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

Russell Weinstein†

August 13, 2018

Abstract

I analyze labor market matching with search and informational frictions, by studying employer recruiting on college campuses. Based on employer and university interviews, I develop a model describing firms' choice of target campuses. The model predicts that with costly screening, firms concentrate (per student) at selective universities over those where high-quality students are larger in number, but smaller in proportion. Further, recruiting is affected by nearby universities' selectivity. This prediction has strong support using data from 39 finance and consulting firms and the Baccalaureate and Beyond. For median-selectivity universities, a better regionally-ranked university is twice as likely to attract a consulting firm, and wages are higher by 4%. Halving screening costs, for example through algorithmic screening, structural estimation shows a 27% increase in the proportion of expected hires from universities outside the top selectivity quartile.

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

*I am grateful to Kevin Lang, Daniele Paserman, Johannes Schmieder, Marc Rysman, and Michael Manove for continued guidance and many helpful conversations. I also thank Kehinde Ajayi, Sandra Black, David Dorn, Peter Ganong, Michael Gechter, Shawn Kantor, Mark McCabe, Dilip Mookherjee, Claudia Olivetti, Elisabeth Perlman, Lawrence Summers, Jonathan Tannen, Miguel Urquiola, Bas Van der Klaauw, Alex Whalley, Wesley Yin, and seminar participants at Boston University, BU-BC Labor Meeting, Econometric Society World Congress, McGill, NYU, RPI, SOLE/EALE World Conference, UNC-Charlotte, University of Pittsburgh, University of Rochester, and Williams College for many useful comments, and to the current and former employees of consulting firms and university career services offices who provided very useful institutional knowledge. Shi Che, Tianyu He, and Kunio Kohama provided excellent research assistance.

†University of Illinois at Urbana-Champaign. E-mail: weinst@illinois.edu

are equally qualified for a job are equally likely to obtain the job. However, it is well-acknowledged that search frictions affect 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 in the US 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 in many industries.[1] While firms have recruited 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 at colleges of varying selectivity, for jobs ranging from

[1] An important exception, Oyer and Schaefer (2012) study 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 at professional services firms. Kuhnen and Oyer (2016) study firm hiring of MBA students, and Kuhnen (2011) studies job search strategies of MBA students. Previous work studies determinants and outcomes of various recruiting methods, e.g. newspapers and referrals (DeVaro 2005, 2008, Holzer 1987). Weinstein (2017b) studies changes in recruiting when firms open and close office locations.

[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).

crop production to finance. In a recent survey of 275 firms across many industries, 76.9% conducted on-campus interviews, and on average 59.4% of full-time entry-level college hires were initially interviewed on campus (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 prestigious finance and consulting firms, as identified by the career resources company Vault, 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.

Labor markets for recent college graduates in the US are quite regional. Defining regions based on employer recruiting patterns (East, Midwest, South, West), I show that one year after graduation approximately 80% of full-time employed individuals live in the same region as their university (using the study's sample from the Baccalaureate and Beyond 2009 Survey). Wozniak (2010) notes that 55% of college graduates live in their birth state.

With screening costs and regional labor markets, the model predicts that controlling for university size, selectivity, and market supply and demand, the university better ranked within its region attracts more firms and its graduates earn higher wages. Undergraduate recruiting for finance and consulting positions is a particularly appropriate setting for testing this prediction. First, these markets are regional as discussed above. Second, 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 recruiting high-quality recent graduates from nearby universities will not have Pennsylvania State near the top of its list, despite its similar selectivity and size as 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

[3]Engineering services and government were the only industries (of 18) in which less than 50% of firms used on-campus interviews (National Association of Colleges and Employers 2014).

markets on recruiting. I approximate the proportion of high-quality workers at the university (selectivity) as the proportion of high math SAT/ACT score students. For two universities at the 25th percentile of selectivity, a university in the East is regionally ranked 60 positions worse than a non-East university. The coefficients suggest consulting firms are three percentage points less likely to recruit at the worse regionally-ranked university in the East, controlling for university size, numerous measures of university quality, as well as market supply and demand measures. I find similar effects at the median selectivity.

The results are economically important. The probability of attracting a consulting firm is 3.1% for universities in the East around the median selectivity, and .7% for universities around the 25th percentile. The results imply that because of their regional rank, median-selectivity universities outside the East are twice as likely, and those at the 25th percentile are five times more likely, to attract a consulting firm. Controlling for the university's regional rank, attending a more selective university does not improve recruiting outcomes.

While equally selective universities in the East have worse regional ranks, they are closer to more finance and consulting firms. Even including this advantage, significantly more selective but worse regionally-ranked universities attract fewer firms. Consider a university in the West at the 25th percentile of selectivity. To attend a university in the East with an equivalent probability of attracting a prestigious firm, the university needs to be at the 55th percentile. This tradeoff of selectivity and regional rank is important for students applying to college.

Using the Baccalaureate and Beyond 2009 (B&B), I test if regional rank's effect on recruiting translates into finance and consulting employment differences one year after graduation. While the sample is small, descriptive evidence shows finance analysts and consultants attended dramatically less selective universities if they graduated outside the East, consistent with recruiting results. With greater access to these prestigious jobs, graduates at less selective universities outside the East have access to earnings up to 35% higher than median opportunities of students at similarly selective universities in the East, based on B&B data.

I also test the model's prediction that high-type students earn more if they attend better regionally-ranked universities, conditional on selectivity. I find students with a 1400 SAT earn over 4% less if their alma mater's regional rank is worse by 30 places, holding constant the university's absolute size and quality. To attend a university with similar average earnings, a student with a 1400 SAT could attend a university in the West at the 25th percentile or in the East at the 60th percentile of selectivity in the regression sample.

One concern is that even controlling for many measures of absolute university and student quality, the university's regional rank may be correlated with unobservable characteristics affecting recruiting and wages. I assess selection on unobservables using coefficient stability to additional controls, adjusted for changes in R-squared, implementing the relatively new approach outlined in Oster (forthcoming). The bias-adjusted treatment effects are still large, and the coefficient stability is consistent with that in a setting of randomized treatment.

Finding reduced-form support for the presence of screening costs and their predicted impact on recruiting and wages, I structurally estimate the model, including the screening cost parameter. This enables directly quantifying the impact of reducing screening costs on recruiting and wages, especially relevant given recent advances in screening-cost-reducing technology. 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 additional finance/consulting productivity over the match is \$50,000 (reasonable if the match is five years), the per-applicant screening cost is approximately \$5,000, and screening costs per hire are \$14,500 at a less selective university in the East. These large estimates are consistent with consultants, with high external billing rates, conducting screening and interviews.[4] Reducing screening costs has large positive effects on high-SAT score students at less selective universities. Halving the screening cost, there is a 27% increase in the the proportion of expected finance and consulting hires from universities outside the top selectivity quartile.

The result is quite intuitive. If screening is costly, a university will more likely be passed over 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 results have important implications for college choice. Many guides and rankings focus on a university's absolute quality, rather than relative quality. Importantly, the well-known US News and World Report rankings of national universities omits this regional quality dimension. I find that a university in the East must be considerably more selective than in the West to have similar average recruiting and wage outcomes. This information may guide students to better regionally-ranked universities outside the East, if they want to work at a prestigious finance or consulting firm and are not admitted to elite universities. Alternatively, the disadvantages of attending a worse regionally-ranked university in the East may reflect the value of living in the East, perhaps the value of living near home.

Related, the literature studying labor market return to university quality has focused on

[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 student's relative standing at his university and career decisions.

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.

Second, the results help us understand access to elite careers and intergenerational mobility. 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. By analyzing employer recruiting strategies, I directly study how university quality affects access to the business elite. I show the importance of the university's regional rank, conditional on university quality, in providing access to elite firms.[8]

This complements recent work showing variation across universities in rates of upward intergenerational mobility (Chetty at al. 2017), and presents an unexplored mechanism that may help explain the variation. In studying the relationship between university and access to the business elite, the paper also complements Zimmerman (forthcoming), who finds that admission into elite university programs in Chile has large effects on attaining top jobs and incomes. Finally, the results also magnify concern for low-income high-achieving students, who are unlikely to apply to selective universities (Hoxby and Avery 2014).

Third, the findings highlight potential impacts of advances in screening technology. Recent developments include identifying high-quality resumes and video interviews through machine learning. The results imply that this technology may increase recruiting at less selective universities, because identifying their talented students is less costly. Consistent with the model's prediction, Goldman Sachs announced adoption of a new screening technology, and ending the practice of first-round on-campus interviews at elite universities.[9] Instead, all applicants, regardless of university, must complete a video interview (Gellman 2016).

Finally, regional rank's importance suggests 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, high-

[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.

[7] Over 300 of McKinsey's nearly 27,000 alumni are CEOs of companies with over 1 billion dollars in annual revenue (McKinsey 2013). Alumni of these firms are also government and nonprofit leaders.

[8] The connection of universities to local firms is consistent with local demand affecting enrollment and major (Cascio and Narayan 2015, Charles, Hurst, and Notowidigdo 2015, Weinstein 2017a).

[9] For summer analyst positions.

skilled workers are still limited in their mobility (noted in Wozniak (2010)). These mobility frictions have implications for productivity if they impede firm-worker match efficiency.

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.[10]

Target Campuses Firms choose a core set of universities at which to target recruiting. Each target campus is managed by a team of human resources personnel and consultants recently graduating from that university. The team visits the campus for recruiting events, and ultimately 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.[11]

Costly Recruiting Firms invest heavily in identifying the best applicants, through a lengthy interview process. I outline the details of this process for one firm at one university. The important components 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, 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.

[10] I describe undergraduate recruiting; MBA recruiting is generally separate, with different staff.
[11] This is particular to management consulting firms.

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 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.

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, following the wage-posting model in Lang, Manove, and Dickens (LMD) (2005). There are two main innovations relative to LMD. First, I incorporate into LMD the division of the labor market into many mutually exclusive pools (in this case university campuses). Second, I include a per-applicant screening cost.

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.[12] 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.[13] All H-type workers have the same productivity, v, at each recruiting firm.

I assume 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 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. Students may have uncertainty

[12]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.

[13]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.

regarding the match between their skills and tasks in an unknown work environment. On the contrary, firms have accumulated knowledge about predictors of worker success.

Consider a three-stage game in which firms first decide at which university to recruit, and then simultaneously make wage offers in the second stage, which they must pay to the worker they hire. In the third stage, students observe the wage offers and simultaneously apply to firms. Each student may apply only to one firm.[14] 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.[15]

I search for the equilibrium of this three-stage game, consisting of the wage offers for each firm at each university, the student application strategies $q^*(W)$ at each university, and the allocation of firms across universities (N^*): $\{W^*,\, q^*(W),\, N^*\}$. I solve the game backwards. The solutions to stages two and three (wages and application strategies) follow LMD quite closely, and so I leave the details in the appendix. I highlight important intuition here.

Equilibrium Application Strategies and Wage Offers

After receiving all its applications, each firm reviews its applicants until identifying, and then hiring, the first H-type student. In the third stage, students observe the posted wages and decide where to apply. In equilibrium, expected income (wage multiplied by the probability of getting the job) must be equal at all firms to which students apply with positive probability. A higher wage would attract more applicants, reducing each's probability of getting the job.

In the second stage, firms choose the wage to maximize profits, where higher wage leads to higher expected number of applicants (z_{ti}). Firm i's payoff from recruiting at university t is expected operating profits:

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

The first term in (1) denotes the probability of filling the vacancy. 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, with known mean z_{ti}. Since there is only a p_t probability that each applicant is an H-type, the expected number of H-type

[14] 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.

[15] As described in Section 2, in actuality firms conduct a first review of all applicants. Firms then conduct a second review of each marginal applicant until all slots are filled. If most slots are filled after the second review then this is quite similar to the presentation in the model.

applicants under the Poisson is pz. The probability of attracting no H-type applicants under the Poisson is e^{-pz}. The second term denotes the worker's productivity v minus the wage offer w minus a term reflecting expected screening costs. Expected screening costs are $(1 - e^{-pz}) * (\frac{c}{p})$, decreasing in p.[16] 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. The per-applicant reviewing cost implies lower screening costs from recruiting at a university with a higher proportion of H-types (p), holding constant the number of H-types.

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 ($z_t = \frac{S_t}{N_t}$) and offer the same wage ($w_t = (\frac{S_t}{N_t})(\frac{p_t v - c}{e^{p_t z_t} - 1})$) for H-type workers, where N_t denotes the number of firms recruiting at university t. Following LMD, the appendix shows equilibrium wages and application strategies are unique.[17]

Equilibrium Allocation of Firms Across Universities

In the first stage, firms allocate across universities given the equilibrium wages and student application strategies at each university, as a function of the number of recruiting firms at each university. The main departure from LMD is this analysis of firm allocation across pools (universities) in equilibrium, and the impact of per-applicant screening costs, university size and selectivity.

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.[18] I reduce the $3R$ conditions governing the equilibrium to $R-1$ profit-equality equations and $R-1$ endogenous variables $(N_1, ..., N_{R-1})$ denoting the number of firms recruiting at each university.[19] Using the profit

[16] Expected screening costs equal the expected number of applicants reviewed multiplied by the screening cost per applicant, c: $c * \sum_{k=1}^{\infty} \left(\frac{z^k e^{-z}}{k!} \sum_{j=1}^{k} (1-p)^{j-1} \right) = c * \frac{(1-e^{-pz})}{p}$. 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 (e.g. $Pr(\text{review second applicant}) = 1-p$, because $Pr(\text{first an H-type}) = p$).

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

[18] Technically, profits may not equalize. Profit at a college with six firms may be greater than profit at a college with four in equilibrium, if seven firms at the former would make profit less than at the latter. Given firms recruit for multiple slots in reality, profits should be close to equal.

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

expression from (1), and substituting in the equilibrium expressions for z_{ti} and w_{ti}, the profit-equality condition for universities 1 and 2 is:

$$(1-e^{-p_1(\frac{S_1}{N_1})})(v-\frac{(S_1(p_1v-c))}{N_1(e^{p_1(\frac{S_1}{N_1})}-1)}-\frac{c}{p_1})$$
$$-(1-e^{-p_2(\frac{S_2}{N_2})})(v-\frac{(S_2(p_2v-c))}{(N_2)(e^{p_2(\frac{S_2}{N_2})}-1)}-\frac{c}{p_2})=0 \quad (2)$$

Equation (2) also shows that if the per-applicant screening cost (c) is zero, the profit from recruiting at each university is equalized when $\frac{p_tS_t}{N_t}=\frac{p_{t'}S_{t'}}{N_{t'}}$ for all universities t, t'. Thus, with $c=0$, firms allocate across campuses based on the number of H-type students (pS), and not the proportion (p). As screening becomes costlier, the proportion of H-types more strongly affects allocation.

For the $T-R$ universities not attracting recruiting firms, a profit inequality condition must hold in equilibrium. This 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:

$$v-\frac{c}{p_{R+1}}<(1-e^{-p_1(\frac{S_1}{N_1})})(v-\frac{(S_1(p_1v-c))}{N_1(e^{p_1(\frac{S_1}{N_1})}-1)}-\frac{c}{p_1}) \quad (3)$$

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.*

- 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).*[20]

implied by the number of recruiting firms at all other universities.

[20]Increasing p_t and decreasing S_t without changing p_tS_t implies reducing the number of L-types at t. To

Formal proofs are in the appendix. Intuitively, holding wage and expected H-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 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.

Proposition 3 asserts changes in recruiting from increasing selectivity (p_t) and decreasing size (S_t) at a university without changing the number of H-type students at the university (p_tS_t), and thus in the region. Put simply, allocation of H-types across universities affects recruiting. This has a natural application to a cross-region comparison. Two regions may have similar numbers of H-type students, but differ in H-type concentration at selective universities. Some regions may have very selective universities, attended mostly by H-type students. Other regions may have fewer of these very selective universities, and instead H- and L-type students attend the same universities. Given that Proposition (3) is derived from a one-region model, applying it across regions implies holding constant number of firms and H-types in the region.

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	0H, 200L

First note that nobody recruits at the universities with 0H, and that the total number of H- and L-types is the same in both regions.

Consider the university with 80H, 100L in Region 1, which has a counterpart in Region 2 (80H, 0L), with higher p_t, lower S_t, but equal p_tS_t (number of H-types). Holding total number of firms constant, Proposition 3 suggests that if screening is costly, 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. I develop intuition for this prediction by first considering the model without screening costs ($c = 0$), for example if the fixed cost of visiting a campus drives recruiting decisions. In this case, firms would allocate across universities in Region 1, equalizing expected number of H-type applicants per firm at each university

keep all else equal, in this proposition I assume the number of L-types in the market is constant (implying L-types increase at another university). The result holds without this assumption.

($\frac{100}{N^{c=0}_{100H,100L}} = \frac{80}{N^{c=0}_{80H,100L}}$). This would also be the allocation in Region 2 because the number of H-type applicants at each university is the same.

With screening costs, this allocation in Region 1 yields higher profits at the university with (100H, 100L) than at the university with (80H, 100L) because (100H, 100L) is relatively more selective and so screening costs are lower. Higher profits will lead firms to substitute into this university when screening becomes costly ($N^{c>0}_{100H,100L,R1} > N^{c=0}_{100H,100L}$), resulting in higher wages and lower probability of filling a vacancy until profits are equalized within the region (consistent with Proposition (1)).

On the contrary, in Region 2 the equilibrium allocation without screening costs yields lower profits at the university with (100H, 100L) if screening is costly. Screening costs are higher at this university relative to the alternative (80H, 0L). Firms will leave this university when screening becomes costly, so profits are equalized in Region 2. Thus, $N^{c>0}_{100H,100L,R2} < N^{c=0}_{100H,100L} < N^{c>0}_{100H,100L,R1}$.

Costly screening implies the university with (100H, 100L) attracts fewer firms in Region 2 than in Region 1, conditional on the number of firms in the region. More simply, 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.

As the example highlights, the model's testable prediction is that universities more selective within their region attract more firms, conditional on university size and selectivity, total number of firms, and number of H-type students at the university relative to the region. These conditional statements are derived from the model. First, as equation (2) shows, firms allocate across universities based on university size (S) and selectivity (p). Comparing universities by their regional ranking, without controlling for absolute size and selectivity, conflates two channels affecting recruiting: absolute university quality and allocation of H-type students across universities in the region.

Second, as discussed above, controlling for number of firms and H-type students in the region is based on applying Proposition (3) to a cross-region setting. If some regions had more firms, this would affect recruiting at each university. Differences in the total number of H-types across region, conditional on university size and selectivity, would also affect recruiting even without screening costs. In the extreme, if a region had only one university with H-type students, the model predicts all firms would recruit at this university. A university of the same size and selectivity in a region with more total H-types (at other universities) would attract fewer firms, simply because the firms will spread themselves across the greater number of H-types. Conditioning on total H-types in the region, I isolate recruiting differences due to costly screening rather than to supply.

To capture the prediction arising from Proposition (3), I use the university's regional rank based on the proportion of H-type students, and control for absolute university quality, total firms in the region, and H-types at the university relative to the total in the region.[21] I estimate an additional specification capturing the predicted importance of the joint distribution of p and S at all universities in the market. For example, the model predicts that the second-ranked university benefits from a smaller first-ranked university. Structural estimation also more directly incorporates the dependence on this joint distribution.

I test the prediction by exploiting variation in the distribution of university quality across the US. 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.[22] Supporting this argument, the US News and World Report (USNWR) does not rank universities by labor market outcomes. I argue the distribution of students across institutions determines recruiting strategies and wages.

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. These firms often have multiple US offices, enabling within firm comparisons across region. This mitigates concerns that firm heterogeneity drives regional variation in recruiting. Second, consulting firms generally recruit on campus for entry-level consultants, fairly homogeneous across firms and across offices within firms.[23] 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 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).[24] For each firm, I identified whether the

[21]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).

[22]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).

[23]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.

[24]Target campuses were collected in Spring 2012 (consulting) and Spring 2013 (finance). I use 2011 firm rankings because Spring 2012 recruiting arguably targets 2012 seniors, who begin recruiting in Fall 2011.

firm's website contained information on undergraduate target campuses, and collected the data if they existed. For example, the management consulting firm Bain's career page has a search field for university. After searching for Texas A&M, the recruiting page loaded makes clear Bain's active recruiting presence there. However, after searching for Pennsylvania State it is clear Bain does not actively recruit at the university (Figures 1a and 1b). Bain's target campuses, as the model predicts, are less selective outside the Northeast (Figure 2).

Target campuses were identified from firm websites for 22 consulting firms, 13 banking firms, and four investment management firms (Appendix Table 1).[25] I denote whether each firm actively recruits undergraduates at each university in Princeton Review's *The Best 376 Colleges* (2012).[26] The recruiting dataset is merged with rich university-level data, from the Integrated Postsecondary Education Data System (IPEDS), the Common Data Set, 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.[27] 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).[28] To measure selectivity among 2012 seniors (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 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 and calculate the distance.

Vault last ranked investment management firms in 2009. See appendix for details.

[25]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.

[26]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.

[27]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.

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

Constructing Separate Labor Markets

I test the model's prediction using variation across region in the distribution of university quality. Following the model's intuition, I define regions so they are consistent with the firm's perceived labor market, where the labor market is the set of universities with students interested in working at that firm's location. Specifically, I infer firms' perceived labor markets from their target campuses; to define regions I assume campuses are targeted by the closest office.[29] 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).[30] For robustness, I use Bureau of Economic Analysis regions.

Using the B&B survey, one year after graduation approximately 80% of full-time employed individuals live in their university's region (Table 1 Panel C), evidence of regional labor markets. Importantly, my reduced-form regression jointly tests for screening costs and regional markets. If markets are not regional, regional rank's coefficient will be insignificant.

Regional rank is calculated based on the proportion of H-type students, p, at the university. I define H-types as students scoring [700, 800] on the SAT Math or [30, 36] on the ACT Math.[31] Clearly the definition of H-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 H-type students. I measure the number of H-type students using $p*$number of students.

Summary Statistics: Firms, Universities, and Recruiting

Firms and universities in my sample are located across the U.S. (Panel A, Table 1). Figure 3 shows the identifying variation for the reduced-form analysis. For given p, regional rank is worse in the East than elsewhere. Consider four universities in different regions: Penn State (p=.171), Miami University (Ohio) ($p = .163$), Texas A&M ($p = .165$), University of Georgia ($p = .161$). Despite similar selectivity p, regional ranks vastly differ. Penn State is 70; Miami University is 38; Texas A&M is 28; University of Georgia is 9.[32] I test the model's predictions using this variation.

Within bins of university selectivity (less than .6) the university attracting the most consulting firms in the West attracts a higher proportion of firms than in the East (Figure

[29] Several sources support this assumption, used only to define regions (see appendix).

[30] See appendix. Texas and California likely share a region because Arizona firms recruit in both.

[31] 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 this measure and the analogous verbal measure in the regression sample is .87.

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

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 firms. The analogous university in the East attracts under 50%. While not controlling for university size, this is consistent with the model's prediction: better regionally-ranked universities attract more firms, conditional on selectivity.

5 Empirical Analysis of Recruiting Strategies

The model's testable prediction is that worse regionally-ranked universities will attract fewer firms, conditional on university size and selectivity, the total number of firms in the region, and number of H-type students at the university relative to the region. Screening costs yield this prediction, as explained in the model's illustrative example. Within their market firms concentrate (per student) at more selective universities, where screening costs are lower.

The prediction translates well into an empirical identification strategy. I compare a given firm's recruiting at universities of equal quality but different regional ranks, 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 from supply effects.

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 H-type students, and number of H-type students relative to the market.[33] Observations are (university, firm) pairs, e.g. (Penn State, Bain). Using OLS, I estimate:

$$\begin{aligned} Recruit_{sf} &= \alpha + \gamma_1 p_s + \gamma_2 RegRank_s + \gamma_3 RegRank_s * p_s \\ &+ \gamma_4 FirmsinRegion_s + \gamma_5 Distance_{sf} + X_s\beta + \delta_f + \epsilon_{sf} \end{aligned} \tag{4}$$

$Recruit_{sf}$ indicates if firm f recruits at university s. X_s is a vector of university characteristics.[34] $Distance_{sf}$ 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 university s's region. 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

[33] Interacting all never-missing variables with p yields similar effects with higher standard errors, as expected (Appendix Table A5).

[34] X includes 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 (analogous to 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 additionally includes interactions between p and the principal explanatory variables.

include only universities with p above the minimum p attracting a firm ($p = .0078$). I exclude universities with $p > .7$ given very limited overlap across regions.[35] 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.[36]

6 Reduced-Form Estimation Results

To build intuition, I first estimate a simple regression including only firm fixed effects and the university's regional rank. Without controls for absolute university quality, this involves comparing recruiting, for example, at universities with regional rank of two versus three. Average selectivity of the third regionally-ranked universities will be lower than the average for the second regionally-ranked universities. As expected given this correlation with selectivity, regional rank's coefficient is negative and statistically significant (Table 2, column 1).

Identification comes from comparing universities of similar absolute size and quality, but different regional ranks. Column 2 includes one measure of absolute quality: the proportion scoring at least 700 on the math SAT or 30 on the math ACT, and column 3 includes the number of high-scoring students. Controlling for absolute university quality and size, worse regionally-ranked universities are more likely to attract firms.

Regional rank's effect may be biased for several reasons. First, among low-selectivity universities, there are very large differences in regional rank, while at more selective universities these differences are much smaller. Column 4 allows for nonlinearities in the regional rank difference, which suggests a negative impact of regional rank for low p universities.

Second, conditional on university quality, worse regionally-ranked universities are more likely to be in the East, where distances between firms and universities are lower. Shorter distance presumably increases likelihood of recruiting. There are also more finance and consulting firm offices in the East, arguably translating to more overall recruiting, including within a firm. Finally, conditional on size and selectivity, if universities have a greater proportion of the region's H-type students, they should attract more firms.

The specification in column 5 controls for firm-university distance, number of firm offices in the region, and H-types relative to the region total. Including these variables suggests

[35] 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.

[36] Interacting every never-missing variable with p, $Consult$, and $p * Consult$ yields similar though less statistically significant results (expected given loss of power) (appendix).

regional rank has a negative impact for most p in the sample. The regional rank coefficients are also jointly significant at the 1% level.[37]

Despite controlling for the proportion and number of high-scoring students, worse regionally-ranked universities may be lower in absolute quality. Column 6 includes the full set of controls for university quality, and this has very little effect on the results. Regional rank statistically significantly affects recruiting decisions, holding constant university selectivity, size, size relative to the region, and total firm offices. The 25th percentile of p in the sample is approximately .06. A Texas university 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. Effects are smaller for median-selectivity universities.[38]

Regional rank's effects are significantly stronger for consulting than finance firms (Table 2, Column 7). For universities with p at the 25th and 50th percentiles, a Texas university is 3 percentage points more likely to attract a consulting firm than a university in the East.[39] Based on the probability of attracting consulting firms in the East, the results imply that due to regional rank, universities outside the East at the 25th percentile of selectivity are five times more likely, and at the median twice as likely, to attract a consulting firm.[40]

Interpreting the coefficients on absolute selectivity p in columns 6 and 7 is difficult given the inclusion of similar variables (e.g. percent admitted, test score percentiles). However, column 5 (which excluded these similar variables) suggested the marginal effect of increasing p is not statistically greater than zero (Appendix Table A14). This implies no recruiting advantage from attending a more selective university if it is equivalently ranked within the region, holding constant the number of H-type students, firm/university distance, firm offices in the region, and high-scoring students relative to the region.

The marginal impact of increasing the number of H-types is based on the coefficients on number of H-types and number relative to the region. Based on column (7), for median-selectivity universities, increasing the number of H-types by one standard deviation (462 students) increases the probability of attracting a consulting firm by 5.5 percentage points.

[37] Including only firm-university distance, rather than also number of firm offices and H-types relative to the region, suggests negative impacts of regional rank for up to the 30th percentile of p.

[38] The appendix presents coefficients on all variables.

[39] 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).

[40] Among universities in the East with selectivity between the 40th and 60th percentiles, there is consulting recruiting in 3.1% of (firm, university) pairs. Among universities in the East with selectivity between the 15th and 35th percentiles, there is consulting recruiting in .7% of pairs.

Conditional on selectivity p, the model suggests universities with more H-type students should attract more firms. If not, profits would be higher because each firm would have more applicants and lower probability of an unfilled vacancy.

Tradeoff between Regional Rank, Number of Firms, and Selectivity

The results support the model's prediction: screening costs and regional labor markets cause more recruiting at better regionally-ranked universities, 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. Students should know the tradeoff between regional rank, number of firms, and selectivity.

I determine the selectivity advantage necessary in the East, if any, to eliminate the regional rank advantage in the West. I estimate a regression similar to equation (4) allowing for industry heterogeneity, but without controlling for measures of selectivity other than p (e.g. US News Rank or SAT/ACT percentiles). These make it difficult to interpret the coefficients on p, and as Table 2 shows they have little effect on the results.

I identify regional rank in the East and West, for a university with p at approximately the 25th percentile.[41] Using these regional ranks and coefficients from the above regression, I identify the predicted probability of attracting a consulting firm for a university in the East and West, assuming they are similar except for regional rank, number of firms in the region, and high-scoring students in the region.[42]

Despite the presence of more firms in the East, there is a substantial recruiting advantage in the West. A university with p at the 25th percentile is approximately 2 percentage points more likely to attract a recruiting firm if the university is in the West (regional rank of 54) relative to the East (regional rank of 117) (Figure 5). While the regional rank coefficients are jointly significant, and the magnitude of the difference in predicted probabilities is large, the confidence intervals of the predicted probabilities are overlapping. The results here are certainly more suggestive.

Using the regression coefficients, I identify the predicted probability for a university in the East with selectivity higher by intervals of .01 (and relevant improvements in regional rank). I compare this predicted probability to that for a university in the West with p at the

[41] This process is detailed in the appendix.

[42] I multiply the number of firm offices in each region by the coefficient on that variable. I divide the average number of high-scoring students at a university in the sample (holding this constant across region) by the total high-scoring students in each region. I then multiply this by the coefficient on high-scoring students relative to the region. Average distance to firms is shorter in the East, but there are many universities outside the East within close proximity of firms. Because students could choose one of these universities, I estimate the predicted probabilities holding firm-university distance constant across region.

25th percentile. For a student to attend a university in the East with a nearly equivalent probability of attracting a prestigious firm (within .1 percentage points), she would need to attend a university with selectivity higher by .09. This is equivalent to moving from the 25th to approximately the 55th percentile of selectivity. This higher p university has a regional rank of 78.5, still worse than the rank of 54 in the West.

Put differently, if the goal is to maximize recruiting outcomes, students should choose worse regionally-ranked universities in the East as long as their selectivity is at the 55th percentile, instead of better regionally-ranked universities in the West at the 25th percentile. If students are not admitted to these significantly more selective universities in the East, they should choose the less selective, better regionally-ranked universities in the West. If considering universities in the West at the median selectivity, students should instead choose worse regionally-ranked universities in the East as long as their selectivity is at the 67th percentile. Otherwise, they should choose the less selective, better regionally-ranked universities in the West (Appendix Figure A3).[43]

Robustness

Estimation using probit and logit yields results for consulting firms that are smaller in magnitude and statistical significance. However, the magnitudes still suggest nontrivial negative effects of a worse regional rank (Appendix Table A6). 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.[44] This yields a smaller, and likely biased sample 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 A8). While the regional rank coefficients are jointly significant, combinations at the 25th and 50th percentile of p are not statistically significant.

[43] Appendix Figure A3 also shows predicted probability of attracting a consulting firm for each East and West university in the sample, based on the values of their explanatory variables. Substantial selectivity differences across regions are needed to yield equivalent recruiting probabilities. For example, based on Appendix Figure A3(a), there is only one university in the East with selectivity p and predicted probability at least .01 above every university in the West with selectivity $\in [0, p + .05]$, and that university has $p > .6$ (one of the most selective in the sample). On the contrary, there are four universities in the West with $p < .3$ and predicted probability at least .01 above every university in the East with selectivity $\in [0, p + .05]$.

[44] For example, for many firms Chicago is the closest office to Washington University in St. Louis. While St. Louis and Chicago are in the same community detection region (Midwest), their OBE regions are different (Plains and 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.

As an alternative to regional rank, I study the effect of the number of high-scoring students at other universities at least as selective. This captures the model's prediction that the second-ranked university benefits from a smaller first-ranked university. This specification yields similar results, described in detail in the appendix.

While I control for many university quality measures, universities with worse regional rank may attract fewer firms due to unobservable differences. I use selection on observables to learn about potential bias from selection on unobservables, an approach formalized in Altonji, Elder, and Taber (AET) (2005). As Oster (forthcoming) clarifies, the typical approach of testing coefficient stability after including controls will be uninformative if the additional controls do not increase the regression R-squared.

Following the approach in Oster (forthcoming), I report whether the stability of regional rank's coefficient, scaled by changes in R-squared, is consistent with coefficient stability in settings with randomized treatment. This is a useful benchmark because when treatment is randomly assigned, we expect high coefficient stability after including additional controls.

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 use only consulting firms since results were strongest for this sample. I restrict the regression to universities with p in the interquartile range of the sample limited to consulting firms. The relation between regional rank and p is more constant in this range.[45] In every regression, I include p, number of high-scoring students and number relative to the region, number of offices in the region, firm fixed effects, and firm-university distance, as these are the foundation for the identification strategy. For robustness, I include only regional rank in the baseline regressions (Appendix Table A12). The specification with the full set of controls includes the same controls as in equation (4), excluding interactions with p.

Following Oster (forthcoming), I show whether the set $[\tilde{\beta}, \beta^*]$ excludes zero, where $\tilde{\beta}$ is regional rank's coefficient from the regression with the full set of controls (with an R-squared of $\tilde{R}$). The coefficient β^* is the bias-adjusted treatment effect, requiring assumptions about the R-squared including all observables and unobservables (R_{max}), and the ratio of selection on unobservables relative to observables. Oster (forthcoming) shows coefficient stability is consistent with stability in settings with randomized treatment if $[\tilde{\beta}, \beta^*]$ excludes zero, β^* is calculated assuming $R_{max} = 1.3\tilde{R}$, and equal selection on observables and unobservables. An equivalent test is to show that to yield a treatment effect of zero, assuming $R_{max} = 1.3\tilde{R}$,

[45]Intuition also suggests no effect for the least and most selective universities. To determine the interquartile range of p ($p = .06$ to $p = .27$), I use the entire sample of firm/university pairs for consulting firms, rather than excluding universities with p below the minimum for attracting a firm and above .7. Because I use only universities in the interquartile range, these high and low p universities will be excluded from the sample used in the Oster implementation.

the level of selection on unobservables relative to observables is greater than 1.

Regional rank's coefficient in the full regression is -.049, slightly smaller than in the restricted regression (-.051) (Table 4, Panel A, columns 1 and 2). While the coefficient is relatively stable, additional regressors yield only a small increase in the R-squared (from .11 to .127). The bias-adjusted coefficient on regional rank (β^*) is still negative, equal to -.028 (Panel B, row 1). For regional rank's coefficient to equal zero, selection on unobservables must be at least 1.244 times larger than selection on observables. These results suggest the level of coefficient stability is consistent with randomized treatment.

7 Regional Rank and Post-College Earnings

The model predicts that high-ability students should earn higher wages if they graduate from a better regionally-ranked university, conditional on absolute university quality. At better regionally-ranked universities, high-ability students have greater access to prestigious finance and consulting firms that pay higher wages. First, I show whether regional rank's effect on finance and consulting recruiting translates into an employment effect in these fields one year after graduation. I then test for overall differences in earnings by the university's regional rank, conditional on absolute quality.

I use the US Department of Education's Baccalaureate and Beyond Survey, 2009 (B&B). The B&B surveys approximately 15,050 college seniors in the 2007-2008 academic year, who are also surveyed in 2009 after receiving their degree. I merge the B&B with university data using the IPEDS ID of the student's Bachelor's degree institution.[46] I limit the sample to graduates of universities nationally ranked 400 or better (based on p), whose state of legal/permanent residence was one of the 50 US states in the 2007-2008 school year and in 2009, with nonmissing SAT/ACT scores and nonmissing income in 2009, 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.[47] Among this sample, I only include individuals with adjusted earnings (defined below) at or above the 5th percentile (approximately $17,720).

Regional Rank, Finance and Consulting Employment, and Earnings Using the respondents' actual reported job title and industry (instead of the aggregated version) in the restricted-access B&B, I identify students working as consultants at a consulting firm, or as finance analysts at a financial firm one year after graduation. I exclude IT consultants and

[46] I use IPEDS data for Freshmen in Fall 2004, as the sample graduates in Spring 2008.
[47] Conditioning on US residence is necessary for adjusting income for regional price parity (see below).

environmental/engineering consultants from my sample of consultants. I include as finance analysts individuals whose industry is finance-related (e.g. investment banking, private equity, finance), and whose job title is similar to analyst or trader. The appendix describes the coding in detail.

Of the 2090 individuals in the sample, approximately 60 are consultants or finance analysts (30 consultants, 30 finance analysts). Because the sample is not large, these results are certainly more suggestive, and I present descriptive findings. Consultants and finance analysts graduating outside the East (30 students) attended much less selective universities. Half attend universities with $p \leq .144$. Dramatically, nearly all of the finance analysts and consultants graduating in the East graduated from universities more selective than this. Median earnings are similar for consultants and finance analysts graduating in the East ($60,000) and outside the East ($57,300), mitigating concerns these are different jobs.

These findings suggest that conditional on attending a less selective university, access to prestigious firms is greater outside the East, where regional ranks are better. This also represents a difference in access to higher than median earnings at these less-selective universities. Median earnings of finance analysts and consultants graduating outside the East from a university with $p \leq .144$ (the median selectivity of their universities) is approximately $50,050. For non-finance analysts and nonconsultants graduating from similarly selective universities outside the East, median earnings is approximately $38,700, and approximately $37,600 for graduates in the East (where nearly noone works as a finance analyst or consultant).

Graduates of non-elite universities outside the East have access to a particular set of jobs with median earnings nearly 35% higher than overall median earnings at similarly selective universities in the East.

Regional Rank's Overall Effect on Earnings Regional rank may affect earnings in the overall sample, other than the direct effect on earnings through impacting finance and consulting employment. First, regional rank may matter for industries besides finance and consulting. Second, higher finance and consulting salaries may create upward wage pressure at better regionally-ranked universities. I test for regional rank's impact in the overall sample.

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. I interact the student's SAT (SAT) with regional rank and key explanatory variables (p, number of high-scoring students, and number relative to the region).[48] Negative effects should be stronger at less selective universities, where regional rank is much worse in the East. While difficult with a small sample, I additionally estimate separate regressions for universities with $p \leq$75th percentile

[48]For robustness, I interact SAT and each never-missing university characteristic (Table 3, Column 5). SAT is SAT or ACT composite converted to SAT.

(approximately .17) and p >75th percentile, as well as include triple interactions with p.[49] Clustering standard errors by university, I estimate:

$$
\begin{aligned}
LogEarnings_{isl} = \alpha + \gamma_1 p_s + \gamma_2 RegRank_s + \gamma_3 SAT_i + \gamma_4 RegRank_s * SAT_i \\
+ \gamma_5 p_s * SAT_i + X_s\beta + Z_i\rho + \gamma_6 AvgWageBAGrad_l + \epsilon_{isl} \qquad (5)
\end{aligned}
$$

$LogEarnings$ 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, 2008).[50] 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.[51] Z_i includes demographics, SAT/ACT score, and interactions between SAT and the key variables listed above.[52] I do not include region fixed effects as these would eliminate the identifying across-region variation.

I calculate university rank using the 25th and 75th percentiles of the Math SAT and ACT scores. 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 percent 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.

Graduating from a worse regionally-ranked university differentially hurts earnings of higher SAT students, holding constant university size and quality (Table 3, Column 1). For students with a 1400 SAT, the coefficients suggest earnings are 4.35% lower if regional rank is worse by 30 places (multiplying the linear combination by .3), the approximate East-West regional rank differential at the 25th and 50th selectivity percentiles in this sample. Effects are much smaller for lower-scoring students. The regional rank coefficients approach conventional significance levels ($p = .11$).[53] Controlling for number of high-scoring students,

[49]Based on 2004 data, p for Texas A&M is about .12 and for Penn State is about .11.

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

[51]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), indicators for public, offers more than a bachelor's, in large or mid-sized city, 2008 USNWR rank, and in- and out-of-state tuition. I include indicators for nonmissing USNWR rank, urbanization, and tuition. See appendix for details.

[52]I include an indicator for 2006 parental income $\geq$ median and $\leq$ 75th percentile in the sample ([78,433.13, 127,775]), and $>$ 75th percentile, and whether the student is black, asian, other race, hispanic, male, and during the 2007/2008 academic year a citizen and a dependent. I adjust parental 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 with non-US residence (in 2007-2008 or 2009).

[53]These linear combinations are similar, though suggest larger negative effects for high-SAT and smaller negative effects for low-SAT students, when using sampling weights (normalized so the weight sum equals the number of observations). The coefficients on regional rank are not jointly significant at the 10% level

and number relative to the region helps identify the effects are due to screening costs.

Splitting the sample at the 75th percentile of p, Column 2 shows the effect for high SAT students is larger in magnitude at less selective universities, and not significant at more selective universities (Column 3), though focusing on selective universities reduces the sample size considerably. Estimating (5) with additional interactions between the key variables and p, the regional rank*p interactions are not jointly significant (Appendix Table A13). However, adding four triple interactions and the requisite lower-level terms is clearly asking much of this small sample.

While I control for many student characteristics and university quality measures, graduates of worse regionally-ranked universities may earn less due to unobservable differences. I estimate an additional regression including only key controls.[54] The results are very similar (column 4) despite the excluded controls' explanatory power (R-squared in column 1 is twice that in column 4)), presenting informal evidence against selection on unobservables.

More formally, I again use the Oster (forthcoming) strategy, to learn about potential bias from selection on unobservables. The level of coefficient stability is consistent with randomized treatment (Table 4). For regional rank's coefficient to equal zero, selection on unobservables must be at least 3.9 times larger than selection on observables (see appendix).

The results support the model's prediction: screening costs and regional labor markets yield higher earnings for graduates of better regionally-ranked universities, holding constant student and university characteristics, and high types at the university relative to the region. However, students should not hold this last variable constant when choosing a university. I identify the selectivity advantage necessary in the East to yield similar average earnings.

I estimate a regression similar to (5), with p as the only measure of selectivity. Allowing for differences in high-scoring students in the region, there is a modest earnings advantage in the West. For students with a 1400 SAT, and graduating from a university with p at the 25th percentile, earnings are approximately 3% higher for students in the West relative to East (Figure 6). Using the procedure in the recruiting section, if the goal is to maximize earnings, students considering a university in the West at the 25th percentile of selectivity should choose a more selective university in the East, only if at the 60th percentile of selectivity (with regional rank worse by 1 to 5 positions). Otherwise, students should choose the less selective, but better regionally-ranked university in the West.

If students are considering median-selectivity universities in the West, they should choose

when using sampling weights. Column 5 shows the results are robust to interacting each of the never-missing university characteristics with student SAT.

[54] These are student SAT, regional rank, p, number of H-type students, and number divided by region total, interactions of these last four with student SAT, and average earnings of college graduates 25-34 in the state of residence (adjusted for state price parity).

a more selective university in the East only if at the 76th percentile (with regional rank worse by 6 to 8 positions). Otherwise, they should attend the less selective, but better regionally-ranked university in the West.

8 Alternative Mechanisms

Prestige, rather than screening costs, may explain regional rank's importance when controlling for absolute quality. Local clients may prefer working with graduates of regionally-prestigious universities, and regional prestige may matter for local office culture. I test this mechanism using staffing policies at consulting firms. Global-staffing firms assign consultants to cases potentially far from their "home" office. For these firms, regional prestige should not matter for clients or office culture, since consultants work outside the region.[55] A worse regionally-ranked university should attract fewer of these firms only due to screening costs, controlling for the number and proportion of H-type students, and market supply and demand. I identify staffing policies using job and travel descriptions on firms' websites.[56]

Regional rank has a large, significant effect on recruiting for global-staffing firms (Column 3, Table 2). This suggests the importance of screening costs. Regional rank coefficients are not jointly significant for local-staffing firms (Column 4), but magnitudes are fairly similar (though larger for higher p universities).

Regional rank may be correlated with offering undergraduate business majors or MBAs, attracting finance and consulting firms.[57] Using data from university websites, these offerings do not explain regional rank's importance (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 may more likely have attended less selective universities. If recruiting is driven by alma mater, they will recruit new employees who also attended less selective universities. This paper can be seen as explaining why in the first period employees at elite firm offices outside the East attended less selective universities, which starts the path-dependent process.

9 Structural Estimation and Counterfactuals

The reduced-form analysis suggests strong support for the predicted impact of screening costs on recruiting and wages. It also quantified the tradeoff between regional and absolute

[55]Global-staffing firms may still recruit regionally since consultants return home by Friday.
[56]I confirmed this coding with an employee of one of the sample firms.
[57]MBA and BA recruiting are often separate, but recruiting on the same campus may be beneficial.

selectivity. In this section, I structurally estimate the screening cost parameter, allowing me to analyze how reducing 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.

In the model, firms care about applicants per job, 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).[58] 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.

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:

$$\pi = (1 - e^{-p_1 \lambda (\frac{S_1}{N_1})})(v - \frac{(\lambda S_1 (p_1 v - c)}{N_1 (e^{p_1 \lambda (\frac{S_1}{N_1})} - 1)} - \frac{c}{p_1}) \tag{6}$$

The unknown parameters c (screening cost) and v (worker productivity) are not separately identified, and I normalize v to 1.[59] 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. 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 (2)). 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

[58] Appendix Table A10 shows parameter estimates for various γ.

[59] 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 $(2v, 2c)$.

find the profit from allocating (in a profit-equalizing manner) across all higher-p universities, using the conditions in (2), but including λ as in (6). 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.[60] I check the solution equalizes profits at all universities.[61]

If recruiting at the higher p universities yields profit greater than at the 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 ($\frac{N_{t,Predicted}}{NTot_{Predicted}} - \frac{N_{t,Observed}}{NTot_{Observed}}$),[62] this error multiplied by p_t, and by $log(S_t)$.[63] 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.[64]

The parameter c is identified by explaining firms' preference for universities with higher proportion, but identical number, of H-types. Non-zero estimates of c reject a simple supply and demand story, which predicts firms allocate based only on the number of H-types. The parameter λ is identified by firms' preference for universities with larger number, but identical proportion, of H-types. 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. 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 present discounted value of the additional productivity of a high type at a finance or consulting firm relative to other industries, over the course of the match.

[60] 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.

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

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

[63] 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).

[64] The solution is not at a grid bound, and the objective function is smooth around the solution (i.e. for given c, the objective function decreases in λ until the solution, and increases in λ afterwards).

The per-applicant screening cost is about 10% of v, additional worker productivity in finance/consulting, though lower in the Midwest (Panel A, Table 5). 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 $(.07, .3)$.[65] Higher profit in the East than West is consistent with a higher p in the East to guarantee a recruiting firm (see appendix). With per-applicant screening costs equal to 9% of worker productivity v in the East, $p_{cutoff} \approx .14$. Eighty five universities in the East have $p < p_{cutoff}$ and 83 have $p \geq p_{cutoff}$.

The model fits reasonably well in each region, comparing the predicted and observed distributions of the proportion of firms recruiting at the university (Appendix Figure A1).

Impact of Screening Costs on Student Outcomes

Structural estimation allows me to identify the impact of reducing screening costs on recruiting and wages.[66] Screening costs negatively impact H-type students at less selective universities (Panel B, Table 5). With per-applicant screening costs that are 9% of additional worker productivity in finance/consulting (v), the model predicts elite finance and consulting firms do not hire from universities below the median selectivity in the East ($p_{cutoff} \approx .137$). Further, 70% of their expected hires are from universities in the top quartile of selectivity.[67]

Halving screening costs, the proportion of expected hires from universities outside the top quartile increases from 30% to 38%, an increase of 27% (columns 1 and 2). This includes 7% of expected hires from universities between the 25th and 50th percentile; with higher screening costs it was not profitable for any firm to hire from these universities. As a result of recruiting at these less selective universities, H-type graduates have access to wages equal to the reservation wage plus 11% of the additional worker productivity (v) at these firms (columns 5 and 6), instead of just the reservation wage. Proportion of recruiting firms by university selectivity (columns 3 and 4) is similar to proportion of expected hires.

Because most firms recruit at selective universities, parameters suggest H-type finance and consulting wages are considerably higher for graduates of more selective, relative to less selective, universities. This premium for selective-university graduates falls by about 50% when halving screening costs (comparing students at the top quartile to those between the 50th and 75th percentile of selectivity). The appendix shows outcomes for three universities of varying selectivity.

[65] Estimates of c are relatively similar, yet λ estimates are higher, when $\gamma = 15$ (Appendix Table A10). With few firms (low γ), recruiting at high-p universities with few H-type students is difficult to explain. This may yield a low λ, so smaller universities do not appear smaller to firms.

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

[67] Expected hires accounts for the nonzero probability of not attracting any H-type applicants.

Cost per Hired Worker I calculate screening cost per hire by multiplying expected number of applicants reviewed (footnote 16) by screening cost per applicant (.09 in the East). At less selective universities, firms on average review more applicants, raising cost per hire. Expected number of applicants reviewed at MIT (p=.86) is .77, so screening cost per hire is about 7% of the worker's additional productivity in finance/consulting (v). Expected number of applicants reviewed at Fordham (p=.14) is 3.2, 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 match (v) is $50,000 (reasonable if the match is five years), this is approximately $14,500. Cost per hire differences 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. Large cost estimates are consistent with screening conducted by consultants with high external billing rates.[68]

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, 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 screening costs have important impacts on where and how firms recruit workers.

Using newly-collected recruiting data 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 wages are driven not just by university size and selectivity, but by the university's selectivity relative to others in the region. For median-selectivity universities, a better regionally-ranked university is twice as likely to attract a consulting firm, and wages are 4% higher.

Recent advances in screening technology raise the possibility of recruiting with lower screening costs. I structurally estimate the model, allowing me to study the impact of counterfactually reducing screening costs. Halving screening costs, there is a 27% increase in the proportion of expected finance and consulting hires from universities outside the top selectivity quartile. This suggests screening costs have very negative impacts on high-ability students at less selective universities.

[68]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, implies nearly $700 per hour as a very rough average hourly rate. Very anecdotal evidence, based on a conversation with a former management consultant, suggested cost per MBA hire is approximately $100,000, and only slightly lower for undergraduates.

The results have important implications for college choice. For students interested in finance and consulting and considering universities in the West at the 25th percentile of selectivity, they should choose a more selective university in the East only if it is at the 55th percentile. The results suggest the benefits of attending the best university in a small pond, despite fewer firms in the pond. The disadvantages of attending a worse regionally-ranked university in the East may reflect the value students place on living close to friends and family. This would be consistent with limited mobility of college graduates (Wozniak 2010).

With elite universities, students at non-elite universities have less access to prestigious firms (if firms would choose differently than universities). Thus, elite universities may obstruct equal access to firms for students equally likely to be hired by the firms. Equity effects are larger if initial jobs affect careers. However, by incurring screening costs, and reducing these for firms, elite universities may increase efficiency.[69]

References

[1] Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2002): "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," http://www.econ.yale.edu/~jga22/website/research_papers/cathrs31lte.pdf.

[2] Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2005): "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, Vol. 113(1).

[3] Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2008): "Using Selection on Observed Variables to Assess Bias from Unobservables When Evaluating Swan-Ganz Catheterization," *American Economic Review: Papers and Proceedings*, Vol. 98(2).

[4] Aten, Bettina H. and Roger J. D'Souza (2008): "Regional Price Parities: Comparing Price Level Differences Across Geographic Areas," *Survey of Current Business*, Bureau of Economic Analysis. http://www.bea.gov/scb/pdf/2008/11%20November/1108_spotlight_parities.pdf.

[5] Berry, Steven, James Levinsohn, and Ariel Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, Vol. 63(4).

[6] Black, Dan and Jeffrey Smith (2004): "How Robust is the Evidence on the Effects of College Quality? Evidence from Matching," *Journal of Econometrics*, 121(1).

[7] Black, Dan and Jeffrey Smith (2006): "Evaluating the Returns to College Quality with Multiple Proxies for Quality," *Journal of Labor Economics*, 24(3).

[69] This is just a transfer unless screening costs are lower for universities than for firms.

[8] Brand, Jennie E. and Charles N. Halaby (2006): "Regression and Matching Estimates of the Effects of Elite College Attendance on Educational and Career Achievement," *Social Science Research*, September.

[9] Brewer, Dominic J., Eric R. Eide, and Ronald G. Ehrenberg (1999): "Does It Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings," *The Journal of Human Resources*, 34(1).

[10] Cascio, Elizabeth U., and Ayushi Narayan (2015): "Who Needs a Fracking Education? The Educational Response to Low-Skill Biased Technological Change," NBER Working Paper 21359.

[11] Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo (2015): "Housing Booms and Busts, Labor Market Opportunities, and College Attendance," NBER Working Paper 21587.

[12] Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan (2017): "Mobility Report Cards: The Role of Colleges in Intergenerational Mobility," Working Paper.

[13] Chevalier, Arnaud and Gavan Conlon (2003): "Does It Pay to Attend a Prestigious University?" *IZA Discussion Paper Series*, Number 848.

[14] Dale, Stacy B. and Alan B. Krueger (2002): "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables." *The Quarterly Journal of Economics*, 117(4).

[15] Dale, Stacy and Alan B. Krueger (2011): "Estimating the Return to College Selectivity Over the Career Using Administrative Earnings Data," *Journal of Human Resources,* 49(2).

[16] Davis, J. A. (1966): "The Campus as a Frog Pond: An Application of the Theory of Relative Deprivation to Career Decisions of College Men." *American Journal of Sociology,* 72(1), 17-31.

[17] DeVaro, J. (2005): "Employer Recruitment Strategies and the Labor Market Outcomes of New Hires," *Economic Inquiry*, 43(2), 263-282.

[18] DeVaro, J. (2008): "The Labor Market Effects of Employer Recruitment Choice," *European Economic Review*, 52(2), 283-314.

[19] Diamond, P. A. (1982): "Wage Determination and Efficiency in Search Equilibrium," *Review of Economic Studies,* 49(2), 217-227.

[20] Galenianos, M. and P. Kircher (2009): "Directed Search with Multiple Job Applications," *Journal of Economic Theory,* 144(2), 445-471.

[21] Gellman, Lindsay (2016): "The Path From Harvard and Yale to Goldman Sachs Just Changed," *Wall Street Journal*, June 23, 2016, http://www.wsj.com/articles/goldman-rethinks-campus-recruiting-efforts-1466709118 (accessed 8/19/2016).

[22] Habbe, S (1948): "College Graduates in Industry; Recruiting, Selecting, Training," National Industrial Conference Board. Studies in Personnel Policy, 89.

[23] Habbe, Stephen (1956): "Employment of the College Graduate," National Industrial Conference Board. Studies in Personnel Policy, 52.

[24] Hill, Andrew (2011): "Inside McKinsey," *FT Magazine*, November 25, http://www.ft.com/cms/s/2/0d506e0e-1583-11e1-b9b8-00144feabdc0.html (accessed 8/25/2016).

[25] Holzer, H. J. (1987): "Hiring Procedures in the Firm: Their Economic Determinants and Outcomes," Working Paper w2185, National Bureau of Economic Research.

[26] Hoxby, Caroline and Christopher Avery (2014): "The Missing 'One-Offs': The Hidden Supply of High-Achieving, Low-Income Students," *Brookings Papers on Economic Activity*, Spring.

[27] Kuhnen, Camelia (2012): "Searching for Jobs: Evidence from MBA Graduates," Working Paper.

[28] Kuhnen, Camelia and Paul Oyer (2016): "Exploration for Human Capital: Evidence from the MBA Labor Market," *Journal of Labor Economics*, Vol. 34(S2).

[29] Lang, K., M. Manove, and W. T. Dickens (2005): "Racial Discrimination in Labor Markets with Posted Wage Offers," *American Economic Review,* 95(4), 1327-1340.

[30] Long, Mark C. (2008): "College quality and early adult outcomes," *Economics of Education Review*, 27.

[31] Long, Mark C. (2010): "Changes in the returns to education and college quality," *Economics of Education Review*, 29.

[32] Loury, Linda Datcher, and David Garman (1995): "College Selectivity and Earnings," *Journal of Labor Economics*, 13(2).

[33] McKinsey. "A Community for Life," Accessed September 2013, http://www.mckinsey.com/careers/aplacetogrow/acommunityforlife.

[34] Mortensen, D. T. (1982a): "The Matching Process as a Noncooperative/Bargaining Game," in J.J. McCall, ed., *The Economics of Information and Uncertainty. University of Chicago Press,* Chicago, IL.

[35] Mortensen, D. T. (1982b): "Property Rights and Efficiency in Mating, Racing, and Related Games," *American Economic Review,* 72(5), 968-979.

[36] National Association of Colleges and Employers (2014): "Recruiting Benchmarks: On-Campus Interviews," Accessed online 6/22/15: http://www.naceweb.org/s03192014/on-campus-interview-benchmarks.aspx.

[37] National Center for Education Statistics, US Department of Education (2013). *Digest of Education Statistics* (Table 318.10).

[38] Newman, M.E.J. (2004): "Fast Algorithm for Detecting Community Structure in Networks," *Physical Review E,* 69(6), 066133.

[39] Oster, Emily (forthcoming): "Unobservable Selection and Coefficient Stability: Theory and Validation," *Journal of Business Economics and Statistics.*

[40] Oyer, P. and S. Schaefer (2012): "Firm/Employee Matching: An Industry Study of American Lawyers," Working Paper w18620, National Bureau of Economic Research.

[41] Pissarides, C.A. (1984): "Efficient Job Rejection," Economic Journal Conference Papers, 94, Supplement: Conference Papers, 97-108.

[42] Pissarides, C.A. (1985): "Short-run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," *American Economic Review,* 75(4), 676-690.

[43] Rivera, Lauren A. (2011): "Ivies, Extracurriculars, and Exclusion: Elite Employers' Use of Educational Credentials," *Research in Social Stratification and Mobility*, Vol. 29.

[44] Rivera, Lauren A. (2012): "Hiring as Cultural Matching: The Case of Elite Porfessional Service Firms," *American Sociological Review*, Vol. 77(6).

[45] Rudolph, F. (1990): *The American College and University: A History,* University of Georgia Press.

[46] "The Best 376 Colleges," The Princeton Review. 2012.

[47] Temin, Peter (1999): "The Stability of the American Business Elite," *Industrial and Corporate Change*, Vol. 8(2).

[48] US News and World Report (2011): "Frequently Asked Questions: College Rankings," US News and World Report. http://www.usnews.com/education/best-colleges/articles/2011/09/12/frequently-asked-questions-college-rankings-2012?scid=related-links:TOP[8/20/2012 2:59:48 PM].

[49] van den Berg, G. and A. van Vuuren (2010): "The Effect of Search Frictions on Wages," *Labour Economics,* 17(6), 875-885.

[50] Weinstein, Russell (2017a): "Local Labor Markets and Human Capital Investments," Working Paper.

[51] Weinstein, Russell (2017b): "Geography and Employer Recruiting," IZA Discussion Paper 11224.

[52] Wozniak, Abigail (2010): "Are College Graduates More Responsive to Distant Labor Market Opportunities?" *Journal of Human Resources*, Vol. 45(4).

[53] Zimmerman, Seth: "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes," *American Economic Review*, Forthcoming.

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

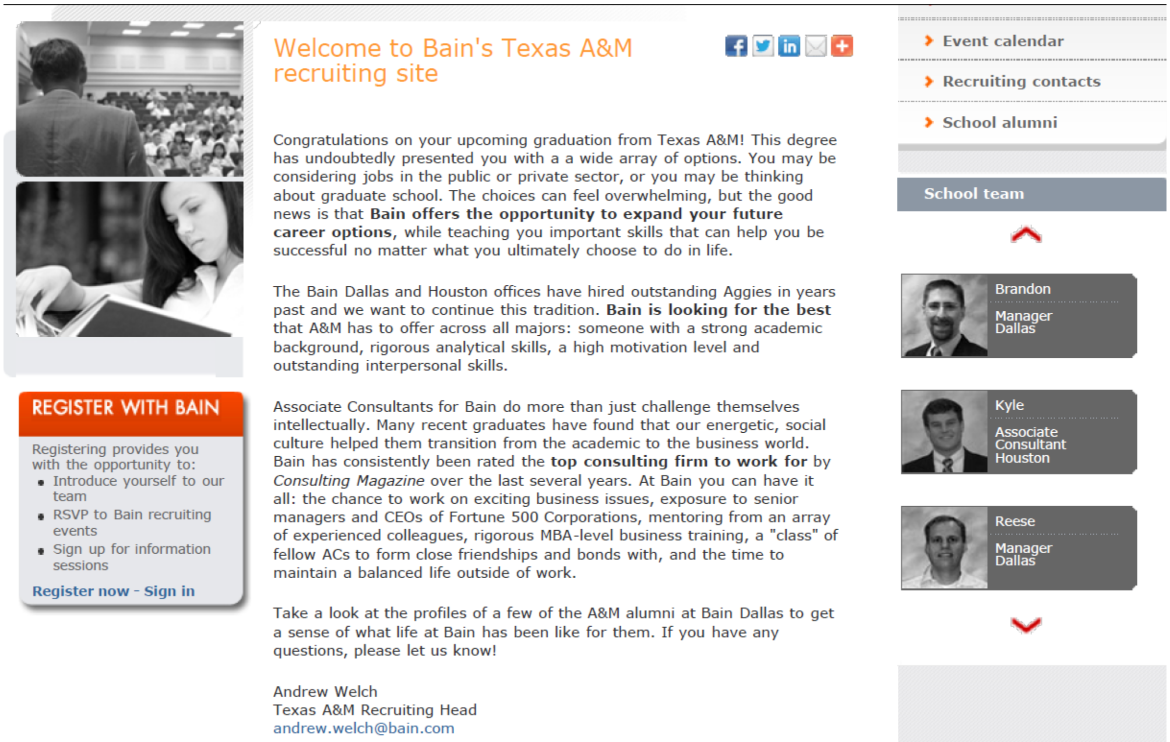


Figure 1b: Bain Recruiting Page for Penn State

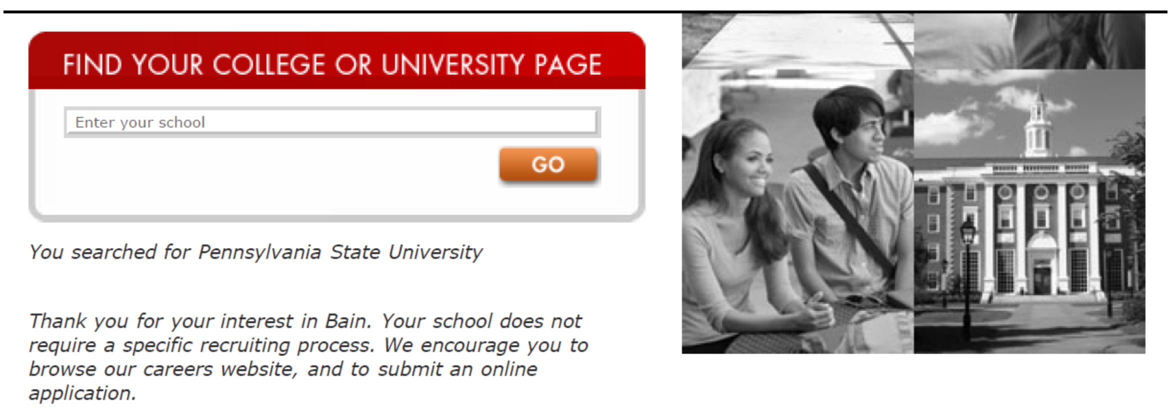
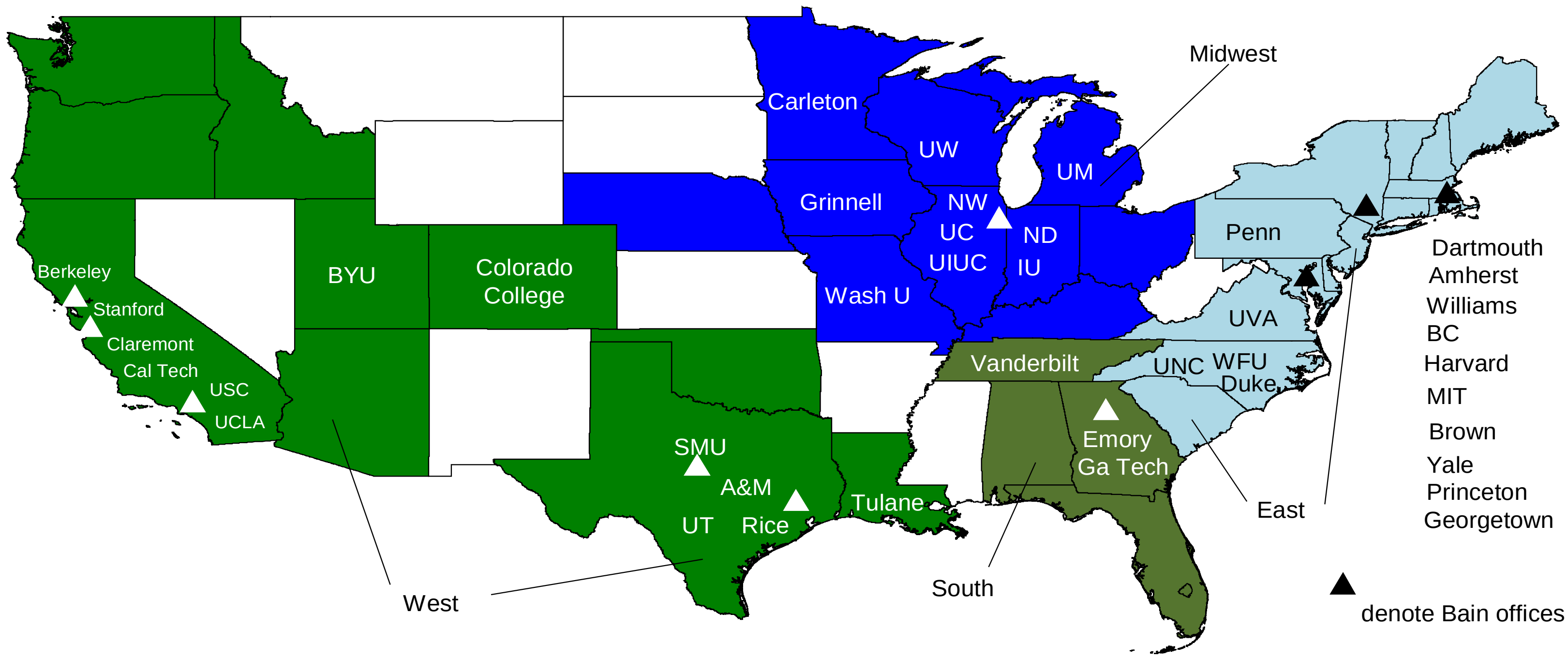


Figure 2: Where does Bain Recruit?



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

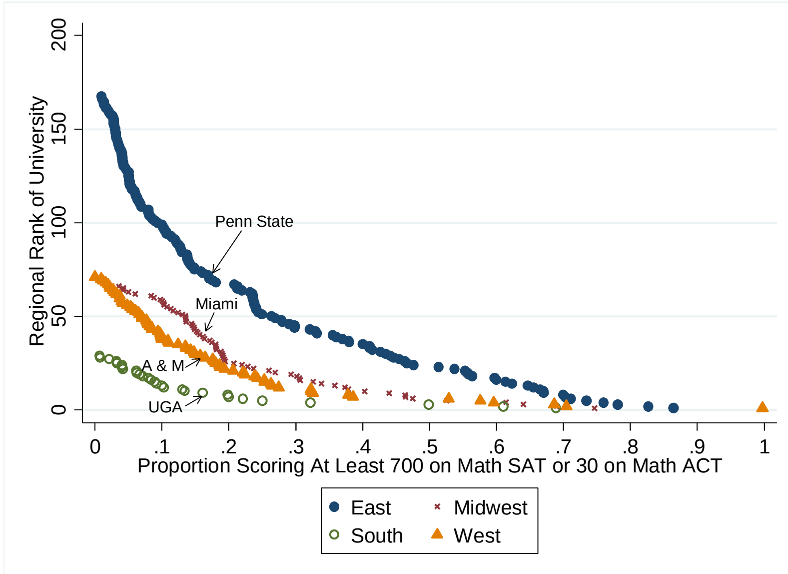
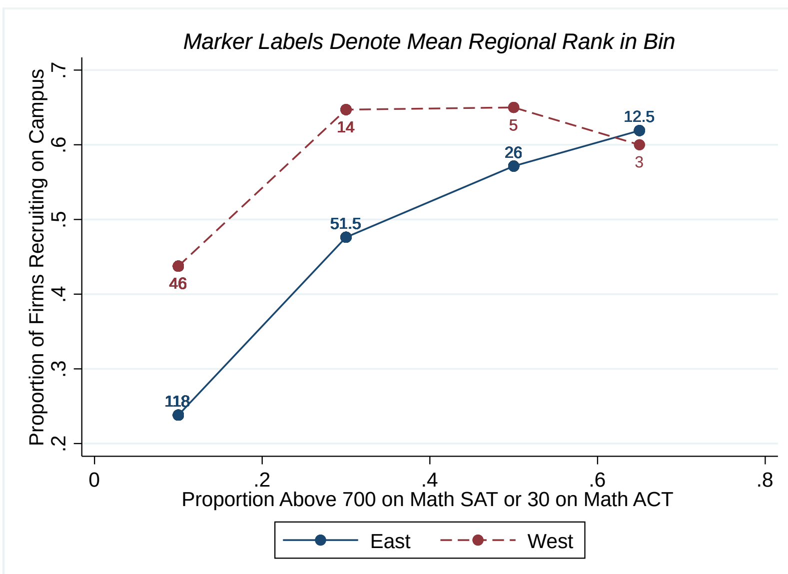


Figure 4: Consulting Recruiting at the University Attracting the Most Firms, by University Selectivity Bin and Region



Note: Figure 3 plots p for universities in the sample (the proportion of freshmen scoring at least 700 on the Math SAT or at least 30 on the Math ACT), and the regional rank of the university based on p. Universities outside the East, West, Midwest, and South are excluded from the plot. See text for region definitions and details on calculating p. 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 $\in$ [0,.2), [.2,.4), [.4,.6), [.6,.7). This exercise is among universities in the regression sample, and so it excludes universities with $p > .7$. These universities are excluded from the regression sample due to limited overlap across regions. As is evident from the mean regional ranks (denoted by marker labels), the sample size of the bins [.4,.6) and [.6,.7) in the West is small.

Figure 5: Difference in Selectivity, Relative to the 25th Percentile, Yielding Equal Recruiting Probabilities in East and West

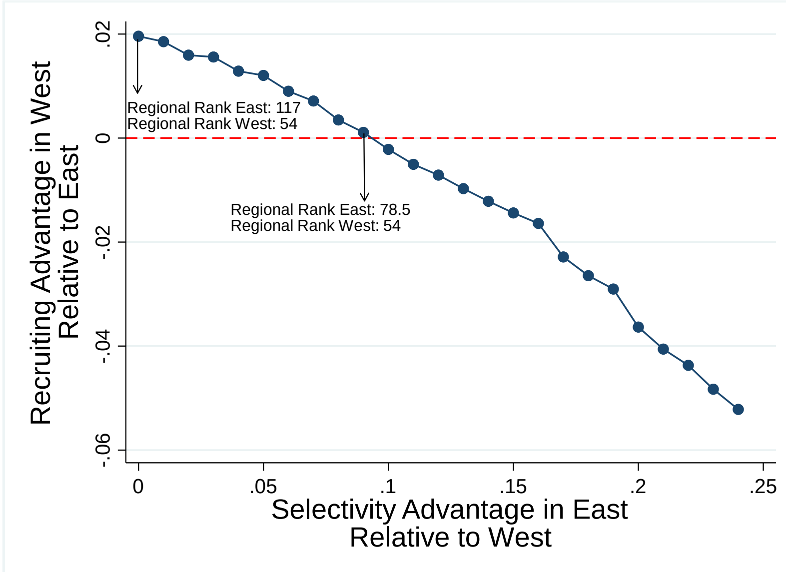
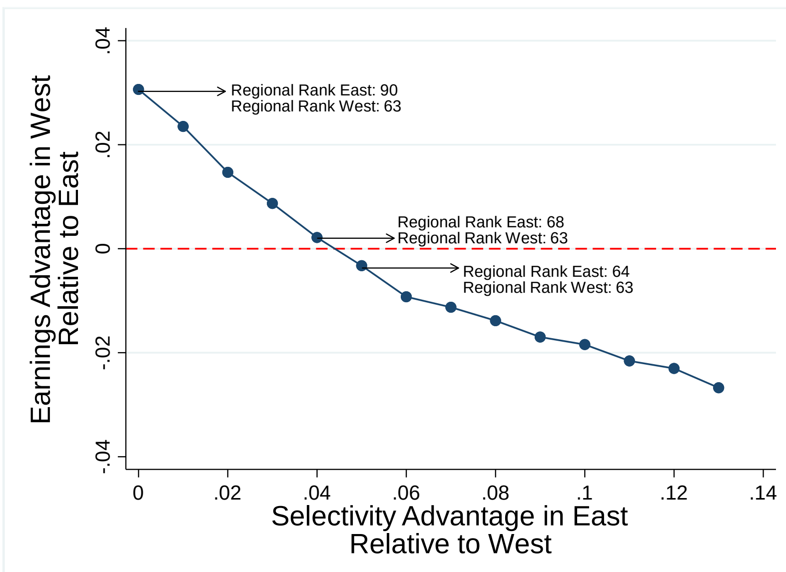


Figure 6: Difference in Selectivity, Relative to the 25th Percentile, Yielding Equal Earnings in East and West



Note: I show the difference in the predicted probability of attracting a recruiting consulting firm (Figure 5) and difference in predicted earnings for students with 1400 SAT (Figure 6) for universities at the 25th percentile of p (at x = 0). The predictions are calculated using regression coefficients from regressions similar to that in Table 2, column 7 (Figure 5) and in Table 3, column 1 (Figure 6), but including p as the only selectivity measure. In calculating the probabilities, I assume the universities in the East and West are observably equal, except for regional rank, high-scoring students relative to the region, and number of firm offices per region (in the case of Figure 5). I then show how the advantage in the West changes as the university in the East increases in selectivity relative to the university in the West (increasing the selectivity advantage away from zero). See text and appendix for details.

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	0.06	0.82	0.02	0.07
South	0.09	0.05	0.76	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 University's Regional Rank on Recruiting, Controlling for University Quality

Y: Recruit (mean = .062)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Regional Rank (hundreds)	-0.091***	0.025**	0.051***	-0.011	-0.037***	-0.038***	-0.039***
	[0.014]	[0.011]	[0.008]	[0.009]	[0.012]	[0.012]	[0.015]
Regional Rank **p*				0.399***	0.094	0.187	0.633***
				[0.139]	[0.182]	[0.185]	[0.205]
p (% High Math Score Students)		0.458***	0.246***	-0.480***	-0.438***	-0.614***	-0.784***
		[0.060]	[0.046]	[0.125]	[0.125]	[0.163]	[0.183]
p^2				0.856***	0.738***	0.774***	0.973***
				[0.229]	[0.232]	[0.203]	[0.223]
# H-Types (thousands)			0.173***	0.116***	0.109***	0.098**	0.135***
			[0.021]	[0.036]	[0.036]	[0.047]	[0.049]
# H-Types**p*				0.183*	0.217**	0.224**	0.060
				[0.099]	[0.107]	[0.104]	[0.111]
Distance to Firm/100					-0.011***	-0.011***	-0.011***
					[0.002]	[0.002]	[0.002]
Firm Offices in Region/100					0.022**	0.024**	0.024**
					[0.011]	[0.010]	[0.011]
Regional Rank*Consult							0.001
							[0.012]
Regional Rank**p** Consult							-0.778***
							[0.179]
H-Types /Region Total	N	N	N	N	Y	Y	Y
All Univ. Quality Controls	N	N	N	N	N	Y	Y
N	10730	10730	10730	10730	10730	10730	10730
R-Squared	0.079	0.136	0.213	0.224	0.23	0.235	0.245
P-value, Joint Test of Regional Rank Coefficients				0.01	0.004	0.004	0.000
Linear Combination of Coefficients on Regional Rank							
Universities with *p* = .06							
Texas	-0.051***	0.014**	0.028***	0.006*	-0.018*	-0.015	-0.026***
(Regional Rank 56)	[.008]	[.006]	[.004]	[.004]	[.01]	[.01]	[.01]
East	-0.108***	0.029**	0.060***	0.014*	-0.038*	-0.033	-0.056***
(Regional Rank 120)	[.016]	[.013]	[.009]	[.008]	[.02]	[.02]	[.021]
Universities with *p* = .14							
Texas	-0.03***	0.008**	0.017***	0.014***	-0.008	-0.004	-0.019*
(Regional Rank 32.5)	[.004]	[.003]	[.003]	[.005]	[.01]	[.009]	[.01]
East	-0.075***	0.02**	0.042***	0.035***	-0.02	-0.011	-0.048*
(Regional Rank 82)	[.011]	[.009]	[.006]	[.012]	[.024]	[.024]	[.026]

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. All regressions include firm fixed effects. All regional rank variables, including in interactions, are measured in hundreds. Number of H-types, including in interactions, is measured in thousands. Standard errors are clustered at the university level. In Column 6, additional controls for university quality include 25th, 75th percentiles of Math and Combined SAT/ACT, weighted by share reporting each exam; percentage in [700, 800] on SAT Verbal/ACT English; 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. I include indicators for whether the following are nonmissing: US News rank, test score percentiles, percent in top 10% of HS class, tuition. Firm Offices in Region is the number of firm offices in the region among all sample firms. The online appendix shows coefficients on every included variable in Column 6. Column 7 also includes interactions between *Consult* and # H-types**p* , # H-types relative to the region**p* , and p^2 , and all lower-level interaction terms (not shown). Column 7 shows linear combinations for consulting firms. See text and online appendix for details.

Table 3: Effect of University's Regional Rank on Earnings After Graduation, Controlling for Student SAT Score and University Quality

Y=ln(Earnings)	(1)	(2)	(3)	(4)	(5)
Regional $Rank_s$ (hundreds)	0.131	0.148	-0.698	0.159	0.134
	[0.235]	[0.287]	[1.077]	[0.226]	[0.207]
Regional $Rank_s$ (hundreds)*SAT_i (hundreds)	-0.020	-0.024	0.042	-0.022	-0.021
	[0.021]	[0.027]	[0.082]	[0.020]	[0.019]
Proportion High Math $Score_s$	2.136***	1.888	0.957	1.331**	1.390
	[0.719]	[3.097]	[1.144]	[0.665]	[1.195]
Proportion High Math $Score_s$*SAT_i (hundreds)	-0.125***	-0.125	-0.063	-0.101**	-0.061
	[0.048]	[0.261]	[0.074]	[0.049]	[0.090]
Linear Combination of Regional Rank Coefficients for:					
1400 SAT	-0.145*	-0.181*	-0.113	-0.149**	-0.153**
	[.078]	[.106]	[.192]	[.072]	[.076]
1000 SAT	-0.066	-0.087	-0.28	-0.061	-0.071
	[.05]	[.054]	[.301]	[.045]	[.046]
P-value on Joint Test of Regional Rank Coefficients	0.113	0.107	0.594	0.062	0.083
Controls for Student SAT and University Quality	Y	Y	Y	Y	Y
Full Set of Controls	Y	Y	Y	N	Y
Universities	All	Less Selective	More Selective	All	All
Interactions of University Controls, Student SAT	Key	Key	Key	Key	All
N	2090	1570	510	2090	2090
R-squared	0.170	0.156	0.243	0.085	0.179

Note: *** p≤0.01, ** p≤0.05, * p≤0.1. 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. All regressions include controls for student SAT score and key measures of absolute university quality: proportion and number of high-scoring students, and number of high-scoring students divided by the total in the region. In each regression, I also control for average earnings of college graduates aged 25-34 in 2009 state of residence, adjusted for state price parity. I additionally include the full set of student and university controls in columns (1) - (3) and (5). The additional university controls include: 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. The additional student controls include: an indicator for 2006 parental income ≥ 50th percentile and ≤ 75th percentile in the sample ([78,433.13, 127,775]), and an indicator for 2006 parental income > 75th percentile, 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 parental income for state price parity based on the 2007-2008 legal state of residence, using the 2006 Bureau of Economic Analysis state price parities. Sample excludes those with earnings below the 5th percentile, adjusted for state price parity ($17,723). Key interactions included in columns (1)-(4) are those between SAT score and the following university characteristics: 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 (approximately .17), and more selective universities in column 3 include those with $p >$ 75th percentile. Column 5 includes interactions between SAT and all never-missing university controls. Sample sizes are rounded to the nearest ten to preserve confidentiality. Standard errors clustered at the university level. See text and online appendix for details.

Table 4: Tests of Coefficient Stability and Selection on Unobservables

Panel A	(1) Y = Recruit	(2) Y = Recruit	(3) Y = ln(Earnings)	(4) Y = ln(Earnings)
(1) Regional Rank (hundreds)	-0.051*	-0.049	-0.143***	-0.133**
	(0.027)	(0.031)	(0.052)	(0.060)
(2) % Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT	-0.138	-0.214	-0.175	0.743
	(0.085)	(0.198)	(0.275)	(0.479)
(3) (# Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT)/1000	0.128***	0.148***	0.039	-0.022
	(0.023)	(0.041)	(0.040)	(0.049)
(4) # Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (thousands)/Total in Region	-0.075	-0.096	-0.108	-0.204**
	(0.149)	(0.168)	(0.069)	(0.099)
(5) # Finance and Consulting Offices in Region (hundreds)	0.018*	0.019		
	(0.011)	(0.012)		
(6) Firm-University Distance (hundreds of miles)	-0.005***	-0.005**		
	(0.002)	(0.002)		
(7) SAT (hundreds)			0.023**	0.018**
			(0.010)	(0.009)
Additional Controls for University/Student Characteristics	No	Yes	No	Yes
Observations	3,115	3,115	1,380	1,380
R-squared	0.110	0.127	0.073	0.163

Panel B	(1)	(2)	(3)	(4)
Result	Baseline Effect, Regional Rank [R^2]	Controlled Effect, including all Observables (Std. Error)[R^2=$\tilde{R}$]	Bias-Adjusted β R_{max} = 1.3$\tilde{R}$	Ratio of Selection on Unobservables to Observables yielding β=0, with R_{max} = 1.3$\tilde{R}$
(1) **Y = Recruit**	-.051 [.110]	-.049 (.031) [.127]	-0.028	1.244
(2) **Y = ln(Earnings)**	-.143 [.073]	-.133 (.060) [.163]	-0.125	3.933

Notes: Columns 1 and 2 in Panel A additionally include firm fixed effects, and include only consulting firms, and only universities with p in the interquartile range of the sample limited to consulting firms (including universities below the minimum *p* for attracting firms and above *p* =.7). Column 2 includes as additional control variables the same variables as included in Table 2, column 6 (excluding the interactions with *p*). Panel A columns (3) and (4) include only universities with p ≤ 90th percentile, and students with SAT at or above the 25th percentile of the main regression sample in Table 3, column 1. Columns 3 and 4 additionally include as a control average earnings of college graduates 25-34 in the state of residence (adjusted for state price parity). Column 4 includes as additional control variables the same as those in Table 3, column 1 (excluding the interactions with student SAT). Panel B column 1 presents the coefficients on regional rank and the R-squared from Panel A, columns 1 and 3. The controls in these baseline regressions provide the foundation for the identification strategy. Panel B column 2 presents the coefficients and standard errors on regional rank and the R-squared from Panel A, columns 2 and 4. Panel B column 3 reports the bias-adjusted coefficient on regional rank, using the approach in Oster (forthcoming). The assumption is that selection on observables is equal to selection on unobservables, and the R-squared from including observables and unobservables (Rmax) is 1.3*R-squared from Panel B column (2).

Table 5: Structural Estimation Results and Counterfactuals

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 a university's 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 additional worker productivity in finance and consulting relative to other industries. See text for detailed explanation of the estimation.

Panel B: Impact on Recruiting and Wages from Halving Screening Costs in the East

	(1)	(2)	(3)	(4)	(5)	(6)
	Expected Hires, as % of Total		Recruiting Firms, as % of Total		Average Wage, as % of Productivity	
	c = .09	c = .045	c = .09	c = .045	c = .09	c = .045
Universities with Selectivity						
≤ 25th percentile	0.000	0.000	0.000	0.000	0.000	0.000
25th to 50th percentile	0.000	0.067	0.000	0.059	0.000	0.114
50th to 75th percentile	0.297	0.314	0.269	0.304	0.176	0.278
> 75th percentile	0.703	0.619	0.731	0.637	0.390	0.384

Note: This table presents the results from counterfactually halving the cost of screening an applicant to .045, from .09 (the estimated value in the East). University selectivity refers to the proportion of students scoring at least a 700 on the Math SAT or 30 on the Math ACT (p). The variable c denotes the cost of screening an applicant, and this is relative to v, the additional worker productivity in finance and consulting relative to other industries. Columns 1 and 2 report expected hires predicted by finance and consulting firms from universities in the given range, as a percent of total expected hires by these firms in the region. Columns 3 and 4 report the total number of firms predicted to recruit at universities in the given range, as a percent of the total number of finance and consulting firms in the region (based on total offices of sample firms). This differs from columns 1 and 2 because of the positive probability that each firm attracts zero H-type applicants, accounted for in the expected hires measure. Columns 5 and 6 report the average of the predicted wage offer by finance and consulting firms to high-type students, across all the universities in the given range. Wage is also relative to this additional worker productivity in finance and consulting. A wage of zero can be understood as the reservation wage, i.e. the wage outside of finance and consulting. See text for details.

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*

August 13, 2018

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 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-

*University of Illinois at Urbana-Champaign. E-mail: weinst@illinois.edu

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,

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

$$SATweight = \frac{\%ReportSAT}{\%ReportSAT + \%ReportACT} \tag{2}$$

$$ACTweight = \frac{\%ReportACT}{\%ReportSAT + \%ReportACT} \tag{3}$$

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 A8. 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]

1.4 Counterfactuals

I show the results of counterfactually eliminating screening costs for three example universities (Appendix Table A11). With per-applicant screening costs that are 9% of additional worker productivity in finance/consulting (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 obtaining offers from these firms 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

[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.

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 p in the East (.86).[4] 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 at these firms 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.

1.5 Identifying Finance Analysts and Consultants

Using the actual responses to the industry and job title questions in the restricted-access B&B, I identify individuals working as a consultants in consulting firms and finance analysts in finance firms. For consultants, I first identify all individuals who respond that they are working in the consulting industry, by determining if the industry string variable contains the word "consult". I exclude individuals whose industry or job title is related to IT consulting, engineering, or the environment. I also exclude individuals whose job title reflects they are serving in a function other than consultant (e.g. administrative, computer programmer).

I further classify as consultants individuals whose industry is missing, but whose job title is consultant or professional services consultant. Regardless of industry, I classify as consultants individuals whose job title is management consultant. I also include individuals whose industry is government contracting or public companies, and whose job title is consultant. As a check, I confirm that the individuals classified as consultants have both job titles and industries that are consistent with the consulting firms in my data (management/business/economic/strategy consulting).

For finance analysts, I first identify individuals whose reported industry is a financial firm. This includes individuals whose industry string contains finance-specific terms, like "financ", "bank", "investm", "brokerage", "private equity", but also individuals whose industry string contains less finance-specific terms, like "professional" and "business services". Of

[4] 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.

those initially classified as working in the finance industry, I then exclude individuals whose industry string contained the language above but were clearly not working as finance analysts at financial firms similar to those in my data (for example, the industry contained "blood" (i.e. from blood bank), "retail", "auto", or job title was manager or teller). I also exclude individuals working in the mortgage or bankruptcy industry since those finance jobs are not consistent with the firms in my recruiting data.

I then define as a finance analyst an individual whose reported industry is a financial firm (defined above), and whose job title is similar to analyst, or contains the string "investm" or "trade". This includes job titles like financial analyst, market analyst, business analyst, structured finance analyst, securities lending associate, trader, and investment banker. I exclude from this group individuals working in the insurance or commercial real estate industries, since these are not similar to the finance firms in my data. I also exclude individuals from this group whose job title contains engineer, admin, or junior accountant. As a check, I confirm that the individuals classified as finance analysts have both job titles and industries that are consistent with the finance firms in my data, and the jobs for which recruiting might increase with university selectivity within a region (i.e. investment banking, trading).

1.6 Tradeoff Between Regional Rank and Selectivity

This section describes identifying differences in regional rank at various values of p, to determine the tradeoff between regional rank and selectivity discussed in Sections 6 and 7 of the paper.

1.6.1 Recruiting Outcomes

I start by identifying the difference in regional rank in the East relative to the West, for a university with p at approximately the 25th percentile. Specifically, I take the average regional rank of universities in the East with p within .002 of the 25th percentile (of the entire regression sample), and similarly for the West. I use a window around the 25th percentile in case no university has p exactly equal to the 25th percentile. Using this difference in regional rank and coefficients from the specification described in the paper, I identify the difference in the probability of attracting a recruiting firm for a university in the West relative to the East, holding everything constant besides regional rank, firm offices in the region, and H-types in the region.

I then identify how this difference changes as the selectivity p of the university in the East increases. As selectivity increases, regional rank improves as well. I identify the regional rank for a university in the East as p increases from the 25th percentile, at intervals of .01. I take the average regional rank within .01 of this higher value of p, in case no university has

p exactly equal to this higher value. Starting with the addition of .14 to the 25th percentile of p, I take the average regional rank within .015 of the higher value of p, since there are fewer universities at these higher values of p. Continuing to look within .01 would result in some instances of not finding a university in the window.

Using the same coefficients from the specification above, I identify the difference in probability of attracting a recruiting firm at a university in the West with regional rank associated with p around the 25th percentile, relative to a university in the East with regional rank associated with p around this higher value. I find the p at which the probabilities are within .1 percentage points (rounded to the nearest .1 percentage point).

The results suggest that in order for a student to attend a university in the East with an equivalent probability of attracting a prestigious firm, the student would need to attend a university whose selectivity is higher by .09. The 25th percentile of p is .058, which suggests a university in the East with selectivity of .148, which is at the 55th percentile of selectivity.

I implement the same procedure for universities at the median selectivity. For a student to attend a university in the East with an equivalent probability of attracting a prestigious firm, the student would need to attend a university whose selectivity is higher by .07. The median selectivity is .136, which suggests a university in the East of .206. I find the university with p closest to this value from below (.2) which is at the 67th percentile of selectivity.

1.6.2 Earnings

I use a similar strategy when looking at wages, although the values of p are slightly different given that the B&B data are from a different year than the recruiting data. I start by identifying the difference in regional rank in the East relative to the West, for a university with p at approximately the 25th percentile. Specifically, I take the average regional rank of universities in the East with p within .001 of the 25th percentile (of the entire regression sample), and similarly for the West. Using this difference in regional rank and coefficients from the specification described in the paper, I identify the difference in earnings for graduates of a university in the West relative to the East, holding everything constant besides regional rank and H-types in the region.

I then identify how this difference changes as the selectivity p of the university in the East increases. I identify the regional rank for a university in the East as p increases from the 25th percentile, at intervals of .0102 (using .01 would result in some windows not including any universities). Using the same coefficients from the specification described in the paper, I identify the difference in earnings for graduates of a university in the West with regional rank associated with p around the 25th percentile, relative to a university in the East with regional rank associated with p around this higher value. I find the p at which the difference is within .1 percentage points (rounded to the nearest .1 percentage point).

The results suggest that in order for a student to attend a university in the East with equivalent average post-graduation earnings, the student would need to attend a university whose selectivity is higher by .05. The 25th percentile of p is .065, which suggests a university in the East with selectivity of .115. To determine the percentile of this p in the distribution, I find the university with p closest to this value from below (.1124), which is at the 60th percentile.

I implement the same procedure for the 50th percentile of university selectivity (.099). The results suggest that in order for a student to attend a university in the East with equivalent average post-graduation earnings, the student would need to attend a university whose selectivity is higher by .09. Given the 50th percentile of p is .099, this suggests a university in the East with selectivity of .189. To determine the percentile of this p in the distribution, I find the university with p closest to this value from below (.183), which is at the 76th percentile.

2 Additional Specifications and Robustness

2.1 Testing for Selection on Unobservables: Earnings

I use the strategy in Oster (forthcoming), to learn about potential bias from selection on unobservables. 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, 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), based on the main regression sample in Table 3 column 1. Greater restrictions are problematic given the small sample.

In every regression, I include p, number of high-scoring students, and number relative to the region, student's SAT, whether they have SAT data, and average earnings of college graduates 25-34 in the state of residence (adjusted for state price parity), as these provide the foundation for the identification strategy.[5] For robustness, I include only the regional rank variable in the baseline regressions. The specification with the full set of controls includes the same controls as those in equation (5) excluding the interactions with SAT_i.

The coefficient on regional rank in the full regression is -.133 (Table 4 column 4), and in the restricted regression is -.143 (column 3). The coefficient is relatively stable, despite

[5] The identification strategy compares 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.

including observables that explain much of the variance in earnings (the R-squared more than doubles). Calculating the bias-adjusted treatment effect (β^*) as in the previous section, regional rank still has a negative coefficient equal to -.125. For the regional rank coefficient to equal zero, selection on unobservables must be at least 3.9 times larger than selection on observables. These results suggest the level of coefficient stability is consistent with randomized treatment.

2.2 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 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 1: 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.[6]

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.

2.3 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.[7] 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

[6] 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.

[7] 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.

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 140, the South has 50, and the West has 140.[8]

2.4 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

[8] 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).

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.[9] 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:

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

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 A7 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.

[9] 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 $CompetingStudents_{s_r}$.

2.5 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 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.

One year after graduation, a high percent of students live in their university's region, from 76% (South) to 88% (West) (Table 1), using data from the US Department of Education's Baccalaureate and Beyond survey. This is also consistent with limited college graduate mobility described in Wozniak 2010. In addition, campuses on Bain's Dallas and Houston websites suggest regional hiring.

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 A9 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 A9 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. The solutions to stages two and three of the game (wages and application strategies, given allocation of firms across universities in stage 1) follow Lang, Manove, and Dickens (2005) very closely, and so were not presented in the main text. Below, I describe the strategies, and the solutions to stages two and three.

3.1 Strategies

The strategy for firm i consists of a choice of university t at which to post the wage, and once at university t a 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.[10] I consider symmetric equilibria, in which all students at a university adopt the same mixed strategy.[11] The expected number of students at university t who apply to firm i will have a Poisson distribution with mean z_{ti}, where

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

As mentioned, the three-stage game is solved backwards, starting with the third stage in which students apply to firms given the firms' wage offers, and then moving to the second

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

[11] 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.

stage in which firms offer wages given their allocation across universities. In the first stage, firms allocate across universities, based on equilibrium wages and application strategies at each university, as a function of the number of firms at each university.

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

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

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.[12] $\{\mathbf{W_t^*}, \mathbf{q_t^*}(\cdot)\}$ is a subgame-perfect competitive equilibrium for each

[12]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.

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

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

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

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

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.

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:

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

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

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

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 $(1 - e^{-p_t z_t})(v - \frac{z_t(p_t v)}{(e^{p_t z_t} - 1)})$. This implies that when $c = 0$, $p_t z_t$ is the same at all universities t in the market. We want to show that with positive screening costs, $p_t z_t$ 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 $c = 0$, $p_t z_t$ 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.

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

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

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

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

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 $p_t S_t$ 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 $(\frac{p_t S_t}{N_t})$ 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 $p_t S_t$, 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. ■

References

[1] Dorans, Neil and Dianne Schneider (1999): "Concordance Between SAT I and ACT Scores for Individual Students," *Research Notes (RN-07)*. New York, NY: The College Board.

[2] Galenianos, M. and P. Kircher (2009): "Directed Search with Multiple Job Applications," *Journal of Economic Theory,* 144(2), 445-471.

[3] Lang, K., M. Manove, and W. T. Dickens (2005): "Racial Discrimination in Labor Markets with Posted Wage Offers," *American Economic Review,* 95(4), 1327-1340.

[4] Newman, M.E.J. (2004): "Fast Algorithm for Detecting Community Structure in Networks," *Physical Review E,* 69(6), 066133.

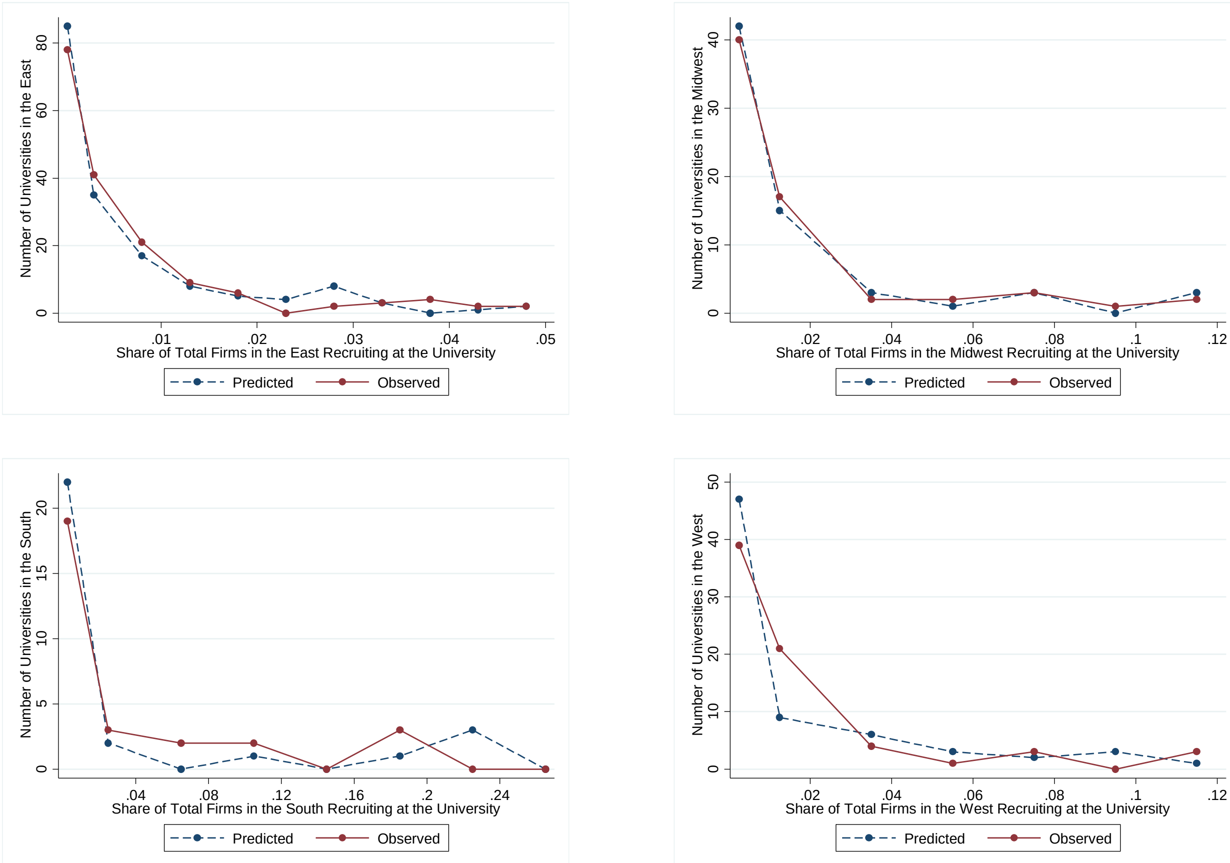
[5] Papke, L. and J. Wooldridge (1996): "Econometric Methods for Fractional Response Variables With an Application to 401(k) Plan Participation Rates," *Journal of Applied Econometrics,* 11(6), 619-632.

[6] Peters, Michael (2000): "Limits of Exact Equilibria for Capacity Constrained Sellers with Costly Search," *Journal of Economic Theory*, Vol. 95.

[7] Wozniak, Abigail (2010): "Are College Graduates More Responsive to Distant Labor Market Opportunities?" *Journal of Human Resources*, Vol. 45(4).

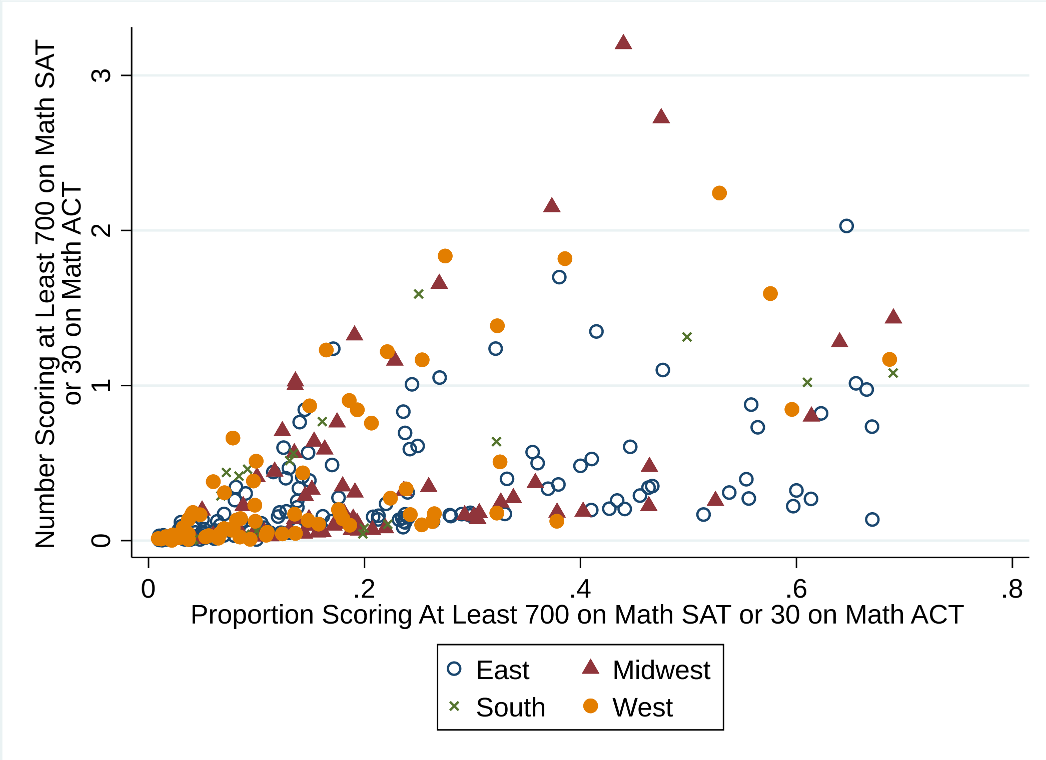
[8] "Best Consulting Firms to Work For: Compensation," Vault, 2011.

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

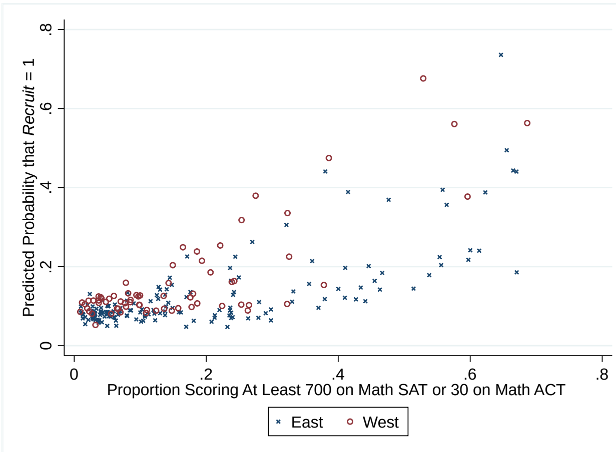


Note: This figure is a scatterplot of the number of high-scoring students at a university on the proportion of high-scoring students at the university. The sample includes universities in the regression sample in the East, Midwest, South, and West. See paper and online appendix for details.

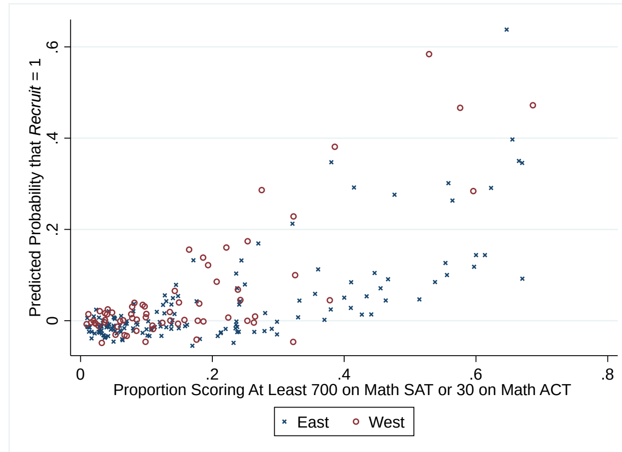
Appendix Figure A3

Panel A: Predicted Probability of Consulting Firm Recruiting on University Selectivity

(a) Firm with 61 Offices

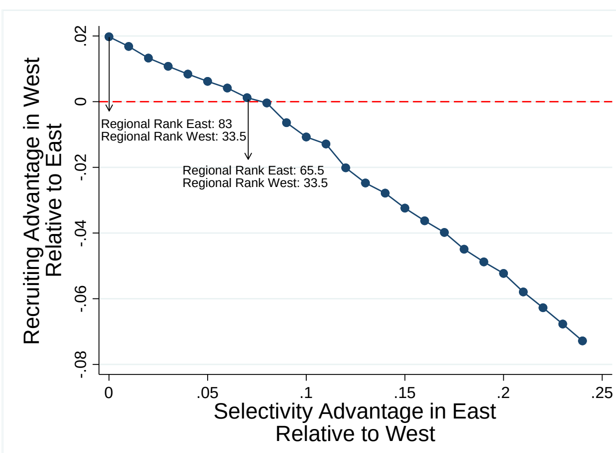


(b) Firm with 20 Offices

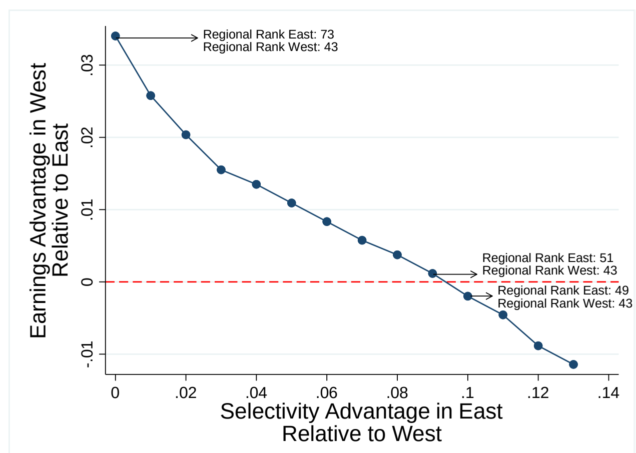


Panel B: Difference in Selectivity Relative to the Median Yielding Equivalent Outcomes

(a) Recruiting



(b) Earnings



Note: In Panel A, the predicted probability that *Recruit*=1 is obtained from the regression allowing for heterogeneity across industry (Column 7 of Table 2). I plot the linear combination of the explanatory variables for each university and the regression coefficients. Given that the sample includes one observation for each firm at each university, the predicted values for a given university will be shifted up or down by the firm fixed effects, but this shift will be the same for each university. The predicted probabilities for a given university will also be shifted up or down by firm-university distance, which will not be the same across universities. For ease of presentation, I show the probabilities here for one firm in (a), Mercer, which had 61 offices across the country that were the closest office to at least one university in the sample. In (b) I show the probabilities for another firm, McKinsey, which had 20 offices across the country that were the closest office to at least one university in the sample. The difference between (a) and (b) will be due to the firm fixed effects, which affect every university equally, and the different distances. Larger number of offices reduce the distance disadvantage for universities in the West if the additional offices are in the West. See Figures 5 and 6 for explanation of Panel B.

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]	[.1]	[.14]	[.13]
Number of Students with SAT Math > 700 or ACT Math > 30	529.27	405.66	382.29	414.54
	[451.47]	[558.57]	[378.13]	[325.04]
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	1176	1050	1077	1066
	[111]	[85]	[94]	[90]
Combined SAT/ACT, 75th Percentile	1368	1256	1279	1281
	[96]	[80]	[75]	[75]
Characteristics of Respondent				
Black	0.06	0.02	0.06	0.02
	[.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]	[176]
Parental Income, 2006 (dependent students)	90292	94433	100092	90286
	[68596]	[64436]	[84486]	[85847]
Income in 2009	41749	44137	44011	42624
	[15856]	[24195]	[15331]	[19810]
Dependent in 2007-2008	0.92	0.85	0.77	0.75
	[.28]	[.36]	[.42]	[.44]
Characteristics of Respondent's State of Residence, 2009				
Average Earnings of College Graduate, 25-34	51578	54079	54844	51936
	[4041]	[2896]	[4763]	[6226]
State Price Parity	110.46	92.4	92.08	103.48
	[17.42]	[10.75]	[10.58]	[16.99]
N	480	770	210	530

Note: Standard deviations in brackets. See paper and online appendix for detailed description of variable construction, sample, and region definitions. Sample size for parental income among dependent students is 440 in the East, 650 in the Midwest, 160 in the South, and 400 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 6. See those notes for details.

Appendix Table A5: Effect of Regional Rank on Firm Recruiting Decisions, Added Interactions and Variables

Dependent Variable: Recruit	(1)	(2)	(3)	(4)	(5)
Regional Rank (hundreds)	-0.032**	-0.031	-0.035**	-0.035**	-0.021
	[0.014]	[0.019]	[0.015]	[0.015]	[0.017]
Regional Rank (hundreds) *p	0.149	0.484**	0.628***	0.099	-0.132
	[0.220]	[0.245]	[0.206]	[0.282]	[0.233]
p (% High Math Score Students)	0.375	0.194	-0.764***	-0.596**	-0.713***
	[0.361]	[0.451]	[0.183]	[0.264]	[0.215]
p^2	-0.530	-0.004	0.950***	0.517	0.826***
	[0.386]	[0.548]	[0.222]	[0.314]	[0.276]
Regional Rank (hundreds) *Consult		-0.002	0.001		
		[0.025]	[0.012]		
Regional Rank (hundreds) *p *Consult		-0.601**	-0.779***		
		[0.278]	[0.179]		
P-value, Joint Test of Coefficients on Regional Rank	0.071	0.013	0.000	0.033	0.408

Linear Combination of Coefficients on Regional Rank

Linear Combination for:	All Firms	Consulting	Consulting	Global	Local
Universities with p = .06					
Texas	-0.013	-0.022**	-0.024**	-0.017	-0.016
(Regional Rank 56)	[.008]	[.01]	[.01]	[.014]	[.013]
East	-0.028	-0.047**	-0.051**	-0.035	-0.035
(Regional Rank 120)	[.018]	[.021]	[.022]	[.03]	[.027]
Universities with p = .14					
Texas	-0.004	-0.016	-0.018*	-0.007	-0.013
(Regional Rank 32.5)	[.009]	[.011]	[.01]	[.015]	[.012]
East	-0.01	-0.04	-0.045*	-0.018	-0.032
(Regional Rank 82)	[.023]	[.027]	[.026]	[.037]	[.031]
Additional Variables	All p interactions	All p *Consult interactions	University offers MBA, BBA and key interactions	None	None
Firms	All	All	All	Global	Local
N	10,730	10,730	10,730	1,958	4,090
Mean(Recruit)	0.062	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. Column 1 includes interactions between p and all never-missing university characteristics; column 2 includes interactions between p* Consult and all never-missing university characteristics (and all necessary lower-level terms). 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 interactions are those between the key university characteristics and p. Key university characteristics are: regional rank, proportion and number of high-scoring students, and number of high-scoring students relative to the region. Column 4 includes only global-staffing firms. Column 5 includes only local-staffing firms. See paper for details.

Appendix Table A6: Marginal Effects on Recruiting 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]
Marginal Effect Evaluated For:	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 percentiles 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 and Appendix Table A5. 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 A7: 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

Linear Combination for:	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 lower-level terms). Key explanatory variables are listed in Appendix Table A5.

Appendix Table A8: 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				
Linear Combination for:	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 lower-level terms). Key explanatory variables are listed in the notes to Appendix Table A5.

Appendix Table A9: 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 A10: 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.

Appendix Table A11: Structural Estimation Counterfactuals: Examples

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). 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 additional worker productivity in finance and consulting relative to other industries. Wage and expected income are also relative to this additional worker productivity in finance and consulting. A wage of zero can be understood as the reservation wage, i.e. the wage outside of finance and consulting. See text for details.

Appendix Table A12: Tests of Coefficient Stability and Selection on Unobservables

	Result	(1) Baseline Includes Key Controls for Student and University Quality	(2) Baseline Effect [R^2]	(3) Controlled Effect, including all Observables (Std. Error)[R^2=$\tilde{R}$]	(4) Bias-Adjusted β R_{max} = 1.3$\tilde{R}$	(5) Ratio of Selection on Unobservables to Observables yielding β=0, with R_{max} = 1.3$\tilde{R}$
	Y=Recruit					
(1)	Regional Rank	Y	-.051 [.110]	-.049 (.031) [.127]	-0.028	1.244
(2)	Regional Rank	N	-.041 [.006]	-.049 (.031) [.127]	-0.906	1.059
	Y = ln(Earnings)					
(3)	Regional Rank	Y	-.143 [.073]	-.133 (.060) [.163]	-0.125	3.933
(4)	Regional Rank	N	-.136 [.013]	-.133 (.060) [.163]	-0.13	2.096

Notes: This table reports coefficients on Regional Rank when the dependent variable is an indicator for whether the firm recruits at the university, and when the dependent variable is ln(Earnings) one year after graduation. The key controls included in row (1), column 2 are: proportion of high math-scoring students (p), number of high math-scoring students and number relative to the region, number of offices in the region, firm fixed effects, and firm-university distance, as these provide the foundation for the recruiting identification strategy. The key controls included in row (3), column 2 are: proportion of high math-scoring students (p), number of high math-scoring students, and number relative to the region, student's SAT, and average earnings of college graduates 25-34 in the state of residence (adjusted for state price parity) as these provide the foundation for the earnings identification strategy. In column 2 rows 2 and 4, the only explanatory variable is Regional Rank. Controls included in column 3, rows (1) and (2) are the same as those in Table 2 column 6, excluding the interactions with p. Controls included in column 3, rows (3) and (4) are the same as those in Table 3 column 1, excluding the interactions with student SAT. In rows (1) and (2) the regressions include only consulting firms, and include only universities with p in the interquartile range of the sample limited to consulting firms (including universities with p below the minimum for attracting a firm and above .7). In rows (3) and (4), I include only universities with $p \leq$ 90th percentile, and students with SAT at or above the 25th percentile of the main regression sample in Table 3, column 1. Column (4) reports the bias-adjusted coefficient on regional rank, using the approach in Oster (forthcoming). The assumption is that selection on observables is equal to selection on unobservables, and the R-squared from including observables and unobservables (R_{max}) is 1.3*R-squared from column (3).

Appendix Table A13: Effect of University's Regional Rank on Earnings After Graduation, Controlling for Student SAT Score and University Quality: Heterogeneity by University Selectivity

Regional Rank$_s$ (hundreds)	-0.093
	[0.427]
Regional Rank$_s$ (hundreds)*SAT$_i$ (hundreds)	-0.001
	[0.036]
Regional Rank$_s$ (hundreds)*p$_s$	3.490
	[4.256]
Regional Rank$_s$ (hundreds)*SAT$_i$ (hundreds)*p$_s$	-0.283
	[0.337]
Proportion High Math Score$_s$	0.608
	[2.469]
Proportion High Math Score$_s$*SAT$_i$ (hundreds)	-0.019
	[0.185]
Proportion High Math Score$_s^2$	2.509
	[2.977]
Proportion High Math Scores$_s^2$*SAT$_i$ (hundreds)	-0.168
	[0.220]
Linear Combination of Regional Rank Coefficients for:	
1400 SAT, High p	-0.193*
	[.106]
1400 SAT, Low p	-0.147*
	[.086]
P-value on Joint Test of Regional Rank Coefficients	0.295
P-Value on Joint Test of Regional Rank Coefficients*p	0.701
Controls for Student SAT and University Quality	Y
Full Set of Controls	Y
Universities	All
Interactions of University Controls, Student SAT	Key
N	2090
R-squared	0.171

Note: *** p≤0.01, ** p≤0.05, * p≤0.1. Results are from estimating the same regression in column 1, Table 3, but including additional interactions between p and the following variables (and lower-level terms): regional rank*SAT, p*SAT, number of high-type students*SAT, and high types relative to the region*SAT. Sample sizes are rounded to the nearest ten to preserve confidentiality. Standard errors clustered at the university level. See text and online appendix for details.

Appendix Table A14: Marginal Effects on Recruiting by University Selectivity

	p = 25th percentile	*p* = 50th percentile	*p* = 75th percentile
Regional Rank	-0.032*	-0.025	-0.014
	(.017)	(.029)	(.049)
p	-0.184	-0.104	0.0336
	(.196)	(.134)	(.092)
Number of High-Type Students	0.122***	0.139***	0.163***
	(.031)	(.026)	(.022)

Note: This table shows marginal effects for selected variables based on the coefficients in column 5 of Table 2. The 25th percentile of *p* is .058, the 50th percentile is .136, and the 75th percentile is .247. I evaluate the marginal effect of *p* at the mean regional rank for universities in the East within .01 of the given value of *p.*