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ABSTRACT

Employer Screening Costs, Recruiting Strategies, and Labor Market Outcomes: An Equilibrium Analysis of On-Campus Recruiting*

This paper analyzes labor market matching in the presence of search and informational frictions, by studying employer recruiting on college campuses. Based on employer and university interviews, I develop a model describing how firms choose target campuses given relevant frictions. The model predicts that with screening costs, the decision to recruit and the wage are driven by the selectivity of surrounding universities, in addition to the university's selectivity. The prediction has strong support using data from 39 finance and consulting firms and the Baccalaureate and Beyond. Structural estimation of an equilibrium model directly quantifies the impact of reducing screening costs.

JEL Classification: J23, J31, D83, I26, M51

Keywords: labor market search, employer recruiting, return to university education, screening costs

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1 Introduction

In a frictionless world, workers and firms costlessly meet. Firms may consider the entire population of workers, facing no limits on the size of their applicant pool. Workers who are equally qualified for a job are equally likely to obtain the job. However, it is well-acknowledged that there are search frictions in this process. These frictions have, in general ways, been incorporated into well-known theoretical models of the labor market (Diamond 1982, Mortensen 1982a,b, Pissarides 1984, 1985). Few papers address the precise nature of these frictions, and their impact on firms and workers.

The cost of screening applicants, for example reviewing resumes and conducting interviews, is one potentially important friction in the matching process. If screening is costly, this may affect where and how firms recruit applicants. Firms may avoid recruiting in applicant pools with many low-quality candidates, since this requires considerable screening before identifying a desirable candidate. This impact of screening costs on recruiting strategies may have important consequences for productivity and equity, as recruiting strategies affect which types of workers have access to particular jobs, industries, and careers. Understanding the impact of screening costs on recruiting is especially important for understanding consequences of new technologies using machine learning to reduce employer screening costs.

I study the impact of screening costs on employer recruiting strategies in the large and important labor market for recent college graduates. This is a particularly interesting setting for studying firm/worker matching. First, students lack significant labor market experience, implying information frictions and screening costs may be especially significant. Second, this market provides a clear and relevant example in which search is directed, not random. There is a segmentation of search activity by campus, the focus of this paper. Firms often choose a core set of target campuses, and concentrate on applications from students attending those universities. Third, this labor market is large, with nearly 1.8 million Bachelor's degrees awarded by US colleges and universities in 2011-2012 (National Center for Education Statistics 2013). The labor market is especially important if first careers influence future outcomes.

Finally, employer recruiting on university campuses is a largely unexplored area of research, despite being a critical hiring mechanism for firms across many industries.[1]

[1]An important exception, Oyer and Schaefer (2012) study firm employee matches and university

While firms have been recruiting on college campuses since the Westinghouse Electric Company in the late 1800's (Habbe 1948), the size and formality of these programs have increased over the past century.[2] Today virtually every industry recruits on college campuses of varying selectivity, for jobs ranging from crop production to finance. A recent survey found that 76.9% of firms conducted on-campus interviews (of 275 surveyed firms), and 59.4% of new hires (at these 275 firms) were recruited through on-campus interviews (National Association of Colleges and Employers 2014).[3]

One potential difficulty in analyzing this market is obtaining firm-level recruiting data. I identified that whether a firm recruits on a given campus is observable on the firm's website. I create a unique dataset of whether 39 of Vault's most prestigious finance and consulting firms recruit at each of approximately 350 universities.

Based on conversations with employers and university career services personnel, I develop a directed search model of how firms choose target campuses. The model incorporates relevant institutional frictions, including the cost of screening applicants to determine if they would be high-quality workers. When recruiting at universities where a higher proportion of the students would be high-quality workers (referred to as the university's selectivity), firms need to review fewer applications (on average) before identifying a high-quality applicant. Given that screening applicants is costly, this implies firms are most attracted to the labor market's most selective universities. Firms recruiting at less selective universities are compensated by attracting more applicants and offering lower wages due to less competition.

With screening costs and regional labor markets, the model predicts that if two universities are the same size and equally selective, the university that is better ranked within its region will attract more firms and its graduates will earn higher wages. Given the importance of quantitative ability in finance and consulting, in the empirical

location with a different focus: the within-firm concentration of lawyers graduating from the same law school. Based on interviews and observation of a hiring committee, Rivera (2011, 2012) studies screening and hiring processes of professional services firms. Kuhnen and Oyer (2016) study firm hiring of MBA students and the impact of an applicant's experience in the same industry. Previous work studies determinants and outcomes of various recruiting methods, e.g. newspapers and referrals (DeVaro 2005, 2008, Holzer 1987). Kuhnen (2011) studies job search strategies of MBA students.

[2] In 1944, it was estimated that 1,000 of the 412,471 incorporated businesses recruited on college campuses. In 1955, of a highly selected sample of 240 firms, approximately 60% visited more than 20 universities to recruit college seniors (Habbe 1948, 1956).

[3] Of the 18 industries with available data, only two industries had less than 50% of the firms using on-campus interviews (engineering services and government) (National Association of Colleges and Employers 2014).

tests I approximate the proportion of high-quality workers at the university (the selectivity) as the proportion of high math SAT score students.

Undergraduate recruiting for finance and consulting positions is a particularly appropriate setting for testing this prediction. Labor markets in this setting are regional, and there is dramatic variation in the distribution of university selectivity across region. The model predicts that with screening costs, a Texas firm looking to hire high-quality recent college graduates from nearby universities will have Texas A&M near the top of its list, since it is one of the region's most selective universities. However, a Philadelphia firm looking to hire high-quality recent graduates from nearby universities will not have Pennsylvania State near the top of its list, even though its selectivity and size are similar to those of Texas A&M. There are many universities more selective than Pennsylvania State in the Philadelphia region.

There is strong evidence for this predicted impact of screening costs and regional labor markets on recruiting. Among universities at the 25th percentile of selectivity, consulting firms are three percentage points less likely to recruit if the university's regional rank is lower by 64 positions (the regional rank difference for this selectivity), controlling for university size, numerous measures of university quality, as well as the number of firm offices per region. I find similar effects at the median selectivity. The magnitude is economically important as there is a recruiting relationship for 6.2% of (university, firm) pairs. Using the Baccalaureate and Beyond 2009 survey, I find students scoring 1400 on the SAT earn 9% less if the regional rank of their alma mater is worse by 50 places, holding constant absolute size and quality of the university.

Finding reduced-form support for the presence of screening costs and their predicted impact on recruiting strategies and wages, I structurally estimate the model, including the screening cost parameter. This allows me to more directly quantify how a reduction in screening costs would impact recruiting and wages. To identify the screening cost parameter, I develop an estimator based on moments equalizing the observed and predicted proportion of firms recruiting at each university. Parameter estimates are relative to the present discounted value of a worker's additional productivity in finance/consulting relative to other jobs, over the course of the match.

The estimated screening cost is large. If the present discounted value of the finance/consulting productivity over the match is equal to $50,000 (reasonable if the match is five years), the per-applicant screening cost is as much as $6,000, and screening costs per hire are $14,500 at a less selective university. These large estimates are consistent with the fact that, for the consulting industry, screening and interviews are conducted by consultants with high external billing rates.[4] Reducing screening costs has large effects on high-SAT score students at less selective universities. Counterfactually setting the screening cost parameter to zero, the number of firms recruiting at a nonselective university in the East more than doubles, and the wage offer increases by 35% of worker productivity.

The result is quite intuitive. A university may be more overlooked if surrounded by higher-quality universities, than if it were the highest-quality university in the region.[5] Despite the straightforward intuition, the result has important and nonobvious implications.

First, the literature studying labor market return to university quality has focused on absolute quality (such as average SAT score), and not quality relative to other universities in the region.[6] My findings suggest the estimates from that literature may be biased. I show that earnings of students attending less selective universities may be quite high if these universities are among the most selective in their region. By comparing highly-selective universities to less-selective universities that are selective relative to others in the region, previous studies may underestimate the importance of university quality for earnings. Importantly, the US News and World Report rankings, one of the most well-known rankings of US universities, also omits this regional quality dimension when ranking national universities.

Second, the university's regional rank should matter only if there are geographic mobility frictions among college graduates, resulting in regional labor markets. This may be surprising given that high-skilled workers are known to be more geographically mobile than low-skilled workers. However, despite this differential, high-skilled workers are still limited in their mobility (Wozniak (2010) notes that 55% of college graduates live in their birth state). These geographic mobility frictions have important implications for aggregate productivity if they impede firm-worker match efficiency.

While the data pertain to finance and consulting firms, these industries are partic-

[4]For a government contract, McKinsey billed approximately $164,000 per week for four consultants and advice from senior leaders (Hill 2011).

[5]Davis (1966) studied the impact of the student's relative standing at his university on career decisions.

[6]See Black and Smith, 2004, 2006, Brand and Halaby 2006, Brewer, Eide, and Ehrenberg 1999, Chevalier and Conlon 2003, Dale and Krueger (2002, 2011), Long 2008, 2010, Loury and Garman 1995.

ularly important for understanding access to elite business careers. The composition of the business elite has implications for economic growth and also reflects the equality of opportunity in society. The firms in my dataset have become pathways to prestigious positions across many sectors of society.[7] While this may be due to selection, it is plausible that the networks developed at these firms help shape future career paths. Temin (1999) argued that the demographic stability of the American business elite during the 1900s reflected unequal access to educational resources. I build on that literature by studying how university quality affects access to the business elite, by directly studying employer recruiting strategies. The findings suggest that students who do not attend regionally selective universities will lack access to elite jobs. This magnifies concern for low-income high-achieving students, who are unlikely to apply to selective universities (Hoxby and Avery 2014).

The results imply that as screening technologies improve firms may recruit at less selective universities, because identifying their talented students is less costly. There has been recent growth in technologies aimed at reducing employer screening costs, using machine learning to identify high-quality resumes and video interviews. Consistent with the model's prediction, Goldman Sachs announced they were adopting one of these screening technologies, and would no longer hold first-round on-campus interviews at elite universities. Instead, they require all applicants, regardless of their university, to complete a video interview (Gellman 2016).

2 The Campus Recruiting Labor Market

I conducted interviews with career services personnel and consulting firm employees (former and current). These conversations elucidated important components of firm hiring procedures, and of the labor market more generally.[8]

Target Campuses Firms choose a core set of universities at which to target their recruiting efforts. Each target campus is managed by a team of human resources personnel and consultants who have recently graduated from that university. The

[7] Alumni of these firms have become CEOs of large businesses and non-profits, as well as government leaders. McKinsey states that more than 300 of their nearly 27,000 alumni are CEOs of companies with over 1 billion dollars in annual revenue (McKinsey 2013).

[8] These components are specific to undergraduate recruiting. Recruiting of MBA students is in general a completely separate process, managed by different staff members.

team visits the campus for recruiting events throughout the semester, and ultimately for first-round interviews. Students at target campuses submit applications to the university-specific team. Students at non-target campuses apply through a general online procedure. Obtaining an entry-level job in this way is the exception and not the rule.[9]

Costly Recruiting Firms invest heavily in identifying the best applicants, through a lengthy interview process. The details of this process are outlined below for one firm at one university. The important components of this procedure are generalizable. The firm decides how many team members will conduct interviews at the university, determining a fixed number of interview slots on that campus. To fill those slots, each team member rates each application. Ratings are based on many factors, including SAT scores, GPA, courses, and extra-curricular involvement. Employees use university-specific knowledge to better evaluate applicants, for example re-weighting GPA by course difficulty. Team members average their ratings for each applicant. After this process, there is a clear consensus to interview certain applicants and to reject others.

Many applicants have ratings between these extremes. The team spends more time reviewing these applications and discussing whether to offer an interview. Once all slots are filled, the team conducts first-round interviews. Applicants are evaluated again, and some are asked for a second-round interview at a firm office (not necessarily by the team, as discussed below). Finally, the firm decides who to hire.

Separate Labor Markets Many firms I spoke with have offices throughout the US. When applying, applicants are asked to rank the locations where they would like to work. Following the initial on-campus interview, the student's application is sent to her first-ranked office. This office can call the student for a second interview, or may pass the student to the second-ranked office. Importantly, firms rarely send a student's application to an unranked office. Those involved in recruiting explain this is to avoid rejected offers after a costly review process. Each office location has a relevant labor market, from which it is able to attract applicants. This suggests firms must choose target universities in the relevant labor market of each office.

[9] This is particular to management consulting firms.

3 A Theoretical Model of Campus Recruiting

Incorporating search frictions and institutional details described above, I develop a directed search model of the campus recruiting labor market. The model extends the wage-posting model in Lang, Manove, and Dickens (LMD) (2005) in several ways. I incorporate into LMD the division of the labor market into many mutually exclusive pools (in this case university campuses), as well as a per-applicant screening cost. The appendix contains details and derivations.

Set-up

I assume a finite mass of identical firms that hire new workers through recruiting on college campuses and posting a wage. They each have one unfilled position, and choose one university at which to recruit.[10] Firms can hire students only from the university at which they recruit. There are two types of students, high ability (H) and low ability (L). I consider a static game, in which firms must hire H-type students, as L-type students have negative productivity. There are many universities (denoted by t) in the market, each with an unobserved random number of students, $\widetilde{S}_t$, interested in applying for jobs with these firms. I assume $\widetilde{S}_t$ is distributed Poisson with known mean S_t. This is the distribution that would arise if students at large universities made independent and equally probable decisions to apply for jobs with these firms. Universities have different proportions of H-type students, denoted p_t.[11] All H-type workers have the same productivity, v, at each recruiting firm.

I assume that students do not know their type, implying that both types apply to vacancies. In order to determine whether an applicant is an H-type firms incur cost c, the cost of reviewing the applicant's resume and conducting an interview. The assumption that students do not know their type is important only because it implies expected screening costs are lower at universities with higher p. Other assumptions, including that students have some, but not perfect, information on their type also yield this result. It is reasonable that students have uncertainty regarding the match between their skills and tasks in an unknown work environment. On the contrary,

[10] The model allows firms to hire for multiple positions, and to recruit for each at different universities, if each firm in the model is interpreted as a vacancy and firms recruit for vacancies within the firm independently.

[11] Firms allocate across universities after observing their size and quality. In this sense, university size and quality are treated as exogenous and general equilibrium effects are not considered.

firms have accumulated knowledge about predictors of worker success.

Consider a two-stage game in which firms simultaneously make wage offers in the first stage, which they must pay to the worker they eventually hire. In the second stage, students observe the wage offers and simultaneously apply to firms. Each student may apply only to one firm.[12] Each firm then evaluates the applicants in its pool sequentially in random order, paying c for each evaluation. The firm continues until identifying the first H-type applicant. At that point the firm hires the H-type student and stops reviewing other applicants. At universities with a lower proportion of H-type students, on average firms will have to review more applicants before reaching an H-type student. Thus, the expected costs of recruiting will be decreasing in p_t.[13]

Formally, expected costs equal the expected number of applicants reviewed multiplied by the screening cost per applicant, c:

$$c * \sum_{k=1}^{\infty} \left(\frac{z^k e^{-z}}{k!} \sum_{j=1}^{k} (1-p)^{j-1} \right) = c * \frac{(1-e^{-pz})}{p} \tag{1}$$

Given the firm chooses a wage to target z applicants, the Poisson probability of every possible number of applicants arriving (k) is multiplied by the expected number of applicants reviewed for that number of arrivals. The firm always reviews the first applicant, with probability $1-p$ it reviews the second (because with probability p the first applicant is an H-type), and so on. The expected cost function, $(1-e^{-p_t z_{ti}})(\frac{c}{p_t})$, is decreasing in p.

Firm i's payoff from recruiting at university t is expected operating profits

$$\pi_{ti} = (1-e^{-p_t z_{ti}})(v - w_{ti} - \frac{c}{p_t}). \tag{2}$$

Given the number of students at each university has a Poisson distribution with known mean S_t, the number applying to firm i also will have a Poisson distribution,

[12] Intuition in Galenianos and Kircher (2009) suggests results will be similar if students can apply to two firms. Their paper suggests that this would yield two wages at each university. Some firms offer the high wage, and some the low wage. The two wages at each university, and the number of firms offering each, should vary by university based on selectivity so profits are equalized.

[13] If there are few individuals who the firm definitely interviews after the first review, then the description in Section 2 is nearly identical to the model. In the model, firms review applicants until finding the first H-type. In actuality, firms review the applicants remaining after the first review until they fill all interview slots.

with known mean z_{ti}. The probability that the firm's vacancy is filled is given by $1 - e^{-p_t z_{ti}}$. While the expected number of applicants is equal to z_{ti}, there is only a p_t probability that each applicant is an H-type. A student's payoff, if hired by firm i, is the firm's wage offer w_{ti}; if the worker is not hired his payoff is zero.

Equilibrium Strategies within Universities

The within-university game between firms and workers is solved backwards following LMD, using as a solution concept subgame-perfect competitive equilibrium (details in appendix). I highlight important intuition here. After the game, each firm reviews its applicants until identifying, and subsequently hiring, the first H-type student. In the second stage, students observe the posted wages and decide where to apply. Students apply such that their expected income (the wage multiplied by the probability of getting the job) is equalized across firms. A higher wage would attract more applicants, reducing each applicant's probability of getting the job.

In the first stage, firms choose the expected number of applicants (z_{ti}) to maximize profits. The central trade-off for firms considering a higher wage is the cost of the wage versus the benefit of attracting more applicants and decreasing the probability of an unfilled vacancy. The first-order condition for profit maximization yields an equilibrium expression for the optimal z and w. The solutions imply that all firms recruiting at university t attract the same number of expected applicants (z_t) and offer the same wage (w_t) for high-type workers. Following LMD, I show the within-university equilibrium is unique (in the appendix).[14]

Equilibrium Allocation of Firms Across Universities

The main departure from LMD is the analysis of firm allocation across pools (universities) in equilibrium, and how this is affected by per-applicant screening costs, university size and selectivity. Furthermore, my set-up involves comparing outcomes of equally productive and desirable individuals who happen to be located in pools (universities) with different characteristics.

With T universities, if firms recruit at $R \leq T$ of those universities, equilibrium profit from recruiting at each of the R universities must be equal. I reduce the $3R$

[14]Specifically, it is unique among those in which all students at university t adopt the same mixed strategy and have the same expected income.

conditions governing the equilibrium to $R-1$ profit-equality equations and $R-1$ endogenous variables $(N_1, ..., N_{R-1})$.[15] For universities 1 and 2, the profit-equality condition is:

$$(1-e^{-p_1(\frac{S_1}{N_1})})(v - \frac{(S_1(p_1 v - c))}{N_1(e^{p_1(\frac{S_1}{N_1})}-1)} - \frac{c}{p_1})$$
$$- (1-e^{-p_2(\frac{S_2}{N_2})})(v - \frac{(S_2(p_2 v - c))}{(N_2)(e^{p_2(\frac{S_2}{N_2})}-1)} - \frac{c}{p_2}) = 0 \quad (3)$$

Equation (3) also shows that if the per-applicant screening cost (c) is zero, the profit from recruiting at each university is equalized when $\frac{p_s S_s}{N_s} = \frac{p_{s'} S_{s'}}{N_{s'}}$ for all universities s, s'. Thus, with $c = 0$, firms allocate across campuses based on the number of high-type students (pS), and not the proportion (p).

For the $T - R$ universities that do not attract recruiting firms, a profit inequality condition must hold in equilibrium. This condition specifies that when an infinitesimally small number of firms recruits at the university, the profit is less than the profit at all of the universities attracting firms. When an infinitesimally small number of firms recruits at the university, each is guaranteed an H-type in the applicant pool, and pays a wage of zero (the reservation wage) since there is no competition. For university $R+1$ which does not attract a firm, and university 1 which does, the condition is:

$$v - \frac{c}{p_{R+1}} < (1-e^{-p_1(\frac{S_1}{N_1})})(v - \frac{(S_1(p_1 v - c))}{N_1(e^{p_1(\frac{S_1}{N_1})}-1)} - \frac{c}{p_1}) \quad (4)$$

I further characterize the equilibrium, deriving the following propositions:

- PROPOSITION 1*: The expected number of applicants, and H-type applicants, per firm is decreasing in p. The wage is increasing in p.*
- PROPOSITION *2: There is a cut-off value of university selectivity p, below which it is not profitable for any firm to recruit.*

[15] The conditions governing equilibrium are: the first-order conditions determining the number of applicants targeted by each firm, at each university (R *conditions*); the profit-equality equations for firms at the R universities ($R-1$ *conditions*); the number of applicants to each firm multiplied by the number of firms must equal the number of students at each university (R *conditions*); and the number of firms recruiting at each university must equal the total number of firms (1 *condition*). I assume the total firms in the market is known, so that N_R is implied by the number of recruiting firms at all other universities.

- PROPOSITION *3: For a given university t, increasing p_t and decreasing S_t without changing p_tS_t has a negative effect on the total number of firms recruiting at other universities in the market, holding constant the total number of firms and total number of H- and L-type students in the market. This change at university t will result in a lower wage offer for at least one of the other universities in the market (not t).*[16]

The formal proofs are in the appendix. Intuitively, holding wage and expected high-type applicants per firm constant, recruiting at universities with higher p is more profitable because expected screening costs are lower. Thus, firms must be compensated for recruiting at universities with lower values of p, either through offering a lower wage or receiving more applicants. In this model, and in other models of this type, firms are compensated through both mechanisms. If each firm receives fewer applicants, there is more competition among firms, and the wage is higher.

The following example illustrates the intuition for Proposition (3). Each cell represents the number of H- and L-type students at a given university:

Region 1	Region 2
100H,100L	80H, 0L
80H, 100L	100H,100L
	0H, 100L

Consider the university with 80H, 100L in Region 1. This university has a counterpart in Region 2 (80H, 0L), with higher p_t, lower S_t, but equal p_tS_t (the number of H-types). Holding constant the total number of firms, Proposition 3 suggests that if screening costs are present, the number of recruiting firms, and the wage, at the university with (100H, 100L) in Region 1 will be higher than at the equivalent university in Region 2. Firms prefer recruiting at universities with a large proportion of H-type students, as this reduces expected screening costs. The university with 100H, 100L in region 2 will be a second-best recruiting choice, while in region 1 it will be the top recruiting choice. This prediction is tested by exploiting variation in the distribution of university quality across regions of the US.

[16] Increasing p_t and decreasing S_t without changing p_tS_t implies that the number of L-type students is lowered at t. To keep all else equal, in this proposition I have assumed that the number of L-type students in the market is kept constant (implying L-types increase at another university). This assumption is not necessary for the result to hold.

Consider the model without per-applicant screening costs ($c = 0$), for example if the fixed cost of visiting a campus drives recruiting decisions. With $c = 0$, profit equalization implies each firm will have the same number of high-types in its pool. Thus, firms allocate based on the number of high-types relative to the market, and not the proportion of high-types. If $c = 0$, the university with 100H, 100L will receive the same number of recruiting firms in both regions.

4 Data on Universities and Firm Recruiting

To test the theoretical predictions of how screening costs impact employer recruiting, I collect data on recruiting strategies of prestigious finance and consulting firms. In addition to being important destinations for recent graduates, finance and consulting are ideal for this study. Firms in these industries often have multiple US offices, enabling within firm comparisons across region. This mitigates concerns that firm heterogeneity drives regional variation in recruiting strategies. Second, consulting firms generally recruit on campus for entry-level consultants, fairly homogeneous across firms and across offices within firms.[17] This reduces concerns that firms recruit for different positions at prestigious and nonprestigious universities. Financial firms often recruit for various positions (e.g. investment banking and IT), so I separate effects by industry.

I identify elite finance and consulting firms using the following rankings by Vault, a career resources company: top 50 consulting firms by prestige (2011), top 50 banking firms by prestige (2012), and top 25 investment management firms (2009).[18] For each of these firms, I attempted to collect data on undergraduate target campuses from the firm's website. For example, Bain's career page has a search field for university. After searching for Texas A&M, the recruiting page that is loaded makes clear Bain's active recruiting presence there (Figure 1a). However, after searching for Pennsylvania State it is clear Bain does not actively recruit at the university (Figure 1b). Bain's target campuses, as the model predicts, are less selective outside the Northeast (Figure 2).

[17] For example, Bain's New York and Dallas websites publicize "Associate consultant" positions for recent BA recipients. Both link to the same page for further position description.

[18] Appendix describes data sources. Target campuses were collected in Spring 2012 (consulting) and Spring 2013 (finance). I use 2011 firm rankings because Spring 2012 recruiting arguably pertains to seniors in 2012, who begin recruiting season in Fall 2011. Vault last ranked investment management firms in 2009.

Target campuses were identified from firm websites for 22 consulting firms, 13 banking firms, and four investment management firms (Appendix Table 1).[19] I denote whether each firm actively recruits undergraduates at each university in Princeton Review's *The Best 376 Colleges* (2012).[20] The recruiting dataset is merged with rich university-level data, from the Integrated Postsecondary Education Data System (IPEDS), the Common Data Set, US News and World Report (USNWR) rankings, and each university's website.

For data on higher quantiles of the academic achievement distribution, likely relevant for elite firms, I collect Common Dataset variables from individual university websites.[21] These include the percentage of enrolled freshmen scoring [700,800] on the SAT Math and Verbal, [30,36] on the ACT Math and English, and percent in the top 10% of their High School class.

Elite finance and consulting firms may value unobservables, such as leadership. If universities value the same unobservables in admissions, this will be captured in the percent admitted, one of the controls. USNWR ranking further captures perceptions of university quality, by including assessments from peer universities and high school guidance counselors (USNWR 2011).[22] To measure selectivity among seniors in 2012 (the year of most of the recruiting data), I use IPEDS and Common Data Set data for Fall 2008 freshmen. Because USNWR rankings include variables which may improve student quality during enrollment, such as student resources, I use 2012 USNWR rankings.

To control for the effect of firm-university distance on recruiting decisions, I collect the latitude and longitude for each university and office location. I find the closest office of each firm to a given university.

[19] I exclude consulting firms with non-consulting divisions. Eight consulting firms do not explicitly differentiate undergraduate and MBA target campuses, though many distinguish university and experienced hires. For at least one firm, the latter include MBA students. Results are robust to excluding these eight firms.

[20] Several universities are excluded: two without IPEDS data, 13 without test scores, three foreign, and five service academies. I create one observation for the five Claremont Colleges.

[21] The Common Data Set is used by The College Board, Peterson's, and USNWR. The central dataset is not public, though many universities put their data on their website.

[22] To avoid dropping liberal arts colleges (not in USNWR), I control for nonmissing rank.

5 Empirical Analysis of Recruiting Strategies

The model predicts that with screening costs and regional markets, recruiting is driven by the number and proportion of high-type students at the university, and the proportion of high-types relative to other universities in the market. To capture the intuition I use the university's regional rank based on the proportion of high-type students.[23] This does not entirely capture the prediction (e.g. the second-ranked university benefits from a smaller first-ranked university). I account for this in a robustness specification and structural estimation.

The distribution of students across institutions is treated as exogenous since many of the universities were founded in the 18th and 19th century, and their selectivity developed independent of firm recruiting.[24] Supporting this argument, the USNWR does not rank universities by graduates' labor market outcomes. I argue the distribution of students across institutions determines recruiting strategies and wages.

Constructing Separate Labor Markets

The relevant labor market for each office location consists of universities with students interested in working at that location. I use the target campuses to infer firms' perceived labor markets; to define regions I assume campuses are targeted by the closest office. Using a community detection algorithm from the network literature (Newman 2004), I define four regions (East, Midwest, South, West) such that firms are likely to recruit within, not outside, these regions (Figure 2).[25] For robustness, I use Bureau of Economic Analysis regions.

The background described above, the B&B, and university data support the assumption that campuses are targeted by the closest office, an assumption used only to define regions. One year after graduation, a high percent of students live in their university's region, from 77% (South) to 88% (West) (Table 1), consistent with limited college graduate mobility (Wozniak 2010). Firms also do not heavily recruit

[23]The relevant variable is not regional rank percentile. Conditional on number of firms (job openings) in the region, a median-ranked university 50th in its region faces more competition (49 preferred universities) than a median-ranked university 5th regionally (4 preferred universities).

[24]Most Ivy League universities were founded before 1770, with non-vocational emphases. Many state universities started as land-grant colleges (established in 1862) with agricultural and mechanical foci. Universities developed consistent with their missions: older colleges were often first with selective admissions, and prioritizing scholarly research (Rudolph 1990).

[25]See appendix. Texas and California are likely in the same region because firms in Arizona recruit in both states.

their home-state students studying in other regions (Table A10).[26] Importantly, my reduced-form regression jointly tests for screening costs and regional markets. If markets are not regional, the coefficient on regional rank will be insignificant.

Regional rank is calculated based on the proportion of high-type students, p, at the university. I define high-types as students scoring [700, 800] on the SAT Math or [30, 36] on the ACT Math.[27] Clearly the definition of high-type students for these firms is more complicated than SAT scores. The assumption is that the proportion of high SAT score students is positively correlated with the true proportion of high-type students. I obtain a measure of the number of high-type students using $p*$number of students.

Summary Statistics: Firms, Universities, and Recruiting

Firms and universities in my sample are located across the country (Panel A, Table 1). Panel B of Table 1 shows dramatic variation in the national rank of the region's best universities. Top universities in the East have top national ranks. However, the 5th ranked university in the Midwest and West ranked around 30 nationally, and the 5th ranked university in the South ranked about 90 nationally. I use this variation to test the model's predictions.

Figure 3 shows the identifying variation for the reduced-form analysis. For given p, regional rank is worse in the East than other regions. Consider four universities in different regions: Penn State (p=.171), Miami University in Ohio (p = .163), Texas A&M (p = .165), University of Georgia (p = .161). Despite similar p, their regional ranks are vastly different. Penn State is 70; Miami University is 38; Texas A&M is 28; University of Georgia is 9.[28]

Within bins of university selectivity (less than .6) the university attracting the most firms in the West attracts a higher proportion of firms than in the East (Figure 4). For universities with $p \in [.2, .4)$, mean regional rank in the West (14) is much better than in the East (51.5). The university in the West attracting the most firms in this bin attracts over 60% of the firms, while the analogous university in the East

[26] In addition, campuses on Bain's Dallas and Houston websites suggest regional hiring.

[27] These are the ranges in the Common Data Set. Appendix describes calculation of p. Math scores define high types due to quantitative nature of finance and consulting. Regressions control for verbal scores. Correlation between percent scoring $\in$ [700, 800] on SAT math and verbal is .88 (Common Data Set).

[28] Figure A2 shows universities across region with similar p and p*#Students.

attracts less than 50%. While not controlling for university size, this suggests support for the model's prediction.

Reduced-Form Empirical Specification

The model suggests universities with worse regional rank may attract fewer firms, holding constant size and selectivity, due to screening costs or differences in supply of students. The East has more high-type students than other regions. If two universities have the same number of high types, the university in the East will attract fewer firms because it has a smaller share of the region's high types. I identify the screening versus supply effect by controlling for the university's high types divided by the region's high types.

For given university quality (p), the difference in regional rank varies dramatically over the distribution of p (Figure 3). To account for these nonlinearities, I allow the effect of regional rank to vary with p. I also interact the principal explanatory variables with $p : p$, number of high-type students, and number of high-type students relative to the market.[29] Observations are (university, firm) pairs, e.g. (Penn State, Bain). Using OLS, I estimate:

$$recruit_{sf} = X_s\beta + \gamma_1 RegRank_s + \gamma_2 RegRank_s * p_s + \gamma_3 FirmsinRegion_s + \gamma_7 Distance_{sf} + \delta_f + \epsilon_{sf} \quad (5)$$

$Recruit_{sf}$ indicates if firm f recruits at university s. X_s is a vector of university characteristics.[30] $Distance_{sf}$ is the distance between university s and firm f's closest office, and δ_f are firm fixed effects. $FirmsinRegion_s$ is the total number of offices, for firms in my sample, in the region of university s. I cluster standard errors by university since p_s does not vary within university.

Because the model implies no effect for universities below p_{cutoff}, I include only universities with p above the minimum p attracting a firm ($p = .0078$). I exclude

[29] Interacting all variables with p yields similar effects with higher standard errors, as expected (Table A6).

[30] These include p; number of high types and number relative to the region; 25th, 75th percentiles of Math and Combined SAT/ACT, weighted by share reporting each exam; percentage $\in$ [700, 800] on SAT Verbal/ACT English (calculated same way as p); percent in top 10% of HS class; USNWR rank; in- and out-of-state tuition; percent admitted; indicators for institution being public, in large city, small or mid-sized city, and offering more than a BA. X_s also includes interactions between p and the principal explanatory variables.

universities with $p > .7$ given very limited overlap across regions.[31] Finance firms recruit for some positions that may value Math scores less, implying smaller effects of regional rank. I interact the regional rank variables, and other variables interacted with p, with an indicator for consulting firm.[32]

6 Reduced-Form Estimation Results

Regional rank has a statistically significant effect on recruiting decisions, holding constant university selectivity, size, and size relative to the region (Table 2, Column 1). The 25th percentile of p in the sample is approximately .06. A university in Texas with this p has a regional rank of 56, while a university in the East with this p has a regional rank of 120. For $p = .06$, and the corresponding regional rank difference of 64, universities in the East are 1.8 percentage points less likely to attract a firm than universities in Texas. This effect is large, given recruiting in only 6.2% of (university, firm) pairs in the sample. I find a smaller effect for universities with the median p.[33]

The effects of regional rank are stronger for consulting than for finance firms (Column 2). The regional rank coefficients are jointly significant at the 1% level, as are the interactions between regional rank and *Consult*. For universities with p at the 25th percentile, a university in Texas is 3 percentage points more likely to attract a consulting firm than a university in the East. The effect is similar for universities with the median p.[34] Regional rank's effect is large, though not as large as some absolute quality variables. For universities with the median p, increasing the number of high types by one standard deviation (462 students) increases the probability of attracting a consulting firm by 5.5 percentage points.[35]

The results support the model's prediction: screening costs and regional labor

[31] I exclude the lowest p attracting a firm to mitigate random factors. Results are robust to including this university. The model implies limited effect for high p universities, given similar regional ranks and low screening costs. Since the prediction relates to recruiting within the firm's region, I drop 10 (university, firm) pairs in different regions.

[32] Interacting every variable with p, *Consult*, and $p*Consult$ yields similar though less statistically significant results (expected given loss of power) (appendix).

[33] The appendix presents coefficients on all variables.

[34] Specifications interacting regional rank and firm rank (as well as firm rank and the other key explanatory variables) suggest better-ranked firms are more sensitive to a university's regional rank (though the interactions are not jointly statistically significant; not shown).

[35] These estimates are the linear combination of the coefficients on number of high types, and number relative to the region.

markets cause more recruiting at universities with better regional ranks, holding constant university and regional characteristics. However, students should not hold regional characteristics constant when choosing a university. More firms in the East may suggest benefits of universities in the East, despite their worse regional rank. To address this, I obtain predicted values of *Recruit* using the regression in Table 2, Column 2. These predicted values account for the effect of attending university in a region with more firms. I estimate a lowess regression of the predicted values on p for consulting firms.

For given p, universities in the East must be significantly more selective than those in the West to attract firms with similar probability (Figure 5). For example, for universities in the West with $.27 \leq p \leq .28$ (University of Texas at Austin), the smoothed predicted probability of attracting a consulting firm reaches .186. To attend a university in the East with an equivalent probability, a student must choose a university with $p \geq .56$ (Tufts University).[36]

Robustness

Estimation using probit and logit yields results for consulting firms that are smaller in magnitude and statistical significance. However, the magnitudes still suggest non-trivial negative effects of a worse regional rank (Appendix Table A7). Using Bureau of Economic Analysis (OBE) regions, there are more observations for which the university and the closest firm office are in different regions, and thus dropped from the analysis. The data, and common sense, suggest these observations should be classified as the same labor market, highlighting the benefit of the community detection algorithm.[37] In addition to being a smaller sample, it is also likely biased due to excluded observations. The results show large effects of regional rank for the least selective universities, though smaller effects for the median university (Appendix Table A9). While the regional rank coefficients are jointly significant, combinations at the 25th and 50th percentile of p are not statistically significant.

[36] This is the minimum p associated with a smoothed predicted probability of attracting a consulting firm within .005 of .186.

[37] For example, Chicago is the closest office of many firms to Washington University in St. Louis. While Missouri and Illinois are in the same community detection region (the Midwest), the OBE region for Missouri is the Plains and for Illinois is the Great Lakes. Many Chicago firms recruit at Washington University in St. Louis and it seems very reasonable that they should be in the same region.

While I control for many measures of university quality, universities with worse regional rank may attract fewer firms due to unobservable differences. Based on the insight formalized in Altonji, Elder, and Taber (AET) (2005), I use selection on observables to learn about potential bias from selection on unobservables. I use the extension of this strategy for a linear model developed in Bellows and Miguel (2009).[38] Given these tests assume no treatment heterogeneity (see AET 2002, 2008 for a discussion), I estimate a specification with regional rank not interacted with p. I restrict the regression to universities with p in the interquartile range, where the relation between regional rank and p is more constant.[39] I use only consulting firms since results were strongest for this sample.

As derived in Bellows and Miguel (2009), selection on unobservables relative to observables needed to explain away the effect is $\frac{\widehat{\gamma}^F}{(\widehat{\gamma}^R - \widehat{\gamma}^F)}$, where $\widehat{\gamma}^F$ is the coefficient on *RegRank* when including all controls and $\widehat{\gamma}^R$ is the coefficient when including limited controls (p, number of high-scoring students and number relative to the region, number of offices in the region, and firm-university distance).[40] The coefficient on *RegRank* in the full regression is -.049, slightly smaller than in the restricted regression (-.051) (Appendix Table A5). If the entire effect was due to unobservable differences, selection on unobservables must be at least 18.84 times larger than selection on observables. This seems unlikely given the richness of the controls in the full regression.[41]

7 Regional Rank and Post-College Earnings

I test the model's wage predictions using the US Department of Education's Baccalaureate and Beyond Survey, 2009 (B&B: 09). The B&B: 09 surveys approximately 15,050 college seniors in the 2007-2008 academic year, who are surveyed again in 2009 after receiving their Bachelor's degree. I merge the IPEDS university data with the

[38] The strategy is also implemented and further described in Nunn and Wantchekon (2011).

[39] I use the interquartile range for the sample restricted to consulting recruiting: $p = .06$ to $p = .27$. Intuition also suggests no effect for the least and most selective universities.

[40] These limited controls were chosen to ensure implementation of the identification strategy: comparing recruiting at universities of equal quality, controlling for number of firms in the region and firm-university distance. Including percent, number, and number of high-scoring students relative to the region separates screening cost effects from supply effects.

[41] AET (2005) obtain a ratio of 3.55, ratios in Bellows and Miguel (2009) range from 5 to 17, and the median ratio in Nunn and Wantchekon (2011) is 4.1.

B&B: 09 using the IPEDS ID of the student's Bachelor's degree institution.[42]

I calculate university rank using the 25th and 75th percentiles of the Math SAT and ACT scores of entering students. Assuming scores are distributed normally, I obtain the mean and standard deviation of each score distribution at each university. Using the normal CDF, and weighting by the percent of students reporting each exam, I calculate p, the percent at each university scoring above 700 on the Math SAT or above 30 on the Math ACT.

I limit the sample to graduates of universities nationally ranked 400 or better (based on p), who were 25 or younger at degree attainment, working one job, for at least 35 hours per week, and never enrolled full time in graduate school after the bachelor's degree. Among this sample, I only include individuals with adjusted earnings (defined below) at or above the 5th percentile (approximately \$17,630). The model predicts fewer elite finance and consulting firms at worse regionally-ranked universities. As a result, high-type students on those campuses are more likely to work at other firms, occupations, or industries, which pay lower wages. To capture this, I include individuals in all occupations and industries. The appendix presents summary statistics.

The model predicts high test score students are hurt most by attending a worse regionally-ranked university, since they could be hired by elite firms. This should be more pronounced at less selective universities, where regional rank is much worse in the East. I interact the student's SAT (SAT) with regional rank and key explanatory variables (p, number of high-scoring students, and number divided by the region total).[43] I then estimate separate regressions for universities with $p \leq$75th percentile (approximately .17) and $p >$75th percentile.[44] I cluster standard errors by university and estimate :

$$\begin{aligned} LogEarnings_{isl} = {} & X_s\beta + Z_i\rho + \gamma_1 RegRank_s + \gamma_2 RegRank_s * SAT_i \\ & + \gamma_6 AvgWageBAGrad_l + \epsilon_{isl} \end{aligned} \tag{6}$$

LogEarnings are from 2009, calculated on an annual basis, for individual i, graduating from university s, living in state l. I adjust for earnings differences across states using 2006 US Bureau of Economic Analysis state price parities (Aten and D'Souza,

[42] I use IPEDS data for Freshmen in Fall 2004, as the sample graduates in Spring 2008.
[43] For robustness, I interact SAT and each university characteristic (Table 3, Column 7).
[44] Based on 2004 data, p for Texas A&M is about .12 and for Penn State is about .11.

2008).[45] Using the American Community Survey, I also control for average earnings of college graduates aged 25-34 in state l, adjusted using state price parities. X_s includes university quality measures.[46] Z_i includes demographics, SAT/ACT score, and interactions between SAT and the key variables listed above.[47] I do not include region fixed effects as these would eliminate the identifying across-region variation.

Results show graduating from a worse regionally-ranked university has a differentially negative effect on earnings for higher SAT students, holding constant university size and quality (Table 3, Column 1). For students scoring 1400 on the SAT, the coefficients suggest earnings are 8% lower if regional rank is worse by 50 places. Effects are much smaller for lower-scoring students. The regional rank coefficients are jointly significant at the 5% level.[48] Controlling for number of high-scoring students, and number relative to the region total helps to identify the effects are due to screening costs. As predicted, effects are larger for students at less selective universities (Column 2), and not significant at more selective universities (Column 3).

While I control for the student's SAT, and many measures of university quality, graduates of worse regionally-ranked universities may earn less due to unobservable differences. I again use the strategy based on AET (2005), and Bellows and Miguel (2009), to learn about potential bias from selection on unobservables. I first estimate the main specification with only the key explanatory variables, and magnitudes are largely unchanged (Column 4).[49] Second, because the strategy assumes no treatment heterogeneity I do not interact regional rank (and other variables) with student SAT. To capture the predicted effect among high SAT students at less selective universities,

[45] This was the closest year with price parity data.

[46] Proportion (p), and number of high math-scoring students at the university, and number divided by the region total, percent admitted, the 25th, 75th percentiles of the math, and combined SAT or composite ACT converted to SAT score (weighted by percent reporting each test), whether the university is public, offers more than a bachelor's, located in large or mid-sized city, 2008 USNWR rank, and in- and out-of-state tuition. I control for whether USNWR rank, urbanization, and tuition are nonmissing. See appendix for details.

[47] I include 2006 income (parental for dependents), SAT or composite ACT converted to SAT score, whether the student is black, asian, other race, hispanic, male, and whether a citizen and a dependent during the 2007/2008 academic year. I adjust 2006 income using the price parity for the 2007-2008 legal state of residence. Because price parities are for the US, I drop approximately 30 individuals whose 2007-2008, or 2009, residence was non-US. Approximately 30 students did not take a test; I control for whether score is nonmissing.

[48] These coefficients are similar, and jointly significant at the 10% level, when using sampling weights (normalized so the weight sum equals the number of observations).

[49] These are the regional rank variables, student SAT, p, number of high-type students, and number divided by region total, and interactions of these last three with student SAT.

I restrict to a more relevant sample: universities with $p \leq 90th$ percentile (approximately $p = .35$), and SAT at or above the 25th percentile (approximately 1040). Greater restrictions are problematic given the small sample.

The results suggest limited selection on observables. The coefficient on regional rank in the full regression is -.137 (column 5), and in the restricted regression is -.145 (column 6).[50] The ratio suggests that if the entire effect was due to unobservable differences, selection on unobservables would have to be at least 16.95 times larger than selection on observables. This seems unlikely given the richness of the controls in the full regression.

8 Alternative Mechanisms

Prestige, rather than screening costs, may explain the importance of regional rank when controlling for absolute quality. Local clients may prefer working with graduates of regionally-prestigious universities. Regional prestige may be important for local office culture. I use differences in personnel practices across consulting firms to test this mechanism. Consulting firms often use global- or local-staffing models. In global-staffing firms, consultants may be assigned cases far from their "home" office. For these firms, regional prestige should not matter for clients or office culture, since consultants work outside the region.[51] Thus, a worse regionally-ranked university should attract fewer of these firms only due to screening costs, controlling for number and proportion of high-type students at the university. I identify staffing policies based on job and travel descriptions on firms' websites.[52]

The results show a large effect of regional rank on recruiting for global-staffing firms (Column 3, Table 2), and the regional rank coefficients are jointly significant ($p = .033$). This suggests the importance of screening costs. While the regional rank coefficients are not jointly significant for local-staffing firms (Column 4), the magnitudes are fairly similar, though they are larger for higher p universities.

Better regionally-ranked universities may more likely offer undergraduate business

[50]The limited controls are p, number of high-scoring students, and number relative to the region, student's SAT, and whether they have SAT data. These were chosen to implement the identification strategy: comparing earnings of students with equivalent SAT and university quality. I include percent, number, and number of high-scoring students relative to the region to separate screening cost from supply mechanisms.

[51]Global-staffing firms may still recruit regionally since consultants return home by Friday.

[52]I confirmed this coding with an employee of one of the sample firms.

majors or MBAs, thus attracting finance and consulting firms.[53] Using data collected from university websites, I find these offerings do not explain the importance of regional rank (see appendix).

Recruiting may be driven by employee alma maters, and in this case likely exhibit hysteresis. Employees at elite firm offices outside the East are more likely to have attended less selective universities. If recruiting is driven by alma mater, they will recruit new employees who also attended less selective universities. However, there must be an explanation for why, in the first period, employees at elite firm offices outside the East attended less selective universities. This paper can be seen as explaining the first-period difference, which starts the path-dependent process.

9 Structural Estimation and Counterfactuals

The reduced-form analysis suggests strong support for the presence of screening costs and their predicted impact on recruiting and wages. In this section, I obtain structural estimates of the screening cost parameter, allowing me to analyze how a reduction in screening costs would impact students and firms. This is especially relevant given new technologies using machine learning to reduce employer screening costs. I make two minor adjustments so the model is more realistic and can better explain the data.

Adjustments to the model

In the model, firms care about the applicants per job, which is affected by the number of other jobs recruiting on that campus. Number of jobs may differ from number of offices because I only count offices for firms in my sample, and each office may hire for multiple jobs. Accounting for these factors, I assume the total number of jobs for which firms recruit in the region equals γ times the number of offices of sample firms in the region. Obtaining reasonable results requires a minimum number of firms. I estimate the model with various γ, and results do not change dramatically for $\gamma > 10$ (except in the Midwest).[54] I present results with $\gamma = 10$, yielding 2800 firms in the East, 1490 in the Midwest, 840 in the South, and 2350 in the West.

[53] While MBA and undergraduate recruiting are often conducted separately within a firm, recruiting both on the same campus may be beneficial.

[54] Appendix Table A11 shows parameter estimates for various γ.

Some students do not apply for finance and consulting jobs, implying the applicant pool is a fraction, λ, of the senior class (S). For simplicity, I assume this unknown λ is common to all schools, and obtain S from IPEDS. Including λ, profits are:

$$\pi = (1 - e^{-p_1 \lambda (\frac{S_1}{N_1})})(v - \frac{(\lambda S_1 (p_1 v - c)}{N_1 (e^{p_1 \lambda (\frac{S_1}{N_1})} - 1)} - \frac{c}{p_1}) \tag{7}$$

The unknown parameters c and v are not separately identified.[55] The productivity parameter, v, is normalized to 1. Put differently, I estimate $\frac{c}{v}$.

Estimation

Among universities with $p_t \geq p_{cutoff}$, for given c and λ there is a unique profit-equalizing allocation of firms across universities. As described, if R universities have $p_t \geq p_{cutoff}$, equilibrium is governed by $R-1$ profit equality conditions in $R-1$ unknowns (number of firms recruiting at each university) (see Equation (3)). I identify parameter estimates for c and λ by finding the values minimizing the difference between the predicted and observed proportion of firms recruiting at a university, using The Generalized Method of Moments (GMM).

My algorithm works as follows. For each guess of the parameters, I identify p_{cutoff}, the p of the university such that profit from being the only recruiting firm at that university equals profit firms receive from allocating across higher-p universities. I identify p_{cutoff} by starting with the lowest p_t such that $p_t \geq c$, since recruiting is unprofitable for $p_t < c$. I calculate the profit from being the only recruiting firm at this university ($v - \frac{c}{p_t}$, described above). I also find the profit firms receive from allocating (in a profit-equalizing manner) across all higher-p universities, using the conditions in (3), but including λ as in (7). As the profit-equalizing allocation is governed by a high-dimensional system of non-linear profit equality equations, solving is not trivial. I find the allocation of firms across universities minimizing the squared norm of the profit equality conditions.[56] I check the solution equalizes profits at all universities.[57]

If profit from recruiting at the higher p universities is greater than profit at the

[55] Doubling v and c doubles profits at each university in the profit equality conditions. This implies that the profit-equalizing values of N_t are the same for (v, c) and $(2v, 2c)$.

[56] I use an interior point algorithm and MATLAB's fmincon routine. I limit the number of function evaluations to 200,000 and the number of iterations to 50,000.

[57] I require that the squared norm of the profit equality equations is $\leq$ 1e-10.

lowest p, deviating to the lowest p is unprofitable and it is not the cut-off. I move to the next lowest p and employ the same routine. Once p_{cutoff} is identified for given c and λ, I find the profit-equalizing allocation of firms across universities with $p_t \geq p_{cutoff}$, using the routine described above.

I briefly discuss identification. I identify parameter estimates for c and λ using GMM. Moments include the difference between the predicted and observed proportion of firms recruiting at each university $(\frac{N_{t,Predicted}}{NTot_{Predicted}} - \frac{N_{t,Observed}}{NTot_{Observed}})$,[58] this error multiplied by p_t, and by $log(S_t)$.[59] This yields three moments for 2 unknown parameters. I estimate the model separately in each region. To find the parameter values minimizing the GMM objective function, I search over λ from .05 to .35 at intervals of .05, and over c from .01 to .2 at intervals of .01.[60]

The parameter c is identified by explaining firms' preference for universities with higher proportion, but identical number, of H-type students. Non-zero estimates of c reject a simple supply and demand story, which predicts firm allocation based only on the number of H-type students. The parameter λ is identified by explaining firms' preference for universities with larger number, but identical proportion, of H-type students. Consider two universities with equal proportion, but different number, of H-types. If the larger university does not attract many more firms, the proportion of students interested in the firms (λ) must be so low that the larger university does not appear much larger to firms.

The parameter v can be interpreted as the present discounted value of the worker's productivity over the match, and w as the present discounted value of the match to the worker. The per-applicant screening cost is about 10% of worker productivity, though lower in the Midwest (Panel A, Table 4). While parameter estimates in the Midwest change when increasing γ from $\gamma = 10$, they do not dramatically change when increasing γ from $\gamma = 15$, when (c, λ) are $(.07, .3)$.[61] Higher profit in the East than West is consistent with a higher p required in the East, than West, to guarantee

[58] $NTot_{Predicted} = \gamma * TotalFirmOffices$ and $NTot_{Observed} = \sum_{t=1}^{T} N_{t,Observed}$

[59] Given that p_t and $log(S_t)$ are exogenous to this error, they can be interacted with the error to yield additional moment restrictions as in Berry, Levinsohn, and Pakes (1995).

[60] I check the solution is not at one of the grid bounds, and that the objective function is smooth around the solution. For example, for given c, the objective function is decreasing in λ until the solution, and increasing in λ afterwards.

[61] Estimates of c are relatively similar, yet λ estimates are higher, when $\gamma = 15$ (Appendix Table A11). With few firms (low γ), recruiting at high-p universities with few high-type students is difficult to explain. This may yield a low λ, so smaller universities do not appear smaller to firms.

at least one recruiting firm (see appendix). With per-applicant screening costs equal to 9% of worker productivity v in the East, $p_{cutoff} \approx .14$. There are 85 universities in the East with $p < p_{cutoff}$ and 83 with $p \geq p_{cutoff}$.

To measure the model's fit, I compare the predicted and observed distributions of the proportion of firms recruiting at the university. The model fits the data reasonably well in each region (Appendix Figure A1).

Impact of Search Frictions on Student Outcomes

Few papers have quantified the impact of search frictions on wages.[62] Structural estimation allows me to identify the impact of reducing screening costs on recruiting and wages.

Screening costs have a very negative impact on high-type students at less selective universities (Panel B, Table 4). A wage of zero can be understood as the reservation wage, for example the wage at a firm outside finance and consulting. Analogously, v can be understood as the additional productivity of a high type at a finance or consulting firm relative to other industries. With per-applicant screening costs that are 9% of worker productivity v, elite finance and consulting firms do not recruit at the University of New Hampshire, where 5% of students have math scores in the highest range. As a result, students receive the reservation wage. However, when it is costless to identify high types, this university attracts these firms and high types earn the reservation wage plus 37% of the additional worker productivity (v) at these firms.

With per-applicant screening costs that are 9% of productivity v, Fordham University attracts few firms, since the percent of high-type students (14%) is just above p_{cutoff}. The wage is the reservation wage plus 2% of the additional worker productivity at these firms. Without screening costs, the number of recruiting firms increases from 6 to over 14. This creates upward pressure on wages for high-type students, now the reservation wage plus 37% of worker productivity at these firms.

With per-applicant screening costs that are 9% of productivity v, over 2.5% of firms recruit at Massachusetts Institute of Technology (MIT), which has the highest

[62] van den Berg and van Vuuren (2010) find search frictions have a small negative effect on the mean wage. While that paper estimates an indicator of search frictions (mean number of job offers in employment before an involuntary job loss), I estimate the search friction itself (screening cost) through structural estimation.

p in the East (.86).[63] The many competing firms at MIT creates upward pressure on wages, yielding high-type student wages equal to the reservation wage plus 45% of the additional worker productivity at these firms. Without screening costs firms recruit more heavily at less selective universities, reducing the number of firms at MIT from 72 to 51, and the wage to the reservation wage plus 37% of the additional productivity at these firms.

When the cost per applicant reviewed goes from .09 to 0, firm profits increase from .32 to .53, relative to worker productivity (v) of 1.

Cost per Hired Worker

I now calculate screening cost per hire by multiplying expected number of applicants reviewed (eq. (1)) by screening cost per applicant (.09 in the East). At less selective universities, firms on average review more applicants, so cost per hire is greater. Expected number of applicants reviewed at MIT (p=.86) is .77, and so screening cost per hire is about 7% of the productivity of one worker (v). Expected number of applicants reviewed at Fordham (p=.14) is about 3.2, and so screening cost per hire is about 29% of one worker's productivity (v). If the present discounted value of the additional productivity in finance/consulting over the course of the match (v) is $50,000 (reasonable if the match is five years), this is approximately $14,500. Differences in cost per hire are equilibrated through the wage and number of H-type applicants. Firms paying more in screening costs have more H-type applicants in their pool and pay lower wages. These high estimated costs are consistent with screening conducted by consultants with high external billing rates.[64]

10 Discussion and Conclusion

This paper analyzes labor market matching in the presence of search and informational frictions, through studying the immensely prevalent, though largely unexplored,

[63] Despite being the most selective university in the East, MIT is surrounded by many selective universities. As a result, even with screening costs, it attracts 2.5% of the firms.

[64] For a government contract, McKinsey charged approximately $164,000 per week for one engagement manager, three non-partner consultants, and guidance from senior leaders (Hill 2011). Assuming 60 hours per week for four consultants, this yields a very rough approximation of nearly $700 per hour as an average hourly rate. Very anecdotal evidence, based on a conversation with a former management consultant, suggested the cost per MBA student hire is approximately $100,000, and only slightly lower for undergraduates.

phenomenon of on-campus recruiting. I incorporate relevant search frictions into a directed search model of the campus recruiting market, and present reduced-form and structural evidence that search frictions exist in this market, and have important impacts on where and how firms recruit workers.

Using a newly collected dataset of target campuses for 39 finance and consulting firms, along with the Baccalaureate and Beyond survey, I find strong support for the model's main prediction. With screening costs, recruiting decisions and graduates' wages are driven not just by university size and selectivity, but by the university's selectivity relative to others in the region. These results suggest the benefits of attending the best university in a small pond. Structural estimation and counterfactual exercises show screening costs are large, and significantly impact high test-score students at less selective universities.

The results highlight possible equity and efficiency consequences of elite universities. With elite universities, students at non-elite universities have reduced access to prestigious firms (if firms would choose differently than an elite university). Thus, elite universities may obstruct equal access to firms for students equally likely to be hired by those firms. If initial jobs affect career paths, equity effects are amplified. However, by incurring screening costs, and reducing these costs for firms, elite universities may increase efficiency.[65]

The results imply limited geographic mobility of recent graduates. I find high SAT score students earn 9% less at universities of equal size and selectivity, but worse regional rank by 50 places. This may reflect the value of attending college, and living in, the Northeast.

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Figure 1a: Bain Recruiting Page for Texas A&M

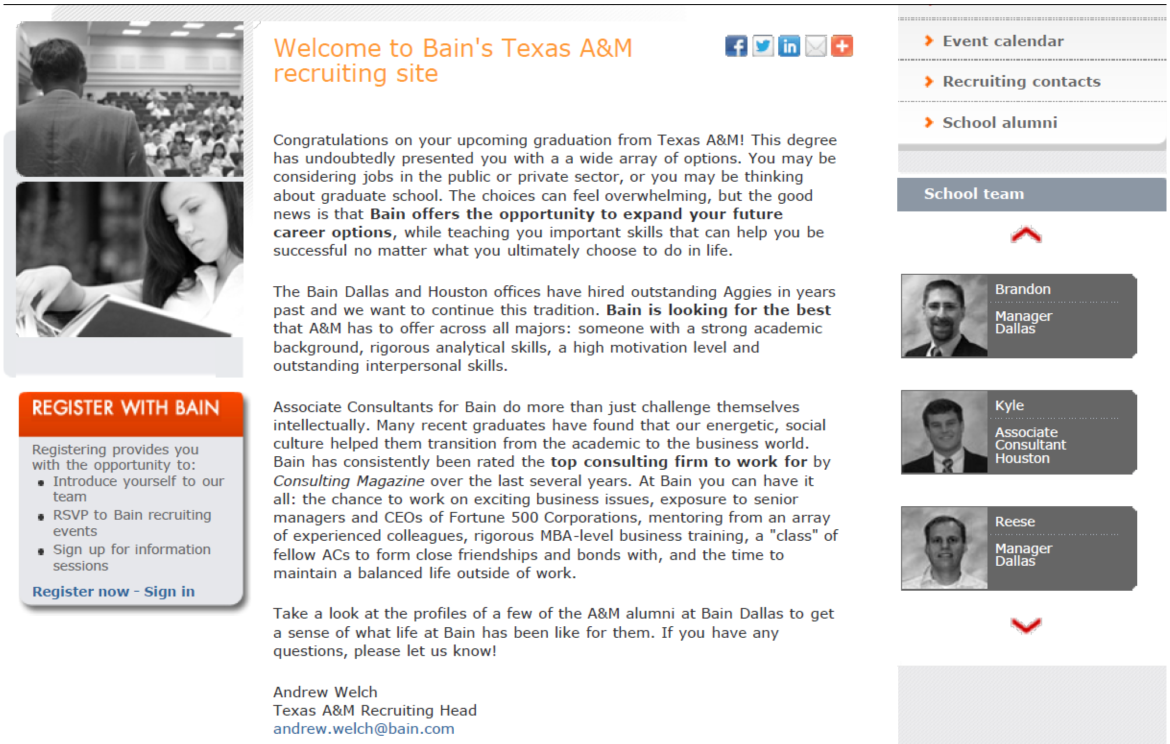


Figure 1b: Bain Recruiting Page for Penn State

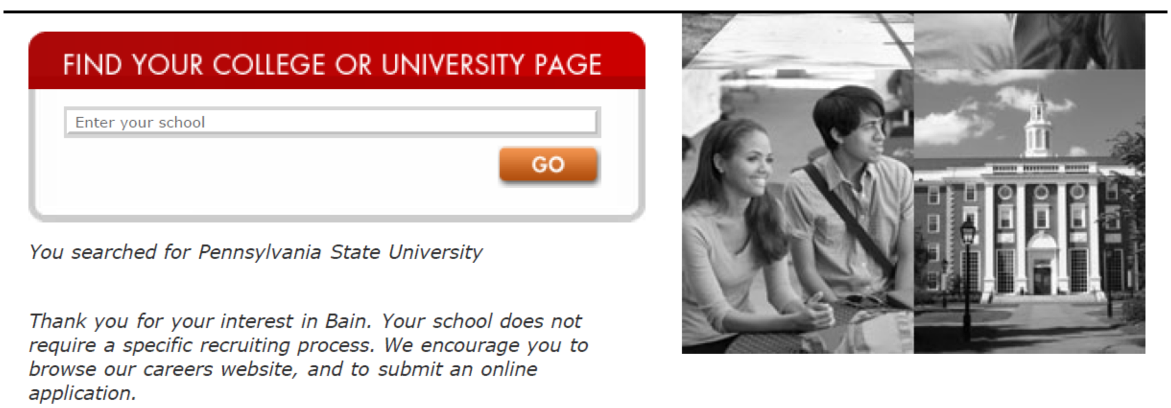
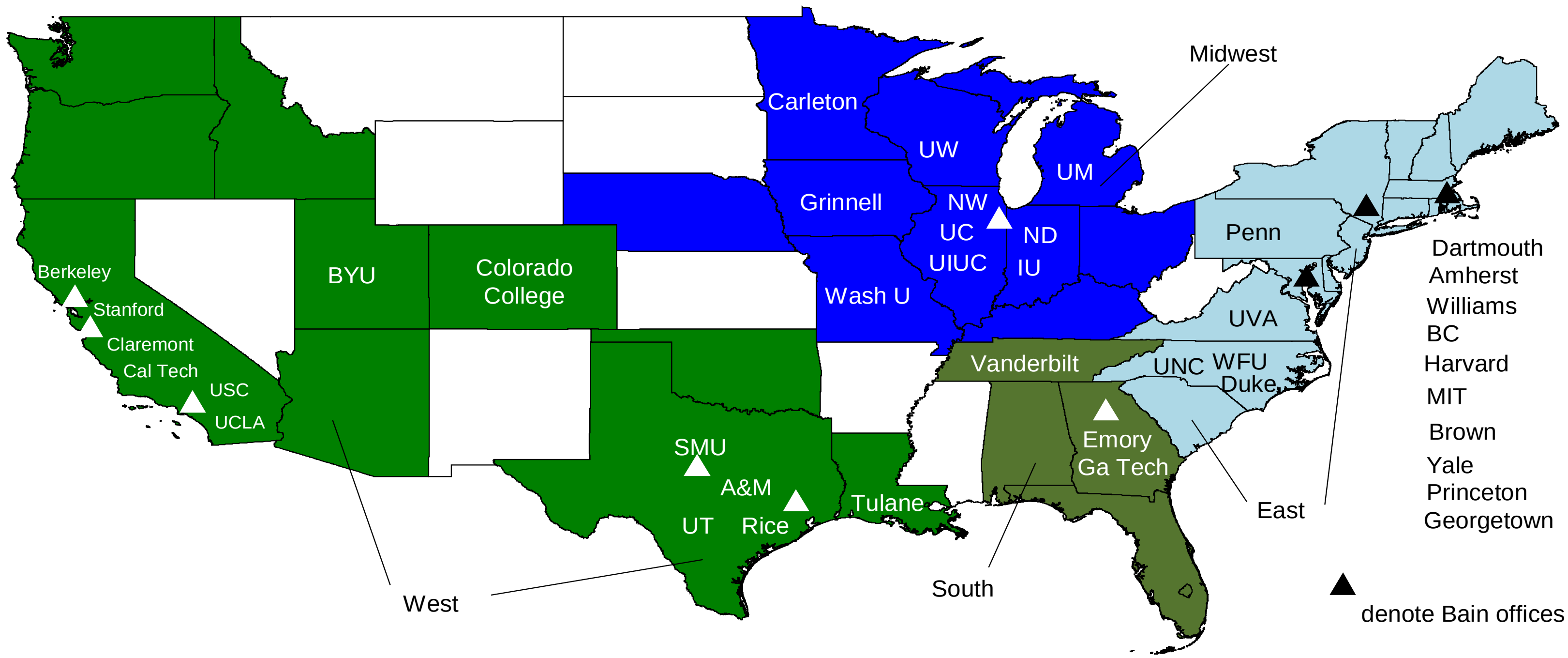


Figure 2: Where does Bain Recruit?



Note: White states are each in their own region. Universities in those states had no recruiting firms, or the only recruiting firms were from the same state and those offices did not recruit in other states.

Figure 3: Differences in Regional Rank for a Given University Selectivity

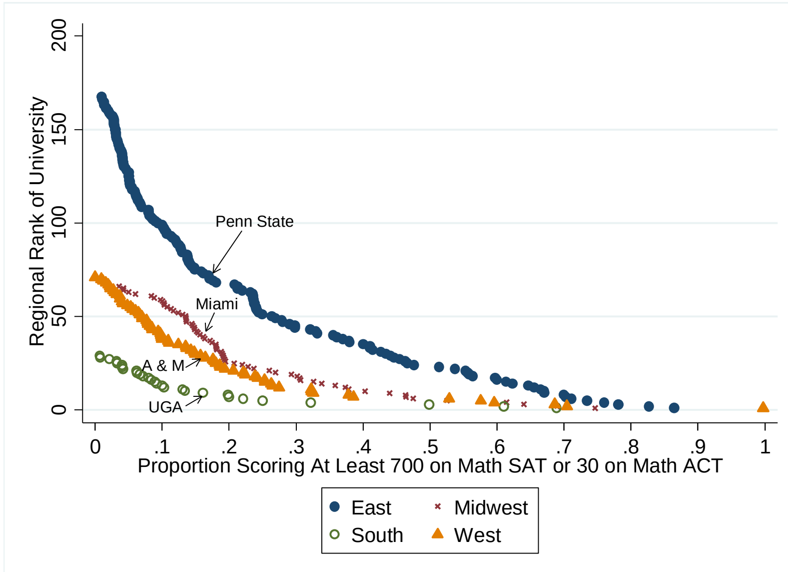


Figure 4: Recruiting at the University Attracting the Most Firms, by University Selectivity Bin and Region

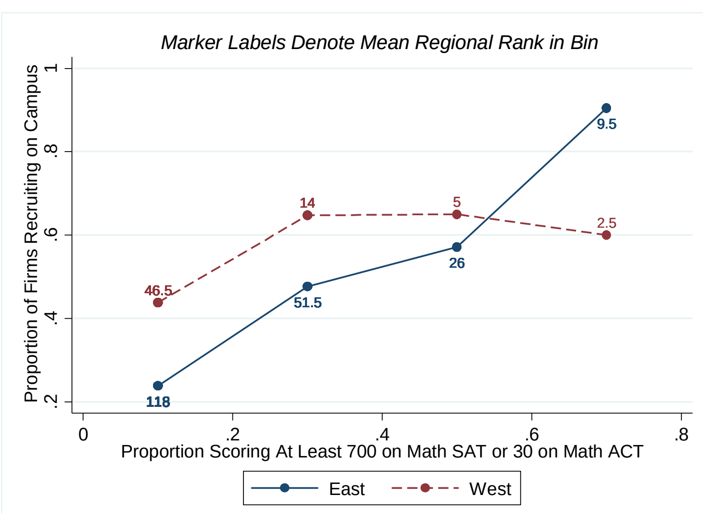
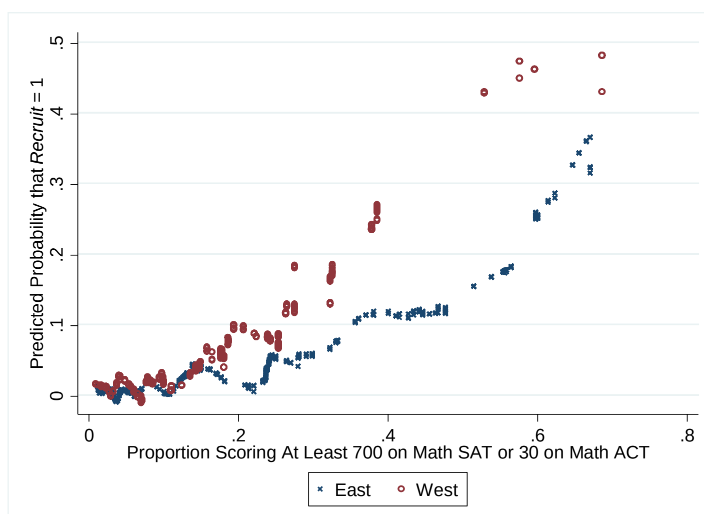


Figure 5: Lowess Predicted Probability of Recruiting on University Selectivity



Note: In Figure 4, I show four university selectivity bins: Proportion of students scoring at least 700 on the Math SAT or 30 on the Math ACT ϵ [0,.2), [.2,.4), [.4,.6), [.6,.8). The bin from [.8,1) is omitted from the plot because it only contains one university from the West (California Institute of Technology) and two from the East (MIT and Franklin Olin College of Engineering). As is evident from the mean regional ranks (denoted by marker labels), the sample size of the bins [.4,.6) and [.6,.8) in the West is also small. In Figure 5, the predicted probability that *Recruit*=1 is obtained from the regression allowing for heterogeneity across industry (Column 2 of Table 2). I estimate a lowess regression of these predicted values on p for consulting firms (bandwidth .1), and plot the lowess fitted values.

Table 1: Summary Statistics by Region

Panel A: Number of Firms

	East	Midwest	South	West
# Consulting Firms	21	19	13	20
# Banking Firms	17	13	10	16
Total Firms	38	32	23	36
# Consulting Firm Offices	152	94	40	141
# Banking Firm Offices	128	55	44	94
Total Firm Offices	280	149	84	235
Number of Universities	168	67	29	71

Panel B: National Rank of Top 5 Regionally-Ranked Universities

	National Rank			
Regional Rank	East	Midwest	South	West
1	2	6	13	1
2	3	12	24	9
3	4	20	37	14
4	5	22	72	27
5	7	35	92	28

Panel C: Post-College Geographic Mobility

	Residence After Graduation (2009)			
	East	Midwest	South	West
University in:				
East	0.85	0.04	0.02	0.07
Midwest	0.07	0.82	0.02	0.07
South	0.09	0.05	0.77	0.08
West	0.05	0.03	0.02	0.88

Note: See paper and online appendix for details on sample construction and variable definitions. In Panel A, number of firms denotes the number of firms with at least one office in the region. There are 39 firms in the dataset. Since "Total Firms" in the East is 38, of the 39 firms in my dataset, 38 have at least one office in the East. Number of firm offices denotes the total number of offices, across all firms, in the region. Number of universities denotes the number of universities in the sample. Panel C presents the share of individuals in the sample living in the same region as their university, using the Baccalaureate and Beyond 2009 survey. Row totals do not add to 1 because of students moving to one of the states in its own region (white states in Figure 2).

Table 2: Effect of Regional Rank on Firm Recruiting Decisions

Dependent Variable: Recruit	(1)	(2)	(3)	(4)
Regional Rank (hundreds)	-0.038***	-0.039***	-0.035**	-0.021
	[0.012]	[0.015]	[0.015]	[0.017]
Regional Rank (hundreds) *p	0.187	0.633***	0.099	-0.132
	[0.185]	[0.205]	[0.282]	[0.233]
Regional Rank (hundreds) *Consult		0.001		
		[0.012]		
Regional Rank (hundreds) *p *Consult		-0.778***		
		[0.179]		
P-value, Joint Test of Coefficients on Regional Rank	0.004	0.000	0.033	0.408
Linear Combination of Coefficients on Regional Rank				
	All Firms	Consulting	Global	Local
Universities with p = .06				
Texas	-0.015	-0.026***	-0.017	-0.016
(Regional Rank 56)	[.01]	[.01]	[.014]	[.013]
East	-0.033	-0.056***	-0.035	-0.035
(Regional Rank 120)	[.02]	[.021]	[.03]	[.027]
Universities with p = .14				
Texas	-0.004	-0.019*	-0.007	-0.013
(Regional Rank 32.5)	[.009]	[.01]	[.015]	[.012]
East	-0.011	-0.048*	-0.018	-0.032
(Regional Rank 82)	[.024]	[.026]	[.037]	[.031]
Firms	All	All	Global	Local
N	10,730	10,730	1,958	4,090
Mean(Recruit)	0.062	0.062	0.031	0.074

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See text and online appendix for details on variable and sample construction, and a full list of variables in the regressions. Regressions include firm fixed effects; standard errors are clustered at the university level. States comprising each region are listed in the online appendix. All columns include interactions between key explanatory variables and p ; column 2 includes triple interactions between key explanatory variables, p , and an indicator for consulting firm (as well as the necessary two-term interactions). Key explanatory variables include p , number of high-scoring students, and number of high-scoring students divided by the region total of this variable.

Table 3: Effect of Regional Rank on Earnings After Graduation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Regional Rank (hundreds)	0.189	0.152	-0.012	0.224*	-0.137**	-0.145***	0.147
	[0.128]	[0.165]	[0.924]	[0.132]	[0.060]	[0.052]	[0.180]
Regional Rank (hundreds)*SAT	-0.025**	-0.024	-0.012	-0.028**			-0.022
	[0.012]	[0.016]	[0.070]	[0.012]			[0.017]
SAT Score (hundreds)	0.041***	0.043*	0.031	0.047***	0.020**	0.024**	
	[0.010]	[0.024]	[0.032]	[0.011]	[0.009]	[0.010]	
Linear Combination of Regional Rank Coefficients for:							
1400 SAT	-0.162***	-0.183**	-0.185	-0.17***			-0.16**
	[.062]	[.085]	[.192]	[.057]			[.072]
1000 SAT	-0.062	-0.088*	-0.136	-0.057			-0.072
	[.045]	[.05]	[.273]	[.04]			[.044]
P-value on Joint Test of Regional Rank Coefficients	0.031	0.092	0.617	0.013			0.066
Universities	All	Less Selective	More Selective	All	SAT ≥ 25th percentile (1040) $p \leq$ 90th percentile (.35)		All
Full Set of Student and University Controls	Y	Y	Y	N	Y	N	Y
Interactions of University Controls, student SAT	Key	Key	Key	Key	None	None	All
N	2120	1600	520	2120	1380	1380	2120
R-squared	0.168	0.154	0.246	0.085	0.161	0.073	0.180

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level. The dependent variable is the natural log of the respondent's earnings in 2009, adjusted for state price parity based on the state of residence in 2009. Sample excludes those with earnings below the 5th percentile, adjusted for state price parities ($17,630). Key interactions include those between SAT score and the following variables: proportion of high-scoring students, number of high-scoring students, and number of high-scoring students divided by the region total of this variable. Less selective universities in column 2 include those with $p \leq$ 75th percentile (.17), and more selective universities in column 3 include those with $p >$ 75th percentile. Sample sizes are rounded to the nearest ten to preserve confidentiality. See text and online appendix for list of explanatory variables, region definitions and details on variable and sample construction.

Table 4: Structural Estimation Results

Panel A: Parameter Estimates

	East	Midwest	South	West
c	0.09	0.03	0.1	0.12
λ	0.1	0.3	0.25	0.15
Profit	0.32	0.84	0.38	0.22
Number of Firms	2800	1490	840	2350

Note: The cost of screening an applicant is denoted by c, the proportion of students interested in working at these firms is denoted by λ, and profit denotes the equilibrium profit every firm receives from recruiting at a university in the region. Profit and parameter estimates for c are relative to student productivity of 1. See text for detailed explanation of the estimation.

Panel B: Counterfactual Exercise-Zero Screening Costs

University	p	c (Screening cost)	% of Firms	# Firms	Wage	H-type Applicants per Firm	Students' Expected Income
University of New Hampshire	0.05	0.09	0.00%	0.00	0.00	N/A	0.00
		0	0.12%	3.22	0.37	1.76	0.01
Fordham University	0.14	0.09	0.22%	6.08	0.02	4.20	0.0007
		0	0.52%	14.48	0.37	1.76	0.02
MIT	0.86	0.09	2.58%	72.27	0.45	1.25	0.22
		0	1.84%	51.38	0.37	1.76	0.15

Note: This table presents the results from counterfactually setting the cost of screening an applicant to zero, from .09 (the estimated value in the East). See text for details. The variable p denotes the proportion of students scoring at least a 700 on the Math SAT or 30 on the Math ACT. The variable c denotes the cost of screening an applicant, and this is relative to worker productivity of 1. Wage and expected income are also relative to worker productivity of 1. A wage of zero can be understood as the reservation wage.

Appendix Table 1: Firms in Dataset, Listed in Order of Firm Rank Within Industry

	Banking Firms	**Consulting Firms**	
4	JP Morgan Investment Bank	McKinsey	1
6	Credit Suisse	Boston Consulting Group	2
8	Barclays Investment Banking	Bain	3
11	Evercore	Booz and Company	4
13	Perella Weinberg	Mercer	6
14	Jefferies	Monitor	7
20	Deloitte Corporate Finance	Oliver Wyman	10
22	Royal Bank of Scotland	AT Kearney	11
31	Piper Jaffray	Parthenon	16
32	BNY Mellon	Towers Watson	17
41	Miller Buckfire	Navigant	19
46	Gleacher	ZS Associates	21
48	Susquehanna	NERA	24
		Huron	27
	Investment Management Firms	Aon Hewitt	32
8	The D. E. Shaw Group	Cornerstone	34
9	Wellington Management	Cambridge Group	35
13	Fidelity	Charles River Associates	36
19	Vanguard	Corporate Executive Board	38
		Advisory Board	39
		Analysis Group	40
		First Manhattan Group	43

Note: Firm ranking is based on Vault rankings, as discussed in the paper.

Employer Screening Costs, Recruiting Strategies, and Labor Market Outcomes: An Equilibrium Analysis of On-Campus Recruiting
Appendix: For Online Publication

Russell Weinstein*

July 19, 2017

1 Data

1.1 Sources

I identify elite finance and consulting firms using the *Vault* industry rankings, obtained from www.vault.com. Vault, a career resources company, publishes annual rankings of the top 50 firms by prestige for various industries. These rankings are calculated by surveying individuals currently working in the industry; individuals cannot rank their own firm.

I obtain data on university characteristics from several datasets, including Integrated Postsecondary Education Data System (IPEDS) and the Common Data Set. IPEDS is a public-use dataset offered by the US Department of Education, with detailed university-level characteristics. The Common Data Set is an annual collaboration between universities and publishers (as represented by The College Board, Peterson's, and US News and World Report). While there is no centralized dataset, many universities publicize on their websites their responses to the Common Data Set questionnaire. I collect the following Common Dataset variables from individual university websites: the percentage of enrolled Freshman who scored [700,800] on the SAT Math and Verbal, [30,36] on the ACT Math and English, the percentage in the

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top 10% of their High School class, the percentage reporting SAT scores and the percentage reporting ACT scores.

Variables obtained from IPEDS include: 25th and 75th percentile SAT and ACT scores, percent reporting SAT and ACT, percent of applicants admitted, enrollment, in- and out-of-state tuition, whether located in a large or a medium-sized city, whether it is a public institution, and whether the university offers more than a Bachelor's degree.

Some universities report SAT percentiles for the Fall, 2008 entering class in the year 2008, and others report these data in 2009. IPEDS contains a variable clarifying which entering class the data pertain to. For the universities that do not report this variable, it is assumed that the 2008 data are reported in 2008, as this is true for the majority of universities. While finance recruiting data pertain to seniors in Spring 2013, I use university characteristics from 2008 not 2009. This is not of great concern given that university characteristics are not expected to change dramatically over one year, and employers may use multi-year averages to evaluate selectivity.

1.2 Data Construction

Calculating p

I do not observe the percent of students scoring in both the highest math and verbal ranges. High-type students are defined by math scores because of the quantitative skills required in finance and consulting. The proportion of high-type students is assumed to be the percentage of students in the incoming class who scored $[700, 800]$ on the SAT math or $[30, 36]$ on the ACT math. These represent the highest ranges of each exam. If each student only reported the SAT or the ACT then the proportion of high-type students, p, would be obtained by averaging the percent of students in the highest SAT range and the percent of students in the highest ACT range. This average would be weighted by the percentage of students reporting each exam. However, some students report both the SAT and ACT, and so the percent reporting SAT and percent reporting ACT does not sum to one. Assuming that those who submit both exams have randomly distributed scores, the denominator in the proportion reporting each exam is instead the sum of the percent reporting SAT and percent reporting

ACT. Specifically,

$$p = SATweight * (\%in[700, 800]_{MathSAT}) + ACTweight * (\%in[30, 36]_{MathACT}) \quad (1)$$

$$SATweight = \frac{\%ReportSAT}{\%ReportSAT + \%ReportACT} \quad (2)$$

$$ACTweight = \frac{\%ReportACT}{\%ReportSAT + \%ReportACT} \quad (3)$$

For universities that have these data from the Common Data Set, p is calculated in this way for the recruiting regressions. However, not all universities had their 2008-2009 Common Data Set publicly available, and even for those which did, some did not report these variables. Many of these universities do report the 25th and 75th percentiles of the test scores in IPEDS. For these universities, it is possible to predict the percent of students falling in the test score range, using their data on test score percentiles. The prediction is calculated using the sample of individuals with both the Common Data Set, and the 25th and 75th percentiles of the test scores, separately for the SAT and ACT, and follows Papke and Wooldridge (1996). While a number of specifications including higher level terms of the test score percentiles were examined, the only specification yielding monotonic results was the linear specification. In other specifications, higher score percentiles sometimes predicted lower values of p.

The predicted percentage falling in the highest range of each exam is then averaged, weighted by the proportion reporting each exam (which here is taken from the IPEDS data since these universities only had IPEDS score data). If the university only reported SAT percentiles and not ACT percentiles, just the SAT data was used to calculate p rather than discarding the observation, similarly for those with only ACT scores. I construct the regional rank of universities based on p. Universities with the same value of p are given their average rank, preserving the sum of the ranks.

SAT and ACT Percentiles

The explanatory variables include the 25th and 75th test score percentiles. Using Dorans (1999), I convert the 25th and 75th percentiles of the ACT Math distribution to SAT Math scores. If the university reports both ACT and SAT Math scores, then I weight each percentile by the percent of students reporting each exam using the weights in (2) and (3). Using College Board (2009), I convert 25th and 75th percentiles of the ACT Composite scores to the sum of the SAT Math and Verbal scores. If the university reports both the ACT Composite scores and SAT Math and Verbal scores I weight each percentile by the percent reporting each test using (2) and (3).

Community Detection Algorithm

Community detection, which has its roots in physics, has been used to study various kinds of networks, from the internet to social networks. These networks are understood to consist of individual nodes, and possible links between the nodes. One area of interest in the study of these networks is identifying communities, groups of nodes that have many links between them and few links outside of them. This is often referred to as the "community structure" of the network. Applying this to firm recruiting, there are certain underlying communities of firms and universities. These communities are characterized by firms that are very likely to recruit at universities in the community, and not outside the community (Newman 2004). The objective is to find those communities and treat them as separate labor markets in the empirical section of the paper.

The algorithm used in this paper is one developed by Newman (Newman 2004) to detect communities in large networks in reasonable time. The Newman algorithm gives similar results as previous algorithms that are intractable for networks with more than 20 or 30 nodes. The algorithm develops a metric for testing whether a particular community division is meaningful, and optimizes that metric over all possible divisions. The metric measures the difference in the number of within-community links for a particular community division, relative to the number of within-community links that would be expected just due to random chance. Specifically, the algorithm starts with each node as the sole member of a community, and then joins communities in pairs always choosing the join that results in the greatest increase (or smallest decrease) in the metric.

The network in this paper has 51 nodes, one for each state and Washington, DC. The links between state A and state B are defined as the number of firms in state A that recruit at a university in state B, or vice versa. The algorithm defines the communities such that there are many recruiting relationships within communities and few across communities. The division that yields the highest value of the metric results in four large communities, and several communities with just one state. The metric value of .8951 represents significant community structure, as values above .3 appear to indicate significant community structure in practice (Newman 2004). The large divisions are the East, Midwest, South, and West. For seven universities, the closest office of every firm was not in their region. Excluding these leaves 342 universities in the dataset.

The East is comprised of Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania, Delaware, Maryland, Washington, DC, Virginia, North Carolina, and South Carolina; the Midwest is comprised of Ohio, Kentucky, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Iowa, Missouri, Nebraska; the South is comprised of Tennessee, Georgia, Florida, Alabama; and the West is comprised of Louisiana, Texas, Oklahoma, Arizona, Colorado, Utah, California, Oregon, Washington, Idaho.

The remaining states were all in their own markets, either because the universities in those states had no recruiting firms, or the only recruiting firms were from the same state and those offices did not recruit in any other state. The states in the latter category were Kansas and New Mexico. Firms recruited at University of Kansas and University of New Mexico, with their closest offices being Kansas City, Kansas and Albuquerque, New Mexico respectively. These offices were not the closest firm offices to any other university, in a different state, where the firm recruited.

Other divisions also yielded metrics with large values. The second highest metric value was .8946, and was the same as the optimal division, but combined the South and the West above. The third highest had a value of .8941 and was the same as the optimal metric but separated the West into two different communities: South-Central West (Louisiana, Texas, Oklahoma, Colorado); and Far West (Arizona, Utah, California, Oregon, Washington, Idaho).

I conduct the analysis using the regions defined by the Bureau of Economic Analysis (OBE regions) for robustness, combining New England and the Mideast. The results are in Appendix Table A9. The eight OBE regions are defined as follows: New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut), Mideast (New York, New Jersey, Pennsylvania, Delaware, Maryland, and Washington DC), Southeast (West Virginia, Virginia, Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Alabama, Mississippi, Arkansas, Louisiana, and Florida), Great Lakes (Wisconsin, Michigan, Illinois, Indiana, and

Ohio), Plains (North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri), Southwest (Arizona, New Mexico, Oklahoma, and Texas), Rocky Mountain (Montana, Idaho, Wyoming, Utah, Colorado), and the Far West (Washington, Oregon, California, Nevada, Alaska, and Hawaii).

The Claremont Colleges

The Claremont Colleges (Claremont McKenna, Harvey Mudd, Pitzer, Pomona, and Scripps) have a joint on-campus recruiting program in which nearly every recruiting firm participates. While a firm may opt out of recruiting at all five colleges, and only recruit at one of the five, conversations with the career services staff at the Claremont Colleges confirmed that this is very unusual. In the data, I treat the five colleges as one, the Claremont Colleges. If a firm recruits at just one of the colleges, I treat it as recruiting at the Claremont Colleges as a whole. The explanatory variables for the Claremont Colleges are constructed by taking the average across all of the universities, weighted by the university populations. Since Pitzer does not report SAT scores, it is assumed that the number of students with high test scores at Pitzer is equal to the average at the four other colleges.

Calculating Distance Between Firms and Universities

Latitude and longitude of universities and firm offices are collected in order to calculate distance between firms and universities. The zip code of each university was obtained from IPEDS, and this was used to match the recruiting dataset to the Census Gazetteer. The Census Gazetteer contains the latitude and longitude at the level of the ZCTA, the most common zip code in a census block. Most of the university zip codes are able to be matched to the ZCTA. For the universities with zip codes that did not match a ZCTA, the latitude and longitude of the city in which the university is located was identified using the Census Gazeteer (The Census Gazetteer contains latitude and longitude at the ZCTA level, and also at the city level). Latitude and longitude were also obtained for each office location (city) of each firm. I compute the length of the great circle arcs connecting each university and each office location for a given firm, located on the surface of a sphere. The arc length, measured in degrees, is then converted to statute miles as measured along a great circle on a sphere with radius 6371 kilometers, the mean radius of the earth. These calculations are performed using the *arclen* and *deg2sm* commands in MATLAB. I then identify the office location with the smallest distance to the university.

1.3 Summary Statistics

Appendix Table A1 provides descriptive evidence that recruiting strategies vary across region. The table compares the characteristics of universities with at least one recruiting firm.[1] Each observation in this table is a university, and the observations are weighted by the number of firms recruiting at the university.[2] Firms recruit at more selective universities in the East than in the other regions. Target universities in the East are also in general smaller, less likely to be public, and less likely to be in large cities. Target universities in the East also charge higher tuition. For many of these variables, the F-test rejects at the .05 level that the averages in the Midwest, South, and West are the same as those in the East.[3]

2 Additional Specifications and Robustness

2.1 Within Region Predictions: Recruiting

Empirical Specification

Proposition 1 relates recruiting outcomes to the proportion of high-type students at the university (p): expected number of applicants per firm decreases in p, expected number of high-type applicants per firm decreases in p, and wage increases in p. While the number of applicants per firm at each university is not known, I am able to calculate the number of students per firm (in my sample) at each university and the number of high-type students per firm. I estimate the following specification separately in each region, where each observation is one university:

$$y_s = \alpha + \beta_1 p_s + \epsilon_s$$

The dependent variables y_s include students per firm and high-type students per

[1] Only the universities in the East, Midwest, South, and West are included in the table, excluding two universities located in states that comprise their own region.

[2] The weights are normalized so that the sum of the weights equals the total number of universities with at least one recruiting firm.

[3] The F-test rejects that the averages in the Midwest, South, and West are the same as those in the East for the following variables: tuition (in-state for public universities), number of students, whether it is a public institution, and regional rank.

firm.

Results

Appendix Table A3 presents the results of the within region predictions, showing the results for each region. The first column reports the results from testing the first part of Proposition 2: the number of students per firm is decreasing in p (the percent of students scoring at least a 700 on the SAT Math or 30 on the ACT Math). The coefficients on p (in tenths) are presented by region. In all but the South, an increase in p is associated with a statistically significant decrease in the number of students per firm. Increasing p by .1 is associated with 250 to 380 fewer students per firm. These magnitudes are not small, as the average of the dependent variable ranges from over 800 in the East to over 1500 in the South. These results are consistent with the first part of Proposition 1.

Column 2 reports the results from testing the second part of Proposition 1: the number of high-type students per firm is decreasing in p. While the sign of the coefficient on p is negative in each region, it is only statistically significant in the Midwest and West. In these regions increasing p by .1 is associated with 18 to 27 fewer high-type students per firm. The average magnitude of the dependent variable in these regions ranges from approximately 218 to 226. While the coefficients in each region are not statistically significant, they are jointly significant.[4]

The second prediction of the model is that there is a cut-off value of p below which no firm will recruit. An alternative way of framing the prediction is that there is some value of p above which all universities should attract at least one firm. To allow for some noise, this cut-off is identified as the second highest value of p which receives no recruiting firms. In the East, this value is .463, in the West it is .263, in the Mid-West it is .358, in the South it is .20. The p required in order to be guaranteed of attracting a recruiting firm is much higher in the East than in the other regions.

[4]The results in Columns 1 and 2 are generally more supportive of Proposition 1 (more negative and statistically significant) when including the number of high-type students at the university as an additional control (not shown). This control is not implied by the model, which suggests the number of students on its own does not matter for profits. In the model number of students always enters relative to the number of firms on campus. Thus, number of students should not be correlated with students per firm. However, if the model's prediction is not true in the data, p may still be significant in this table due to bias from omitting number of students.

2.2 Within Region Predictions: Earnings

The third column of Appendix Table A3 directly tests the last part of Proposition 1: within a region, the wage is increasing in p. This prediction is relevant for high-type students, as these are the students hired in the model. As such, only individuals scoring greater than or equal to the 75th percentile of the SAT/ACT score (1280) are included in the estimation.[5] Each cell presents the coefficient on p_s in the following regression, estimated separately in each region:

$$LogEarnings_{isl} = \alpha + \beta_1 p_s + \beta_2 AvgWageCollegeGrad_l + \epsilon_s$$

The variable $AvgWageCollegeGrad$ is the average earnings of college graduates aged 25-34 in the respondent's state of residence in 2009. Both this variable and $LogEarnings$ are adjusted using state price parities. The construction of these variables is further described in the paper. I have experimented with clustering the standard errors at the university level. However, these within-region regressions have few observations and few clusters. Given the problems clustering in these settings, it is unsurprising that clustering at the university level resulted in smaller standard errors in some regressions. With few observations per cluster, failing to account for the group error is not expected to significantly bias the standard errors. For these reasons, I have presented unclustered, robust standard errors in the third column of Appendix Table A3.

While power is limited due to small sample size, the results provide suggestive evidence that the wage prediction in Proposition 1 is supported in the data. In each region recent graduate earnings are increasing in the proportion of high-type students at the university. Increasing p by .1 is associated with an increase in earnings of anywhere from 1.3% (South) to 3.3% (East). The coefficient in the East is statistically significant at the .01 level. The East has about 200 observations, the Midwest has about 150, the South has 50, and the West has 140.[6]

[5] The SAT/ACT conversion was conducted by the Department of Education using the following concordance table: Dorans, N.J. (1999). Correspondences Between ACT and SAT I Scores (College Board Report No. 99-1). New York: College Entrance Examination Board. Retrieved from http://professionals.collegeboard.com/profdownload/pdf/rr9901_3913.pdf.

[6] When including number of high-type students at the university as an additional control, the magnitude of the effect in the East is similar and statistically significant at the 5% level. The effects in the other regions remain imprecisely estimated and statistically insignificant from zero (not shown).

2.3 Alternative Reduced-Form Specification: Accounting for Size of Neighboring Universities

While regional rank captures important intuition from the model, it does not account for size and selectivity of the other universities in the region. For example, it is worse to be ranked number two in the region when the number one university is very large. A further specification tests whether firms are less likely to recruit at a university when there is a larger pool of competition to that university's graduates. The pool of competition to a given university's graduates includes the students at equally, or more, selective universities in the region. This too is an approximation because it is not just the aggregate number that matters, but rather how many are at each university of a given selectivity.

For firms f in region r, the decision to recruit at university s in r depends on

$$CompetingStudentsPerFirm_s \equiv \frac{CompetingStudents_{s_r}}{CompetingFirms_r} \tag{4}$$

$CompetingStudents_{s_r}$ denotes the pool of competition to a university's graduates, defined as the total number of high-type students enrolled at universities at least as selective (in terms of p).

Following the model, firms care how many other firms will be competing for the pool of $CompetingStudents_{s_r}$, as this will affect the probability of filling the vacancy and the wage that will be offered. $CompetingStudents_{s_r}$ is normalized by $CompetingFirms_r$, which is equal to the number of firm offices in region r. If a firm has multiple offices in region r, then each office counts separately. For robustness, the number of firms with offices in region r is used as the denominator. In this case, if a firm has multiple offices in region r, they do not count separately. For example, if Bain has an office in Boston and New York, this would count as two firms using the main definition, and one firm using the robustness definition.

$CompetingStudents_{s_r}$ varies considerably across regions. For the universities in the regression sample falling in the interquartile range of p, the average number of students with high math test scores at a university at least as selective is over 41,000 for universities in the East, while only 7,700 for universities in the South. The values of $CompetingStudentsPerFirm_{s_r}$ also exhibit similar regional variation.[7] Plots of $CompetingStudentsPerFirm_{s_r}$ by p look similar to the plots of $RegionalRank$ by p (not shown).

For a given university size and selectivity, I test whether firms are less likely to recruit at a university if there is a larger pool of competition to the university's graduates. The following linear probability model is estimated:

$$recruit_{sf} = X_s\beta + \gamma_1 CompetingStudentsPerFirm_s + \gamma_2 p_s + \gamma_3 CompetingStudentsPerFirm_s * p_s + \gamma_4 Distance_{sf} + \delta_f + \epsilon_{sf} \quad (5)$$

The university characteristics in X_s are the same as those described in the principal specification, as is the variable $Distance_{sf}$. I do not control for the number of firm offices per region separately, given that this is in the denominator of the main explanatory variable.

Appendix Table A8 shows the results are similar in interpretation to those when $RegRank$ is the main reduced form variable. The coefficients on Competing Students Per Firm are not jointly significant in column 1. However, the magnitudes are suggestive of important effects. For a university in Texas with $p = .14$, there are 92.4 competing students per firm office. For a university in the East with $p = .14$, there are 149.6 competing students per firm office. The coefficients suggest firms are approximately .9 percentage points less likely to recruit at the university in the East.

Column 2 presents the results allowing for heterogeneity by industry. The coefficients on Competing Students Per Firm are jointly significant in this regression, and suggest consulting firms are 2.2 percentage points less likely to recruit at a university in the East with $p = .14$. The effect in Table 2 was 2.9 percentage points.

2.4 Separate Labor Markets

As described above, the labor markets were defined using the recruiting relationships between universities and firms. These market definitions rely on the assumption

[7] Interestingly, the value of $CompetingStudentsPerFirm_{s_r}$ is higher in the Midwest than in the East for universities in this range. This is likely largely driven by the fact that the University of Illinois at Urbana Champaign (UIUC) is a very large university, with a high percentage of students scoring greater than or equal to 700 on the Math SAT or 30 on the Math ACT (44%). Thus, each of the universities in the interquartile range for the Midwest (p between .058 and .247) will have the students at UIUC counted in their $CompetingStudents_{s_r}$.

that the recruiting relationship is between the university and the firm's closest office to the university. A particular concern is that firms from other regions recruit their home-state students studying at universities in the East. This would suggest that when I see a firm recruiting at a university, it is in fact each office of the firm that is recruiting at the university. For example, if we see that Bain recruits at Harvard, the recruiting relationships are between Bain Dallas and Harvard, as well as between Bain Boston and Harvard. This would suggest that the labor market is national, not regional. A national labor market would imply that firms should have no preference for Texas A&M over Penn State, because they are the same size and selectivity, and have the same "regional rank", where the region is just the country as a whole. Even though I have calculated differences in regional rank between Texas A&M and Penn State, this should have no effect on recruiting outcomes if the market is national. If I have incorrectly assumed regional markets, then the coefficient on regional rank should be zero.

The regional rank specification does not take into account the size of the surrounding universities. If Texas firms can recruit East Coast students who are interested in moving to Texas, then Texas A&M is in the same region as Harvard. However, the relevant size of Harvard for Texas firms is only the number of students at Harvard who are interested in moving to Texas. As discussed, there are other reduced-form specifications that account for the size of surrounding universities. In this section I show that accounting for the possibility of recruiting home-state students should have little effect on a measure of regional competition. The number of students returning to their home region does not appear large.

Table 1, Panel C shows limited geographic mobility of students post-graduation. To further explore the extent to which students return to their home-state, I collect university-level data on student mobility post-graduation. Many universities survey their graduating seniors about future plans, including where they will be living or working. For a subsample of universities, I assemble the survey results from university websites for the graduating classes of 2011 or 2012. I combine these survey results with IPEDS data on the number of students in the freshman class from each state, for each university. The freshman migration numbers are taken from the Fall of 2007 (for the graduating class of 2011) or the Fall of 2008 (for the graduating class of 2012). For most universities the 2011 graduating student survey was used. However, the 2012 survey was used when the 2011 survey was unavailable or the IPEDS data was unavailable for the Fall of 2007.

The percentage of students moving to a given region after graduation is compared with the percentage originally from that region. If a sizable number of a region's students study at a particular university in the Northeast, and they all return to their home region, this suggests that firms from the home region may recruit at universities in the Northeast.

Appendix Table A10 compares geographic flows to and from a subsample of universities. Each university defines region somewhat differently in their graduating student survey, and some not at all. The table lists the states included by the university in the region definition. Since many students come from other regions to study at elite universities in the East, these are the universities presented in the table. Among elite universities, those with the most detailed and extensive data are shown. Panel A shows that students from the Midwest are a small percentage of the class at elite universities in the East. Secondly, a smaller proportion of students move to the Midwest post-college than came from the Midwest pre-college. For example, while 9.4% of Princeton's class comes from the Midwest, only 5.1% of Princeton students move to the Midwest following graduation. This suggests that employers do not heavily recruit, or are not successful in recruiting, their home-region students at universities in other regions. Panel B shows a similar pattern between the Southwest and elite universities in the East and Midwest.

Panel C shows post-graduation mobility to the West from other regions. These percentages present a slightly different picture. A much higher proportion of the student body at elite universities come from the West than from the Midwest or the Southwest. Further, the percentage that move to the West from these other regions after graduation is also much higher. In a few cases the percentage moving to the West post-graduation is actually higher than the percentage from the West pre-college.

Panel D shows post-graduation mobility to the Northeast from elite universities in other regions. For Washington University and Vanderbilt, the percentage of students in the class originally from the Northeast is quite high, and the percentage moving to the Northeast post-graduation is also very high. While the percentage of students at UCLA and UC Berkeley from the Northeast is quite small (less than 3%), the percentage of students moving to the Northeast post-graduation is slightly higher.

This analysis suggests that firms in the Midwest and Southwest do not heavily recruit at elite universities in the East. However, the possibility that California firms consider recruiting at elite East Coast universities remains a concern. Importantly, the size of Dartmouth in the California labor market is limited to only those Dartmouth students interested in moving to California (Appendix Table A10 shows this is approximately 10% of Dartmouth's class). Introducing a university of that size into the West is unlikely to significantly affect the results.

Finally, there is a concern that firms in the East consider recruiting at universities in other regions. Many students move to the Northeast following graduation, but again these numbers are small compared to the percent staying in the Northeast following graduation. Travel costs may prevent firms in the East from recruiting outside the region, especially given the number and quality of elite universities in the East. If firms in the East did consider recruiting at elite universities in other regions, this would magnify the disadvantage of graduating from a non-elite university in the East.

3 Theoretical Appendix

This Appendix presents the derivations and proofs of the propositions stated in Section 3 of the paper.

First, the details for deriving the equilibrium are presented. These follow Lang, Manove, and Dickens (2005) very closely, and so were not presented in the main text.

3.1 Strategies

The strategy for firm i at university t consists of its wage offer w_{ti}. $\mathbf{W_t} \equiv \langle w_{ti} \rangle$ denotes the profile of wage offers at university t. Students will generally adopt a mixed strategy, given by a vector-valued function of the form $\mathbf{q}(\mathbf{W_t}) \equiv \langle \mathrm{q_i}(\mathbf{W_t}) \rangle$, where each $q_i(\mathbf{W_t})$ is the probability that the student applies to firm i. The outcome of this mixed strategy will be application to one firm.[8] I consider symmetric equilibria, in which all students at a university adopt the same mixed strategy.[9] The expected number of students at university t who apply to firm i will have a Poisson distribution with

[8]Student strategy choices are restricted to those consistent with the anonymity of firms: if $w_{ti} = w_{tk}$ then $q_i(\mathbf{W_t}) = q_k(\mathbf{W_t})$.

[9]As discussed in Lang, Manove, and Dickens (2005) and Galenianos and Kircher (2009), this assumption is reasonable in large labor markets. Asymmetric mixed strategies in these settings require an implausible amount of coordination, as each student would have to know her exact strategy and that of the other students.

mean z_{ti}, where

$$z_{ti} = q_i(\mathbf{W_t})S_t. \tag{6}$$

As mentioned, the two-stage game is solved backwards, starting with the second stage in which students apply to firms given the firms' wage offers, and then moving to the first stage in which firms offer wages.

3.1.1 Students' Equilibrium Strategy

Let z_{ti} be the expected number of applicants from university t to firm i. Since p_t is the probability that any applicant is actually an H-type, $p_t z_{ti}$ is the expected number of applicants to firm i who are H-types. The probability that an additional applicant will be hired is given by

$$f(z_{ti}, p_t) \equiv p_t \sum_{n=0}^{\infty} \frac{1}{n+1} \frac{e^{-p_t z_{ti}}(p_t z_{ti})^n}{n!} \tag{7}$$

where $\frac{e^{-p_t z_{ti}}(p_t z_{ti})^n}{n!}$ represents the Poisson probability that n other H-type applicants would appear, and $\frac{1}{(n+1)}$ is the probability that the additional applicant would be hired. The expression inside the sum represents the probability of being hired given that the applicant is an H-type. However, not all applicants are H-types, and so the summation is multiplied by the probability of being an H-type, p_t. Manipulating the series yields

$$f(z_{ti}, p_t) = \begin{cases} p_t & for \quad z_{ti} = 0 \\ p_t(\frac{1-e^{-p_t z_{ti}}}{p_t z_{ti}}) & for \quad z_{ti} > 0 \end{cases} \tag{8}$$

Thus, if K_{ti} denotes the expected income or payoff that the student from university t can obtain by applying to firm i, we have

$$K_{ti} = w_{ti} f(z_{ti}, p_t) \tag{9}$$

Suppose that firms have set wage offers $\mathbf{W_t} \equiv \langle \mathrm{w_{ti}} \rangle$ at university t, and that the student application subgame has an equilibrium in which all students adopt the same mixed strategy. Then let $K_t = max_i\{K_{ti}\}$ denote the maximum expected income available to students at university t in that equilibrium.

Students will choose to apply only to firms for which $K_{ti} = K_t$, so we can think of K_t as the market expected income at university t.

Thus, in any symmetric equilibrium of the student application subgame,

$$K_{ti} = \begin{cases} K_t & for \quad w_{ti} \geq K_t \\ w_{ti} & for \quad w_{ti} < K_t \end{cases} \tag{10}$$

z_{ti} satisfies

$$\begin{aligned} z_{ti} > 0 \quad for \quad w_{ti} > K_t \\ z_{ti} = 0 \quad for \quad w_{ti} \leq K_t \end{aligned} \tag{11}$$

and

$$z_{ti} = f^{-1}(\frac{K_t}{w_{ti}}) \mid p_t \, for \, w_{ti} \geq K_t \tag{12}$$

The above line follows since p_t is exogenous, and it is thus possible to take the inverse of f with p_t given. This implies that given $\mathbf{W_t}$, the total expected number of applicants at all firms recruiting at university t is

$$\sum_{i=1}^{N_t} z_{ti} \equiv \sum_{\{i|w_{ti} \geq K_t\}} (f^{-1}(\frac{K_t}{w_{ti}}) \mid p_t) \tag{13}$$

which depends only on the value of K_t.

Therefore, in equilibrium K_t must take on a value that satisfies

$$\sum_{\{i|w_{ti} \geq K_t\}} (f^{-1}(\frac{K_t}{w_{ti}}) \mid p_t) = S_t \tag{14}$$

because S_t is the parametrically fixed expected number of applicants from university t.

f^{-1} is strictly decreasing in K_t, and the summand can lose but not gain terms as K increases, and so the left hand side of the equation is strictly decreasing in K. Thus, the equation has a unique solution for K_t, denoted by $K_t^*(\mathbf{W_t})$.

Equations (10) through (12) and $q_{ti}S_t = z_{ti}$ yield a vector of application probabilities $\mathbf{q_t^*}(\mathbf{W_t})$ that defines a unique symmetric equilibrium of the student application subgame with offered wages $\mathbf{W_t}$ to applicants at university t.

3.1.2 Firms' Equilibrium Strategy

As mentioned above, firms may only hire at one university. We begin by searching for a subgame perfect competitive equilibrium of the two-stage game at all universities t. Subgame-perfect competitive equilibrium is a simplification of standard subgame-perfection in which aggregate variables are assumed constant with respect to the changes in the strategy of an individual agent.[10] $\{\mathbf{W_t^*}, \mathbf{q_t^*}(\cdot)\}$ is a subgame-perfect competitive equilibrium for each t, symmetric among the workers, if:

1. Each firm's w_{ti}^* is a best response to the other components of $\mathbf{W_t^*}$ and to the students' strategies $\mathbf{q_t^*}(\cdot)$ on the assumption that the market expected income $K_t^*(\mathbf{W_t})$ remains fixed at $K_t^*(\mathbf{W_t^*})$ and is not sensitive to the firm's own wage; and

2. $\mathbf{q_t^*}(\mathbf{W})$ is a best response of each worker to any vector of offered wages, $\mathbf{W_t}$, and to the choice of $\mathbf{q}^*(\mathbf{W_t})$ by all other workers.

Let $r_t \equiv S_t/N_t$ denote the ratio of the expected number of applicants at university t to the number of firms recruiting students at t. N_t denotes the number of firms recruiting at university t, and $N \equiv \sum_{t=1}^{T} N_t$.

Proposition: *The game between firms and workers at university t has a subgame-perfect competitive equilibrium $\{\mathbf{W_t^*}, \mathbf{q_t^*}(\cdot)\}$ that is unique among those in which all students at university t adopt the same mixed strategy. In this equilibrium, all students adopt the strategy $\mathbf{q_t^*}(\cdot)$, as defined above, and all firms adopt the strategy w_{ti}^* as given by*

$$w_t^* = \frac{r_t(p_t v - c)}{e^{r_t p_t} - 1} \tag{15}$$

The expected income of each worker is

$$K_t^*(\mathbf{W_t^*}) = (\mathrm{p_t v - c})\mathrm{e}^{-\mathrm{r_t p_t}} \tag{16}$$

[10] Peters (2000) studies finite versions of matching models of this type (sellers announce prices, buyers understand that higher prices affect the queue and probability of trade). He shows as the number of buyers and sellers becomes large, payoff functions faced by firms converge to payoffs satisfying the market expected income property (one firm's deviation does not affect overall market expected income). This result is conditional on assuming student application strategies are symmetric, and an exponential matching process. While the study is limited to elite firms, if all firms ranked in the top 50 are treated as elite, this is over 100 firms (consulting, banking, and investment management). Relaxing the assumption that firms are price-takers would complicate the model. However, intuition suggests the main result must hold: firms must be compensated for recruiting at less selective universities, either by facing less competition or offering lower wages, or both.

and the operating profit of each firm is

$$\pi_t^* = [1 - (1 + p_t r_t)e^{-p_t r_t}](v - \frac{c}{p_t}) \tag{17}$$

As r_t goes from 0 to ∞, π_t^* goes from 0 to $v - \frac{c}{p_t}$, w_t^* goes from $v - \frac{c}{p_t}$ to 0 and $K_t^*(\mathbf{W_t^*})$ goes from $p_t v - c$ to 0.

I list the main steps of the derivation. Substitution of equation (12) into Equation (2) in the paper yields

$$\pi_t = (1 - e^{-p_t z_{ti}})(v - \frac{c}{p_t}) - z_{ti} K(\mathbf{W_t^*}) \tag{18}$$

With $K_t^*(\mathbf{W_t^*})$ held constant, the first-order condition for profit maximization implies

$$z_{ti}^*(\mathbf{W_t}) = \frac{1}{p_t} log \frac{p_t v - c}{K_t^*(\mathbf{W_t^*})} \tag{19}$$

and it follows that $z_{ti}^*(\mathbf{W_t})$ is the same for all firms i recruiting at university t. Since each worker applies to just one firm, we have that $z_{ti}^* = S_t/N_t = r_t$, so then (16) follows from (19). Equations (12) and (18) and the definition of f then yield equations (15) and (17).

3.2 Proposition 1: *The expected number of applicants per firm, z, and high-type applicants per firm, is decreasing in p. The wage offered at university t, $z_t(\frac{p_t v - c}{(e^{p_t z_t} - 1)})$, is increasing in p.*

Proof:

Part A: Expected number of applicants per firm is decreasing in p.

Since profits have to be equal for all firms, regardless of whether they recruit at a university with a high p or a lower p, we can use the expression for profits to see what must happen to z when we change p. Using the implicit function theorem:

$$\frac{\partial}{\partial p}\left((1-e^{-pz})(v-z(\frac{pv-c}{(e^{pz}-1)})-\frac{c}{p})\right)=\frac{e^{-pz}\left(p^3vz^2+c(-1+e^{pz}-pz(1+pz))\right)}{p^2} \tag{20}$$

$$\frac{\partial}{\partial z}\left((1-e^{-pz})(v-z(\frac{pv-c}{(e^{pz}-1)})-\frac{c}{p})\right)=e^{-pz}\left(p(pv-c)z\right) \tag{21}$$

$$\frac{\partial z}{\partial p}=\frac{z^2p^2(-pv+c)}{p^3(pv-c)z}+\frac{c(1-e^{pz}+pz)}{p^3(pv-c)z} \tag{22}$$

Note that the first term in equation (22) is less than zero, since if firms recruit at a university, $pv \geq c$. When $pz=0$, the numerator of the second term in equation (22) is zero. The numerator is decreasing in pz, and so for $pz>0$, the numerator will be negative. Thus, $\frac{\partial z}{\partial p}<0$.

Part B: The expected number of high-type applicants per firm, pz, is decreasing in p.

Proof: When $c=0$, the profit from recruiting at each university, seen in equation (2) in the paper is $(1-e^{-p_tz_t})(v-\frac{z_t(p_tv)}{(e^{p_tz_t}-1)})$. This implies that when $c=0$, p_tz_t is the same at all universities t in the market. We want to show that with positive screening costs, p_tz_t is decreasing in p. We know that profits will continue to be equalized at all universities after the increase in c. This implies that for all t we must have

$$\frac{d\pi_t}{dc}=k \tag{23}$$

We write

$$\frac{d\pi}{dc}=\frac{\partial\pi}{\partial c}+\frac{\partial\pi}{\partial z}\frac{\partial z}{\partial c} \tag{24}$$

Using the expression for profit in equation (18), we find that

$$\frac{\partial\pi}{\partial c}=\frac{e^{-pz}(1-e^{pz}+pz)}{p} \tag{25}$$

When $c=0$, p_tz_t is the same for all universities t, so the numerator of equation (25) is the same at all universities. Thus, for universities with higher p, the magnitude of $\frac{\partial\pi}{\partial c}$ will be lower. Since $\frac{\partial\pi}{\partial c}$ is negative, this means that it will be less negative for universities with higher p.

Similarly, we see that

$$\frac{\partial \pi}{\partial z} = e^{-pz} pz(pv - c). \tag{26}$$

Since pz is the same at all universities, we see that $\frac{\partial^2 \pi}{\partial z \partial p} > 0$. Equation (24) then implies that since $\frac{d\pi}{dc}$ is the same regardless of p, because $\frac{\partial \pi}{\partial c}$ is more negative for lower p, and $\frac{\partial \pi}{\partial z}$ is smaller for lower p, then $\frac{\partial z}{\partial c}$ must be larger for lower p, $\frac{\partial^2 z}{\partial c \partial p} < 0$. Thus, when $c = 0$, $p_t z_t$ is the same for all universities t, and when c is increased $p_t z_t < p_s z_s$ for $p_s < p_t$.

Intuitively, we can understand that when c is increased, profits immediately fall more at universities with lower p because firms at these universities have to read through more applications and so are more affected by the applicant reviewing cost. When increasing z, profits increase more at universities with higher p because there is a higher probability that each added applicant will be an H-type, and so the marginal benefit of adding an applicant is higher. After c is increased, since profits fall more at universities with lower p, firms will move from these universities to universities with higher p. This will result in a greater number of high-types per firm at universities with lower p than before c was raised. However, in this case, the number of high-types per firm at universities with higher p will actually fall because of the in-flow of firms from universities with lower p.

This is equivalent to showing that when we increase the application costs from zero, $\frac{\partial^2 z}{\partial c \partial p} < 0$.

Part C: The wage offered at university t, $z_t(\frac{p_t v - c}{(e^{p_t z_t} - 1)})$, *is increasing in p.*

Proof: We find the total derivative of the equilibrium expression for w, with respect to p. Taking the total derivative allows for z to be affected by changes in p as well.

$$\frac{dw}{dp} = \frac{\partial w}{\partial p} + \frac{\partial w}{\partial z} \frac{dz}{dp}$$

The partial derivatives are obtained from $w = z_t(\frac{p_t v - c}{(e^{p_t z_t} - 1)})$, while $\frac{dz}{dp}$ is obtained using the implicit function theorem as in the proof of Proposition 1, Part A.

$$\frac{\partial w}{\partial p} = \frac{-vz + e^{pz} z(v - z(pv - c))}{(e^{pz} - 1)^2}$$

$$\frac{\partial w}{\partial z} = \frac{-(pv - c)(1 + e^{pz}(pz - 1))}{(-1 + e^{pz})^2}$$

$$\frac{dz}{dp} = \frac{-p^3z^2v + c(1 - e^{pz} + pz(1 + pz))}{p^3(pv - c)z}$$

$$\frac{dw}{dp} = \left(\frac{c(-1 + 2e^{pz} + e^{2pz}(-1 + pz) - pz(1 + pz))}{(-1 + e^{pz})^2pz}\right)\left(\frac{1}{p^2}\right)$$

The denominator of $\frac{dw}{dp}$ is greater than zero. To check that $\frac{dw}{dp} > 0$, we need that $(-1+2e^{pz}+e^{2pz}(-1+pz)-pz(1+pz)) > 0$. This expression is zero when $pz = 0$, and positive for positive values of pz. Thus, the wage offer will be higher at universities with higher p, and the difference in the wages will be even greater as application costs increase.■

3.3 Proposition 2: ***The equilibrium implies a cut-off value of*** p, p_{cutoff}, ***such that for universities with*** p ***below the cut-off, it is not profitable for any firm to recruit.***

Proof: We want to find the value of p_{cutoff} such that the profit from being the only firm to recruit at a university with this value of of p, is equal to the profit from recruiting at one of the universities with $p > p_{cutoff}$, when all firms are recruiting at these universities. Note that the profit is equal at all universities with higher p since they each have recruiting firms. Since we have a mass of firms, we consider the case when the number of firms recruiting at the university with $p = p_{cutoff}$ is infinitesimally small, which implies that the number of expected applicants per firm is infinite. This implies that firms find an H-type applicant with probability 1, but they will have to go through many applicants to do so because p_{cutoff} is low. The wage that will be offered at this university will be the outside offer, since there is no competition among firms at this university. Thus, the equation determining p_{cutoff}, where $p_1 > p_{cutoff}$ is

$$v - \frac{c}{p_{cutoff}} = (1 - e^{-p_1(\frac{S_1}{N_1})})(v - w_1 - \frac{c}{p_1}) = \pi^* \tag{27}$$

This implies that

$$p_{cutoff} = \frac{c}{v - \pi^*} \tag{28}$$

It is clear that a higher equilibrium level of profit decreases the denominator, and so implies a higher value for p_{cutoff}. ■

This implies that the cut-off depends on the level of profit in the market, which is determined by the parameters (c, v) and the (p, S) combination at each university in the market.

3.4 Proposition 3: ***For a given university t, increasing p_t and decreasing S_t without changing p_tS_t has a negative effect on the total number of firms recruiting at other universities in the market, holding constant the total number of firms and total number of H- and L-type students in the market. This change at university t will result in a lower wage offer for at least one of the other universities in the market (not t).***

Proof: I have shown that the expected number of high-type applicants per firm $(\frac{p_tS_t}{N_t})$ is decreasing in p (Proposition 1, Part B). Thus, the change described at university t will result in fewer expected high-type applicants per firm. Since there is no change in p_tS_t, this implies that N_t must be higher. Holding the total number of firms constant, this implies that there are fewer firms recruiting at other universities. I have also shown that the wage is increasing in p (Proposition 1, Part C). Since the expected number of high-type applicants per firm is decreasing in p, this implies that the wage is decreasing in high-type applicants per firm. Since the change at university t results in fewer firms recruiting from at least one other university, and the number of high-type students is not changing at the other universities, this implies that high-type applicants per firm must be increasing for at least one university. Thus, wage offers must be falling for at least one university. ■

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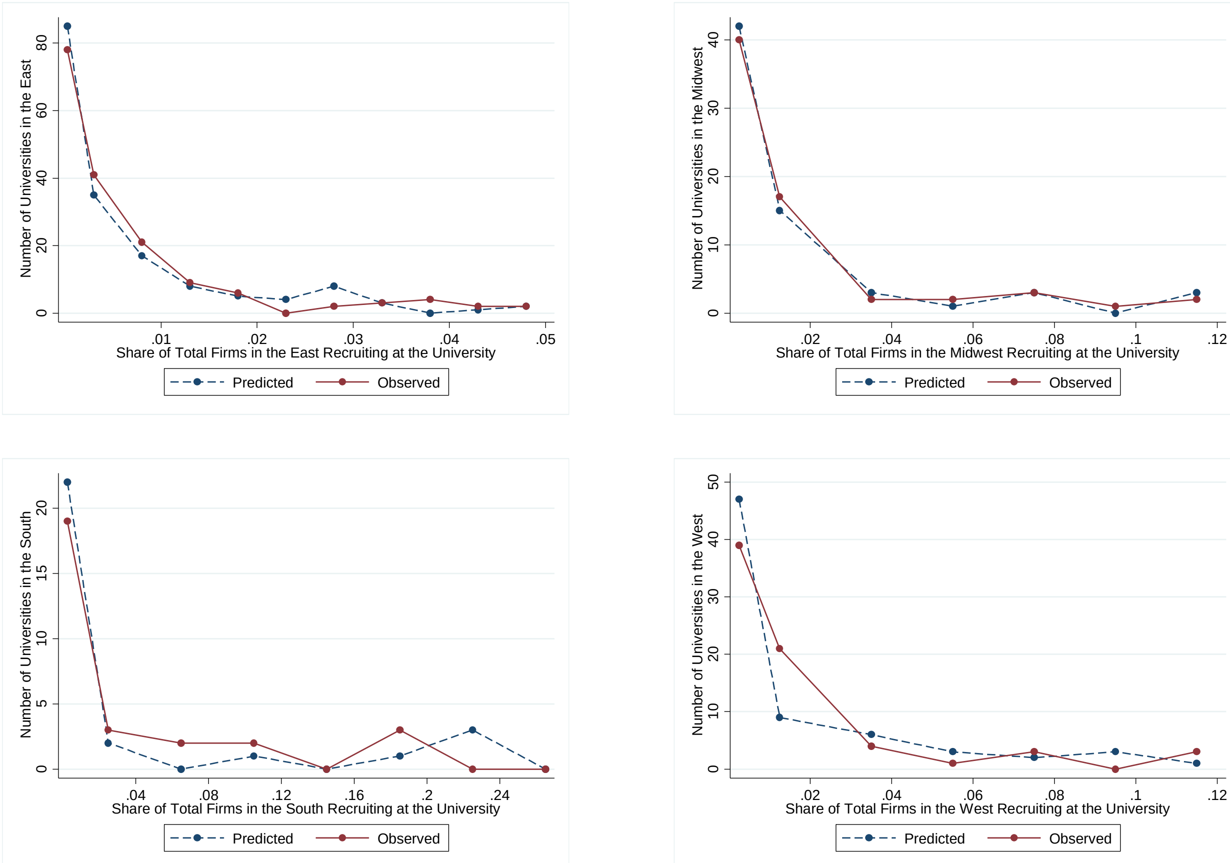
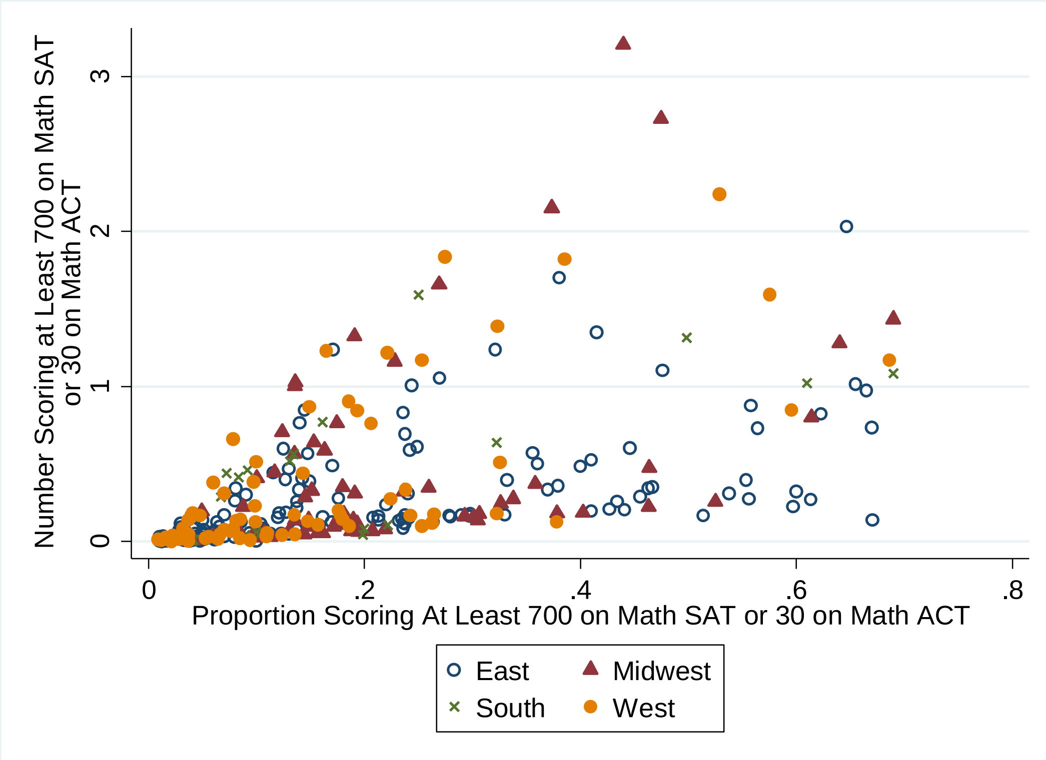
Appendix Figure A1: Share of Firms Recruiting at the University: Observed vs. Predicted



Note: These figures graphically show the goodness-of-fit of the structural model. The last bin in each plot includes all universities with share of total recruiting firms greater than or equal to the amount in the bin.

Appendix Figure A2: Universities Across Region with Similar Proportion and Number of High-Scoring Students



Note: This figure is a scatterplot of the number of high-scoring students at a university on the proportion of high-scoring students at the university. The sample includes universities in the regression sample in the East, Midwest, South, and West. See paper and online appendix for details.

Appendix Table A1: Summary Statistics for Universities with at Least One Recruiting Firm, by Region

	East	Midwest	South	West
Proportion of Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (*p*)	0.49	0.45	0.41	0.4
	[.24]	[.22]	[.26]	[.23]
Regional Rank	34.09	15.56	6.97	14.14
	[34.79]	[18.16]	[8.55]	[13.69]
National Rank	64.33	67.4	95.15	79.38
	[75.63]	[66.39]	[110.22]	[69.36]
US News Ranking	30.48	41.6	43.83	43.54
	[35.32]	[35.92]	[38.51]	[34.77]
Fraction in Top 10 Percent of HS Class	0.75	0.63	0.67	0.72
	[.24]	[.26]	[.21]	[.25]
# Students	2120.11	3962.84	2715.45	3829.9
	[1433.15]	[2409.14]	[1712.44]	[2247.45]
Public	0.2	0.55	0.48	0.51
	[.41]	[.51]	[.53]	[.51]
Large City	0.31	0.26	0.52	0.4
	[.46]	[.45]	[.53]	[.5]
Tuition (in-state for public universities)	29263.42	20898.17	18488.24	16227.78
	[11905.58]	[13984.71]	[16151.22]	[15671.7]
N	90	27	10	32

Note: Standard deviations are in brackets. Sample only contains universities with at least one recruiting firm. Each university is weighted by the number of firms recruiting there, and the weights are normalized so that the sum of the weights equals the total number of universities with at least one recruiting firm. Regional and national ranks are calculated based on p. Detailed description of the calculation of p is included in the paper and the online Appendix. A number of universities are missing values for US News ranking, fraction in top 10 percent of HS class, and tuition. The means of these variables are calculated only over the non-missing values.

Appendix Table A2: Summary Statistics of Individual-Level Data, by Region of Bachelor's Degree Institution

	East	Midwest	South	West
Characteristics of Respondent's University				
Proportion of Students with SAT Math > 700 or ACT Math > 30	0.27	0.14	0.14	0.14
	[.22]	[.11]	[.14]	[.12]
Number of Students with SAT Math > 700 or ACT Math > 30	529.33	405.27	385.58	417.17
	[453.55]	[556.58]	[380.28]	[324.86]
Number of Students with SAT Math > 700 or ACT Math > 30/Total in Region	0.02	0.02	0.05	0.02
	[.01]	[.02]	[.05]	[.01]
Combined SAT/ACT, 25th Percentile	1175	1049	1077	1066
	[111]	[86]	[94]	[90]
Combined SAT/ACT, 75th Percentile	1367	1256	1280	1281
	[96]	[81]	[75]	[75]
Characteristics of Respondent				
Black	0.06	0.02	0.06	0.01
	[.24]	[.15]	[.23]	[.12]
Hispanic	0.05	0.03	0.08	0.11
	[.22]	[.17]	[.28]	[.31]
Combined SAT/ACT Score	1231	1131	1123	1153
	[168]	[164]	[179]	[175]
Income in 2006 (Parental if Dependent)	83,301	82,638	81,568	70,913
	[69346]	[65305]	[82027]	[80738]
Income in 2009	41,678	44,195	44,124	42,435
	[15846]	[24100]	[15383]	[19678]
Dependent in 2007-2008	0.92	0.84	0.77	0.74
	[.28]	[.36]	[.42]	[.44]
Characteristics of Respondent's State of Residence, 2009				
Average Earnings of College Graduate, 25-34	51,579	54,080	54,878	51,908
	[4040]	[2893]	[4777]	[6244]
State Price Parity	110.48	92.47	92.03	103.64
	[17.41]	[10.8]	[10.58]	[17.05]
N	490	780	210	540

Note: Standard deviations in brackets. See paper and online appendix for detailed description of variable construction, sample, and region definitions. Mean SAT/ACT score calculated only over those individuals with data. The sample size for the Combined SAT/ACT score is 480 in the East, 770 in the Midwest, 210 in the South, 530 in the West. Sample sizes are rounded to the nearest ten to preserve confidentiality. Income in 2006 (2009) is adjusted for state price parity based on the respondent's legal state of residence in 2007-2008 (2009). Average Earnings of College Graduate is from the American Community Survey, and is adjusted for state price parity based on the respondent's state of residence in 2009.

Appendix Table A3: Relationship between University Selectivity, Students per Firm, and Earnings

	Students Per Firm	High Type Students Per Firm	Ln(Earnings)
East	-253.1***	-4.648	0.0332***
	[35.50]	[3.515]	[0.0110]
Midwest	-382.2***	-27.36**	0.0156
	[73.15]	[11.98]	[0.0204]
South	-314.7	-2.288	0.0126
	[184.8]	[26.33]	[0.0279]
West	-329.1***	-17.63*	0.0222
	[74.67]	[8.645]	[0.0144]

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Robust standard errors in brackets. Each cell represents a separate regression, and contains the coefficient on the proportion of students at the university scoring at least 700 on the Math SAT or 30 on the Math ACT (in tenths). The dependent variable is denoted at the top of the column, and the region is denoted at the beginning of the row. Separate regressions are estimated for each region. In columns 1 and 2, each observation is a university in the sample with at least one recruiting firm. In column 3, each observation is an individual in the sample who graduated in the previous year from a university in the specified region, and whose SAT/ACT score was at or above the 75th percentile (1280). See paper for detailed explanation of the regression sample. The dependent variable in the third column is adjusted for state price parity as described in the paper. The average wage of college graduates age 25-34 in the individual's state of residence is included as an additional control variable in the third column, also adjusted for state price parity. The earnings data is from the Baccalaureate and Beyond 2009 survey, described in the text. In columns 1 and 2, there are 90 observations in the East, 27 in the Midwest, 9 in the South, and 32 in the West. In column 3 there are 200 observations in the East; 140 in the Midwest; 50 in the South; and 140 in the West. Sample sizes in the third column are rounded to the nearest ten to preserve confidentiality.

Appendix Table A4: Effect of Regional Rank on Firm Recruiting Decisions

	Recruit
Regional Rank (in hundreds)	-0.038***
	[0.012]
Regional Rank (in hundreds)*p	0.187
	[0.185]
Proportion of Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT	-0.614***
	[0.163]
# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands)	0.098**
	[0.047]
# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands)/Total in Region	0.265*
	[0.143]
# Finance and Consulting Offices in Region (in hundreds)	0.024**
	[0.010]
Distance between School and Firm (in hundreds of miles)	-0.011***
	[0.002]
US News Ranking (in tens)	-0.003
	[0.002]
US News Ranking Nonmissing	-0.013
	[0.018]
% of Students Admitted	-0.005**
	[0.002]
Math SAT/ACT, 25th percentile	0.001**
	[0.000]
Math SAT/ACT, 75th percentile	-0.000
	[0.001]
Combined SAT/ACT, 25th percentile	-0.001***
	[0.000]
Combined SAT/ACT, 75th percentile	0.000
	[0.000]
SAT/ACT Percentiles Nonmissing	-0.070
	[0.133]
Fraction in Top 10 Percent of HS Class	-0.055
	[0.036]
Fraction in Top 10 Percent of HS Class Nonmissing	0.031**
	[0.013]
Tuition (in-state for public universities)	-0.000
	[0.000]
Tuition (out-of-state)	0.000
	[0.000]
Tuition Nonmissing	0.054
	[0.042]

Appendix Table A4: Effect of Regional Rank on Firm Recruiting Decisions

Public	-0.056*
	[0.030]
Institution in Large City	-0.008
	[0.010]
Institution in Small/Midsized City	-0.007
	[0.007]
Institution Offers More than a Bachelor's Degree	-0.002
	[0.007]
Proportion of Seniors with ≥ 700 on Verbal SAT or ≥ 30 on English ACT	0.216***
	[0.075]
(Proportion of Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT)^2	0.774***
	[0.203]
# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands)*p	0.224**
	[0.104]
(# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands)/Total in Region)*p	-0.978
	[0.784]
Constant	0.103
	[0.136]
Observations	10,730
R-squared	0.235

Note: This table presents the results on all coefficients from the principal specification in Table 2, Column 1. See those notes for details.

Appendix Table A5: Test for Degree of Selection on Unobservables

Dependent variable: Recruit	(1)	(2)
Regional Rank (in hundreds)	-0.049	-0.051*
	[0.031]	[0.027]
Proportion of Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT	-0.214	-0.138
	[0.198]	[0.085]
# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (thousands)	0.148***	0.128***
	[0.041]	[0.023]
# Finance and Consulting Offices in Region (hundreds)	0.019	0.018*
	[0.012]	[0.011]
Distance between University and Firm (hundreds of miles)	-0.005**	-0.005***
	[0.002]	[0.002]
Full Controls	Y	N
Observations	3,115	3,115
R-squared	0.127	0.110
Ratio		18.84

Note: This table presents the results from the test for selection on unobservables for a linear model proposed by Bellows and Miguel (2009). The sample is restricted to consulting firms, and universities with p in the interquartile range (.06 to .27) of that sample. See paper for details. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A6: Effect of Regional Rank on Firm Recruiting Decisions, Added Interactions and Variables

Dependent Variable: Recruit	(1)	(2)	(3)
Regional Rank (hundreds)	-0.032**	-0.048***	-0.035**
	[0.014]	[0.018]	[0.015]
Regional Rank (hundreds) **p*	0.155	0.489**	0.628***
	[0.231]	[0.245]	[0.206]
Regional Rank (hundreds) *Consult		0.029	0.001
		[0.021]	[0.012]
Regional Rank (hundreds) **p* *Consult		-0.589**	-0.779***
		[0.276]	[0.179]
P-value, Joint Test of Coefficients on Regional Rank	0.077	0.036	0.000

Linear Combination of Coefficients on Regional Rank

	All Firms	Consulting	Consulting
Universities with *p* = .06			
Texas	-0.013	-0.014	-0.024**
(Regional Rank 56)	[.008]	[.01]	[.01]
East	-0.028	-0.03	-0.051**
(Regional Rank 120)	[.018]	[.021]	[.022]
Universities with *p* = .14			
Texas	-0.004	-0.011	-0.018*
(Regional Rank 32.5)	[.009]	[.011]	[.01]
East	-0.009	-0.027	-0.045*
(Regional Rank 82)	[.023]	[.028]	[.026]

Additional Variables	All *p* interactions	All *p* *Consult interactions	University offers MBA, BBA and key interactions
Firms	All	All	All
N	10,730	10,730	10,730
Mean(Recruit)	0.062	0.062	0.062

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See text and online appendix for details on variable and sample construction, and a full list of variables in the regressions. Regressions include firm fixed effects; standard errors are clustered at the university level. States comprising each region are listed in the online appendix. Column 1 includes interactions between *p* and all university characteristics; column 2 includes interactions between *p** Consult and all university characteristics (and all necessary two-term interactions). Column 3 is the principal specification (with interactions between *p*, Consult, and only key university characteristics). In addition, this specification includes indicators for whether the university offers a BBA, and whether it offers an MBA. Key university characteristics are listed in the paper.

Appendix Table A7: Marginal Effects from Probit and Logit Estimation

Marginal Effect of Regional Rank (hundreds)	(1)	(2)	(3)	(4)
p =.06	-0.011	-0.032	-0.011	-0.037
	[0.017]	[0.021]	[0.018]	[0.025]
p =.14	0.007	-0.030	0.009	-0.033
	[0.021]	[0.021]	[0.023]	[0.024]
p =.25	0.040	-0.030	0.046	-0.029
	[0.046]	[0.031]	[0.053]	[0.034]
Firms	All	Consulting	All	Consulting
Estimation	Probit	Probit	Logit	Logit
P-value on Joint Test of Regional Rank Coefficients	0.161	0.000	0.143	0.000
N	10,464	10,464	10,464	10,464

Notes: *** p<0.01, ** p<0.05, * p<0.1. This table presents the marginal effect of regional rank (in hundreds) from probit and logit estimation at the 25th, 50th, and 75th percentile of *p* . The specifications in columns 1 and 3 do not allow for heterogeneity by industry, while columns 2 and 4 include interactions between key explanatory variables, *p* , and an indicator denoting consulting firms. Key explanatory variables are listed in the paper. The marginal effects in columns 2 and 4 are reported for consulting firms. Standard errors are clustered at the university level, and are presented in brackets. When restricting the sample to universities with $p \leq .7$ to obtain common support, one firm has *recruit* = 0 for all universities. This explains the smaller sample size compared to the main regressions.

Appendix Table A8: Effect of Pool of Competing Students on Firm Recruiting Decisions

Dependent Variable: Recruit	(1)	(2)
Competing Students Per Firm Office (hundreds)	0.008	-0.001
	[0.016]	[0.020]
Competing Students Per Firm Office (hundreds) **p*	-0.176	0.123
	[0.143]	[0.162]
Competing Students Per Firm Office (hundreds) *Consult		0.015
		[0.017]
Competing Students Per Firm Office (hundreds)**p* *Consult		-0.509***
		[0.149]
P-value, Joint Test of Coefficients on Competing Students Per Firm Office	0.358	0.000

Linear Combination of Coefficients on Competing Students Per Firm Office

	All Firms	Consulting
Universities with *p* = .06		
Texas	-0.003	-0.01
(Competing Students Per Office: 108.6)	[.012]	[.013]
East	-0.004	-0.015
(Competing Students Per Office: 170.0)	[.019]	[.02]
Universities with *p* = .14		
Texas	-0.015	-0.036***
(Competing Students Per Office: 92.4)	[.012]	[.013]
East	-0.024	-0.058***
(Competing Students Per Office: 149.6)	[.019]	[.021]
Firms	All	All
N	10,730	10,730
Mean(Recruit)	0.062	0.062

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Competing Students Per Firm Office varies at the university level, and captures the competition for that university's students, coming from students at other universities at least as selective in the same region. See text and online appendix for details on variable and sample construction, and a full list of variables in the regressions. Regressions include firm fixed effects; standard errors are clustered at the university level. States comprising each region are listed in the online appendix. All columns include interactions between key explanatory variables and *p* ; column 2 includes triple interactions between key explanatory variables, *p* , and an indicator for consulting firm (as well as the necessary two-term interactions). Key explanatory variables are listed in the paper.

Appendix Table A9: Effect of Regional Rank on Firm Recruiting Decisions, OBE Regions

Dependent Variable: Recruit	(1)	(2)	(3)	(4)
Regional Rank (hundreds)	-0.048**	-0.049**	0.001	-0.045
	[0.022]	[0.024]	[0.036]	[0.031]
Regional Rank (hundreds) **p*	0.456**	0.774***	0.782***	0.082
	[0.209]	[0.242]	[0.296]	[0.301]
Regional Rank (hundreds) *Consult		0.006		
		[0.014]		
Regional Rank (hundreds) **p* *Consult		-0.540***		
		[0.198]		
P-value, Joint Test of Coefficients on Regional Rank	0.001	0.000	0.016	0.171
Linear Combination of Coefficients on Regional Rank				
	All Firms	Consulting	Global	Local
Universities with *p* = .06				
Texas	-0.003	-0.005	0.007	-0.006
(Regional Rank 15)	[.004]	[.004]	[.007]	[.006]
East	-0.024	-0.032	0.046	-0.042
(Regional Rank 104.5)	[.029]	[.029]	[.047]	[.044]
Universities with *p* = .14				
Texas	0.001	-0.001	0.009*	-0.003
(Regional Rank 8.5)	[.003]	[.004]	[.005]	[.005]
East	0.01	-0.009	0.077*	-0.025
(Regional Rank 73)	[.03]	[.03]	[.047]	[.046]
Firms	All	All	Global	Local
N	9,319	9,319	1,695	3,548
Mean(Recruit)	0.064	0.064	0.033	0.077

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See text and online appendix for details on variable and sample construction, and a full list of variables in the regressions. Regressions include firm fixed effects; standard errors are clustered at the university level. States comprising each region are listed in the online appendix. All columns include interactions between key explanatory variables and *p* ; column 2 includes triple interactions between key explanatory variables, *p* , and an indicator for consulting firm (as well as the necessary two-term interactions). Key explanatory variables are listed in the paper.

Appendix Table A10: Pre- and Post-College Student Geographic Mobility

University	Origin	Destination
Panel A: Midwest		
Dartmouth[1]	6.5%	3.0%
Princeton[2]	9.4%	5.1%
Georgetown[3]	4.5%	1.5%
Panel B: Southwest		
Dartmouth[4]	4.8%	1.5%
Georgetown[5]	3.6%	1.6%
Washington University[6]	8.6%	5.0%
Panel C: West		
Dartmouth[7]	12.9%	10.4%
Princeton[8]	15.9%	13.0%
Georgetown[9]	10.0%	4.2%
Washington University[10]	8.3%	10.0%
Duke[11]	8.6%	10.1%
Panel D: Northeast		
Washington University[12]	23.3%	20.0%
Vanderbilt[13]	16.8%	17.8%
UCLA[14]	2.2%	5.0%
UC Berkeley[14]	2.5%	2.9%

Notes: This table compares the percentage of a university's student population originally from the specified region to the percentage moving to that region following graduation. Data sources are described in this appendix. Superscripts denote the following regions: 1 (WI, IL, IN, MI, OH), 2 (ND, SD, NE, KS, MO, IA, MN, IL, WI, IN, OH, MI), 3 (IL), 4 (TX, OK, AR, LA), 5 (TX), 6 (TX, OK, CO, NM, AZ), 7 (CA, OR, WA), 8 (TX, OK, NM, AZ, CA, NV), 9 (CA), 10 (CA, OR, WA, UT, ID, WY, MT), 11 (CA), 12 (NJ, NY, CT, RI, MA, VT, NH, ME), 13 (CT, MA, ME, NH, NJ, NY, RI, VT), 14 (Exact states not provided, census regions inferred: New England, Middle Atlantic, South Atlantic, East South Central).

Appendix Table A11: Parameter Estimates of (c, λ) for different values of γ

	East	Midwest	South	West
γ=5	(.09, .05)	(.01, .2)	(.12, .1)	(.02, .3)
γ=10	(.09, .1)	(.03, .3)	(.1, .25)	(.12, .15)
γ=15	(.09, .15)	(.07, .3)	(.11, .35)	(.11, .3)

Note: This table presents structural estimates of the parameters c (per-applicant screening cost) and λ (proportion of students at a university interested in finance/consulting jobs) for different values of γ (multiplicative factor relating number of offices to number of job vacancies). See paper for details.