0.42
Change Brand	0.42
Eigenvalue	1.75
Fraction of Variance	35.1%
Number of Firms	657
Number of Observations	1,116

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

Additional Details on Backward-Looking Sample and Recruiting Measures

Sample Construction

The Backward-Looking sample is constructed by merging the Job Outlook and Recruiting Benchmarks surveys. In this section we provide additional detail on the measures used.

As discussed in the text, we restrict our backward-looking sample to observations for which the ratio of hires to vacancies is not more than 2.5. 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). Table B.5 shows results using alternative sample restrictions.

Recruiting Measures

One measure we use for recruiting effort is the interval between the interview and offer. Here we offer more discussion of this variable and why we think it is an appropriate measure of recruiting effort. Although our primary interpretation is that a shorter duration between the interview and offer indicates the employer is expending more effort to fill the position, 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. However, whether a shorter interval between interview and offer reflects expedience or less screening, both are consistent with greater recruiting intensity and desire to fill the vacancy. The negative eigenvector on this variable in the effort index, and a positive eigenvector on career fairs attended, further reflect this.

Another measure of recruiting effort in our backward-looking index is the time between offer and deadline to accept the offer. 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 their offer is ultimately rejected, and upon rejection they may extend more offers. As a result, we interpret longer deadlines as consistent with greater effort and as another benefit to the applicant. We show in Table B.6 that our main results are robust to excluding this component from the effort index.

Next we provide more information on the selectivity variables. One of the variables was whether the firm preferred applicants with relevant experience. This comes from a survey question in which firms were asked whether they preferred applicants with relevant experience when hiring a new college graduate for an entry-level position, whether they preferred any experience, regardless of relevance; and experience does not factor into the decision when hiring a new college graduate.

In each year respondents in the Recruiting Benchmarks survey are asked about the types of universities targeted, specifically in the previous year's recruiting. 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 selectivity measure. Further, firms may say they screen on GPA, while not actually screening on GPA, which may add noise to the recruiting selectivity index as well. This would make it less likely we would identify a negative relationship between our recruiting selectivity index and vacancy yield.

If firms are adjusting their recruiting selectivity 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 less-selective universities, and less likely to prefer relevant experience. Not only would these actions widen the pool of applicants, but they would also potentially include applicants who are more likely to accept offers given that these applicants may have worse outside options.[20] The fact that there is a negative eigenvector on "recruit from non-four year public/nfp" in the recruiting selectivity index, while the eigenvectors on "screen on GPA" and "prefer relevant experience" are positive, is consistent with this variable reflecting a decision about selectivity.

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

[20] An alternative story is that 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 selectivity, high quality applicants may not apply to firms with low selectivity, and as a result those firms may make fewer offers.

interviewing, online advertising, or pre-employment assessment tests.

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.

Recruiting Indices

We construct the indices using the main regression sample, restricted to observations without missing the variables that comprise all of the indices.

Appendix Table A.7 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. Appendix Table A.8 shows the eigenvectors for the first component from our analysis of the recruiting selectivity variables. This component quite intuitively measures selectivity. 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 selectivity and less recruiting intensity (e.g., trying to fill the vacancy). This component explains roughly 40% of the overall variance.[21]

As we will be taking logs of the recruiting effort and selectivity 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.

[21]Appendix Tables A.9 and A.10 show similar eigenvectors when constructing the index on the sample of firms when we include firm fixed effects in the regression.

Table A.6: Summary Statistics, Backward-Looking Sample Restricted to Firms Observed in Multiple Years

% by Industry:		
Manufacturing	0.35	
Finance & Insurance	0.1	
Management, Scientific, and Technical Consulting Services	0.1	
Retail	0.09	
Construction	0.05	
Architectural and Engineering Services	0.03	
All Other	0.28	
% by Company Size (# Employees):		
> 10,000	0.43	
5,001-10,000	0.13	
2,501-5,000	0.15	
1,001-2,500	0.11	
501-1,000	0.06	
≤ 500	0.12	
	Mean	SD
Hires Last Year	260.55	830.65
Vacancies Last Year	277.12	916.3
Participate in On-Campus Recruiting	0.87	0.34
Days from Interview to Offer	22.48	19.7
Days from Offer to Deadline	15.79	13.65
Career Fairs Attended	42.77	56.43
Screen on GPA	0.78	0.42
Recruit from non-Four Yr. Public/NFP Univ.	0.15	0.36
Prefer Relevant Experience	0.67	0.47
Gave Signing Bonus	0.57	0.5
Firms	81	
Observations	217	

Notes: Table is analogous to Tables 1 and 2 for the backward-looking sample, but restricting to firms observed in multiple years.

Table A.7: 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 A.8: Backward-Looking Recruiting Selectivity 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 A.9: Backward-Looking Recruiting Effort Index, Sample of Firms in Firm Fixed Effects Specification

	Eigenvector
On-Campus Recruiting	0.7427
Days from Offer to Deadline	0.5282
Career Fairs Attended	0.3265
Days from Interview to Offer	-0.2508
Eigenvalue	1.18
Fraction of Variance	30.0%
Number of Firms	81
Number of Observations	217

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

Table A.10: Backward-Looking Recruiting Selectivity Index, Sample of Firms in Firm Fixed Effects Specification

	Eigenvector
Screen on GPA	0.6218
Prefer Relevant Experience	0.6489
Recruit from non-Four Yr. Public/NFP	-0.4386
Eigenvalue	1.29
Fraction of Variance	43.0%
Number of Firms	81
Number of Observations	217

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

B Additional Results

Additional Results: Hiring Plans, Beliefs, and Recruiting

In this section we present additional results about hiring plans and beliefs about labor market tightness, using the forward-looking sample. These results correspond to Section 3 in the main text. In Table B.1 we investigate the relationship between these measures and the size of the bonus in panel A and two selectivity measures (planning to hire associate's degree holders and planning to hire international students for U.S. jobs) in panels B and C. Point estimates are generally small and not statistically significant for hiring plans. However in Panel C we do see that employers who believe the labor market will be tight are more likely to consider hiring international students, suggesting they are seeking ways to broaden the applicant pool when they believe there will be more competition for candidates.

In Table B.2, we show how recruitment plans differ based on disaggregated measures of the state of the labor market. Recruiting effort and salary increases are both increasing with beliefs about tightness.

Table B.1: Relationship Between Hiring Plans, Beliefs, and Recruiting, Additional Measures

	(1)	(2)	(3)	(4)
Panel A: Log Bonus (deflated)				
Plan Increase Hires	0.029	0.017	-0.049	-0.088
	(0.076)	(0.077)	(0.089)	(0.092)
Plan Decrease Hires	0.073	0.030	-0.041	-0.146
	(0.098)	(0.113)	(0.152)	(0.156)
Believe Labor Market will be Tight	-0.155	-0.157	0.191	0.209
	(0.097)	(0.101)	(0.132)	(0.126)
Firms	272	272	74	74
Observations	387	387	189	189
R-squared	0.007	0.020	0.730	0.750
Test Plan Inc. = Plan Dec.	0.64	0.91	0.96	0.66
Panel B: Planning to Hire Associate's Degree Holders?				
Plan Increase Hires	0.039	0.040	0.020	0.019
	(0.026)	(0.027)	(0.028)	(0.030)
Plan Decrease Hires	-0.045	-0.022	-0.078**	-0.056
	(0.034)	(0.037)	(0.039)	(0.043)
Believe Labor Market will be Tight	-0.009	0.002	0.017	0.016
	(0.032)	(0.033)	(0.047)	(0.047)
Firms	624	624	233	233
Observations	1,044	1,044	653	653
R-squared	0.005	0.009	0.693	0.695
Test Plan Inc. = Plan Dec.	0.02	0.09	.02	.1
Panel C: Planning to Hire International Students?				
Plan Increase Hires	0.050	0.057*	0.024	0.025
	(0.031)	(0.031)	(0.034)	(0.034)
Plan Decrease Hires	0.035	0.057	-0.019	-0.008
	(0.039)	(0.043)	(0.047)	(0.053)
Believe Labor Market will be Tight	0.143***	0.135***	0.066	0.062
	(0.032)	(0.033)	(0.042)	(0.044)
Firms	655	655	247	247
Observations	1,107	1,107	699	699
R-squared	0.018	0.022	0.673	0.674
Test Plan Inc. = Plan Dec.	0.73	0.99	0.41	0.53
Firm FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes

Notes: Coefficients from estimates of Equation 4. Standard errors clustered at the firm level, $***p < 0.01, **p < 0.05, *p < 0.1$. For each specification, we perform a Wald test for the equality of the coefficients for plan to increase hires and plan to decrease hires, and we report the p-values. The mean plan to hire associate's degree graduates in columns three and four is .17 with standard deviation .38, and the mean plan to hire international students for U.S. jobs in columns three and four is .28, with standard deviation .45.

Table B.2: Recruiting and Beliefs About the State of the Labor Market for New Graduates

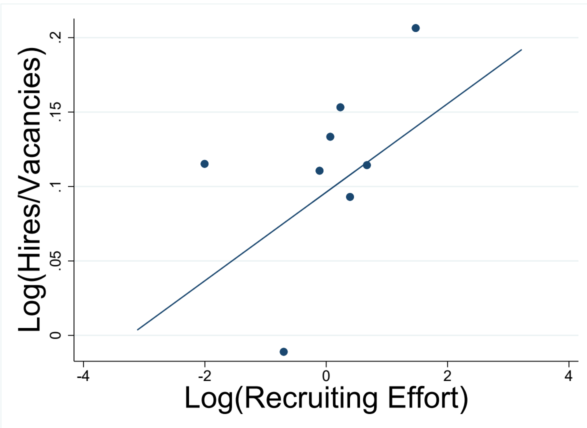
	(1)	(2)	(3)
	Forward-Looking Recruiting Effort Index	% Change in Real Salary	Bonus Indicator
Fair	0.092	1.610**	-0.082
	(0.147)	(0.690)	(0.241)
Good	0.555***	1.856**	-0.043
	(0.163)	(0.766)	(0.250)
Very Good	0.768***	2.450***	-0.008
	(0.171)	(0.751)	(0.256)
Excellent	0.938***	3.865***	0.097
	(0.182)	(1.222)	(0.260)
Firms	250	146	238
Observations	709	376	669
R-squared	0.532	0.467	0.581

Notes: All regressions include firm and year 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.

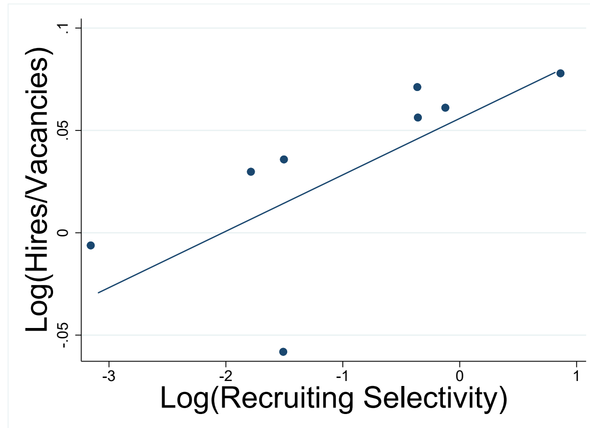
Additional Results: Recruiting and Vacancy Yields

In this section, we provide additional results corresponding to Section 4, based on the backward-looking sample.

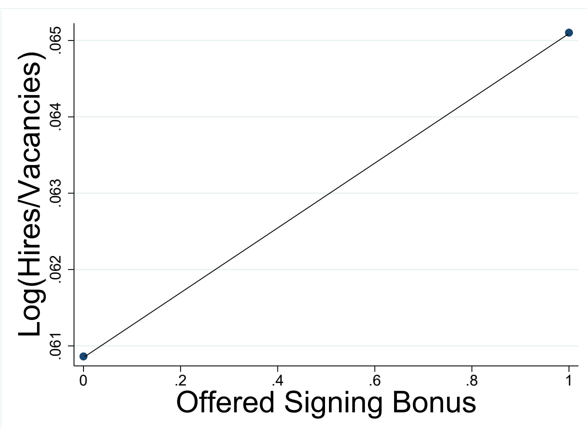
Figure B.1: Recruiting and Firm-Level Vacancy Yield



(a) Effort Index



(b) Selectivity 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 B.3: Relationship Between Recruiting and Vacancy Yield, Including Individual Variables from Selectivity Index

Y = ln(H/V)	(1)	(2)
Recruiting Effort,	0.0372**	0.118**
standardized	(0.0160)	(0.0463)
Screen on GPA	0.0424	0.167
	(0.0401)	(0.105)
Recruited from non-Four Yr. Public/NFP Univ.	-0.0127	-0.00132
	(0.0350)	(0.0573)
Prefer Relevant Experience	0.0358	-0.0462
	(0.0334)	(0.0373)
Offered Signing Bonus	-0.00704	-0.0342
	(0.0241)	(0.0420)
ln(Vacancies)	-0.0462***	-0.00848
	(0.0164)	(0.0388)
Observations	405	217
R-squared	0.156	0.621
Industry FE, Size FE	Y	N
Firm FE	N	Y
Year FE	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Standard errors clustered at the firm level. See notes to Table 4.

Table B.4: Relationship Between Recruiting and Vacancy Yield, Excluding Control for Vacancies

Y = ln(H/V)	(1)	(2)	(3)	(4)
Recruiting Effort,	0.0154	0.117**	0.0220	0.118**
standardized	(0.0140)	(0.0464)	(0.0197)	(0.0483)
Recruiting Selectivity,	0.0345*	0.0335	0.0324	-0.00828
standardized	(0.0203)	(0.0331)	(0.0223)	(0.0299)
Offered Signing Bonus	-0.0140	-0.0353	0.0194	-0.0251
	(0.0248)	(0.0415)	(0.0337)	(0.0448)
Firms	269	81	269	77
Observations	405	217	405	201
R-squared	0.128	0.619	0.363	0.703
Industry FE	Y	N	N	N
Size FE	Y	N	N	N
Firm FE	N	Y	N	Y
Year FE	Y	Y	N	N
Ind-Year FE	N	N	Y	Y
Size-Year FE	N	N	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. This table is the same as Table 4, but excludes the control for vacancies.

Table B.5: Relationship Between Recruiting and Vacancy Yield, Robustness

	(1)	(2)	(3)	(4)	(5)
	ln(H/V)	ln(H/V)	ln(H/V)	ln(H/V)	ln(H/V)
Recruiting Effort,	0.0348**	0.0353**	0.0492**	0.0734***	
standardized	(0.0169)	(0.0175)	(0.0209)	(0.0279)	
Recruiting Selectivity,	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(Vacancies)	-0.0547**	-0.0649***	-0.0868***	-0.124***	-0.0545***
	(0.0220)	(0.0216)	(0.0261)	(0.0372)	(0.0188)
ln(Career Fairs),					0.0664**
standardized					(0.0275)
Firms	264	270	273	274	266
Observations	397	409	414	416	396
R-squared	0.225	0.228	0.207	0.204	0.137
Included values of H/V	$\leq$ 1.3	$\leq$ 2.29	$\leq$ 7.5	All	.28$\leq$H/V$\leq$2.5
(percentiles)	(95th)	(98th)	(99th)	(All)	(1st to 98.6th)
Industry FE	Y	Y	Y	Y	Y
Size FE	Y	Y	Y	Y	Y
Year FE	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 Selectivity in columns 1 through 4 are calculated as described in Table 4 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 4 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 4. See Table 4 and text for details.

Table B.6: Relationship Between Vacancies, Recruiting, and Vacancy Yield, Recruiting Effort Index without Time to Deadline

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

Notes: Table is analogous to Table 4 but constructs the recruiting effort index without number of days between offer and deadline. See Table 4 for details.

Table B.7: 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.

Additional Results: Recruiting 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. The advantage of using hiring plans and beliefs is that it allows us to look at how firms adjust recruiting effort with plans, rather than based on the outcome of the process. However, we show results using realized hires for several reasons. First, using realized hires, rather than hiring plans, allows us to analyze the relationship with realized recruiting measures which are different than our planned recruiting measures (our realized recruiting measures in the backward-looking sample pertain to the year prior to the question about hiring plans). 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, and is similar to the analysis in Carrillo-Tudela et al. (2020) and Lochner et al. (2021).

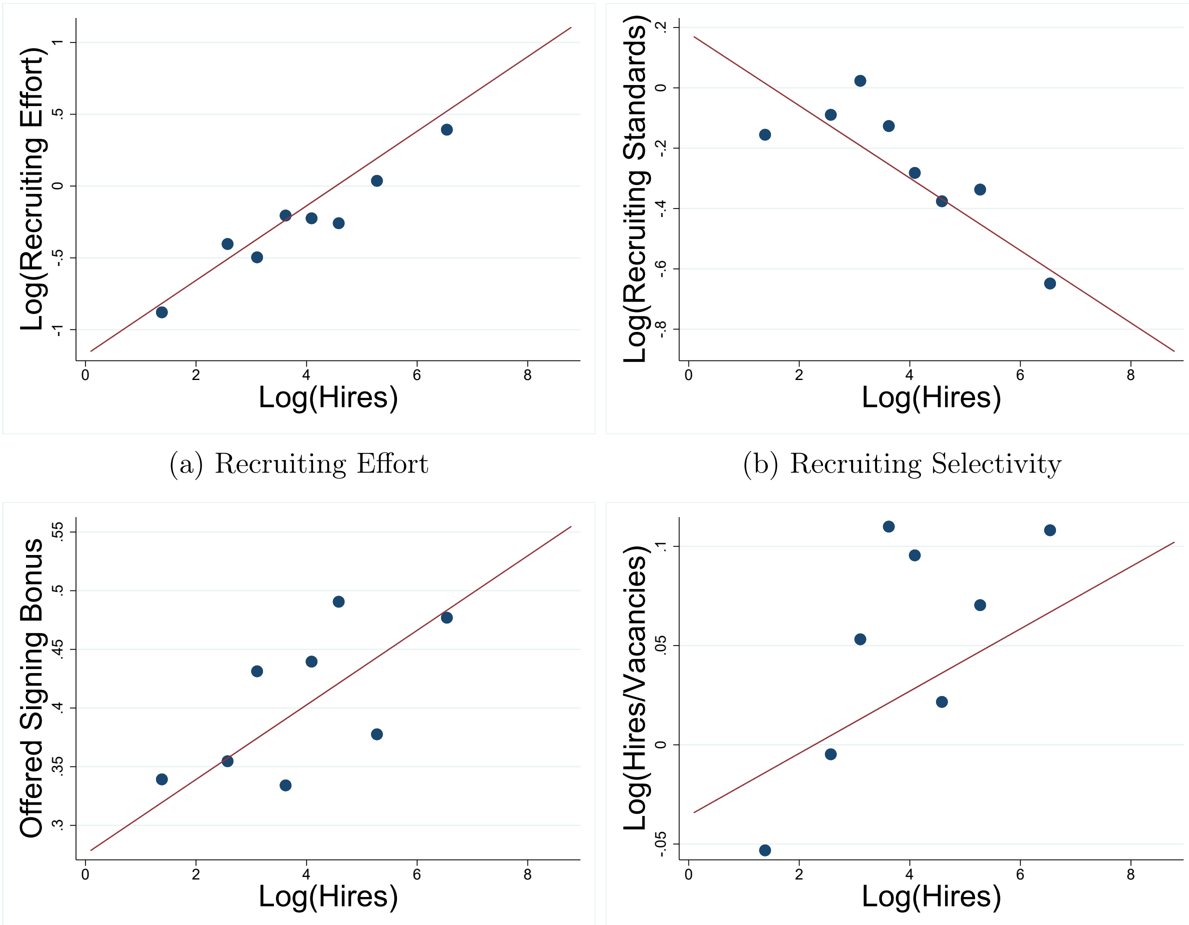
In Figure B.2 we show average outcomes using binned scatter plots based on dividing observations into bins based on log(hires) and adjusting for industry, firm size group, and year, using the binsreg command. We show results using eight bins.[22] When firms hire more individuals they have higher recruiting effort, lower selectivity, and are more likely to offer a signing bonus. Columns one through six of Table C.1 show these relationships by estimating linear regressions, with and without firm fixed effects.

This relationship between hires and recruiting may simply indicate that recruiting is scaling with vacancies. In Section 4 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 B.2 and columns nine and ten of Table C.1), 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 B.3 and column 10 of Appendix Table C.1). When firms increase hires they are not simply increasing vacancies proportionally, as the

[22]Given there are 405 observations, using more than eight bins implies fewer than 50 observations per bin. We see similar patterns when using the optimal number of bins as calculated by the binsreg command (ranging between three and seven bins), and when using 12 bins.

Figure B.2: Hires, Recruiting, and the Vacancy Yield



(a) Recruiting Effort

(b) Recruiting Selectivity

(c) Offered Signing Bonus

(d) Vacancy Yield

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

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.

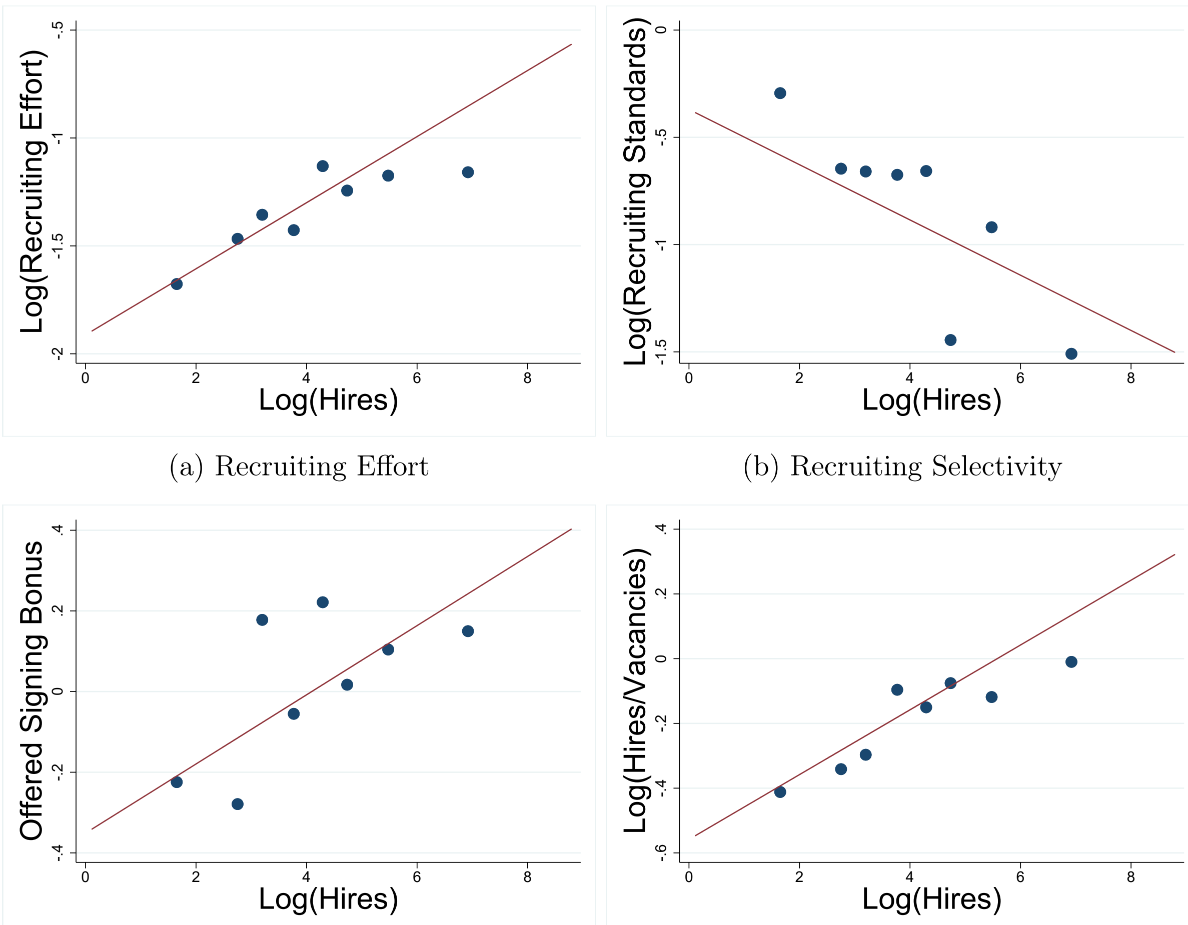
Second, the vacancy yield is constructed by using vacancies reported for a given graduating class for the last year, and hires of new college graduates reported in the last year, both reported in the same survey. This implies elasticities will not be upward biased due to time aggregation issues, as the 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.[23] 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 our sample), the average establishment size is 202, using the firm size distribution from the NACE data. In Appendix Table B.7, 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.

[23] 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.

Figure B.3: Hires, Recruiting, and the Vacancy Yield, Including Firm Fixed Effects



(a) Recruiting Effort

(b) Recruiting Selectivity

(c) Offered Signing Bonus

(d) Vacancy Yield

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

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

One of the striking results from Davis et al. (2013) was the positive elasticity of the vacancy yield with respect to hires. Standard search and matching models imply that hires are proportional to vacancies, and this result showed this implication is not consistent with the data. As in Davis et al. (2013) we decompose this elasticity, to determine what fraction can be explained by vacancies and recruiting intensity. Importantly, our decomposition differs from that in Davis et al. (2013) because we have firm-level data on recruiting.

In particular, we return to Equation (5) and differentiate with respect to the total number of hires.[24]

$$\frac{dlnf_{et}}{dlnh_{et}} = \frac{dln\tilde{f}_t}{dlnh_{et}} + (\gamma - 1)\frac{dlnv_{et}}{dlnh_{et}} + \delta_f \frac{dlnx_{f_{et}}}{dlnh_{et}} + \delta_s \frac{dlnx_{s_{et}}}{dlnh_{et}} + \delta_c \frac{dlnx_{c_{et}}}{dlnh_{et}} \tag{7}$$

Table C.1 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 4 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 (7). For example, the contribution of recruiting effort is the product of two terms: the impact of recruiting effort on the vacancy yield, and the elasticity of recruiting effort with respect to hires. Note that there are similarities between this decomposition and a Oaxaca-Blinder decomposition.[25]

Using our estimates from Table 4 and Table C.1, 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. Using the results from the specification with firm fixed effects (Table C.1), 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

[24] 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.

[25] 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 recruiting measures and vacancies.

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.

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, 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. This exercise represents another way in which to identify how recruiting intensity contributes to labor market relationships.

Table C.1: Relationship Between Recruiting, Vacancies, Vacancy Yield, and Hires

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Effort		Selectivity		Bonus		ln(Vacancies)		ln(H/V)	
ln(Hires)	0.260***	0.153**	-0.120***	-0.129	0.0318	0.0858	0.984***	0.900***	0.0157	0.100***
	(0.0405)	(0.0690)	(0.0455)	(0.117)	(0.0238)	(0.0592)	(0.0133)	(0.0317)	(0.0133)	(0.0317)
Firms	269	81	269	81	269	81	269	81	269	81
Observations	405	217	405	217	405	217	405	217	405	217
R-squared	0.328	0.828	0.227	0.731	0.139	0.630	0.977	0.991	0.110	0.594
Industry FE	Y	N	Y	N	Y	N	Y	N	Y	N
Size FE	Y	N	Y	N	Y	N	Y	N	Y	N
Firm FE	N	Y	N	Y	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. See Table 4 for details on variables.

D Implications for 2021 Graduates

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.[26] 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).[27] 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.

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

[27] 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.