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

Eliza Forsythe, University of Illinois, Urbana-Champaign†

Russell Weinstein, University of Illinois, Urbana-Champaign‡

January 3, 2025

Abstract

We investigate employer recruiting behaviour, using detailed firm-level data from a national survey of employers hiring recent college graduates. We find this behaviour is responsive to the business cycle, beliefs about labour market tightness, and the intended number of hires. Specifically, employers adjust planned recruiting effort and compensation. We then show that when firms expend greater recruiting effort they ultimately hire more individuals per vacancy. These results suggest that when firms want to increase hires they adjust both the quantity of vacancies and the recruiting intensity per vacancy. If this is true more broadly in the labour market, it may help explain the breakdown in the standard matching function during the Great Recession.

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

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

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

1 Introduction

In the aftermath of the Great Recession, the core relationship between vacancies, unemployment, and hires broke down (Elsby, Michaels, & Ratner, 2015). Despite high numbers of 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 behaviour 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. For example, Mongey and Violante (2020) develop a new measure of aggregate recruiting intensity based on hires, vacancies, and employment, and show its cyclicality is driven by firms optimally reducing recruiting when labour markets are slack.

However, there is scant research 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 planned recruiting effort and compensation in response to the business cycle, perceived labour market tightness, and their own hiring objectives. Second, we investigate whether employers fill more of their vacancies when they increase recruiting intensity, conditional on market tightness. This would indicate employers are using recruiting intensity per vacancy to adjust hires.

Our data richly describe a particular labour market: that of 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 labour market for new college graduates is a large and consequential labour market, matching millions of young workers with their first entry-level positions. Recruiting on college campuses is often quite structured, which we rely on for understanding how vacancies, recruiting behaviour,

[1] Weinstein (2018), Weinstein (2022), and Weinstein (in press) 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.

and hires are determined. Employers value this market, with over 75% of the firms in our sample having departments whose main focus is university relations and recruiting. This market is also 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 labour market in which roughly 50% of U.S. workers are employed (Statistics of U.S. Business, U.S. Census Bureau, 2018).[3]

A key contribution of our paper is in the richness of our data, which allows us to compare various ways in which employers adjust recruiting intensity, including compensation generosity, search effort, and screening selectivity.[4] We find that employers increase planned recruiting effort and compensation generosity when they plan to hire more individuals, conditional on beliefs about labour market tightness. Employers also increase their planned recruiting effort and compensation generosity when they believe the labour market will be tight. Further, we show that employers reduced recruiting effort and compensation generosity during the Great Recession, and increased recruiting effort and compensation generosity through the recovery.

We next investigate whether firm-level adjustments in recruiting behaviour are correlated with the share of vacancies filled. Within firms, we find that a one-standard-deviation decrease in recruiting effort is associated with an 11.7% decrease in the firm's vacancy yield (i.e. the number of hires per vacancy), conditional on labour market tightness. While we caution that these relationships are not necessarily causal, this is consistent with firms using recruiting intensity to adjust hires.

We find our measure of recruiting effort can account for 18% of the elasticity within firms. This supports the Davis et al. (2013) hypothesis that the vacancy yield varies with hires because employers adjust recruiting intensity per vacancy to adjust the number of hires.

Although the matching function between job seekers and vacancies is a fundamental tool for understanding the labour market, it is well-known that this 'black box' function is sensitive to the behaviour of job seekers and employers (see Petrongolo and Pissarides (2001) for a review). While there is a well-developed literature exploring how the search behaviour

[2]See Kahn (2010), Oreopoulos, Von Wachter, and Heisz (2012), Oyer (2006), Liu, Salvanes, and Sørensen (2016), and Arellano-Bover (2024).

[3]This refers to the fraction employed at firms with at least 500 employees. We calculate that the firms in our sample employ roughly 2.8% of U.S. employment, using the binned firm size distribution in Table A.1 and the 2016 Statistics of U.S. Business, U.S. Census Bureau (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 (2023). 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.

of job seekers can influence the properties of the aggregate job-finding rate,[5] the literature connecting employer behaviour to job filling is more nascent. Recent theoretical papers with 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 behaviour, few papers are able to connect this to the vacancy yield.[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., 2023; 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. (2023) show this relationship at the labour-market level. Second, we have many detailed measures of firm-level recruiting effort, such as the number of career fairs and the extent of travel in recruiting. Other data sources typically do not have information on firms' labour market beliefs, and use fewer, and coarser, measures of effort, such as the number of search methods used (Roper, 1988; Carrillo-Tudela et al., 2023; Lochner et al., 2021) or the number of hours spent on search (Barron, Bishop, & Dunkelberg, 1985). Third, we focus on different labour markets; our paper richly describes recruiting and hiring for large firms recruiting new college graduates in the U.S. — a large and consequential labour market.

Our evidence suggests pro-cyclical recruiting intensity serves to dampen the responsiveness of the matching function over the business cycle in the market for new graduates. Although we caution that our results are specific to this segment of the labour market, if the large employers in our sample behave similarly when they hire more broadly then our results suggest recruiting behaviour 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 organisation focusing on the development and employment of college-

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

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

[7]Several recent papers have found changes in the content of firms' job postings with market tightness (Hershbein & Kahn, 2018; Modestino, Shoag, & Ballance, 2016, 2020; Ma & Samaniego de la Parra, 2021). Weinstein (2022) finds that, when opening new offices, firms adjust recruiting and 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.

educated individuals. Its members include over 8000 college career services professionals from over 2000 colleges in the United States, as well as over 3000 recruiting professionals from over 900 employers. NACE conducts multiple surveys of its members each year. We use data from the Recruiting Benchmarks (2008–2016) (NACE, 2017) and Job Outlook (2006–2016) (NACE, 2018b) surveys, both sent to members who recruit new college graduates for entry-level jobs. These surveys richly describe these firms' recruiting, vacancy posting, and hiring behaviour.

The labour market for new college graduates is a highly structured, annual process. Employers typically make hiring plans in the summer or early fall and take actions throughout the year to adjust the recruitment process. By late spring, most employers will have hired new graduates who will start 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 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, focusing on hiring and recruiting intentions and labour market beliefs. To measure the relationship between realised recruiting and the firm's vacancy yield, we merge the two surveys, referring to this as our backward-looking sample. Both samples use surveys administered from 2011 through 2016. We discuss the data in detail in Appendix A.

In Table A.1 we show summary statistics. We restrict the forward-looking sample to firms with multiple observations, while for the backward-looking statistics we do not, given the smaller sample. Imposing this restriction yields very similar similar summary statistics (Appendix Table A.7).[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 U.S. workers (Statistics of U.S. Business, U.S. Census Bureau, 2018), even though they comprise a small percentage of U.S. firms. There are potentially significant differences in hiring and recruiting by firm size; we see our results as informative for understanding recruiting by large firms.

Forward-Looking Measures

To measure recruiting intentions for the coming year, we construct an index using five indicator variables: plans to increase career fairs, plans to travel more for recruiting, plans to use more technology in recruiting, plans to use more social networks in recruiting, and

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

plans to change the brand in recruiting.[9] While Section 3 focuses on hiring and recruiting plans, Appendix B.3 shows concordance between planned and actual recruiting behaviour for a subset of measures.

To reduce the dimensionality of the recruiting effort variables, we perform principal component analysis and keep the component with the largest eigenvalue. We normalise this measure to have mean zero and standard deviation one, and refer to it as the Forward-Looking Recruiting Effort Index. We investigate two 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. Details are discussed in Appendix A.

Respondents are asked if they plan to increase, decrease, or maintain hiring in the coming year, which we use to measure hiring plans. Respondents are also asked to rate the labour 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 labour market. Summary statistics are reported in Table 1.

Backward-Looking Measures

The second set of recruiting measures includes 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 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. 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 to negotiate, increasing the employer effort required.

We construct a recruiting selectivity index 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 (e.g., two-year colleges and for-profit universities), and whether the firm prefers candidates with relevant experience. These measures reflect how broad of an applicant pool the firm is willing to consider.

We use principal component analysis to construct the recruiting effort and selectivity indices. Because our main specifications will be estimated in logs, we standardise the log of the index to be mean zero and standard deviation one, rather than standardising the level. Our measure of compensation generosity is whether the firm gave signing bonuses.

[9]Branding refers to the employer's brand on campus, potentially developed through recruiting materials, events, and relationships.

Table 1: 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 labour 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 Real Offered Starting Salary	0.46	3.05
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 Year 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 -1.3 to 2.4. The percent change in real salary ranges from -3.2 to 23.5, and is deflated using the CPI-U. 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. The sample size for the backward-looking sample is 405.

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.

Due to concerns about data quality, we drop potential outliers in our constructed measure of hires per vacancy. In Appendix A we discuss this restriction in more detail and show our results are robust to a variety of alternative sample restrictions. Panel B of Table 1 shows summary statistics for the backward-looking measures.

3 Hiring Plans, Beliefs about Tightness, and Recruiting Intensity

In this section we investigate how firms adjust planned recruiting intensity with their hiring plans and beliefs about labour market tightness. We begin by introducing 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, determined by the matching function μ and 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 labour 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 per vacancy.

Formally, we generalise 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. We focus on three dimensions of recruiting intensity: effort ($x_{f_{et}}$), selectivity ($x_{s_{et}}$), and compensation generosity ($x_{c_{et}}$). Thus, we write

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

where $\tilde{f}_t$ depends on the aggregation of effective vacancies across all employers in the market.

Equation 3 shows the number of hires continues to depend on the aggregate state of the labour market ($\tilde{f}_t$). Holding a firm's vacancies and recruiting intensity fixed, if the labour market is tight then the aggregate fill rate will fall, and thus firm-level hires will fall. Second, conditional on labour market tightness, increases in a firm's vacancies or in recruiting intensity will increase firm-level hires.

If employers use recruiting activities to adjust hires, Equation 3 implies two relationships. Conditional on their labour market beliefs, firms will increase recruiting activities when they want to increase hires. Second, firms will increase recruiting activities when they believe the market will be tight, conditional on their hiring plans. This counterbalances the lower aggregate fill rate, helping to achieve their hiring target. Although we abstract from the firm's optimisation problem, our framework is consistent with the model of Gavazza et al. (2018), which analyses when firms will use recruiting activities in addition to vacancy posting to meet targeted hiring.

This leads us to estimate Equation 4, which is estimated at the firm (e) by year (t) level.

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

By including firm fixed effects (Ω_e) we measure how recruiting plans change with changes in the firm's hiring plans or beliefs. The coefficients on "Plan Increase Hires" and "Plan Decrease Hires" are relative to the omitted group "Plan Maintain Hires". 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. We additionally include year fixed effects to control for changes in recruiting behaviour unrelated to tightness or hiring, such as technology adoption or inflation.

Table 2 shows the results from estimating Equation 4. In Panel A, the dependent variable is the Forward-Looking Recruiting Effort Index. When employers plan to increase hires more than in the prior year, they are more likely to plan on increasing recruiting effort compared to when they plan on maintaining hires. The magnitude of the increase is 0.3 standard deviations when including employer and year fixed effects. This result provides direct evidence that employers adjust on margins in addition to vacancies when they want to increase hiring, in contrast to the standard search and matching model in which employers increase hires only through increasing vacancies.

Employers increase planned recruiting effort by about 0.4 standard deviations when they believe the labour market will be tight. This shows that employers are responsive to perceived

Table 2: 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 labour 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.	$\leq$ 0.0001	$\leq$ 0.0001	.0004	.0007
Panel B: Planned % Increase in Offered Starting Salary (Real)				
Plan Increase Hires	0.466	0.690**	0.708	1.003**
	(0.290)	(0.277)	(0.455)	(0.395)
Plan Decrease Hires	0.202	-0.030	0.162	0.017
	(0.335)	(0.310)	(0.328)	(0.353)
Believe labour Market Will Be Tight	1.110***	0.610***	1.066**	0.419
	(0.256)	(0.230)	(0.411)	(0.339)
Firms	471	471	146	146
Observations	701	701	376	376
R-squared	0.021	0.166	0.409	0.528
Test Plan Inc. = Plan Dec.	.48	.04	.28	.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 labour 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-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .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.

difficulty in hiring and that they adjust recruiting effort, in addition to vacancies, accordingly. The magnitude of the point estimates for employers who "Plan to Decrease Hires" are smaller than those for "Plan to Increase Hires", suggesting adjustment of recruiting effort may not be symmetric between firms that are increasing or decreasing hires. However 95% confidence intervals are wide and cannot rule out large declines in recruiting effort for firms that plan to decrease hiring.

In Panel B of Table 2 we see a rise in the planned percent increase in real starting salary when employers plan to increase hires, ranging from about 0.5% in the cross-section to 1% when including firm fixed effects. While the coefficients on "Plan to Decrease Hires" are not statistically significant, we can reject that they are equal to the coefficient on "Plan to Increase Hires" in the specifications with year fixed effects. Similarly, employers plan to increase salaries when they believe the labour market will be tight. We do not find clear evidence that employers use bonuses to adjust hiring (Panel C of Table 2).

In Appendix Table B.1 we show how firms adjust recruiting selectivity. While under-powered, the results provide suggestive evidence that firms expand the hiring pool when planning to increase hires and when they believe the labour market is tight, namely by planning to hire associate's degree graduates or international students for U.S. jobs. This complements other papers showing a relationship between selectivity and market tightness, including Hershbein and Kahn (2018); Modestino et al. (2016, 2020).

Recruiting Intensity over the Business Cycle

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

Figure 1 illustrates within-firm changes in select recruiting variables 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 that we have an unbalanced panel; however, the coefficient in each year can be interpreted as the average within-employer change in recruiting relative to 2007–2008, given we restrict the sample to firms with data in that year.

Relative to the planned increase in real starting salary offers in 2007–2008, the planned increase was 1.4 percentage points lower in 2008–2009 (Panel A). The increase was also

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. The 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, Panel B using 604 observations from 165 firms, Panel C using 506 observations from 143 firms, and Panel D using 554 observations from 147 firms. The number of career fairs is missing in 2010.

substantially below the 2007–2008 salary increase in other years up to 2012–2013.[10] 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 (Panel B). 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

[10]In Appendix Figure B.1, we show an even stronger decline for planned salary increases in nominal terms.

fairs attended fell roughly 33% in 2010–2011. By 2013–2014, the decline was much smaller; we cannot rule out that career fair attendance had returned to 2007–2008 levels.[11] 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 during the recovery.

Thus, across a range of measures, we find that recruiting intensity fell during the Great Recession and then slowly recovered. These results are consistent with the previous section, showing changes in recruiting plans with changes in hiring plans and labour market beliefs. In addition, they provide firm-level evidence consistent with previous papers suggesting firms reduce recruiting when labour markets are slack, which may have caused a breakdown in the matching function (Davis et al., 2013; Mongey & Violante, 2020).

4 Do Recruiting Adjustments Influence Vacancy Yields?

We have shown that firms plan to increase effort and compensation generosity when they plan to increase hires. While increases in compensation generosity reflect increases in recruiting intensity per vacancy, increases in recruiting effort could reflect constant scaling with the number of vacancies. In this section we test whether recruiting increases are associated with increases in the firm's vacancy yield (the proportion of vacancies that are filled), using a specification that includes all three of our recruiting measures. If adjustments in recruiting simply reflected adjustments in vacancies, the vacancy yield would be unchanged. The unique features of our data allow us to connect recruiting behaviour to the vacancy yield, providing important evidence for how this typically unmeasured variable may affect predicted hires from a standard matching function.

To analyse the effect of each recruiting measure on the vacancy yield, we continue the notation from Section 3. Following Davis et al. (2013), we allow for economies of scale in vacancies and recruiting and define 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 governs the economies of scale in vacancies, while δ_f, δ_s, and δ_c govern the economies of scale in the three recruiting dimensions. We then rewrite the employer's job filling rate, or vacancy yield, f_{et} as follows:

$$f_{et} = \frac{h_{et}}{v_{et}} = \frac{\tilde{f}_t v_{et}^{\gamma} x_{f_{et}}^{\delta_f} x_{s_{et}}^{\delta_s} x_{c_{et}}^{\delta_c}}{v_{et}} \tag{5}$$

[11] 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.

where $\tilde{f}_t$ depends on effective vacancies aggregated to the market level.

We then express this relationship in logs and estimate the following:

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

where Γ_t are year fixed effects, which absorb the aggregate fill rate $\tilde{f}_t$.[12] Because there may be differences in recruiting, hires, and vacancies across industries and firm sizes, we include industry and firm-size-bin fixed effects.[13]

We additionally estimate a specification with firm fixed effects. In this case, the identification assumption is that within-firm recruiting changes are not correlated with other firm-specific changes that affect vacancy yield, controlling for average changes in the vacancy yield at other firms that year. This addresses several potential sources of bias.

First, firms with higher recruiting effort may differ in ways that are correlated with the vacancy yield. For example, firms with higher recruiting effort may be larger, and larger firms have been shown to have lower vacancy yields (Davis et al., 2013). Although we control for firm size, the size bins are wide, hence estimates without firm fixed effects may bias downward the effort coefficient in Equation (6).

Second, employers search in different markets, for example for different occupations, and there may be cross-sectional differences in tightness across these markets. These differences will not be captured by industry or year fixed effects. We expect a positive correlation between effort and this tightness facing the firm, and a negative correlation between this tightness and the firm's vacancy yield. This will lead to a downward bias on the effort coefficient. Including firm fixed effects reduces these concerns as we no longer compare across firms searching in different markets.

Finally, the firms exerting greater effort may also be firms that have higher vacancy yields, but for reasons unrelated to recruiting effort. Including firm fixed effects addresses these potential biases, but also decreases the sample size, as fewer firms respond to both surveys in multiple years.

Although including firm fixed effects addresses many of the potential biases, if there are other recruiting adjustments that we do not measure these could bias the estimates of the

[12] β_1 equals the return to scale in vacancies (γ) minus 1, as Equation (5) involves dividing by v. If we assumed no economies of scale in vacancies ($\gamma = 1$ in Equation (5)), log vacancies would not be on the right-side of Equation (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 $\beta_1 + 1$.

[13] As we noted, due to the recruiting timeline, vacancies and effort may not be completely jointly determined. However, even if they were jointly determined, then 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.

return to any particular recruiting activity. The sign of this bias depends on whether these activities enter as substitutes or complements in the firm's optimisation problem. A benefit of using principal component analysis to construct our recruiting effort measure is that estimates of the returns to this measure will also capture returns to omitted effort actions that are positively correlated with our effort index. However, if firms substitute between observed and non-observed activities, it would bias downward the estimated relationship between our recruiting measures and the vacancy yield. Further, a given firm may increase effort when they expect their vacancy yield to be lower, due to occupation-specific changes in market tightness. This would also lead to a downward bias in the estimated relationship between effort and vacancy yield.

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.

Column 1 in Table 3 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. 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.[14] Given there are only a few employer size bins, vacancies may be additionally capturing employer size. This may negatively bias the coefficient on vacancies, as vacancy yields in JOLTS are negatively correlated with employer size.[15] Consistent with this, the coefficient decreases substantially and is no longer significant when including firm fixed effects.[16]

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. Increasing recruiting effort by one standard deviation is associated with an 11.7% increase in the vacancy yield ($p \leq .05$; column 2). This larger effect is consistent with the sources of bias without fixed effects discussed above, although the confidence interval includes the column 1 effect. The coefficients on the selectivity index and offering a signing bonus continue to be statistically indistinguishable from zero, and we cannot rule out modest effects in the expected direction.[17]

[14]Because the coefficient on vacancies is the return to vacancies minus one, it still suggests a positive relationship between vacancies and hires.

[15]See Appendix Table B.7.

[16]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 size bins. Further, employment may be correlated with vacancy yield for reasons other than its relationship with vacancies, violating the exclusion restriction.

[17]Table B.9 includes all the index components as separate variables in the regression, with and without firm fixed effects. While the coefficient on career fairs is roughly similar in the two regressions, there are

Table 3: Relationship between Recruiting and Vacancy Yield

Y = ln(H/V)	(1)	(2)	(3)	(4)
Recruiting Effort,	0.0371**	0.117**	0.0418*	0.117**
Standardised	(0.0160)	(0.0464)	(0.0227)	(0.0470)
Recruiting Selectivity,	0.0253	0.0314	0.0246	0.0140
Standardised	(0.0192)	(0.0336)	(0.0215)	(0.0301)
Offered Signing Bonus	-0.00702	-0.0332	0.0208	-0.0312
	(0.0242)	(0.0418)	(0.0334)	(0.0524)
ln(Vacancies)	-0.0461***	-0.0100	-0.0383**	-0.0381
	(0.0165)	(0.0391)	(0.0185)	(0.0429)
Firms	269	81	269	81
Observations	405	217	405	217
R-squared	0.156	0.619	0.377	0.878
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 component 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 standardise 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 labour Statistics due to the already smaller sample.

While we have evidence that firms adjust selectivity (Table B.1; Hershbein and Kahn (2018); Modestino et al. (2016, 2020)), the relationship between selectivity and the vacancy yield is imprecise. We are cautious in over-emphasising the imprecise coefficient. This coefficient may be biased upwards if year fixed effects do not adequately measure the tightness facing the firm. In this case, the positive coefficient on selectivity may reflect increases in selectivity in more slack markets, when vacancy yields are higher. Alternatively, the coefficient on selectivity is consistent with these tools playing a smaller role than effort in affecting hires.

differences in the other effort components, although the confidence intervals are wide. We discuss this further in Appendix A.5.3.

Robustness

We estimate a number of additional specifications for robustness. As we discussed, vacancies are included in Equation (6) to allow for returns to scale in vacancies. Excluding vacancies in our firm fixed effects regression yields a very similar coefficient on recruiting effort (Appendix Table B.4).[18] Columns 3 and 4 in Table 4 include industry-year and firm size-year interactions as a way to allow market tightness by year to vary by industry and firm size, which yields similar effects. However, we are cautious with this specification given the very small sample sizes within industry-year and size-year cells, which makes this less likely to be capturing overall differences in market tightness by size or industry.[19] When using career fairs as our only measure of recruiting effort we continue to see a positive relationship with the vacancy yield, which is statistically significant without firm fixed effects and similar in magnitude with firm fixed effects but less precisely estimated (Appendix Table B.6). Appendix Table B.5 shows our results are robust to our definition of outliers for the vacancy yield.[20]

5 How Much of the Variation in Vacancy Yields Can Be Accounted For 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. This is not consistent with standard search and matching models, according to which hires are proportional to vacancies. As in Davis et al. (2013) we decompose this elasticity to determine what fraction can be explained by recruiting intensity; importantly, we extend that decomposition by using our firm-level recruiting data.

We take logs of Equation (5) and differentiate with respect to total hires:[21]

$$\frac{d\ln f_{et}}{d\ln h_{et}} = \frac{d\ln \tilde{f}_t}{d\ln h_{et}} + (\gamma - 1)\frac{d\ln v_{et}}{d\ln h_{et}} + \delta_f \frac{d\ln x_{f_{et}}}{d\ln h_{et}} + \delta_s \frac{d\ln x_{s_{et}}}{d\ln h_{et}} + \delta_c \frac{d\ln x_{c_{et}}}{d\ln h_{et}} \tag{7}$$

Thus, the elasticity of the fill rate with respect to hires can be decomposed into the con-

[18]Excluding vacancies in the specification without firm fixed effects results in a smaller and insignificant coefficient on effort, although the 95% confidence interval includes the effect in Table 3. This is consistent with vacancies capturing firm size when we do not include firm fixed effects, a positive correlation between size and recruiting effort, and a negative correlation between firm size and vacancy yield.

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

[20]Dropping the six singleton observations from column 1 of Table 3 yields similar standard errors. The coefficient on effort in column 1 of Table 3 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.

[21]We do not differentiate with respect to hires per employment (as in Davis et al. (2013)) because we have only bins of firm size. We discuss this further in Appendix B.6.

tributions of the aggregate fill rate, vacancies, and each recruiting dimension. For example, the recruiting effort contribution is the product of two terms: the impact of recruiting effort on the vacancy yield (δ_f) and the elasticity of recruiting effort with respect to hires ($\frac{d \ln x_{f_{et}}}{d \ln h_{et}}$). We note similarities between this and a Oaxaca-Blinder decomposition.

Following Equation (7), we calculate the contributions using our estimates of $\hat{\gamma} - 1$, $\hat{\delta}_f$, $\hat{\delta}_s$, and $\hat{\delta}_c$ in Table 3, and our estimates of the elasticities with respect to hires in Appendix Table C.1.

Using estimates from our firm-fixed-effects specification, and applying the appropriate caveats, recruiting effort explains roughly 18% of the elasticity of the vacancy yield with respect to hires (Appendix Table C.2).[22] The estimates based on recruiting selectivity and compensation generosity are closer to zero.

The unexplained portion of the elasticity may be due to unmeasured changes in recruiting intensity. Perhaps most notably, our only measure of compensation generosity for this analysis is whether the firm offers a signing bonus, and we do not observe starting salaries. Alternatively, firms that are increasing hires may also be experiencing changes in match efficiency for reasons other than firm actions, for example decreases in skill or geographic mismatch.

6 Conclusions

Using unique firm-level data, we provide evidence that large firms recruiting new college graduates adjust recruiting behaviour, in addition to vacancies, to meet their hiring needs and in response to beliefs about labour market tightness. When firms expend greater recruiting effort they fill a greater fraction of their vacancies.

Our data focus on a specialised but important labour 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 for labour, we also provide insights into which types of workers will be most affected. When firms reduce recruiting effort and increase selectivity, this will affect employment opportunities for students at universities where firms stops attending career fairs, students with lower GPAs, students attending two-year colleges, and students with less relevant experience. Firm recruiting behaviour is thus one potential channel for the adverse labour market outcomes

[22] With firm fixed effects our estimate of the elasticity of the vacancy yield with respect to hires is .10 (Table C.1), $\hat{\delta}_f$ is .117 (Table 3), and $\frac{d \ln x_{f_{et}}}{d \ln h_{et}}$ is .153 (Table C.1). Thus $.117 \times .153 = .0179$, which is roughly 18% of .10.

that have been documented for these disadvantaged groups during economic downturns.

References

Arellano-Bover, J. (2024). Career consequences of firm heterogeneity for young workers: First job and firm size. *Journal of Labor Economics*, *42*(2), 549–589.

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. (2023). Recruitment policies, job-filling rates, and matching efficiency. *Journal of the European Economic Association*, *21*(6), 2413–2459.

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.

Enterprise Statistics Program, U.S. Census Bureau. (2016). *Table 2. Selected enterprise statistics by employment size by sector in the U.S.: 2012.* https://www2.census.gov/programs-surveys/esp/tables/2012/esp-results/esp2012_table2.xlsx (accessed: 07.18.2023).

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? *The Economic Journal*, *132*(645), 1765–1789.

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 U.S. 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), 1737–1772.

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*(S2), S255–S286.

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., & Sørensen, E. Ø. (2016). Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession. *European Economic Review*, *84*, 3–17.

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*.

Modestino, A. S., Shoag, D., & Ballance, J. (2016). Downskilling: changes in employer skill requirements over the business cycle. *Labour Economics*, *41*, 333–347.

Modestino, A. S., Shoag, D., & Ballance, J. (2020). Upskilling: Do employers demand greater skill when workers are plentiful? *Review of Economics and Statistics*, *102*(4), 793–805.

Mongey, S., & Violante, G. L. (2020). Macro recruiting intensity from micro data. *NBER working paper*(w26231).

NACE. (2017). *Recruiting benchmarks survey data.* (Provided to authors October-December 2017)

NACE. (2018a). *Crosswalk between 2014 recruiting benchmark id and firm name.* (Provided to authors May 2018)

NACE. (2018b). *Job outlook survey data.* (Provided to authors January 2018)

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), 143–160.

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. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, *39*(2), 390–431.

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.

Statistics of U.S. Business, U.S. Census Bureau. (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*, 282–299.

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), 1–46.

Weinstein, R. (in press). The Great Recession and the widening income gap between alumni of elite and less selective universities. *American Economic Journal: Economic Policy*.

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

Eliza Forsythe and Russell Weinstein

The Online Appendix consists of three 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 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. The data we received included firm name and respondent ID. For the Recruiting Benchmarks data in 2014, the data included only respondent ID. We then received a crosswalk file for this survey to merge respondent ID to firm name (NACE, 2018a).

A.1 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 Standardised 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.

A.2 Construction of Variables

Beginning in 2013, NACE began asking employers to report hires separately for domestic and international positions; however, 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.; 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 options: less than one week, one week, two weeks, three weeks, one month, and more than one month. To make this consistent with the earlier years, we imputed 3.5 days for less than one week, 7 days for one week, 14 days for two weeks, 21 days for three weeks, and 30 days for one month. For more than one month, we replaced this variable with the mean number of days for respondents in prior years who reported more than 30 days.

A.3 Descriptive Characteristics of Firms in the Sample

In this subsection we provide more details on the characteristics of firms in the sample. In Table A.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 A.1 we combine the two largest size categories (10,001–20,000 and > 20,000), 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 10,000 and 20,000. We present additional summary statistics on the distribution of years in the sample (Figure A.2), and number of observations per firm (Table A.2).[23]

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.3, we compare the forward-looking sample industry distribution for NACE firms to the distribution for all firms and for large firms, from the U.S. Census Enterprise Statistics Program (ESP).[24] The NACE sample is more similar to the distribution of large

[23] Appendix Figure A.1 shows the distribution of hires per vacancy in the backward-looking regression sample (column 1 of Table 3).

[24] We note that the ESP program excludes several two-digit NAICS codes, including Agriculture, Management of Companies and Enterprises, and Public Administration, along with several three-, four-, and five-digit NAICS codes. Our forward-looking sample from the Job Outlook survey has very few firms in

Table A.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
$\leq$ 500	0.11	0.16
Firms	269	250
Observations	405	709

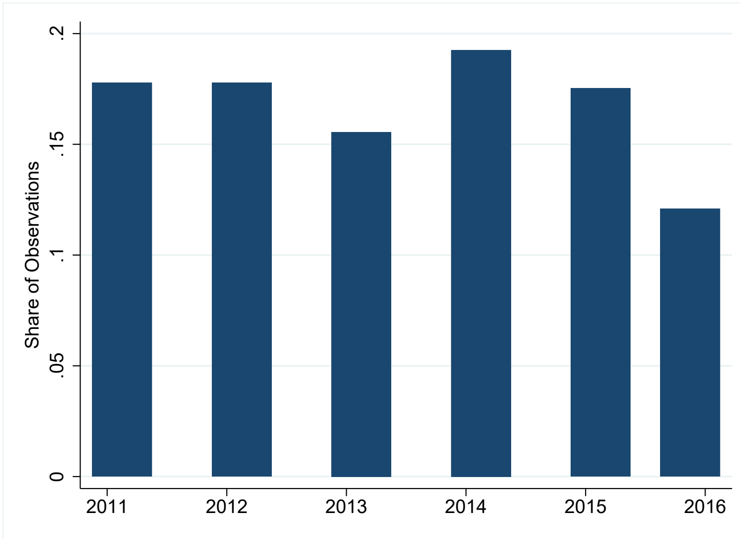
Notes: Column 1 presents summary statistics for the backward-looking regression sample while column 2 presents summary statistics for the forward-looking sample. The forward-looking sample is restricted to firms with at least two observations, reflecting hiring from 2012 through 2017. The size categories 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.

Figure A.1: Distribution of Hires per Vacancy in the Backward-Looking Regression Sample, Column 1 of Table 3

Table A.2: 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 (column 1 of Table 3) and the forward-looking sample (column 1, panel A of Table 2). Note that the preferred forward-looking sample restricts to firms with at least two observations, which yields 250 firms.



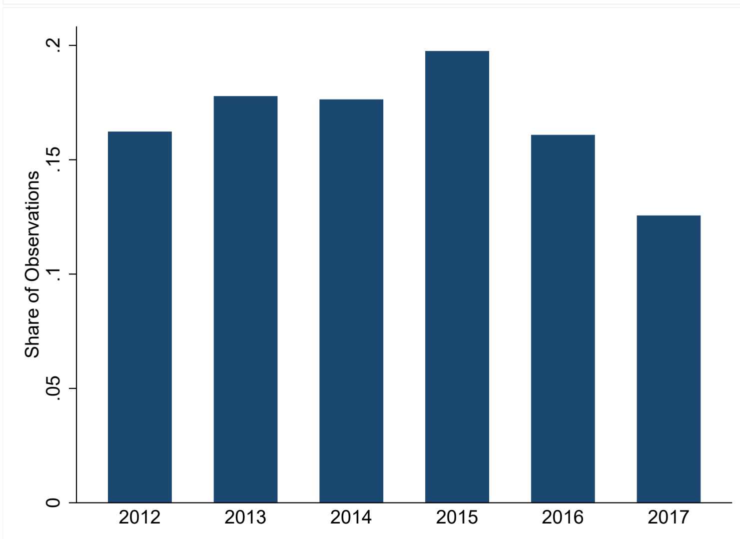


Figure A.2: Distribution of Observations in the Backward-Looking Regression Sample (top) and Forward-Looking Regression Sample (bottom).

The forward-looking regression sample is restricted to firms with at least two observations. Note that the year refers to the spring of the academic year, so 2011 refers to the 2010–2011 academic year.

firms, which is unsurprising given the NACE sample consists of very large firms. Relative to all large firms, both 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 according to the Census ESP, while the share in the NACE survey 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.

While the types of firms recruiting on campus will not necessarily match the overall distribution of firms for the reasons discussed, as a robustness exercise we weight observations so that the industry distribution of our NACE samples are representative of the industry distribution of enterprises with at least 5000 employees, using data from the ESP (Enterprise Statistics Program, U.S. Census Bureau, 2016). Table B.3 shows that including these weights yields results very similar to the results in Table 2. Similarly, Table B.8 shows that including these weights yields results very similar to those in Table 3.

Table A.3: 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 (column 3, panel A of Table 2) 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 A.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 ESP data, we add in the other subsectors of NAICS code 54.

Public Administration (3.8%), Agriculture (.28%), and Management of Companies and Enterprises (.14%).

A.4 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.

A.4.1 Sample Construction

The sample is constructed as follows. 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 the number of hires in the coming year, and how they rate the quality of the labour market in the coming year. These variables are key for the main specifications in Table 2, however, as the hiring plans are only included in the survey questionnaire beginning in 2011, our analysis is limited to the 2011–2012 through 2016–2017 academic years. For some specifications we only include firms present in this sample for at least 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 labour market in the coming year. This allows us to examine recruiting behaviour over the Great Recession. The samples are restricted to firms that answered the question about salary increases (panel A) or plan 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.

A.4.2 Recruiting Measures and Measure of labour 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 their planned percent increase in starting salaries, to 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: the firm's 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 summarised in the notes of Table B.1.

In Table A.4 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 labour 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 2009–2010 academic year, with beliefs improving over the subsequent years.

Table A.4: 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: This table reports the number of observations in each cell, restricted to the regression sample in columns 3 and 4 of panel A of Table 2. This reflects 709 observations over 250 unique firms.

A.4.3 Forward-Looking Recruiting Index

Table A.5 shows how each binary variable is weighted in the index before standardisation, and Table A.6 shows this when not restricting to firms with multiple observations (sample in column 1, panel A of Table 2). As expected, each of these variables has positive loadings, making it intuitive to interpret this as a recruiting effort index.

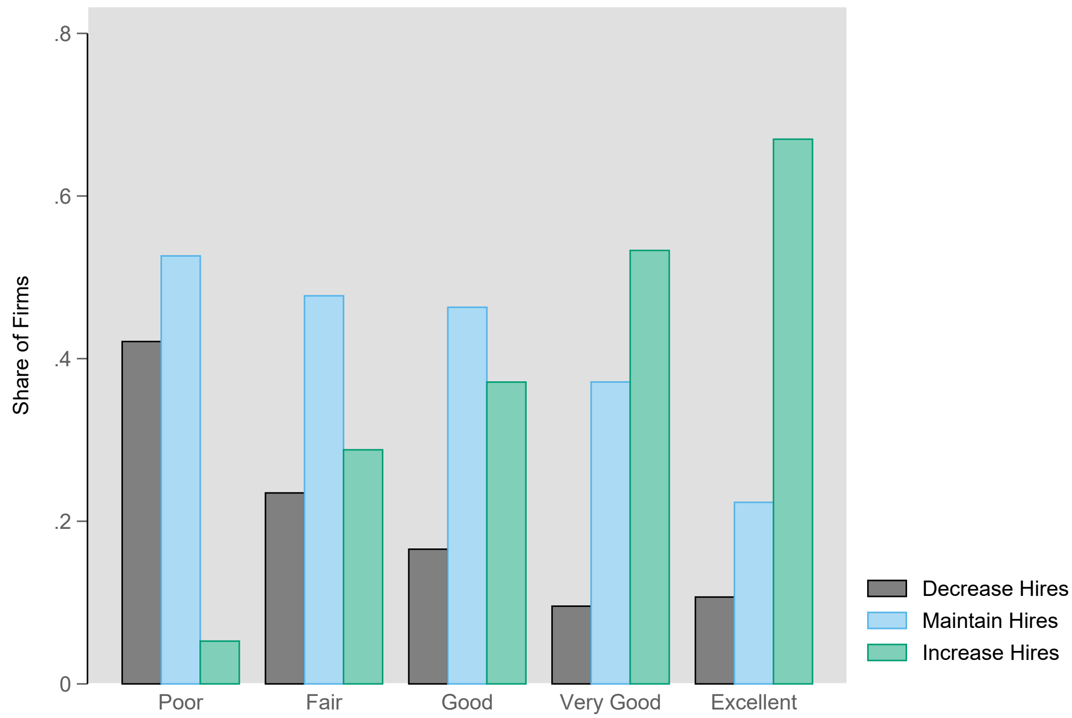


Figure A.3: Share of Observations Showing Plans to Decrease, Maintain, or Increase Hiring by Beliefs about the State of the labour Market.

Notes: Observations are restricted to the regression sample in column 3, panel A of Table 2. This reflects 709 observations over 250 unique firms.

Table A.5: 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 are associated with the first principal component of these variables.

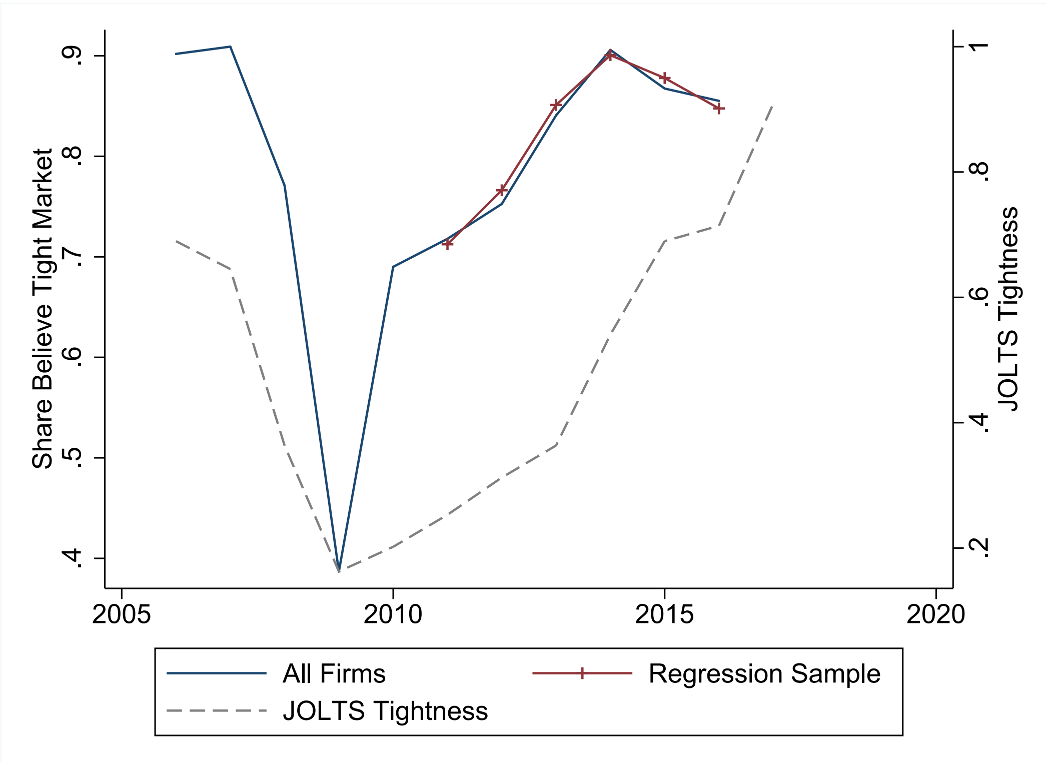


Figure A.4: Share of Firms Who Believe the State of the labour Market Will Be Good, Very Good, or Excellent Plotted Against the Ratio of the Stock of Vacancies to the Stock of Unemployed, Retrieved from JOLTS.

The blue line includes all firms surveyed; the red line includes all firms in the main forward-looking regression sample (column 3, panel A of Table 2). For the labour market beliefs, the year corresponds to the year of the fall semester (i.e. 2009 refers to the 2009–2010 academic year). JOLTS data is nationally representative and measures average tightness in August and September of the year, which corresponds to when the firms responded to the NACE survey.

Table A.6: 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 are associated with the first principal component of these variables.

A.5 Additional Details on Backward-Looking Sample and Recruiting Measures

A.5.1 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 non-missing log hires, log vacancies, log career fairs, industry and firm size, and excluding the singletons from this restricted sample based on including year, industry, and firm-size fixed effects. Dropping instead the 99th percentile and above would imply keeping an additional two observations for which the ratios are 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.

A.5.2 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 significant 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 the offer and the deadline to accept the offer. Conditional on labour 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.[25]

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 about their preferences when hiring a new college graduate for an entry-level position, choosing between three options: (a) they preferred applicants with relevant experience, (b) they preferred any experience, regardless of relevance; or (c) 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

[25]The one exception is that, when we include industry-year and firm size-year interactions with firm fixed effects, the coefficient on effort is much smaller and not statistically significant. As we discuss in the paper, this is a specification we are cautious about, given the large number of parameters this introduces in a very small sample. The change in the coefficient appears due to greater weight on time to offer when excluding time to deadline in the principal component analysis, combined with a positive coefficient on time to offer only when including industry-year and size-year interactions.

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.[26] 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 that these surveys have many other variables that capture recruiting intensity, however 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 the number of HR staff involved in university recruiting, total recruiting budget, and whether the firm is using video interviewing, online advertising, or pre-employment assessment tests.

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.

A.5.3 Recruiting Indices

We construct the indices using the main backward-looking regression sample with and without firm fixed effects, restricted to observations not missing the variables that comprise all of the indices (regression samples in columns 1 and 2 of Table 3).

Appendix Table A.8 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 positive loading on time to offer deadline. This component explains roughly 31% of the

[26] An alternative explanation 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, due to the lack of screening the vacancy yield may be lower. However, 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.

Table A.7: 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 (# of 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 Year 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 A.1 and 1 for the backward-looking sample, but restricting to firms observed in multiple years.

overall variance. Appendix Table A.9 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 and 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.

Appendix Tables A.10 and A.11 show similar eigenvectors when constructing the index on the sample of firms when we include firm fixed effects in the regression.

As we will be taking logs of the recruiting effort and selectivity index, which has mean zero, we first shift the mean by ten and then take the log. We then standardise, so the log index is mean zero and standard deviation one, to make the results easier to interpret. Results are similar when shifting the mean of the index by five or shifting the mean by 15 instead of by ten.

Table A.8: 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.9: Backward-Looking Recruiting Selectivity Index

	Eigenvector
Screen on GPA	0.6315
Prefer Relevant Experience	0.5532
Recruit from Non-Four Year 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.10: 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.11: 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 Year 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.

Table A.12: Backward-Looking Measures of Hires and Vacancies by Firm-Size Bin

	Mean	SD
Hires Last Year, by Firm-Size Bin		
$\leq$ 500	22.24	26.54
501–1,000	21.37	20.56
1,001–2,500	47.7	75.97
2,501–5,000	89.32	106.8
5,001–10,000	74.6	72.26
10,001–20,000	258.36	768.45
$>$ 20,000	479.57	1068.64
Vacancies Last Year, by Firm-Size Bin		
$\leq$ 500	22.36	26.6
501–1,000	24	21.72
1,001–2,500	54.54	95.13
2,501–5,000	99.35	118.24
5,001–10,000	84.76	89.16
10,001–20,000	262.52	788.57
$>$20,000	511.08	1199.97

Notes: This table shows hires and vacancies for observations in the backward-looking sample (column 1 of Table 3), for each of the firm-size bins used in the estimation of Equation (6).

In Table B.9 we show the results from estimating Equation (6), but including all of the index components as individual covariates, instead of the index itself. We estimate these specifications with and without firm fixed effects. The coefficients on career fairs attended are very similar in the two specifications, but the standard error is much higher when including firm fixed effects and the coefficient is not significant at conventional levels. While the coefficient on days from offer to deadline is positive in both specifications, it is much larger with firm fixed effects. However, the confidence intervals are wide and include the effect without firm fixed effects. The coefficient on participate in on-campus recruiting is large and significant when including firm fixed effects, but not without the fixed effects. All else being equal, when a firm participates in on-campus recruiting the vacancy yield is higher by 21%, although the confidence intervals are wide and we cannot rule out magnitudes between 3% and 39% as the true effect. The coefficient on days from interview to offer is small and insignificant in both specifications. The reason for the differences in the coefficients with and without firm fixed effects may be explained by the sources of potential bias we discuss in Section 4, though we also do not want to overstate the differences in magnitudes given the smaller sample size and wide confidence intervals.

B Additional Results

B.1 *Additional Results: Hiring Plans, Beliefs, and Recruiting*

In this section we present additional results about hiring plans and beliefs about labour market tightness, using the forward-looking sample. These results correspond to Section 3 in the main text. In Figure B.1, we show that the nominal salary increase firms plan to offer declined dramatically during the Great Recession period, which is even more stark than the real salary increase we show in Figure 1.

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 labour 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 labour market. Recruiting effort and salary increases are both increasing with beliefs about tightness.

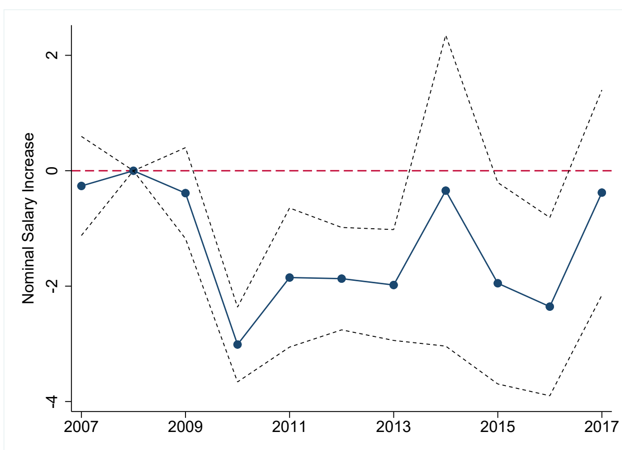


Figure B.1: Planned % Increase in Offered Salary (Nominal)

Notes: Figure includes firm-fixed effects, and is restricted to firms with data for 2007–2008. Standard errors are clustered at the firm level. Plots show 95% confidence intervals. The year corresponds to the spring semester of the academic year (i.e. 2007 refers to the 2006–2007 academic year). The figure is estimated using 426 observations from 125 firms from the forward-looking sample.

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	-0.048	-0.088
	(0.076)	(0.077)	(0.089)	(0.092)
Plan Decrease Hires	0.069	0.030	-0.045	-0.146
	(0.098)	(0.113)	(0.152)	(0.156)
Believe labour Market Will Be Tight	-0.156	-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	0.751
Test Plan Inc. = Plan Dec.	0.66	0.91	0.98	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 labour 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 labour 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-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .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 3 and 4 is .17 with standard deviation .38, and the mean plan to hire international students for U.S. jobs in columns 3 and 4 is .28, with standard deviation .45.

Table B.2: Recruiting and Beliefs about the State of the labour 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 labour market for new college graduates disaggregated into five categories, with "poor" omitted. Standard errors clustered at the firm level; *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Firms measures the number of non-singleton firms in the sample.

Table B.3: Relationship between Hiring Plans, Beliefs, and Recruiting, with Industry Weights

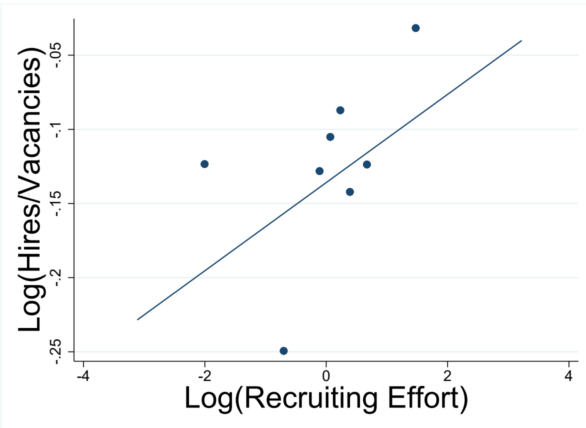
	(1)	(2)	(3)	(4)
Panel A: Forward-Looking Recruiting Effort Index				
Plan Increase Hires	0.686***	0.654***	0.542***	0.432***
	(0.161)	(0.115)	(0.110)	(0.115)
Plan Decrease Hires	-0.131	-0.274*	0.146	-0.009
	(0.143)	(0.156)	(0.159)	(0.154)
Believe labour Market Will Be Tight	0.313**	0.311**	0.114	0.353**
	(0.124)	(0.125)	(0.187)	(0.162)
Firms	657	657	250	250
Observations	1,116	1,116	709	709
R-squared	0.153	0.204	0.551	0.591
Test Plan Inc. = Plan Dec.	$\leq$ 0.0001	$\leq$ 0.0001	.0125	.0064
Panel B: Planned % Increase in Offered Starting Salary (Real)				
Plan Increase Hires	1.500**	1.402***	1.249	1.599**
	(0.712)	(0.468)	(0.773)	(0.665)
Plan Decrease Hires	0.141	-0.596	0.346	0.333
	(0.444)	(0.418)	(0.465)	(0.459)
Believe labour Market Will Be Tight	1.582***	0.457	1.545**	0.789
	(0.468)	(0.322)	(0.647)	(0.514)
Firms	471	471	146	146
Observations	701	701	376	376
R-squared	0.083	0.279	0.398	0.515
Test Plan Inc. = Plan Dec.	0.057	$\leq$ 0.0001	.137	.0337
Panel C: Plan to Offer a Signing Bonus				
Plan Increase Hires	0.046	-0.051	0.009	0.037
	(0.098)	(0.061)	(0.045)	(0.042)
Plan Decrease Hires	0.005	-0.134*	-0.006	0.041
	(0.075)	(0.078)	(0.078)	(0.083)
Believe labour Market Will Be Tight	0.175***	0.150**	0.040	0.029
	(0.067)	(0.064)	(0.085)	(0.096)
Firms	628	628	238	238
Observations	1,059	1,059	669	669
R-squared	0.019	0.140	0.643	0.649
Test Plan Inc. = Plan Dec.	0.7082	.3117	.8578	.9674
Firm FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes

Notes: This table is the same as Table 2, but weighting observations so that the industry distribution of the sample in each column is representative of the industry distribution of enterprises with at least 5000 employees using data from the U.S. Census Enterprise Statistics Program (ESP) (Enterprise Statistics Program, U.S. Census Bureau, 2016). The ESP data do not cover agriculture, management of companies and enterprises, or public administration. A small share of our NACE sample are in these excluded industries (roughly 3–4%), and for these observations we apply a weight of one. For firms in industries covered by ESP, we calculate the weight as the industry share from ESP among firms with at least 5000 employees divided by the industry share in our regression sample. See text and Table 2 for details.

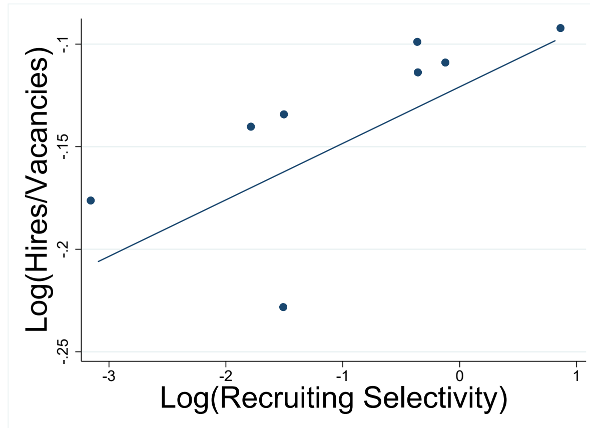
B.2 Additional Results: Recruiting and Vacancy Yields

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

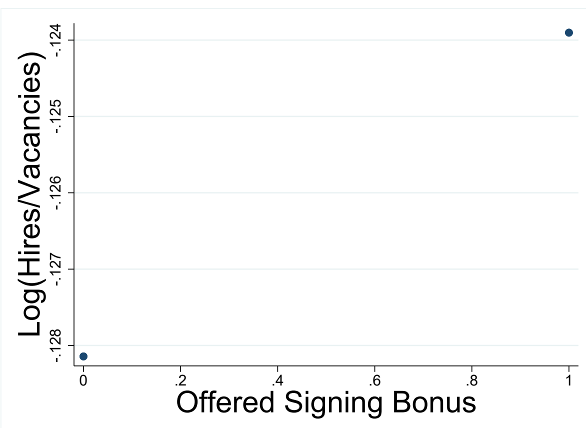
Figure B.2: Recruiting and Firm-Level Vacancy Yield



(a) Effort Index



(b) Selectivity Index



(c) Offered Signing Bonus

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

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**
Standardised	(0.0140)	(0.0464)	(0.0197)	(0.0483)
Recruiting Selectivity,	0.0345*	0.0335	0.0324	-0.00828
Standardised	(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 3, but excludes the control for vacancies.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(H/V)	ln(H/V)	ln(H/V)	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***	0.0898**	0.0919**	0.151***	0.131**
Standardised	(0.0169)	(0.0175)	(0.0209)	(0.0279)	(0.0429)	(0.0380)	(0.0527)	(0.0549)
Recruiting Selectivity,	0.0385*	0.0305	0.0206	-0.00101	-0.0129	-0.0103	-0.0134	-0.0516
Standardised	(0.0214)	(0.0217)	(0.0245)	(0.0312)	(0.0347)	(0.0343)	(0.0423)	(0.0548)
Offered Signing Bonus	0.0336	0.0311	0.0711*	0.101**	0.0402	0.0257	0.0435	0.0800
	(0.0332)	(0.0338)	(0.0387)	(0.0440)	(0.0572)	(0.0564)	(0.0602)	(0.0693)
ln(Vacancies)	-0.0547**	-0.0649***	-0.0868***	-0.124***	-0.0572	-0.0482	-0.0971	-0.236*
	(0.0220)	(0.0216)	(0.0261)	(0.0372)	(0.0594)	(0.0568)	(0.0678)	(0.128)
Firms	264	270	273	274	79	82	83	84
Observations	397	409	414	416	212	221	224	226
R-squared	0.225	0.228	0.207	0.204	0.553	0.553	0.533	0.575
Included Values of H/V	≤ 1.3	≤ 2.29	≤ 7.5	All	≤ 1.3	≤ 2.29	≤ 7.5	All
(Percentiles)	(95th)	(98th)	(99th)	(All)	(95th)	(98th)	(99th)	(All)
Industry FE, Size FE	Y	Y	Y	Y	N	N	N	N
Firm FE	N	N	N	N	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: *** p-value $\leq$ .01, ** p-value $\leq$ .05, * p-value $\leq$ .1. Standard errors clustered at the firm level. Recruiting effort and selectivity are calculated as described in Table 3 and in the text, but only on the regression sample specific to each column. Percentiles are relative to the sample of observations without firm fixed effects and with non-missing values of ln(career fairs), industry, size, ln(vacancies), and ln(hires), and excluding the singletons from this restricted sample based on including year, industry, and firm-size fixed effects. See Table 3 and text for details.

Table B.6: Relationship between Recruiting and Vacancy Yield, Alternative Specifications

Y = ln(H/V)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recruiting Effort,					0.0396**	0.0573**	0.0406*	0.0106
Standardised					(0.0161)	(0.0273)	(0.0218)	(0.0292)
Recruiting Selectivity,	0.0263	0.0204	0.0104	0.0258	0.0259	0.0335	0.0248	0.0127
Standardised	(0.0192)	(0.0352)	(0.0152)	(0.0391)	(0.0192)	(0.0361)	(0.0215)	(0.0315)
Offered Signing Bonus	-0.00611	-0.0335	-0.0139	-0.0343	-0.00822	-0.0416	0.0185	-0.0404
	(0.0237)	(0.0426)	(0.0231)	(0.0508)	(0.0242)	(0.0401)	(0.0332)	(0.0540)
Fairs, Standardised	0.0424**	0.0380						
	(0.0177)	(0.0269)						
ln(Career Fairs), Standardised			0.0665**	0.0243				
			(0.0275)	(0.0367)				
ln(Vacancies)	-0.0429***	-0.0271	-0.0545***	-0.0236	-0.0450***	-0.0163	-0.0352*	-0.0520
	(0.0160)	(0.0435)	(0.0189)	(0.0449)	(0.0164)	(0.0431)	(0.0182)	(0.0512)
Observations	405	217	396	210	405	217	405	217
R-squared	0.149	0.582	0.137	0.473	0.152	0.600	0.371	0.859
Effort Variables	Fairs		Ln(Fairs)		All, but Time to Deadline			
Industry FE	Y	N	Y	N	Y	N	N	N
Size FE	Y	N	Y	N	Y	N	N	N
Firm FE	N	Y	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y	N	N
Ind-Year FE	N	N	N	N	N	N	Y	Y
Size-Year FE	N	N	N	N	N	N	Y	Y

Notes: Columns 1 through 4 are analogous to columns 1 and 2 of Table 3 but use a measure of career fairs attended in the past academic year instead of the recruiting effort index. Columns 5 through 8 are analogous to Table 3 but construct the recruiting effort index without number of days between offer and deadline. See Table 3 for details.

Table B.7: JOLTS Vacancy Yield by Establishment Size

Establishment Size	Vacancy Yield
1–9	1.26
10–49	1.29
50–249	1.16
250–999	0.97
1000–4999	0.71
5000+	0.46

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

Table B.8: Relationship between Recruiting and Vacancy Yield, with Industry Weights

Y = ln(H/V)	(1)	(2)	(3)	(4)
Recruiting Effort,	0.035**	0.131***	0.0552**	0.113**
Standardised	(0.017)	(0.042)	(0.0238)	(0.0528)
Recruiting Selectivity,	0.021	0.015	0.0254	-0.00313
Standardised	(0.030)	(0.028)	(0.0264)	(0.0317)
Offered Signing Bonus	-0.005	-0.056	0.00677	-0.0451
	(0.029)	(0.044)	(0.0370)	(0.0538)
ln(Vacancies)	-0.037**	-0.030	-0.0231	-0.0357
	(0.017)	(0.033)	(0.0196)	(0.0479)
Firms	269	81	269	81
Observations	405	217	405	217
R-squared	0.298	0.748	0.534	0.920
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. This table is the same as Table 3, but weights observations so that the industry distribution of the sample in that column is representative of the industry distribution of enterprises with at least 5000 employees using data from the U.S. Census Enterprise Statistics Program (ESP) (Enterprise Statistics Program, U.S. Census Bureau, 2016). The ESP data do not cover agriculture, management of companies and enterprises, or public administration. A small share of our NACE sample are in these excluded industries (roughly 3–4%), and for these observations we apply a weight of one. For firms in industries covered by ESP, we calculate the weight as the industry share from ESP among firms with at least 5000 employees divided by the industry share in our regression sample. See text and Table 3 for details.

Table B.9: Recruiting and the Vacancy Yield, Separating All Index Components

$Y = \ln(\text{H/V})$	(1)	(2)
Participate in On-Campus Recruiting	0.00571	0.208**
	(0.0443)	(0.0901)
Days from Interview to Offer, Standardised	-0.00948	0.0138
	(0.0131)	(0.0199)
Days from Offer to Deadline, Standardised	0.0186	0.0902*
	(0.0124)	(0.0517)
Career Fairs Attended, Standardised	0.0429**	0.0359
	(0.0176)	(0.0264)
Screen on GPA	0.0431	0.162
	(0.0402)	(0.102)
Recruited from Non-Four Year Public/NFP Univ.	-0.0128	7.49e-06
	(0.0349)	(0.0574)
Prefer Relevant Experience	0.0354	-0.0433
	(0.0334)	(0.0368)
Offered Signing Bonus	-0.00710	-0.0349
	(0.0242)	(0.0422)
ln(Vacancies)	-0.0454***	-0.00834
	(0.0162)	(0.0389)
Observations	405	217
R-squared	0.155	0.622
Industry FE	Y	N
Size FE	Y	N
Firm FE	N	Y
Year FE	Y	Y

Notes: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. This table is the same as Table 3, but includes all of the components of the recruiting effort and selectivity indices as separate variables. See text and Table 3 for details.

B.3 Are Employers' Plans Reflective of What They Actually Do?

Our results in Table 2 show that when employers plan on increasing hires, they are also more likely to plan on increasing recruiting effort. This is consistent with employers using tools other than vacancies to increase hires. A natural question is whether employers actually increase recruiting effort, or whether they ultimately decide to simply increase vacancies rather than follow through with their recruiting plans. Of course, actual behaviour may differ from plans for other reasons, for example because hiring needs changed over the course of the year. As a basic descriptive statistic regarding the firms in this sample, we think it is important to understand the extent to which their plans are realised.

We address this question using prospective and retrospective questions in the surveys.

B.3.1 Career Fairs

First, the Recruiting Benchmarks survey in early summer asks firms for the number of career fairs they participated in over the previous academic year. Employers are also asked for the number of career fairs they plan on attending in the coming academic year.[27] For firms that respond to the survey in consecutive years, we construct a measure of whether the firm attended more career fairs in year t than in year $t-1$:

$$\text{MoreFairs}_{Actual,t} = \text{Fairs}_t > \text{Fairs}_{t-1}. \tag{8}$$

We construct a measure of whether the employer had planned on attending more fairs during the year t ($\text{MoreFairs}_{\text{Planned},t}$) in two ways. First, we determine whether the number of fairs the employer plans on attending in the coming academic year is greater than the number they reported attending in the past academic year. These numbers, plans for t and attended in $t-1$, are both reported in Recruiting Benchmarks survey year $t-1$. We construct:

$$\text{MoreFairs}_{\text{Planned,Benchmark},t} = \text{FairsPlanned}_{\text{Benchmark},t} > \text{Fairs}_{t-1}. \tag{9}$$

The variable $\text{FairsPlanned}_{\text{Benchmark},t}$ denotes the number of fairs the employer reported planning for t in year $t-1$. If this number is greater than the number of fairs they reported attending in the same survey (Fairs_{t-1}), then $\text{MoreFairs}_{\text{Planned,Benchmark},t} = 1$. The benefit of constructing the measure in this way is that we do not require that the firm responded to

[27] Note that our analysis in Table 2 does not use these variables. That analysis uses questions in the Job Outlook survey about career fair plans, allowing us to analyse the relationship with hiring plans without merging across surveys.

both the Recruiting Benchmark and Job Outlook surveys.

As an additional measure, we construct $\text{MoreFairs}_{\text{Planned,Outlook},t}$ using the forward-looking Job Outlook survey, and using the merged Recruiting Benchmark and Job Outlook sample. We construct this measure of whether the employer had planned on attending more career fairs in year t using the direct question in the Job Outlook survey regarding whether the employer plans on attending more fairs in the coming academic year. We construct the measure of whether the employer actually attended more fairs in t ($\text{MoreFairs}_{\text{Actual},t}$) in the same way as above. This construction of the plans measure allows us to compare the plans variable we are using in our current analysis (Table 2) to actual recruiting behaviour. However, given that we are merging across surveys, the sample size falls.

We see that the fraction who attend more fairs among those who did not plan on attending more fairs is roughly 45%. This percentage is roughly 20–25 percentage points higher among those who planned on attending more fairs.

Table B.10: Actual and Planned Recruiting behaviour

	More Fairs Actual	More Fairs Actual	Signing Bonus Actual
More Fairs Planned, Benchmark	0.259***		
	(0.045)		
More Fairs Planned, Outlook		0.203***	
		(0.063)	
Signing Bonus Planned			0.348***
			(0.035)
Constant	0.430***	0.460***	0.342***
	(0.025)	(0.033)	(0.027)
Observations	509	319	675
R-squared	0.059	0.035	0.120

Notes: This table compares actual and planned recruiting behaviour. Column 1 constructs a measure of whether the employer planned on attending more fairs using the Recruiting Benchmark survey, while column 2 uses the Job Outlook measure. Sample size falls in column 2 as it relies on employers responding to both surveys. Column 3 uses the forward- and backward-looking measures in the Job Outlook survey. Standard errors are clustered at the employer level. See text for details.

B.3.2 Signing Bonuses

We additionally study the relationship between recruiting plans and actual behaviour using information on signing bonuses. The Job Outlook survey asks whether employers gave a signing bonus in the last year, and whether employers plan on giving a signing bonus in the coming year. Using employers who respond to consecutive surveys, we analyse the relationship between plans stated in the previous year's survey and actual behaviour in the current survey.

Table B.10 shows that 34% of those who did not plan on offering a signing bonus actually did give one. That percentage is roughly 35 percentage points higher among those who planned on offering a signing bonus.

B.4 Additional Results: Recruiting and Hires

We have shown that firms adjust planned 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 realised hires are correlated with realised recruiting measures, using the backward-looking sample. Recruiting decisions at the beginning of the hiring process are made based on hiring plans not realised hires, and so this is an advantage of our main specification.

However, we show results using realised hires for several reasons. First, using realised hires, rather than hiring plans, allows us to analyse the relationship with realised recruiting measures, which are different than our planned recruiting measures (our realised 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 realised 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. (2023) and Lochner et al. (2021).

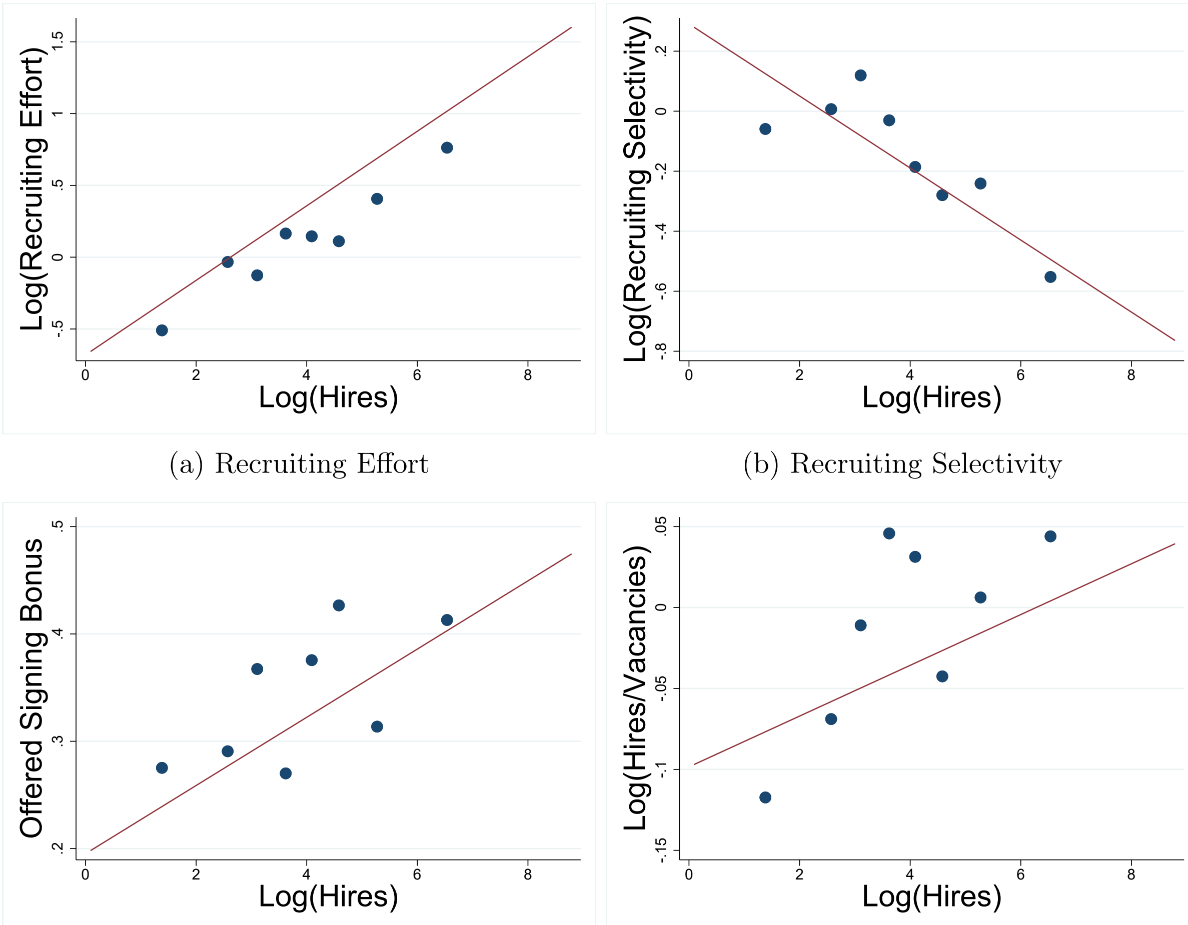
In Figure B.3 we show average outcomes using binned scatter plots based on dividing observations into bins based on log(hires) and adjusting for industry, firm size group, and year, using the "binsreg" command. We show results using eight bins.[28] When firms hire more individuals they have higher recruiting effort, lower selectivity, and are more likely to offer a signing bonus. Columns 1 through 6 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 analyse 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.3 and columns 9 and 10 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.4 and column 10 of Appendix Table C.1). When firms increase hires they are not simply increasing vacancies proportionally, as the

[28]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.3: 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 bin, 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 found 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, in which 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 formalised process, organised 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.

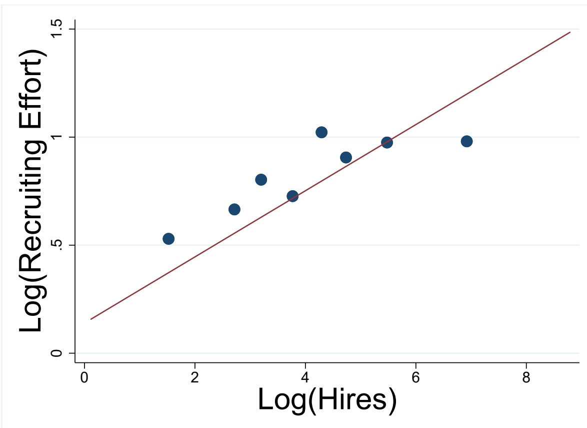
Second, the vacancy yield is constructed by using vacancies reported for a given graduating class for the last year and hires of new college graduates reported in the last year, both reported in the same survey. This implies elasticities will not be upward biased due to time aggregation issues, as the 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 at a level 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.

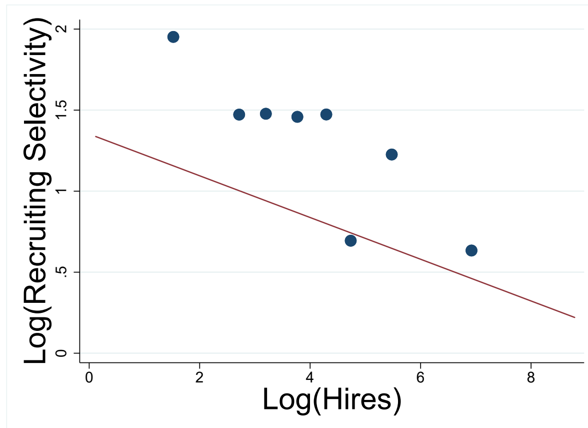
In addition, our sample is skewed toward larger firms and industries with larger establishments, which tend to have lower vacancy yields.[29] According to Statistics of US Businesses Census (SUSB) data from 2012, the average establishment size was 16.3. In contrast, if we re-weight the SUSB data to match the NACE firm size and industry distribution, the average establishment size for our sample is 100. Further, for manufacturing firms (which comprise one third 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.

[29] 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.

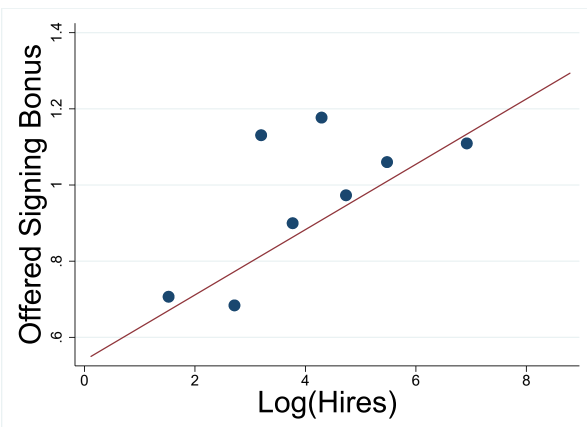
Figure B.4: Hires, Recruiting, and the Vacancy Yield, Including Firm Fixed Effects



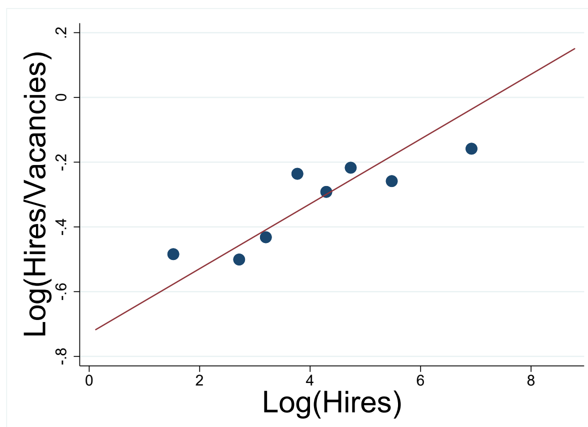
(a) Recruiting Effort



(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.

B.5 *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 connected 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. The validity of this counterfactual relies on the assumption that our estimates have uncovered the causal relationship between recruiting and the vacancy yield, for our sample of firms hiring new college graduates. 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.[30]

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–

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

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.

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 ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See Table 3 for details on variables.

Table C.2: Decomposition of the Elasticity of the Fill Rate with Respect to Hires

	Estimate	Estimate
Elasticity of Fill Rate with Respect to Hires	0.02	0.10
Contribution of Effort	61%	18%
Contribution of Hiring Standards	-19%	-4%
Contribution of Compensation	-1%	-3%
Contribution of Vacancies	-289%	-9%
Industry FE	Y	N
Size FE	Y	N
Firm FE	N	Y
Year FE	Y	Y

Notes: Calculation of the share of the elasticity of the fill rate with respect to hires based on the decomposition in Equation 7. Estimates drawn from Tables 3 and C.1.

B.6 Decomposition Discussion

There are two key differences in our decomposition of the elasticity of the vacancy yield with respect to hires (Equation (7)) compared to 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 and so do not translate the problem into the daily analogue. 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 emphasise that the vacancy yield may vary with total hires, rather than only hires per employment, though as we discuss in Appendix B.4 differentiating with respect to hires could lead to a downward bias in the elasticity.

Using estimates of our specification without firm fixed effects, and applying the appropriate caveats, our recruiting effort measure explains roughly 61% of the elasticity of the vacancy yield with respect to hires. When using the specification with firm fixed effects, the recruiting effort measure explains 18%. This difference is due to a much smaller elasticity of the vacancy yield with respect to hires without firm fixed effects, as opposed to a larger $\delta_f \frac{d \ln x_{f_{et}}}{d \ln h_{et}}$. This is consistent with larger firms, which have more hires, having lower vacancy yields, thus leading to a downward bias in the elasticity.

C 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 labour market would be fair or poor for new college graduates, greater than at the lowest point of the Great Recession (2010) when 61% of employers believed the labour market to be fair or poor.[31] 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).[32] We show that one of the ways in which firms decrease hires is through decreasing recruiting effort, conditional on vacancies. This suggests that 2021 graduates faced a sharp decline in hiring that was above and beyond what was 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 that graduating during recessions can lead to long-

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

[32] 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.

term earnings losses (Kahn, 2010; Oreopoulos et al., 2012). This suggests graduates in 2020 and 2021 deserved particular attention from policy makers at the time.