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

Russell Weinstein†

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**Abstract**

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

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†Rensselaer Polytechnic Institute. E-mail: weinsr@rpi.edu

# 1 Introduction

Firm hiring is critical for the functioning of the economy, affecting employer productivity and worker investments. The matching of workers to firms has been a central topic in both labor and macroeconomics. It is well-acknowledged that there are frictions in this matching process, and these frictions have, in general ways, been incorporated into well-known theoretical models of the labor market (Diamond 1982, Mortensen 1982a,b, Pissarides 1984a,b). However, there has been little work analyzing empirically relevant search frictions and their effect on recruiting strategies, firm profits, and worker outcomes.

This paper studies employer recruiting in the presence of search and informational frictions, by studying the large and important labor market for recent college graduates. This is a particularly interesting setting for studying the matching between firms and workers. First, informational frictions are significant. Employers incur large costs in order to identify qualified applicants. Second, this market provides a clear and relevant example in which search is directed, not random. Most notably, there is a segmentation of search activity by campus, which is the focus of this paper. Firms in this market often choose a core set of target campuses, and concentrate on applications from students attending those campuses. This suggests a further search friction: student job prospects are linked to the firms recruiting on *their* campus.

Third, this is a large labor market in the economy. Nearly 1.8 million Bachelor's degrees were awarded by US colleges and universities in 2011-2012 (National Center for Education Statistics 2013). The labor market is especially important if first careers influence future outcomes.

Finally, employer recruiting on university campuses is a largely unexplored area of research, despite being a critical hiring mechanism for firms across many industries.[1] While firms have been recruiting on college campuses since the Westinghouse Electric Company in the late 1800's (Habbe 1948), the size

[1] Oyer and Schaefer (2012) study firm employee matches and relation to university location with a different focus: the within-firm concentration of lawyers graduating from the same law school. Previous work studies determinants and outcomes of various recruiting methods, e.g. newspaper ads and employee referrals (DeVaro 2003, 2005, Holzer 1987).

and formality of these programs have increased over the past century.[2] Today virtually every industry recruits on college campuses of varying selectivity, for jobs ranging from crop production to finance. In 2011-2012, 19% of the Harvard senior class accepted a job through the on-campus recruiting program (Harvard University Office of Career Services 2012). In the 2010-2011 year, 20% of employed undergraduate business school graduates at Virginia Tech found their jobs through the on-campus recruiting program, and 14% through the Career Fair (Career Services at Virginia Tech 2012).

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 finance and consulting firms recruit at each of approximately 350 universities.

Based on conversations with employers and university career services personnel, I develop a directed search model of how firms choose target campuses that incorporates the relevant frictions. Given that reviewing applicants is costly, and these costs are decreasing in the proportion of high-quality students, firms are most attracted to the labor market's most selective universities.[3] Firms recruiting at less selective universities are compensated by attracting more applicants and offering lower wages due to less competition.

With screening costs and regional labor markets, the central reduced-form prediction is that holding university size, selectivity, and other measures of quality constant, firms are less likely to recruit, and they offer lower wages, at a university with a lower regional rank, with rank based on the proportion of high-quality students.[4] This prediction is a joint test for the presence of screening costs and regional labor markets. Without screening costs, employers allocate across campuses based only on the number of high-quality students. Exploiting regional markets allows me to compare universities with an equal

[2]In 1944, there were 412,471 incorporated businesses, and it was estimated that 1000 of them sent representatives to recruit on college campuses. Many businesses that recruited, however, did so extensively. In 1955, of a highly selected sample of 240 firms, approximately 60% visited more than 20 universities to recruit college seniors (Habbe 1948, 1956).

[3]Selectivity will refer to the percent of high-quality students at a university, not to the percent of applicants admitted. Student quality refers to industry-specific match quality.

[4]Lower rank refers to worse rank.

number of high-quality students and equal selectivity.[5]

Undergraduate recruiting for finance and consulting positions is a particularly appropriate setting for testing this prediction. Labor markets in this setting are regional, and there is dramatic variation in the distribution of university selectivity across region. The model predicts that with screening costs, a Texas firm looking to hire high-quality recent college graduates from nearby universities will have Texas A&M near the top of its list, since it is one of the region's most selective universities. However, a Philadelphia firm looking to hire high-quality recent graduates from nearby universities will not have Pennsylvania State near the top of its list, even though its SAT scores, selectivity, and size are similar to those of Texas A&M. There are many universities more selective than Pennsylvania State in the Philadelphia region.[6]

Reduced-form results show strong empirical support for the presence of screening costs. Firms are nearly three percentage points less likely to recruit at a university if its regional rank is lower by 50 positions (a relevant magnitude for universities of similar selectivity), even after controlling for numerous measures of university size, selectivity, and quality. This effect is economically important as there is an active recruiting relationship for 7.4% of (university, firm) pairs. The effects are stronger for consulting than for finance firms, arguably because finance firms recruit for some positions which benefit less from lower screening costs (e.g. IT compared to investment banking). I control for the distance between the firm and the university, as well as the number of firm offices in each region, to account for regional differences in labor demand.

Using the Baccalaureate and Beyond 2009 survey, I find earnings of recent graduates are 4.25% lower if the regional rank of their alma mater was worse by 50 places, conditional on the university's size, selectivity, and the individual's SAT score. As predicted, this effect is much stronger for those with the highest SAT scores, as these students are targeted by prestigious firms. For these

[5] Controlling for selectivity helps to mitigate bias if selectivity causes students to be higher quality.

[6] For the finance and consulting industries, the proportion of high-quality matches is described well by the general selectivity of the university. In other industries another measure may better capture the proportion of high-quality matches.

students, lowering the regional rank by 50 places decreases earnings by 21%.

Finding support for the presence of screening costs through reduced-form predictions, I structurally estimate the model, including the screening cost parameter. This allows me to directly test the impact of the search frictions, by counterfactually setting the screening cost parameter to zero. I then evaluate the impact on firm recruiting strategies, wages, and profits.

The model predicts the number of firms recruiting at each university based on the profit equality conditions that hold across universities in equilibrium. I develop an estimator based on moments equalizing the observed and predicted proportion of firms recruiting at each university. I find that the screening cost is large, costing firms up to $12,000 to review an applicant. The screening costs per hire range from $6900 at a selective university, to nearly $29,000 at a much less selective university. A conversation with a former management consultant involved in campus recruiting suggested that the cost per MBA student hire is approximately $100,000, and is only slightly lower for undergraduates.

Counterfactually setting the screening cost parameter to zero, firms have greater incentives to recruit from less selective universities, which increases the wages offered there. In the absence of screening costs, the number of firms recruiting at a non-selective university in the East more than doubles, and the wage offer increases from $2,000 to $37,000 above the reservation wage.

The paper has several important policy implications. First, it contributes to the large policy (and academic) debate about whether high tuition is justified by better labor market outcomes. Previous literature has analyzed the effect of university characteristics on future outcomes. This paper suggests that quality of surrounding universities is also important. This has obvious implications for students applying to college and for policymakers considering tying education funding and student loan interest rates to college quality.

Second, this paper has important implications for the composition of society's elite. Finance and consulting firms have become pathways to prestigious positions across many sectors of society.[7] While this may be the result of

[7]Alumni of these firms have become CEOs of large businesses and non-profits, as well as government leaders. McKinsey states that more than 300 of their nearly 27,000 alumni are

selection, it is plausible that the powerful networks developed at these firms help shape future career paths. I find that this pathway is most accessible to students graduating from the most selective universities in each region; in the East these universities are the most elite in the country.

Finally, this paper suggests the effect of one's pool on labor market outcomes.[8] I address the university's place in the pool, rather than the student's (Davis 1966), finding advantages of the best university in a small pond.

## 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.[9]

**Target Campuses** Firms choose a core set of universities at which to target their recruiting efforts. Each target campus is managed by a team of human resources personnel and consultants who have recently graduated from that university. The team visits the campus for recruiting events throughout the semester, and ultimately for first-round interviews. For students at target campuses, their applications are submitted 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.

**Costly Recruiting** Firms invest heavily in identifying the best applicants, through a lengthy interview process. The details of this process are outlined below for one firm at one university. The important components of this procedure are generalizable. The firm decides how many team members will conduct interviews at the university, determining a fixed number of interview slots on

CEOs of companies with over 1 billion dollars in annual revenue (McKinsey 2013).

[8]Previous literature has also analyzed discrimination in the labor market when workers are divided into pools (Lang, Manove, and Dickens 2005).

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

that campus. To fill those slots, each team member rates each application. Ratings are based on many factors, including SAT scores, GPA, courses, and extra-curricular involvement. Employees use university-specific knowledge to better evaluate applicants, for example re-weighting GPA by course difficulty. Team members average their ratings for each applicant. After this process, there is a clear consensus to interview certain applicants and to reject others.

Many applicants have ratings between these extremes. The team spends more time reviewing these applications and discussing whether to offer an interview. Once all slots are filled, the team conducts first-round interviews. Applicants are evaluated again, and some are asked for a second-round interview at a firm office (not necessarily by the team, as discussed below). Finally, the firm decides who to hire. This review process conveys search frictions (in the form of screening costs) appear important in this market.

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

# 3 A Theoretical Model of Campus Recruiting

Incorporating search frictions and institutional details described above, I develop a directed search model of the campus recruiting labor market. The model, in which firms post wages, is an extension of Lang, Manove, and Dickens (LMD) (2005). I highlight important intuition below; for full details see online appendix.

**Set-up**

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

I assume that students do not know their type, implying that both types apply to vacancies. In order to determine whether an applicant is an H-type firms incur cost $c$, which represents the cost of reviewing the applicant's resume and conducting an interview. The assumption that students do not know their type is motivated by students' uncertainty regarding the match between their skills and the tasks in an unknown work environment. On the contrary, firms have accumulated knowledge about predictors of worker success.[12]

Consider a two-stage game in which firms simultaneously make wage offers in the first stage, which they must pay to the worker they eventually hire. In the second stage, students observe the wage offers and simultaneously apply

[10]The model can trivially be extended to allow firms to hire for multiple positions, and to recruit for each at different universities. This requires that a firm recruits for different positions within the firm independently.

[11]Firms allocate across universities once they observe the size and quality of the universities in their market. In this sense, size and quality of the university are treated as exogenous and no general equilibrium effects are considered.

[12]Assuming students do not observe their type is important only because it ensures expected reviewing costs are lower at universities with higher $p$. This achieves the result because L-types will apply to firms. Other assumptions also yield this result.

to firms. Each student may apply only to one firm.[13] Each firm then evaluates the applicants in its pool sequentially in random order, paying $c$ for each evaluation. The firm continues until identifying the first H-type applicant. At that point the firm hires the H-type student and stops reviewing other applicants. At universities with a lower proportion of H-type students, firms will have to review more applicants before reaching an H-type student. Thus, the expected costs of recruiting will be decreasing in $p_t$.[14]

The expected cost function is given by the expected number of applicants reviewed multiplied by the cost per application reviewed, $c$. The expected number of applicants reviewed is:

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

Given the firm chooses a wage to target $z$ applicants, the Poisson probability of every possible number of applicants arriving is multiplied by the expected number of applicants reviewed for that number of arrivals. The firm always reviews the first applicant, with probability $1-p$ it reviews the second (because with probability $p$ the first applicant is an H-type), with probability $(1-p)^2$ it reviews the third, and so on. The expected cost function, $(1-e^{-p_t z_{ti}})(\frac{c}{p_t})$, is decreasing in $p$.

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

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

Given that the number of students at each university has a Poisson distribu-

[13]Galenianos and Kircher (2009) consider workers applying to multiple firms. Intuition in that paper suggests that if students can apply to two firms, there are two wages at each university. Some firms offer the high wage, and some the low wage. Students should apply to one high wage and one low wage firm so their expected income is equalized. The two wages at each university, and the number of firms offering each type, should vary across university based on selectivity so profits are equalized.

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

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

**Equilibrium**

I search for an equilibrium vector of wages and student application strategies, for each university, of the wage-posting game that is symmetric among students. Following LMD, subgame-perfect competitive equilibrium is used as the solution concept for the entire wage-posting game. This is the same as subgame-perfection, except a competitive equilibrium is substituted for a Nash equilibrium in the first-stage of the game. In equilibrium firms are required to be price-takers in that the expected income they must offer applicants is taken as given and dictated by the market.[15]

The game is solved backwards. While the details of the solution are in the online appendix, the following paragraphs highlight important intuition. In the final stage, each firm reviews its applicants until identifying, and subsequently hiring, the first H-type student.

In the penultimate stage, students observe the posted wages and decide where to apply. Students apply such that their expected income (the wage multiplied by the probability of getting the job) is equalized across firms. If one firm offered a higher wage, it would attract more applicants such that their expected income would be equivalent to that at a lower wage firm.

In the first stage, firms choose the expected number of applicants ($z_{ti}$) to maximize profits. The number of applications a firm receives is a random variable; with positive probability the firm receives no applications. Without

[15] 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.

applicants, firms cannot hire or produce. 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 the vacancy goes unfilled.

Following LMD, I arrive at the following proposition (see online appendix for details):

Let $r_t \equiv S_t/N_t$, where $N_t$ is the number of firms recruiting at university $t$.

PROPOSITION 1: *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*

$$w_t^* = \frac{r_t(p_t v - c)}{e^{r_t p_t} - 1} \tag{3}$$

The first-order condition for profit maximization is independent of the firm, $i$ :

$$z_{ti}^*(\mathbf{W_t}) = \frac{1}{p_t} log \frac{p_t v - c}{K_t^*(\mathbf{W_t^*})} \tag{4}$$

This equilibrium is unique among those in which all students at university $t$ have the same expected income.

If there are $T$ universities, and firms recruit at $R \leq T$ of those universities, then the equilibrium profit from recruiting at each of the $R$ universities must be the same. There are $3R$ conditions that govern the equilibrium: the first-order conditions determining the number of applicants targeted by each firm, at each university ($R$ *conditions*); the equality of profit equations for firms recruiting at the $R$ universities ($R-1$ *conditions*); the number of applicants to each firm multiplied by the number of firms must equal the number of students at each university ($R$ *conditions*); and the number of firms recruiting at each university must equal the total number of firms (1 *condition*).

I reduce the $3R$ conditions governing the equilibrium to $R-1$ equations and $R-1$ endogenous variables $(N_1, ..., N_{R-1})$. The following equation shows the equality of profit condition for firms at university 1 and university 2.

$$(1 - e^{-p_1(\frac{S_1}{N_1})})(v - \frac{(S_1(p_1 v - c)}{N_1(e^{p_1(\frac{S_1}{N_1})} - 1)} - \frac{c}{p_1})$$
$$- (1 - e^{-p_2(\frac{S_2}{N_2})})(v - \frac{(S_2(p_2 v - c)}{(N_2)(e^{p_2(\frac{S_2}{N_2})} - 1)} - \frac{c}{p_2}) = 0 \quad (5)$$

Analogous equations exist for firms at university 1 and all of the remaining universities attracting firms. The number of firms recruiting at university $R$ is defined as the total number of firms, assumed to be a known parameter, minus the total number of firms recruiting at universities 1 through $R - 1$.

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

$$v - \frac{c}{p_{R+1}} < (1 - e^{-p_1(\frac{S_1}{N_1})})(v - \frac{(S_1(p_1 v - c)}{N_1(e^{p_1(\frac{S_1}{N_1})} - 1)} - \frac{c}{p_1}) \quad (6)$$

I further characterize the equilibrium, deriving the following propositions:

- Proposition 2*: The expected number of applicants, and H-type applicants, per firm is decreasing in p. The wage is increasing in p.*

- Proposition *3: The equilibrium implies a cut-off value of p such that for universities with p below the cut-off, it is not profitable for any firm to recruit. This cut-off value of p is increasing in the equilibrium level of profit,* $\pi^*(p, S, N, c, v)$

- Proposition *4: 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).*[16]

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

The following example illustrates the intuition for Proposition (4). Each cell represents the number of H and L type students at a given university:

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

Consider the university with 80H, 100L in Region 1. This university has a counterpart in Region 2 (80H, 0L), with higher $p_t$, lower $S_t$, but equal $p_tS_t$ (the number of H-types). Holding constant the total number of firms, Proposition 4 suggests that if screening costs are present, the number of recruiting firms, and the wage, at the university with (100H, 100L) in Region 1 will be higher than at the equivalent university in Region 2. Firms prefer recruiting at universities with a large proportion of H-type students, as this reduces expected reviewing costs. As such, the university with 100H, 100L in region 2 will be a second-best recruiting choice, while in region 1 it will be a top recruiting choice.

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

Without screening costs, the model suggests firms allocate based only on the number of high-types relative to the market. This implies that with zero screening costs, the university with 100H, 100L would receive the same number of recruiting firms in both regions. This prediction is tested by exploiting variation in the distribution of university quality across regions of the US.

# 4 Data on Universities and Firm Recruiting

In addition to being important destinations for recent graduates, finance and consulting are ideal industries for this study. Firms in these industries often have multiple offices across the US. This enables a comparison of recruiting strategies across region for the same firm, mitigating concerns that firm heterogeneity across region drives regional variation in recruiting strategies. Second, consulting firms generally recruit on campus for entry-level consulting positions, fairly homogeneous across firms and across offices within a firm.[17] This reduces concerns that firms recruit for different positions at prestigious compared to nonprestigious universities. Financial firms often recruit for various positions (e.g. investment banking and IT), so I separate effects by industry.

I identify elite finance and consulting firms using the following Vault rankings: top 50 consulting firms by prestige (2011), top 50 banking firms by prestige (2012), and top 25 investment management firms (2009).[18] For each of these firms, I attempted to collect data on undergraduate target campuses from the firm's website.[19] Figures 1a and 1b show data collection for the consulting firm Bain. Bain's career page has a search field for university. After typing Texas A&M in the field, a university-specific page with recruiting

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

[18]Data sources are described in the online appendix. Target campuses were collected in Spring 2012 for consulting firms, and Spring 2013 for finance firms. Recruiting data in Spring 2012 arguably pertain to the senior class of 2012, which participates in recruiting starting in Fall 2011. Thus, I use firm rankings from 2011. The most recent Vault ranking of investment management firms is 2009.

[19]Some firms list target campuses; others require that each university is typed into a search field to determine recruiting information.

information is loaded, making clear Bain's active recruiting presence there. However, after typing Pennsylvania State University it is clear that Bain does not actively recruit at the university.[20] Figure 2 shows Bain's target campuses, which as the model predicts, are less selective outside the Northeast.

Target campuses were identified from firm websites for 22 consulting firms, 13 banking firms, and four investment management firms.[21] I denote whether each of these firms actively recruits undergraduates at each of the universities in Princeton Review's *The Best 376 Colleges* (2012). The firm recruiting dataset is merged with a rich dataset containing university characteristics, constructed from the Integrated Postsecondary Education Data System (IPEDS), the Common Data Set, US News and World Report (USNWR) rankings, and each university's website.

For data on higher quantiles of the academic achievement distribution, likely relevant for elite firms, I use the Common Data Set.[22] The central dataset is not publicly available, though many universities publicize their questionnaires on their website. I collect several Common Dataset variables from individual university websites, including the percentage of enrolled freshmen who scored [700,800] on the SAT Math and Verbal, [30,36] on the ACT Math and English, and the percentage in the top 10% of their High School class.

Elite finance and consulting firms may value unobservables, such as leadership ability. If universities value the same unobservables in admissions, this will be captured in the percent of students admitted, one of the controls. USNWR ranking further captures perceptions of university quality, by including peer university and high school guidance counselor assessments (USNWR 2011).[23]

The important measure of university selectivity is arguably from when the

[20]Eight of the 22 consulting firms do not explicitly differentiate undergraduate and MBA target campuses, although it seems that they are recruiting undergraduates. For example, many firms distinguish between university and experienced hires. For at least one firm, the latter include MBA students. Results are robust to excluding these eight firms.

[21]These firms are listed in Appendix Table 1. Some consulting firms had recruiting data, but because the firm had divisions other than consulting, these data were not used.

[22]The data used by The College Board, Peterson's, and US News and World Report.

[23]The USNWR university ranking does not include liberal arts colleges. To avoid dropping these colleges, I include an indicator for nonmissing ranking.

job candidates applied to the university. Since the majority of the recruiting data pertain to college seniors in Spring 2012, IPEDS and Common Data Set data are obtained for Fall 2008 freshmen.[24] Because the USNWR rankings also include variables which may improve student quality during enrollment, such as student resources and the faculty, I use the 2012 USNWR rankings.

To control for the effect of distance between the firm and the university 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.[25]

Several universities in the Princeton Review's Best 376 Schools were excluded: two did not have IPEDS data, three are located outside of the United States, 13 did not report any test score data, and five are service academies. The five Claremont Colleges were replaced by one joint observation.[26]

# 5 Empirical Analysis of Recruiting Strategies

The model's central prediction suggests that with screening costs, the number of firms recruiting at a university depends on the number and proportion of high types at each university in the region. This is not easily transformed into a reduced-form specification. To capture the intuition, I use as a reduced-form variable the university's regional rank, based on the proportion of students with high Math standardized test scores. With screening costs and regional labor markets, this affects recruiting decisions and earnings separately from national rank, the number of high-quality students, and other measures of university and student quality.[27] Regional rank does not capture that recruiting outcomes depend on the exact size and proportion of high-quality students

[24] Recruiting data for finance firms pertain to seniors in Spring 2013; however, I use university characteristics from Fall 2008 not 2009. This is not of great concern as these variables are not expected to change dramatically over one year, and employers may use multi-year averages to evaluate selectivity.

[25] These methods are explained in the online appendix.

[26] Explained in the online appendix.

[27] The model suggests that the relevant variable is regional rank, not the percentile of the regional rank. Conditional on the number of firms in the region, a median-ranked university that is 50th in its region faces more competition than a median-ranked university that is 5th in its region. Firms have 49 preferable choices in one region and only 4 in the other.

at each university in the region. The model predicts it is more advantageous to be ranked second in the region when the first-ranked university is small, and cannot support many recruiting firms. I account for this in a robustness reduced-form specification and in the structural estimation.

The model's central prediction is an equilibrium relation between the distribution of students across universities, firm recruiting decisions, and wages; this paper argues that the relation is causal. The distribution of students across institutions is treated as exogenous since many of the universities in the sample were founded hundreds of years ago, and their prestige and selectivity developed for reasons independent of firm recruiting.[28] Further supporting this argument, one of the most well-known rankings of US universities (USNWR) does not rank universities by the labor market outcomes of their graduates. This paper argues that the distribution of students across institutions determines firm recruiting strategies and wages.

### Constructing Separate Labor Markets

The relevant labor market for each office location consists of the universities with students interested in working at that location. I use the target campuses to infer the firms' perceived labor markets. I do not observe the particular firm office recruiting at the university (students often choose for which location they interview). However, based on the institutional background described above, to define regions I assume that each university was targeted to fulfill the hiring needs of the closest office to that university.[29] Using university data on post-

[28]Most Ivy League institutions were founded before 1770, with the general mission of educating "the men who would spell the difference between civilization and barbarism." These institutions trained students in subjects completely non-vocational. In contrast, many of today's state universities started as land grant colleges devoted to agricultural and mechanical education (legislation established Land Grant colleges in 1862). These universities developed in ways consistent with their missions: the older colleges were often the first to design selective admissions policies, and to develop into leading scholarly research institutions (Rudolph 1990). The mission of the university determined its prestige and selectivity, rather than selectivity being driven by the firms recruiting or hiring the university's graduates.

[29]The Bain Dallas and Bain Houston websites list the following US universities in the on-campus recruiting section: Brigham Young, Rice, Southern Methodist, Texas A&M, The University of Texas at Austin, Vanderbilt, and Washington University. Their proximity to

college geographic mobility, I find little evidence that firms heavily recruit their home-state students studying in other regions.[30]

Using a community detection algorithm from the network literature (Newman 2004), I define four large regions (East, Midwest, South, and West) such that firms are very likely to recruit within, but unlikely to recruit outside, these regions. Figure 2 presents the regions, where the white states are each in their own region.[31] For robustness, I exogenously define labor markets as the universities in the same Bureau of Economic Analysis (OBE) region as the firm.[32] For seven universities, the closest office of every firm was not in their region. Excluding these leaves 342 universities in the dataset. If labor markets are not regional, then the coefficient on regional rank will be zero.

The university's regional and national rank are calculated based on the proportion of high-type students, $p$, at the university. I define high-type students as those scoring [700, 800] on the SAT Math or [30, 36] on the ACT Math. For universities with data from the Common Data Set, the percent of students scoring in the test's highest range is weighted by the percent reporting that test.[33] For universities without these data, $p$ is predicted using test score percentiles from IPEDS. The prediction is based on universities with both the Common Data Set and IPEDS, and follows Papke and Wooldridge (1996).[34]

### Summary Statistics: Firms, Universities, and Recruiting

Panel A of Table 1 shows that the firms in my sample are located across the country. Of the 39 firms in the dataset, 38 have at least one office in the East

the Dallas and Houston offices suggests regional hiring.

[30] Western firms do recruit in the East, but this is not a large distortion (online appendix).

[31] Either 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 other states.

[32] I combine New England and Mideast. Online appendix has algorithm and region details.

[33] I do not observe the percent of students scoring in 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 regressions control for verbal scores. Using the Common Data Set, the correlation between the percent of students scoring in the 700-800 range on the SAT math and SAT verbal is .88. This mitigates concerns that defining regional rank using verbal scores would dramatically affect the results.

[34] See the online appendix for a detailed description of the calculation of $p$.

and 23 have at least one office in the South. The last row of Panel A shows that universities in the sample are also geographically distributed. Panel B of Table 1 shows dramatic variation in the national rank of the region's best universities. The top universities in the East also have top national ranks. However, the 5th ranked university in the Midwest and West ranked around 30 nationally, and the 5th ranked university in the South ranked about 90 nationally. I use this variation to test the model's predictions.

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

Figure 4 shows the proportion of consulting firms recruiting on campus, for the campus that attracts the most firms in the bin of $p$. Marker labels denote the mean regional rank in the bin. Holding the bin of $p$ constant, regional rank is substantially better in the West than in the East. Further, for selectivity less than .6, the university attracting the most firms in the West attracts a higher proportion of firms than in the East. For universities with $p\epsilon[.2, .4)$, the mean regional rank in the West is 14 while in the East it is 51.5. The university in the West attracting the most firms in this bin attracts over 60% of the firms, while the analogous university in the East attracts less than 50%. This does not control for the size of the university, which clearly affects the number of recruiting firms. However, the plot suggests support for the model's main prediction, which will be tested more formally in a regression framework.

### Reduced-Form Empirical Specification

Observations are (university, firm) pairs, e.g. (Penn State, Bain). I estimate:

$$recruit_{sf} = X_s\beta + \gamma_1 RegionalRank_s + \gamma_2 FirmsinRegion_s + \gamma_3 Distance_{sf} + \delta_f + \epsilon_{sf} \tag{7}$$

$Recruit_{sf}$ indicates whether firm $f$ recruits at university $s$. $X_s$ is a vector of university characteristics.[35] $RegionalRank_s$ denotes the rank of the university within its region based on $p$. $Distance_{sf}$ denotes the distance between university $s$ and firm $f$'s closest office. I include firm fixed effects, and cluster standard errors at the university level since $RegionalRank_s$ does not vary within university. Since the empirical prediction is related to recruiting within the firm's region, I drop 10 (university, firm) pairs not in the same region.

# 6 Reduced-Form Estimation Results

Column 1 of Table 2 shows that holding university size and selectivity constant, if the university's regional rank is lower by 50 places, firms are 2.85 percentage points less likely to recruit (significant at the .01 level). I evaluate the regional rank coefficient for a change in rank of 50 places, based on differences in regional rank across region for given $p$ in Figure 3. This effect is large, given recruiting in only 7.4% of (university, firm) pairs. Other coefficients have the expected sign, though there is likely high collinearity in the university quality variables. Increasing distance between the firm and university by 100 miles (the standard deviation is approximately 175 miles) reduces the probability that a firm recruits at the university by 1.3 percentage points.

Financial firms recruit for some positions that may place less value on Math scores, implying that regional rank may have a heterogenous effect across industry. I interact $RegionalRank$ and all university characteristics with indicators for the firm's industry (banking is the omitted industry). Column 2 of Table 2 shows that consulting firms are approximately 3.5 percentage points less likely to recruit at a university if the regional rank is lower by 50 places (statistically significant). This effect is 1.35 percentage points stronger than

[35] These include national rank (based on $p$); 25th and 75th percentiles of Math and Verbal SAT and Math and English ACT; percentage reporting SAT, and ACT, scores; percentage scoring [700, 800] on SAT Verbal; percentage scoring [30, 36] on ACT English; percentage in top tenth of High School Class; US News Ranking; in-state and out-of-state tuition; senior class enrollment; percent of applicants admitted; the number of students with SAT Math scores in [700, 800] or ACT Math scores in [30, 36]; indicators for public institution, location in a large city, small or mid-sized city, and offering more than a BA.

for banking firms, a statistically significant difference.[36]

Figure 3 shows the difference in regional rank across region decreases in $p$. For $p \approx 0$, the regional rank difference between the East and West is about 100, but close to 40 when $p = .2$. To allow non-linear effects, I include through the quartic of regional rank and the absolute quality variables. While adding 60 variables decreases power, coefficients on the $RegionalRank$ terms are jointly significant at the .05 level.[37] Firms are 2.6 percentage points less likely to recruit at a university if the regional rank is lower by 50 places, though this is not statistically significant (not shown). The effect more than doubles, to 6.2 percentage points, when evaluated at a change of 100 ranks (p=.13).[38]

For robustness, I estimate the specification allowing for industry heterogeneity using probit and logit. The results are generally smaller in magnitude and statistical significance (see online appendix). Evaluated at regional rank of 60, if regional rank is worse by 50 places, consulting firms are approximately 1.6 percentage points less likely to recruit at the university (p=.107). This is smaller than the OLS estimate, though still large given the dependent variable's mean is .074. Using OBE regions, the principal specification results are similar, though the effect of regional rank is stronger (see online appendix).

# 7 Regional Rank and Post-College Earnings

I test the model's wage predictions using the US Department of Education's Baccalaureate and Beyond Survey, 2009 (B&B: 09). The B&B: 09 surveys approximately 15,050 college seniors in the 2007-2008 academic year, who are surveyed again in 2009 after receiving their Bachelor's degree. The dataset has detailed information on student demographics, post-college outcomes, and contains the IPEDS ID of the student's Bachelor's degree institution. I use this to merge the IPEDS institution-level data with the B&B: 09.

I calculate university rank using the 25th and 75th percentiles of the Math

[36] Better-ranked firms are not more sensitive to a university's regional rank, conditional on interacting all absolute quality measures with firm rank (not shown).

[37] The joint test drops the constraint on the quartic term, perhaps due to high collinearity.

[38] Step-wise variable deletion produces results with a fairly similar interpretation.

SAT and ACT score distribution for entering students. Assuming test scores are distributed normally, I obtain from the percentiles the mean and standard deviation of each test score distribution at each university. Using the normal CDF, and weighting by the percent of students reporting each exam, I calculate $p$, the percent at each university scoring above 700 on the Math SAT or above 30 on the Math ACT. I rank universities nationally and regionally by $p$.

I limit the sample to graduates of universities with national rank better than or equal to 400, who were 25 or younger at degree attainment. I only include those with one job, working at least 35 hours per week, and never enrolled full time in graduate school between the bachelor's degree and interview. University characteristics pertain to Freshmen in Fall 2004, as the sample is college graduates in Spring 2008. The online appendix presents summary statistics.

I cluster standard errors at the university level and estimate :

$$LogEarnings_{isl} = X_s\beta + Z_i\rho + \gamma_1 RegionalRank_s + \gamma_2 TestScore_{is} + \gamma_3 AvgWageBAGrad_l + \epsilon_{sf} \quad (8)$$

*LogEarnings* are from the primary job in 2009, calculated on an annual basis, for individual $i$, who graduated from university $s$, and lives in state $l$.[39] I adjust for earnings differences across states using 2006 US Bureau of Economic Analysis state price parities (Aten and D'Souza, 2008).[40] 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 the university's national rank, percent admitted, number of Freshmen, and number with SAT Math above 700 or ACT Math above 30 (number of students * $p$). $Z_i$ includes 2006 income (parental for dependent students),[41] and indicators for whether the student is black, asian, other race, hispanic, male, and both whether a citizen and a dependent during the 2007/2008

[39] All individuals in the sample have non-zero earnings.

[40] The closest year to 2009 with price parity data was 2006. I adjust earnings using the price parity for their 2009 state of residence.

[41] I adjust 2006 income using the price parity for the legal state of residence in 2007-2008. Because these price parities are only for US states, I drop approximately 30 individuals whose legal residence in 2007-2008, or 2009, were not within the US.

academic year. $TestScore$ is the individual's score from the combined SAT or the composite ACT converted to an SAT score.[42] I do not include region fixed effects as these would eliminate the identifying across-region variation.

Column 1 of Table 3 shows that controlling for the individual's SAT score, university size and selectivity, if the university's regional rank is 50 places lower then earnings are 4.25% lower (significant at the .1 level). Given these firms hire elite students, the model predicts they will be hurt most by a worse regional rank. In Column 2 the sample only includes individuals with combined SAT score of at least 1400. With the caveat that sample size is reduced, lowering the regional rank of the individual's university by 50 places results in earnings that are 21% lower (significant at the .05 level).[43]

# 8 Alternative Mechanisms

Attending a more selective university, nationally or regionally, may provide students with unobservable benefits. This suggests firms may go further down the unobserved quality distribution at worse regionally-ranked universities, holding selectivity constant. There is no obvious test between this and the screening cost mechanism. However both yield the prediction, which has strong empirical support: recruiting decisions and graduates' earnings are driven by the selectivity of surrounding universities. Given finance and consulting firms expend considerable time and resources reviewing resumes and interviewing, it seems unlikely that screening costs do not affect recruiting strategies.

Universities with better regional ranks may more likely offer undergraduate business majors or MBAs, which attract finance and consulting firms. While MBA and undergraduate recruiting are often conducted separately within a

[42] Approximately 30 individuals did not take either exam. I include an indicator for whether the individual has test score data.

[43] I also estimate these regressions weighting observations by the survey's sampling weights (normalized so the sum of the weights equals the number of observations). Without the test-score sample restriction, the weights yield a slightly stronger coefficient on regional rank (-.1097 compared to -.0851 without the weights), statistically significant at the .1 level. With the test-score restriction, the weights yield a smaller, not statistically significant coefficient (-.223 compared to -.426 without the weights). The magnitude still suggests a large effect.

firm, recruiting both on the same campus may be beneficial. Data were collected from university websites on whether each offered an undergraduate business major and an MBA. Column 3 of Table 2 shows that including these variables does not dramatically affect the coefficient on $RegionalRank$.

Recruiting decisions may be driven by the alma mater of the employees. If employees working at firm offices outside the East attended less selective universities, and recruiting is driven by alma maters, this could explain the main result. However, outside the East, graduates of less selective universities may have greater access to elite firms given fewer very selective universities. Thus, the alma mater mechanism can be explained by the model's central mechanism, making it hard to argue it is the dominating mechanism.

Without screening costs, firms allocate across universities based on the number of high-type students relative to the market total. Holding constant size and selectivity, a better regionally-ranked university will attract more firms if its proportion of the region's high types is larger. Column 4 of Table 2 shows including the region's total high-type students has little effect. Structural estimation also provides evidence against a simple supply and demand story.

# 9 Structural Estimation and Counterfactuals

The reduced-form analysis suggests strong support for the presence of screening costs. To more directly address the impact of search frictions on labor market outcomes, I structurally estimate the model.

The model implies recruiting at universities with $p_t < c$ is unprofitable, where $p_t$ is the proportion of high-type students at university $t$ and $c$ is the per-applicant reviewing cost. Even for universities with $p_t \geq c$, there is a cut-off $p$ below which recruiting is unprofitable. If $R$ universities have $p_t \geq p_{cutoff}$, equilibrium is governed by $R-1$ profit equality conditions in $R-1$ unknowns, where the unknowns are the number of firms recruiting at each university. Since the total number of firms ($NTot$) is assumed to be known, $N_R = NTot - \sum_{i=1}^{R-1} N_i$. Equation (5) shows the profit equality condition for universities 1 and 2. These equations are governed by $p$, $S$ (number of graduating students at the university), $c$, $v$ (worker productivity), and $NTot$. I obtain $S$ from IPEDS, and calculate $p$ as described above. I make two minor adjustments so the model is more realistic and can better explain the data.

### Adjustments to the model

**Calculating Number of Firms per Region** I assume the number of finance and consulting offices in the region (among firms in my data) reflects the total number of firms in each region. In the model, firms care about the applicants per job, driven by the number of jobs seeking applicants on that campus. Number of jobs may differ from number of offices because I do not count offices for firms not in my data, and each office may hire for multiple jobs. Accounting for these factors, I assume the total number of jobs for which firms recruit is equal to $\gamma$ times the number of offices. Obtaining reasonable results requires a minimum number of firms. I estimate the model with various levels of $\gamma$, and results do not change dramatically for $\gamma > 10$ (except in the Midwest). 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.

**Calculating the Total Number of Potential Applicants** Some students do not apply for finance and consulting jobs, implying the applicant pool is a fraction, $\lambda$, of the senior class. For simplicity, this unknown $\lambda$ is assumed to be common to all schools. The profit function including the parameter $\lambda$ is:

$$\pi = (1 - e^{-p_1\lambda(\frac{S_1}{N_1})})(v - \frac{(\lambda S_1(p_1 v - c)}{N_1(e^{p_1\lambda(\frac{S_1}{N_1})} - 1)} - \frac{c}{p_1}) \tag{9}$$

The parameters $c$ and $v$ are also unknown, though they are not separately identified.[44] The productivity parameter, $v$, is normalized to 1, leaving two unknown parameters $c$ and $\lambda$. Put differently, I estimate $\frac{c}{v}$.

[44]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 $(2v, 2c)$.

## Estimation

Among universities with $p_t \geq p_{cutoff}$, for given $c$ and $\lambda$ there is a unique profit-equalizing allocation of firms across universities. I identify parameter estimates for $c$ and $\lambda$ by finding the values that minimize the difference between the predicted proportion of firms recruiting at a university and the data, using The Generalized Method of Moments (GMM).

My algorithm works as follows. For each guess of the parameters, I identify $p_{cutoff}$, the $p$ corresponding to the university such that the profit from being the only recruiting firm at that university equals the profit each firm receives from allocating across universities with higher $p$. If a firm is the only one recruiting at a university, it receives all of the H-type applicants, and fills its vacancy with probability 1. The wage will be zero as the firm faces no competition. Profits at the cut-off university are $v - \frac{c}{p_t}$.

I identify the cut-off by starting with the lowest $p_t$ such that $p_t \geq c$, since recruiting at universities with $p < c$ is unprofitable. I calculate the profit from being the only recruiting firm at this university. I also find the profit firms receive from allocating (in a profit-equalizing manner) across all higher $p$ universities, using the profit equality conditions in (5), though including $\lambda$ as in (9). 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.[45] I check the solution equalizes profits at all universities.

If profit from recruiting at the higher $p$ universities is greater than profit at the lowest $p$, deviating to the lowest $p$ is unprofitable and it is not the cut-off. I move to the next lowest value of $p$ and employ the same routine. Once the cut-off university is identified for given $c$ and $\lambda$, 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 $\lambda$ by finding the values minimizing the difference between the model's pre-

[45] 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.

dictions and the data, using GMM. Moments include the difference between the predicted and observed proportion of firms recruiting at each university $(\frac{N_{t,Predicted}}{NTot_{Predicted}} - \frac{N_{t,Observed}}{NTot_{Observed}})$,[46] this error multiplied by $p_t$, and by $log(S_t)$. This yields three moments for 2 unknown parameters. The model is estimated separately in each region. To find the parameter values minimizing the GMM objective function, I search over $\lambda$ from .05 to .35 at intervals of .05, and over $c$ from .01 to .2 at intervals of .01.

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

If employment lasts for one year, $v$ is worker productivity that year, and $w$ is the annual wage.[47] Panel A of Table 4 shows for $v = 100,000$, values of $c$ are around \$10,000 except $c = \$3,000$ in the Midwest. While parameter estimates in the Midwest change when increasing $\gamma$ from $\gamma = 10$, they do not dramatically change when increasing $\gamma$ from $\gamma = 15$. At $\gamma = 15$, estimates of $(c, \lambda)$ in the Midwest are $(.07, .3)$.[48] Panel A also shows high estimated profits in the Midwest, due to low screening costs there. Higher profit in the East than the West is consistent with evidence that a higher $p$ is required in the East, than West, to guarantee at least one recruiting firm (see online appendix).

To measure the model's goodness-of-fit, I compare the predicted and observed distributions of the proportion of firms recruiting at the university. The

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

[47] Alternatively, $v$ 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.

[48] Estimates of $c$ are relatively similar, yet $\lambda$ estimates are higher, when $\gamma = 15$. With few firms (low $\gamma$), it is hard to explain recruiting at universities with high $p$, but few high-type students. This may yield a low $\lambda$, so smaller universities do not appear smaller to firms.

online appendix shows that the model fits the data reasonably well in the East.

### Impact of Search Frictions on Student Outcomes

Few papers have quantified the impact of search frictions on wages.[49] Through counterfactuals, structural estimation allows me to identify the impact of screening costs on recruiting decisions and wages. To understand the impact of the estimated screening cost, I counterfactually set the cost to zero.

Without screening costs, firms equalize profits by equalizing the expected number of high-type applicants at each university. Reviewing more applicants at less selective universities has no additional cost. This incentivizes recruiting at less selective universities, creating upward pressure on wages there. If enough firms leave selective universities, wages there may fall in the absence of screening costs. With screening costs of .09 ($9,000) in the East, the cut-off $p$ below which recruiting is unprofitable is approximately .14. There are 85 universities in the East with $p < p_{cutoff}$ and 83 with $p \geq p_{cutoff}$.

Panel B of Table 4 shows the effect of removing screening costs for various universities in the East. Screening costs have the greatest impact on the least selective universities. With screening costs of $9,000 per applicant, firms are not willing to recruit at the University of New Hampshire, where 5% of the students score $[700, 800]$ on the Math SAT or $[30, 36]$ on the Math ACT. As a result, all students receive the reservation wage (zero here can be understood as the students' reservation wage). However, this university does attract recruiting firms when it is costless to identify high-type students. It does not attract many firms since there are not many high-type students, but the wage for high-type students is $37,000 above the reservation wage.

With screening costs of $9,000 per applicant Fordham University attracts only a few firms, since the percentage of high-type students (14%) is just above the cut-off required to attract a firm. With few firms, the wage is only about

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

$2,000 above the reservation wage. 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 $37,000 above the reservation wage.

With screening costs of $9,000 per applicant, over 2.5% of firms recruit at Massachusetts Institute of Technology (MIT), which has the highest $p$ in the East (.86).[50] The many competing firms at MIT creates upward pressure on wages, yielding high-type student wages $45,000 above the reservation wage. Without screening costs firms recruit more heavily at less selective universities, reducing the number of firms at MIT from 72 to 51, and the wage to $37,000 above the reservation wage.

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

### Cost per Hired Worker

Having estimated the screening cost per applicant, I calculate the screening cost per hired worker: expected number of applicants reviewed (equation (1)) multiplied by screening cost per applicant. At less selective universities, firms on average review more applicants, so the cost per hired worker is greater. Expected number of applicants reviewed at MIT ($p$=.86) is .77, and the screening cost per hired worker is about $6900. Expected number of applicants reviewed at Fordham ($p$=.14) is approximately 3.2, and the screening cost per hired worker is $28,700. Differences in cost per hired worker 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.

## 10 Discussion and Conclusion

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

[50]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.

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 search frictions exist in this market, and have large impacts on recruiting strategies.

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

The results highlight possible equity and efficiency consequences of elite universities. With elite universities, students at non-elite universities have reduced access to prestigious firms (if firms would choose differently than an elite university). Thus, elite universities may obstruct equal access to firms for students equally likely to be hired by those firms. If initial jobs affect career paths, equity effects are amplified. However, by incurring screening costs, and reducing these costs for firms, elite universities may increase efficiency.[51] Higher screening costs for firms in the absence of elite universities may outweigh the benefit from choosing differently than an elite university.

The results imply limited geographic mobility of recent graduates. I find high SAT score students earn 20% less at universities of equal size and selectivity, but lower regional rank by 50 places. This may reflect the value of attending college, and living in, the Northeast.

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

REGISTER WITH BAIN

Registering provides you with the opportunity to:
- Introduce yourself to our team
- RSVP to Bain recruiting events
- Sign up for information sessions

**Register now - Sign in**

## Welcome to Bain's Texas A&M recruiting site

Congratulations on your upcoming graduation from Texas A&M! This degree has undoubtedly presented you with a a wide array of options. You may be considering jobs in the public or private sector, or you may be thinking about graduate school. The choices can feel overwhelming, but the good news is that **Bain offers the opportunity to expand your future career options**, while teaching you important skills that can help you be successful no matter what you ultimately choose to do in life.

The Bain Dallas and Houston offices have hired outstanding Aggies in years past and we want to continue this tradition. **Bain is looking for the best** that A&M has to offer across all majors: someone with a strong academic background, rigorous analytical skills, a high motivation level and outstanding interpersonal skills.

Associate Consultants for Bain do more than just challenge themselves intellectually. Many recent graduates have found that our energetic, social culture helped them transition from the academic to the business world. Bain has consistently been rated the **top consulting firm to work for** by *Consulting Magazine* over the last several years. At Bain you can have it all: the chance to work on exciting business issues, exposure to senior managers and CEOs of Fortune 500 Corporations, mentoring from an array of experienced colleagues, rigorous MBA-level business training, a "class" of fellow ACs to form close friendships and bonds with, and the time to maintain a balanced life outside of work.

Take a look at the profiles of a few of the A&M alumni at Bain Dallas to get a sense of what life at Bain has been like for them. If you have any questions, please let us know!

Andrew Welch
Texas A&M Recruiting Head
andrew.welch@bain.com

- Event calendar
- Recruiting contacts
- School alumni

School team

Brandon
Manager
Dallas

Kyle
Associate Consultant
Houston

Reese
Manager
Dallas

Figure 1b: Bain Recruiting Page for Penn State

FIND YOUR COLLEGE OR UNIVERSITY PAGE

Enter your school

GO

*You searched for Pennsylvania State University*

*Thank you for your interest in Bain. Your school does not require a specific recruiting process. We encourage you to browse our careers website, and to submit an online application.*

Figure 2: Where does Bain Recruit?

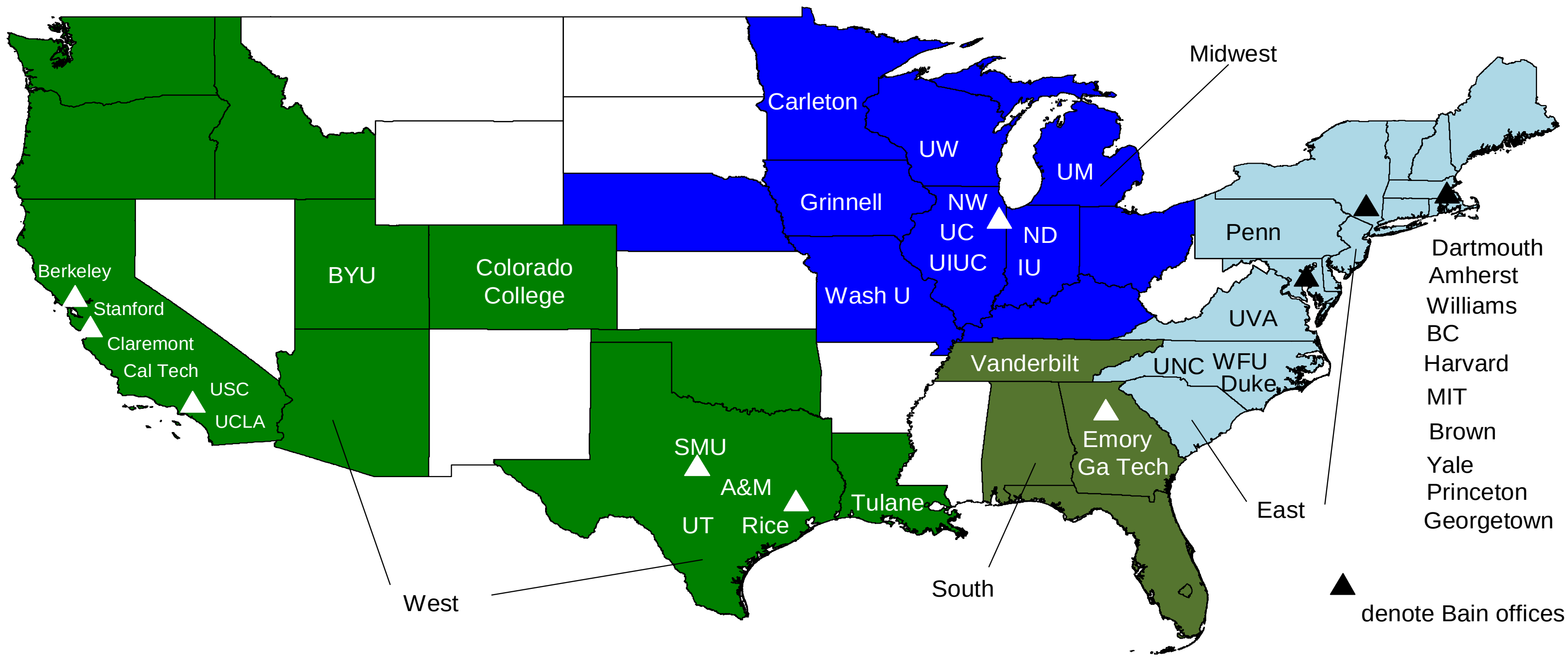


Figure 3: Differences in Regional Rank for a Given University Selectivity

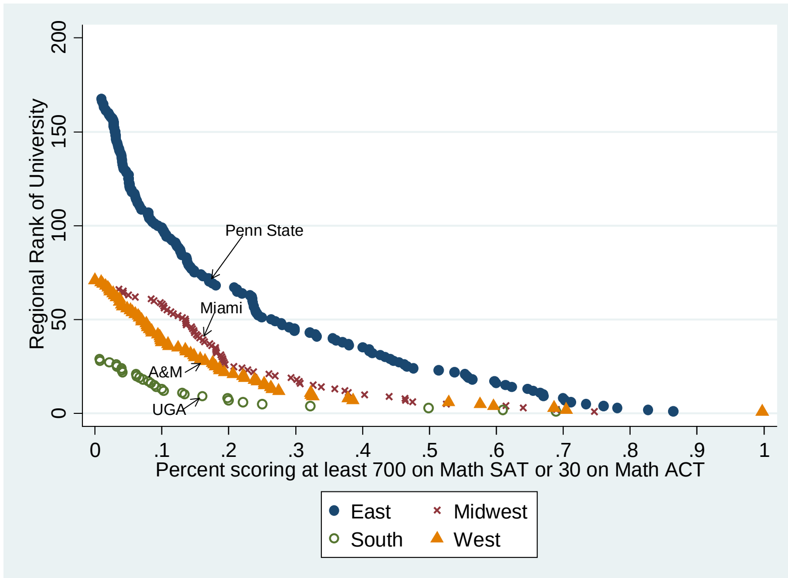
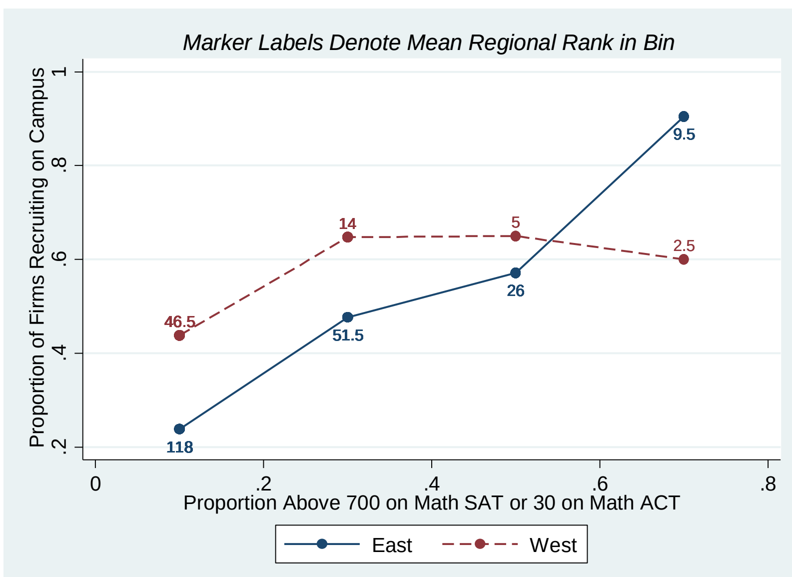



Figure 4: Recruiting at the University Attracting the Most Firms, by university selectivity bin and region




Note: See text for calculation of regional rank and percent scoring at least 700 on the math SAT or 30 on the math ACT. Figure 4 shows recruiting activity on the campus attracting the most firms in each bin of university selectivity. Recruiting activity is denoted by the total number of consulting firms recruiting on campus divided by the total number of consulting firms in the dataset with offices in the same region as the university. Marker labels denote the mean regional rank of universities in the bin, where regional rank is based on the proportion of students scoring above 700 on the Math SAT or 30 on the Math ACT. I show four university selectivity bins: Proportion of students scoring above 700 on the Math SAT or 30 on the Math ACT ϵ [0,.2), [.2,.4), [.4,.6), [.6,.8). The bin from [.8,1) is omitted from the plot because it only contains one university from the West (California Institute of Technology) and two from the East (MIT and Franklin Olin College of Engineering). As is evident from the mean regional ranks, the sample size of the bins [.4,.6) and [.6,.8) in the West is also small. See paper 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 |

Note: Regions and university ranks are as defined in the paper. Number of firms denotes the number of firms with at least one office in the region. 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. Sample construction is described in the paper.

**Table 2: Effect of Regional Rank on Firm Recruiting Decisions**

| Dependent Variable: Recruit | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Regional Rank (in hundreds) | -0.0567*** | -0.0431** | -0.0416** | -0.0450** |
| | [0.0178] | [0.0194] | [0.0195] | [0.0214] |
| Regional Rank (in hundreds) *Consulting | | -0.0268** | -0.0267** | -0.0267** |
| | | [0.0118] | [0.0117] | [0.0118] |
| Regional Rank (in hundreds) *Investment Management | | 0.00903 | 0.0114 | 0.00901 |
| | | [0.0329] | [0.0328] | [0.0329] |
| # Finance and Consulting Offices in Region (in hundreds) | 0.0254** | 0.0258** | 0.0246** | 0.0248** |
| | [0.0107] | [0.0107] | [0.0108] | [0.0111] |
| US News Ranking (in tens) | -0.00608** | -0.00563** | -0.00536* | -0.00563** |
| | [0.00238] | [0.00280] | [0.00276] | [0.00280] |
| # Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands) | 0.223*** | 0.202*** | 0.200*** | 0.202*** |
| | [0.0391] | [0.0491] | [0.0489] | [0.0491] |
| Institution in Large City | -0.00951 | -0.00641 | -0.00823 | -0.00626 |
| | [0.0112] | [0.0138] | [0.0138] | [0.0139] |
| Distance between School and Firm (in hundreds of miles) | -0.0131*** | -0.0127*** | -0.0125*** | -0.0126*** |
| | [0.00215] | [0.00215] | [0.00215] | [0.00216] |
| Offer MBA | | | 0.0246*** | |
| | | | [0.00861] | |
| Students in Region Scoring ≥ 700 on Math SAT or ≥ 30 on Math ACT | | | | 2.32e-09 |
| | | | | [9.84e-09] |
| N | 11,192 | 11,192 | 11,192 | 11,192 |
| Mean(Recruit) | 0.074 | | | |

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Regional Rank refers to the rank of the university within its region. See text and online Appendix for details on variable and sample construction, as well as a full list of variables in the regressions. Regressions include firm fixed effects, and standard errors are clustered at the university level. For variables with missing data, indicators denote whether the variable is non-missing for a particular university. Regions are defined using a community detection algorithm, and include the East, South, Midwest, and West. States comprising these regions are listed in the online Appendix. Columns 2 through 4 contain interactions between every university-level characteristic and indicators for Consulting and Investment Management. Column 3 additionally includes an indicator for whether the university offers a Bachelor's of Business Administration.

**Table 3: Effect of the Alma Mater's Regional Rank on Recent Graduate Earnings**

| | (1) All Students | (2) SAT ≥ 1400 |
|---|---|---|
| SAT/ACT Score | 0.0324*** | -0.0218 |
| | [0.00651] | [0.0556] |
| University's Regional Rank | -0.0851* | -0.426** |
| | [0.0488] | [0.179] |
| Average Earnings of College Graduate in State of Residence (in thousands) | 0.0222*** | 0.0136*** |
| | [0.00239] | [0.00490] |
| Observations | 2230 | 200 |

Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$. Standard errors are clustered at the university level. The dependent variable is the natural log of the respondent's earnings in 2009, adjusted for state price parity based on the state of residence in 2009. Average Earnings of College Graduate is the average earnings of college graduates aged 25-34 in the respondent's state of residence in 2009. See text and online Appendix for details on variable construction and the regression sample. Additional explanatory variables include: income in 2006 (parental for dependent and respondent for independent), national rank of the student's university (based on p), number of students in the entering class scoring above 700 on the Math SAT or 30 on the Math ACT (number of students * p), number of entering students at the university in 2004, percent of applicants admitted by the university, and indicators for whether the student is black, asian, other race, hispanic, male, US Citizen, dependent in 2007-2008, and whether the student reported her test score. Sample sizes are rounded to the nearest ten to preserve confidentiality.

**Table 4: Structural Estimation Results**

**Panel A: Parameter Estimates**

| | East | Midwest | South | West |
|---|---|---|---|---|
| c | 0.09 | 0.03 | 0.1 | 0.12 |
| $\lambda$ | 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 reviewing an applicant is denoted by c, the proportion of students interested in working at these firms is denoted by $\lambda$, and profit denotes the equilibrium profit every firm receives from recruiting at a university in the region. Profit and parameter estimates for c are relative to student productivity of 1. See text for detailed explanation of the estimation.

**Panel B: Counterfactual Exercise-Zero Screening Costs**

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

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

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

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

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

*Appendix: For Online Publication*

Russell Weinstein*

April 2, 2015

# 1 Data

## 1.1 Sources

I identify elite finance and consulting firms using the*Vault* industry rankings. 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 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 these data from individual university websites. I collect the following Common Dataset variables from individual university websites: the percentage of enrolled Freshman who scored [700,800] on the SAT Math

*Rensselaer Polytechnic Institute. E-mail: weinsr@rpi.edu

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-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.

## 1.2 Data Construction

**Calculating** $p$

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

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

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

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

For universities that have these data from the Common Data Set, $p$ is calculated in this way. 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. 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. Universities with the same value of $p$ are given their average rank, preserving the sum of the ranks.

**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. 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.

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 A6. 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

Latitude and longitude of universities and firm offices are collected in order to calculate distance. 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 find 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 higher quality universities in the East than in the other regions. Target universities in the East are in general smaller, less likely to be public, and less likely to be in large cities. Despite higher tuition, students at target universities in the East are less likely to be receiving financial aid of any form. 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] While it is impossible to know who is hired, this table suggests that the pool of applicants looks different across regions for the same set of firms.

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

[2] The weights are normalized so that the sum of the weights of the universities in the table (only those in the East, Midwest, South, and West) equals the total number of universities in these four regions 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), percent admitted, 75th percentile of ACT English, number of students, whether it is a public institution, the percent hispanic and black, the percent receiving pell grants, the percent receiving any aid, and regional rank.

# 2 Additional Specifications and Robustness

## 2.1 Within Region Predictions: Recruiting

### Empirical Specification

Proposition 2 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 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 2: the number of students per firm is decreasing in $p$ (the percent of students scoring at least a 700 on the SAT Math or 30 on the ACT Math). The coefficients on $p$ (in tenths) are presented by region. In all but the South, an increase in $p$ is associated with a statistically significant decrease in the number of students per firm. Increasing $p$ by .1 is associated with 250 to 400 fewer students per firm. These magnitudes are not small, as the average of the dependent variable ranges from nearly 900 in the East to nearly 1500 in the West. These results are consistent with the first part of Proposition 2.

Column 2 reports the results from testing the second part of Proposition 2: the number of high-type students per firm is decreasing in $p$. While the sign of the coefficient on $p$ is negative in all but the South, it is only statistically significant in the Midwest and West. In these regions increasing $p$ by .1 is associated with 20 to 30 fewer high-type students per firm. The average magnitude of the dependent variable in these regions ranges from approximately 230 to 250. While the evidence that the number of high-type students per firm is decreasing in $p$ is less strong, this is mainly driven by the coefficient in the South. The coefficients in the other three regions are jointly significant at the .01 level.

**Cut-off Level of University Selectivity** The third 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.

## 2.2 Within Region Predictions: Earnings

The third column of Appendix Table A3 directly tests the last part of Proposition 2: 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 at least 1400 on the SAT or ACT (converted to SAT score) are included in the estimation.[4] 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

[4]This 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.

errors in some regressions. With few observations per cluster, failing to account for the group error is not expected to significantly bias the standard errors. For these reasons, I have presented unclustered, robust standard errors in the third column of Appendix Table A3.

While power is limited due to small sample size, the results provide suggestive evidence that the wage prediction in Proposition 2 is supported in the data. In each region (except the South) 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% (West) to 8% (Midwest). The coefficient in the Midwest is statistically significant at the .05 level. The results in the South should be treated with the most caution, as they are based on approximately 10 observations. The Midwest and West both have approximately 50 observations, while the East has approximately 90.

## 2.3 Probit and Logit Estimation

For robustness, the specification separating the effects by finance and consulting is estimated using probit and logit. The results are present in Appendix Table A4. The probit estimates suggest that there is no statistically significant effect of regional rank for the banking firms, evaluated at regional rank of 10, 30 and 60. Recall that the regional rank of Texas A & M is about 30, while Penn State is about 70. However, the effect of regional rank is stronger for consulting firms than for banking firms. If the regional rank is worse by 50 places, when evaluated at regional rank of 10 or 30, consulting firms are over 2 percentage points less likely to recruit at the university relative to banking firms (both statistically significant at the .1 level). Combining the coefficient on regional rank and regional rank interacted with consulting, consulting firms are approximately 1.8 to 2 percentage points less likely to recruit at the university if the regional rank is worse by 50 places (evaluated at regional rank of 10 and 30 respectively), though these are not significant at the .1 level.

When evaluated at regional rank of 60, if the regional rank is worse by 50 places, consulting firms are approximately 1.9 percentage points less likely than banking firms to recruit at the university (statistically significant at the .05 level). Combining the coefficient on regional rank and regional rank interacted with consulting, consulting firms are approximately 1.6 percentage points less likely to recruit at a university if the regional rank is worse by 50 places, with p=.107. This effect is about 2 percentage points smaller than the analogous OLS estimate from Column 2 of Table 2 in the paper. However, the effect is still large given that the mean of the dependent variable is .074. The magnitudes from the logit estimation are similar. The differential effect of regional rank for consulting firms approaches conventional levels of statistical significance (p=.094) when evaluated at a regional rank of 60. However, the total effect as well as the coefficients evaluated at regional ranks of 10 and 30 are not statistically significant at the .1 level.

## 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, elite 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 elite. The eliteness of a university is defined in terms of $p$.

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

$CompetingStudents_{s_r}$ varies considerably across regions. For the universities falling in the interquartile range of $p$, the average number of students with high math test scores at a university at least as elite is over 41,000 for universities in the East, while only 7,500 for universities in the South. The values of $CompetingStudentsPerFirm_{s_r}$ also exhibit similar regional variation.[5] Plots of $CompetingStudentsPerFirm_{s_r}$ by $p$ look very similar to the plots of $RegionalRank$ by $p$ (not shown).

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

$$recruit_{sf} = X_s\beta + \gamma_1 CompetingStudentsPerFirm_s + \gamma_2 Distance_{sf} + \sum_{f=1}^{39}\delta_f + \epsilon_{sf} \tag{5}$$

The university characteristics in $X_s$ are the same as those described in the principal specification, as is the variable $Distance_{sf}$.

Appendix Table A5 shows that the results are similar in interpretation to those when $RegionalRank$ is the main reduced form variable. The difference in $CompetingStudentsPerFirm$, in hundreds, between the East and South/West is approximately .5 to .7 for $p$ below .5. Reduced form estimates in Column 2 suggest that consulting firms are 2.2 percentage points less likely to recruit if the pool of competition per firm is larger by 50 students. This effect is 1.7 percentage points larger than for banking firms. The magnitude of the results is larger when using OBE regions (not shown).

[5] Interestingly, once the number of firm offices is controlled for, 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 .13 and .30) 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.

To 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 A7 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 A7 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.

### 2.6 Goodness of Fit

Appendix Figure A1 displays the goodness-of-fit of the structural model in the East.

## 3 Theoretical Appendix

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

First, the details for deriving Proposition 1 are presented. These follow Lang, Manove, and Dickens (2005) very closely, and so were not presented in the main text.

### 3.1 Strategies

The strategy for firm $i$ at university $t$ consists of its wage offer $w_{ti}$. $\mathbf{W_t} \equiv \langle w_{ti} \rangle$ denotes the profile of wage offers at university $t$. Students will generally adopt a mixed strategy, given by a vector-valued function of the form $\mathbf{q}(\mathbf{W_t}) \equiv \langle \mathrm{q_i}(\mathbf{W_t}) \rangle$, where each $q_i(\mathbf{W_t})$ is the probability that the student applies to firm $i$. The outcome of this mixed strategy will be application to one firm.[6] I consider symmetric equilibria, in which all students at a university adopt the same mixed strategy.[7] 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 two-stage game is solved backwards, starting with the second stage in which students apply to firms given the firms' wage offers, and then moving to the first stage in which firms offer wages.

### 3.1.1 Students' Equilibrium Strategy

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

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

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

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

Thus, if $K_{ti}$ denotes the expected income or payoff that the student from university

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

[7] 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.

$t$ can obtain by applying to firm $i$, we have

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

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

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

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

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

$z_{ti}$ satisfies

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

and

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

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

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

which depends only on the value of $K_t$.

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

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

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

$t$.

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

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

### 3.1.2 Firms' Equilibrium Strategy

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

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

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

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

Proposition 1: *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* $\infty$, $\pi_t^*$ *goes from 0 to* $v - \frac{c}{p_t}$, $w_t^*$ *goes from* $v - \frac{c}{p_t}$ *to 0 and* $K_t^*(\mathbf{W_t^*})$ *goes from* $p_t v - c$ *to 0.*

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

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

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

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

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

## 3.2 Proposition 2: *The expected number of applicants per firm, $z$, and high-type applicants per firm, is decreasing in $p$. The wage offered at university t, $z_t(\frac{p_t v - c}{(e^{p_t z_t} - 1)})$, is increasing in $p$.*

Proof:

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

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

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

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

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

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

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

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

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

We write

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

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

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

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

Similarly, we see that

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

Since $pz$ is the same at all universities, we see that $\frac{\partial \pi}{\partial z \partial p} > 0$. 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 2, 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 3: ***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. This cut-off value of*** $p$ ***is increasing in the equilibrium level of profit,*** $\pi^*(p, S, N, c, v)$

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

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

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 PROPOSITIONS 4: *For a given university $t$, increasing $p_t$ and decreasing $S_t$ without changing $p_tS_t$ has a negative effect on the total number of firms recruiting at other universities in the market, holding constant the total number of firms and total number of H- and L-type students in the market. This change at university $t$ will result in a lower wage offer for at least one of the other universities in the market (not $t$).*

Proof: I have shown that the expected number of high-type applicants per firm $(\frac{p_tS_t}{N_t})$ is decreasing in $p$ (Proposition 2, Part B). Thus, the change described at university $t$ will result in fewer expected high-type applicants per firm. Since there is no change in $p_tS_t$, this implies that $N_t$ must be higher. Holding the total number of firms constant, this implies that there are fewer firms recruiting at other universities. I have also shown that the wage is increasing in $p$ (Proposition 2, 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. ■

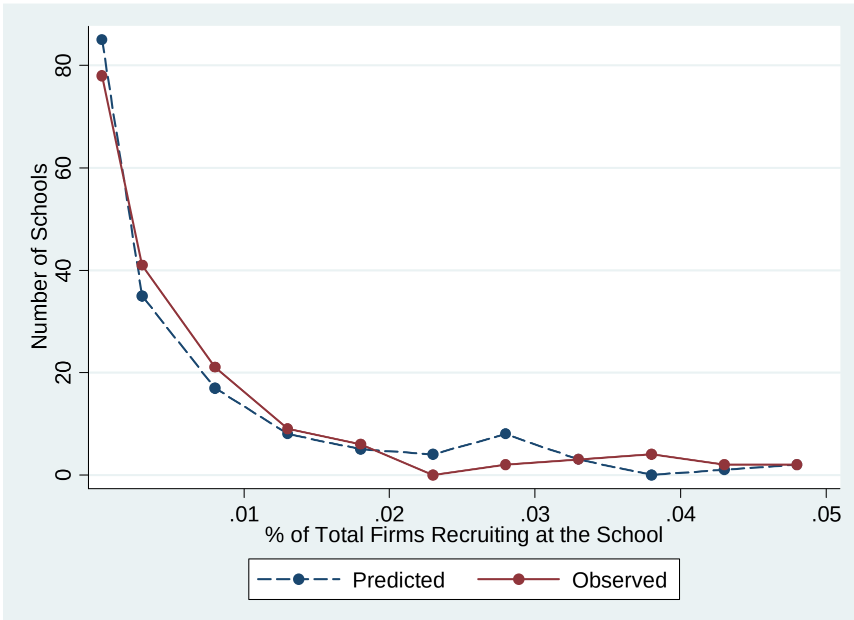
## References


[1] 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.

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

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

Appendix Figure A1: Percent of Firms Recruiting at the University: Observed vs. Predicted in the East




Note: This figure graphically displays the goodness-of-fit of the structural model. The last bin includes all universities with greater than .0455 of the recruiting firms.

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

| | East | Midwest | South | West |
|---|---|---|---|---|
| p (Proportion of High-Types) | 0.49 | 0.45 | 0.4 | 0.41 |
| | [.24] | [.21] | [.26] | [.23] |
| Regional Rank | 34.07 | 15.32 | 7.47 | 13.52 |
| | [35.21] | [18.07] | [8.79] | [13.28] |
| National Rank | 64.44 | 66.72 | 102.2 | 76.1 |
| | [76.58] | [66.18] | [112.89] | [67.61] |
| US News Ranking | 30.59 | 40.81 | 46 | 40.85 |
| | [36.] | [35.26] | [39.81] | [33.04] |
| % in Top 10 Percent of HS Class | 0.75 | 0.64 | 0.66 | 0.74 |
| | [.25] | [.26] | [.21] | [.24] |
| # Students | 2090.85 | 3977.84 | 2790.97 | 3790.94 |
| | [1434.24] | [2415.08] | [1769.29] | [2247.61] |
| Public | 0.19 | 0.55 | 0.5 | 0.52 |
| | [.39] | [.51] | [.53] | [.51] |
| Large City | 0.31 | 0.24 | 0.5 | 0.42 |
| | [.47] | [.43] | [.53] | [.5] |
| % Receiving Any Aid | 67.28 | 73.42 | 78.8 | 71.85 |
| | [13.04] | [10.6] | [15.75] | [8.2] |
| % Black | 6.93 | 4.92 | 16.37 | 4.04 |
| | [7.04] | [1.62] | [25.5] | [1.78] |
| % Hispanic | 5.31 | 4.22 | 5.5 | 10.09 |
| | [2.06] | [1.86] | [4.86] | [3.86] |
| Tuition (in-state for public universities) | 29772.61 | 20888.49 | 17793.9 | 16696.95 |
| | [11440.72] | [13956.22] | [16014.63] | [15797.48] |
| 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 in the sample (in the East, Midwest, South, and West; not including the universities in the regions comprised of just one state). The variable p denotes the proportion of students scoring [700, 800] on the Math SAT or [30, 36] on the Math ACT. 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 SAT and ACT percentiles, US News ranking, % 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** | | | | |
| National Rank | 128 | 194 | 234 | 189 |
| | [107] | [102] | [122] | [99] |
| Regional Rank | 49 | 62 | 19 | 40 |
| | [30] | [38] | [11] | [23] |
| Number of Students | 2197.44 | 2605.25 | 3211.42 | 3140.36 |
| | [1446.79] | [2229.21] | [2192.36] | [1977.81] |
| Number of Students with SAT Math > 700 or ACT Math > 30 | 524.73 | 407.15 | 381.47 | 406.88 |
| | [453.87] | [565.78] | [383.16] | [323.35] |
| **Characteristics of Respondent** | | | | |
| Black | 0.06 | 0.02 | 0.06 | 0.01 |
| | [.24] | [.15] | [.24] | [.12] |
| Hispanic | 0.06 | 0.03 | 0.09 | 0.1 |
| | [.23] | [.16] | [.28] | [.3] |
| Combined SAT/ACT Score | 1227 | 1130 | 1120 | 1151 |
| | [169] | [164] | [180] | [175] |
| Income in 2006 (Parental if Dependent) | 82,526 | 83,225 | 81,124 | 71,003 |
| | [69115] | [65904] | [81041] | [80975] |
| Income in 2009 | 39,918 | 42,936 | 42,957 | 40,630 |
| | [16837] | [24492] | [16299] | [20327] |
| Dependent in 2007-2008 | 0.92 | 0.85 | 0.77 | 0.75 |
| | [.28] | [.36] | [.42] | [.43] |
| **Characteristics of Respondent's State of Residence, 2009** | | | | |
| Average Earnings of College Graduate, 25-34 | 51,521 | 54,071 | 54,738 | 51,716 |
| | [4014] | [2863] | [4758] | [6263] |
| State Price Parity | 111.04 | 92.56 | 92.24 | 104.28 |
| | [17.26] | [10.72] | [10.64] | [17.2] |
| N | 520 | 810 | 220 | 580 |

Note: Standard deviations in brackets. Regional and National rank are based on the proportion of students scoring above 700 on the Math SAT or 30 on the Math ACT. See paper and online Appendix for detailed description of variable construction, sample, and region definitions. Mean SAT/ACT score calculated only over those individuals with data. The sample size for the Combined SAT/ACT score is 510 in the East, 800 in the Midwest, 220 in the South, 570 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 | -267.4*** | -6.158 | 0.0192 |
| | [37.31] | [4.035] | [0.0199] |
| Midwest | -422.1*** | -30.87** | 0.0769** |
| | [80.88] | [12.94] | [0.0341] |
| South | -224.9 | 16.63 | -0.0556 |
| | [154.2] | [23.81] | [0.0339] |
| West | -364.8*** | -20.31** | 0.0115 |
| | [79.00] | [8.495] | [0.0225] |

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 high-types at the university (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 with at least one recruiting firm. In column 3, each observation is an individual who graduated in the previous year from a university in the specified region, and scored at least a 1400 on the SAT or ACT (converted to SAT score). 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, 10 in the South, and 32 in the West. In column 3 there are 90 observations in the East; 50 in the Midwest; 10 in the South; and 50 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-Marginal Effects from Probit and Logit Estimation**

| | Probit | | | Logit | | |
|---|---|---|---|---|---|---|
| Marginal Effect Evaluated at Regional Rank of: | 10 | 30 | 60 | 10 | 30 | 60 |
| (1) Regional Rank (in hundreds) | 0.008 | 0.007 | 0.006 | 0.010 | 0.009 | 0.008 |
| | [0.025] | [0.023] | [0.021] | [0.030] | [0.028] | [0.025] |
| (2) Regional Rank (in hundreds) * Consulting | -0.047* | -0.043* | -0.038** | -0.046 | -0.043 | -0.038* |
| | [0.027] | [0.023] | [0.019] | [0.032] | [0.028] | [0.023] |
| Combination (1) + (2) | -0.039 | -0.036 | -0.032 | -0.036 | -0.033 | -0.030 |
| | [0.030] | [0.026] | [0.020] | [0.034] | [0.030] | [0.023] |
| Observations | 11,192 | 11,192 | 11,192 | 11,192 | 11,192 | 11,192 |

Note: *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.1. This table presents the results from probit and logit estimation of specification (8) in the text of the paper. The coefficients presented are the marginal effects at varying levels of regional rank. See this appendix for details.

**Appendix Table A5: Effect of Competing Students on Firm Recruiting Decisions**

| Dependent Variable: Recruit | (1) | (2) | (3) |
|---|---|---|---|
| Competing Students Per Firm Office (in hundreds) | -0.0220** | -0.00941 | -0.00872 |
| | [0.0108] | [0.0126] | [0.0128] |
| Competing Students Per Firm Office (in hundreds) *Consulting | | -0.0339*** | -0.0333*** |
| | | [0.0122] | [0.0122] |
| Competing Students Per Firm Office (in hundreds) *Investment Management | | -0.0189 | -0.0168 |
| | | [0.0354] | [0.0354] |
| US News Ranking (in tens) | -0.00693*** | -0.00606** | -0.00570** |
| | [0.00224] | [0.00266] | [0.00262] |
| # Seniors with ≥ 700 on Math SAT or ≥ 30 on Math ACT (in thousands) | 0.208*** | 0.195*** | 0.194*** |
| | [0.0358] | [0.0470] | [0.0467] |
| Institution in Large City | -0.0110 | -0.00791 | -0.00954 |
| | [0.0115] | [0.0139] | [0.0139] |
| Distance between School and Firm (in hundreds of miles) | -0.0124*** | -0.0125*** | -0.0123*** |
| | [0.00214] | [0.00213] | [0.00210] |
| Offer MBA | | | 0.0248*** |
| | | | [0.00849] |
| N | 11,192 | 11,192 | 11,192 |
| Mean(Recruit) | 0.074 | | |

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 elite in the same region. See the text of this appendix for details and for all explanatory variables included in the regression. Regressions include firm fixed effects, and standard errors are clustered at the university level. The regression is restricted to observations for which the school and firm are located in the same region. For variables for which some universities are missing data, an indicator is included for whether the variable is non-missing so that no universities are discarded from the sample. Regions are defined using a community detection algorithm, and include (but are not limited to) the East, South, Midwest, and West. States comprising these regions are listed in this appendix. Columns 2 and 3 contain interactions between every university-level characteristic and indicators for Consulting and Investment Management. Column 3 additionally includes an indicator for whether the university offers a Bachelor's of Business Administration.

**Appendix Table A6: Effect of Regional Rank on Firm Recruiting Decisions, OBE regions**

| Dependent Variable: Recruit | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Regional Rank (in hundreds) | -0.0615* | -0.0328 | -0.0276 | -0.0394 |
| | [0.0368] | [0.0380] | [0.0382] | [0.0384] |
| Regional Rank (in hundreds) *Consulting | | -0.0466*** | -0.0460*** | -0.0463*** |
| | | [0.0144] | [0.0143] | [0.0144] |
| Regional Rank (in hundreds) *Investment Management | | -0.0439 | -0.0454 | -0.0403 |
| | | [0.0380] | [0.0381] | [0.0380] |
| # Finance and Consulting Offices in Region (in hundreds) | 0.00355 | 0.00417 | 0.00231 | -0.00118 |
| | [0.0181] | [0.0183] | [0.0183] | [0.0182] |
| Distance between School and Firm (in hundreds of miles) | -0.0153*** | -0.0152*** | -0.0154*** | -0.0147*** |
| | [0.00271] | [0.00271] | [0.00273] | [0.00269] |
| Offer MBA | | | 0.0273*** | |
| | | | [0.00984] | |
| Students in Region Scoring above 700 on Math SAT or above 30 on Math ACT | | | | 1.27e-08 |
| | | | | [7.84e-09] |
| N | 9,719 | 9,719 | 9,719 | 9,719 |
| Mean(Recruit) | 0.077 | | | |

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. Regions are defined using the OBE regions, combining New England and the Mideast. States comprising these regions are listed in this appendix. Regional Rank refers to the rank of the university within its region. Detailed description of the construction of this variable is included in the paper and this Appendix. See paper for all explanatory variables included in the regression. Regressions include firm fixed effects, and standard errors are clustered at the university level. The regression is restricted to observations for which the school and firm are located in the same region. For variables for which some universities are missing data, an indicator is included for whether the variable is non-missing so that no universities are discarded from the dataset. Columns 2 through 4 contain interactions between every university-level characteristic and indicators for Consulting and Investment Management. Column 3 additionally includes an indicator for whether the university offers a Bachelor's of Business Administration.

**Appendix Table A7: Pre- and Post-College Student Geographic Mobility**

| School | Home Region | % of University's Students from Home Region | % of University's Students Moving to Home Region |
|---|---|---|---|
| **Panel A: Flows to the Midwest Post-Graduation** | | | |
| Dartmouth | East North Central[1] | 6.5% | 3.0% |
| Princeton | Midwest[2] | 9.4% | 5.1% |
| Georgetown | Illinois | 4.5% | 1.5% |
| **Panel B: Flows to the Southwest Post-Graduation** | | | |
| Dartmouth | West South Central[3] | 4.8% | 1.5% |
| Georgetown | Texas | 3.6% | 1.6% |
| Washington University | Southwest[4] | 8.6% | 5.0% |
| **Panel C: Flows to the West Post-Graduation** | | | |
| Dartmouth | Pacific[5] | 12.9% | 10.4% |
| Princeton | Southwest/West[6] | 15.9% | 13.0% |
| Georgetown | California | 10.0% | 4.2% |
| Washington University | West[7] | 8.3% | 10.0% |
| Duke | California | 8.6% | 10.1% |
| **Panel D: Flows to the Northeast Post-Graduation** | | | |
| Washington University | Northeast[8] | 23.3% | 20.0% |
| Vanderbilt | Northeast[9] | 16.8% | 17.8% |
| UCLA | Eastern US[10] | 2.2% | 5.0% |
| UC Berkeley | Eastern US[10] | 2.5% | 2.9% |

Notes: This table compares the percentage of a university's student population originally from the specified "Home 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 (TX, OK, AR, LA), 4 (TX, OK, CO, NM, AZ), 5 (CA, OR, WA), 6 (TX, OK, NM, AZ, CA, NV), 7 (CA, OR, WA, UT, ID, WY, MT), 8 (NJ, NY, CT, RI, MA, VT, NH, ME), 9 (CT, MA, ME, NH, NJ, NY, RI, VT), 10 (Exact states not provided, census regions inferred: New England, Middle Atlantic, South Atlantic, East South Central).