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

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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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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.\footnote{An important exception is Oyer and Schaefer (2012), who 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).} While firms have been recruiting on college campuses since...
the Westinghouse Electric Company in the late 1800’s (Habbe 1948), the size and formality of these programs have increased over the past century.\textsuperscript{2} Today virtually every industry recruits on college campuses of varying selectivity, for jobs ranging from crop production to finance.\textsuperscript{3} A recent survey found that 76.9\% of firms conducted on-campus interviews (of 275 surveyed firms), and 59.4\% of new hires were recruited through on-campus interviews (National Association of Colleges and Employers 2014).

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

Based on conversations with employers and university career services personnel, I develop a directed search model of how firms choose target campuses. The model incorporates relevant institutional frictions, including the cost of screening applicants due to informational frictions. When recruiting at more selective universities, firms need to review fewer applications (on average) before identifying a high-quality applicant. Given that reviewing applicants is costly, this implies that firms are most attracted to the labor market’s most selective universities.\textsuperscript{4} Firms recruiting at less selective universities are compensated by attracting more applicants and offering lower wages due to less competition.

With screening costs and regional labor markets, the model predicts that if two universities are the same size and selectivity, the university that is better ranked within its region will attract more firms and its graduates will earn

\textsuperscript{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).

\textsuperscript{3}The importance of on-campus recruiting varies with the industry. While 93.3\% of management consulting firms use on-campus interviews, 46.2\% of engineering firms and 33\% of government agencies use on-campus interviews (National Association of Colleges and Employers 2014).

\textsuperscript{4}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.
higher wages. This prediction is a joint test for the presence of screening costs and regional labor markets. Exploiting regional markets allows me to compare universities with an equal 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. Among universities at the 25th percentile of selectivity, consulting firms are three percentage points less likely to recruit if the university’s regional rank is lower by 64 positions (the regional rank difference for this selectivity), controlling for university size, numerous measures of university quality, as well as the number of firm offices per region. I find similar effects at the median level of university selectivity. The magnitude is economically important as there is a recruiting relationship for 6.2% of (university, firm) pairs. The effects are stronger for consulting than finance, arguably because finance firms recruit for some positions which benefit less from lower screening costs (e.g. IT compared to investment banking).

The model predicts that graduating from a university with worse regional rank will differentially affect earnings of higher SAT students, holding con-

\(^5\)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.
stant university size and quality. Given that elite firms target high test score students, these students will be negatively affected by attending a worse regionally-ranked university. Using the Baccalaureate and Beyond 2009 survey, I find that students with SAT scores of 1400 earn 9% less if the regional rank of their alma mater is worse by 50 places, holding constant absolute size and quality of the university. As the model predicts, these effects are stronger for high test score students at less selective universities. While less selective universities outside the East coast may still be highly ranked within the region, this is not true for less selective universities in the East.

Finding support for the presence of screening costs through reduced-form predictions, I structurally estimate the model, including the screening cost parameter. The model predicts the number of firms recruiting at each university based on the equilibrium profit equality conditions across universities. I develop an estimator based on moments equalizing the observed and predicted proportion of firms recruiting at each university. I test the impact of the screening costs by counterfactually setting the screening cost parameter to zero.

The estimated screening cost is large, costing firms up to $12,000 to review an applicant, relative to worker productivity of $100,000. 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 suggested the cost per MBA student hire is approximately $100,000, and only slightly lower for undergraduates. Counterfactually setting the screening cost parameter to zero, the number of firms recruiting at a nonselective university in the East more than doubles, and the wage offer increases by 35% of worker productivity.

The paper has several important policy implications. First, it contributes to the large policy and academic debate about whether high tuition at more selective universities is justified by better labor market outcomes. Previous literature has mostly found that graduating from a higher quality university increases earnings.\footnote{See Black and Smith, 2004, 2006, Brand and Halaby 2006, Brewer, Eide, and Ehrenberg} I show that earnings of students attending less selective Universities
universities may be quite high if these universities are among the most selective in their region. By omitting this regional dimension of university quality, previous studies may have underestimated the importance of university quality for earnings. The importance of regional rank also has implications for policymakers considering tying education funding and student loan interest rates to college quality. There may be reasons for governments to incentivize attending universities with a worse national rank but better regional rank.

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. While this may be the result of selection, it is plausible that the powerful networks developed at these firms help shape future career paths. I find 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. 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.

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

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

10 These components are specific to undergraduate recruiting. Recruiting of MBA students is in general a completely separate process, managed by different staff members.
**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.\textsuperscript{11}

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

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

\textsuperscript{11}This is particular to management consulting firms. As stated in the introduction, in other industries hiring through on-campus interviews is less common though still quite prevalent.
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. 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, $\tilde{S}_t$, interested in applying for jobs with these firms. I assume $\tilde{S}_t$ is distributed Poisson with known mean $S_t$. This is the distribution that would arise if students at large universities made

\footnote{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. Allowing firms to recruit from multiple campuses for a single vacancy would be complicated, since students would need to account for the firm’s recruiting strategies at other universities.}
independent and equally probable decisions to apply for jobs with these firms. Universities have different proportions of H-type students, denoted $p_t$. All H-type workers have the same productivity, $v$, at each recruiting firm.

I assume that students do not know their type, implying that both types apply to vacancies. In order to determine whether an applicant is an H-type firms incur cost $c$, the cost of reviewing the applicant’s resume and conducting an interview. The assumption that students do not know their type is 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.

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

The expected cost function is given by the expected number of applicants

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13 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.

14 Assuming students do not observe their type is important only because it ensures L-types apply, and thus expected reviewing costs are lower at universities with higher $p$. Other assumptions, including that students have some information on their type, also yield this result.

15 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. 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.

16 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.
reviewed multiplied by the cost per application reviewed, $c$. The expected number of applicants reviewed is:

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

(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, $(1 - e^{-pz}i)(\frac{c}{p})$, is decreasing in $p$.

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

$$\pi_{ti} = (1 - e^{-pz_{ti}})(v - w_{ti} - \frac{c}{p_{t}}).$$

(2)

Given that the number of students at each university has a Poisson distribution, the number applying to firm $i$ also will have a Poisson distribution. The probability that the firm’s vacancy is filled is given by $1 - e^{-pz_{ti}}$. 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.\footnote{Peters (2000) studies finite versions of matching models of this type (sellers announce prices, buyers understand that higher prices affect the queue and probability of trade). He shows as the number of buyers and sellers becomes large, payoff functions faced by firms converge to payoffs satisfying the market expected income property (one firm’s deviation does not affect overall market expected income). This result is conditional on assuming student application strategies are symmetric, and an exponential matching process. While the study is limited to elite firms, if all firms ranked in the top 50 are treated as elite, this is over 100 firms (consulting, banking, and investment management). Relaxing the assumption that firms are price-takers would complicate the model. However, intuition suggests the main result must hold: firms must be compensated for recruiting at less selective universities, either by facing less competition or offering lower wages, or both.}

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 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 $S_t$ is the number of students at university $t$ and $N_t$ 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 $\{W^*_t, q^*_t(\cdot)\}$ 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 $q^*_t(\cdot)$, as described above, and
all firms adopt the strategy $w_i^*$ as given by

$$w_i^* = \frac{r_i(p_tv - c)}{e^{r_ip_i} - 1} \quad (3)$$

Recall that $p_t$ denotes the proportion of high types at university $t$, $v$ denotes worker productivity, and $c$ denotes the per-applicant screening cost. The first-order condition for profit maximization is independent of the firm, $i$:

$$z_i^*(W_t) = \frac{1}{p_t} \log \frac{p_tv - c}{K_i^*(W_t)} \quad (4)$$

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.

$$(1 - e^{-p_1(s_1/N_1)})(v - \frac{(S_1(p_1v - c)}{N_1(e^{p_1(s_1/N_1)} - 1)} - \frac{c}{p_1})$$

$$- (1 - e^{-p_2(s_2/N_2)})(v - \frac{(S_2(p_2v - c)}{N_2(e^{p_2(s_2/N_2)} - 1)} - \frac{c}{p_2}) = 0 \quad (5)$$

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 \( R - 1 \). Equation (5) also shows that if the per-applicant reviewing cost \((c)\) equals zero, the profit from recruiting at each university is equalized when \( \frac{p_s{S_s}}{N_s} = \frac{p_s'{S_s'}}{N_s'} \) for all universities \( s, s' \). Thus, with \( c = 0 \), firms allocate across campuses based on the number of high-type students, and not the proportion.

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 recruit 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:

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

(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 \( t \)).\(^{18}\)

\(^{18}\)Increasing \( p_t \) and decreasing \( S_t \) without changing \( p_t S_t \) implies that the number of L-
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:

<table>
<thead>
<tr>
<th>Region 1</th>
<th>Region 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>100H,100L</td>
<td>80H, 0L</td>
</tr>
<tr>
<td>80H, 100L</td>
<td>100H,100L</td>
</tr>
<tr>
<td>0H, 100L</td>
<td>100L</td>
</tr>
</tbody>
</table>

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.

Consider the model without per-applicant screening costs ($c = 0$), for example if recruiting decisions are driven only by the fixed cost of visiting a campus. With $c = 0$, profit equalization across universities implies each firm will have the same number of high-type applicants in its pool. Thus, firms allocate based on the number of high-types relative to the market, and not type students is lowered at $t$. To keep all else equal, in this proposition I have assumed that the number of L-type students in the market is kept constant (implying L-types increase at another university). This assumption is not necessary for the result to hold.
the proportion of high-types. As a result, if $c = 0$, the university with 100H, 100L will 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. 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). For each of these firms, I attempted to collect data on undergraduate target campuses from the firm’s website. 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 information is loaded, making clear Bain’s active recruiting presence there.

\[19\] For example, the websites for Bain’s New York and Dallas offices each publicize the “Associate consultant” position for recent BA recipients. Both websites link to the same page for further position description.

\[20\] 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.

\[21\] Some firms list target campuses; others require that each university is typed into a search field to determine recruiting information.
However, after typing Pennsylvania State University it is clear that Bain does not actively recruit at the university.\footnote{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.} 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.\footnote{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.} I denote whether each of these firms actively recruits undergraduates at each of the universities in Princeton Review’s \textit{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.\footnote{The data used by The College Board, Peterson’s, and US News and World Report.} 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).\footnote{The USNWR university ranking does not include liberal arts colleges. To avoid dropping these colleges, I include an indicator for nonmissing ranking.}

The important measure of university selectivity is arguably from when the 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. 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 firm-university distance on recruiting decisions, I collect the latitude and longitude for each university and office location. I find the closest office of each firm to a given university.

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.

5 Empirical Analysis of Recruiting Strategies

The model’s central prediction suggests that with screening costs and regional labor markets, recruiting decisions are driven not only by the number and proportion of high-type students at the university, but importantly by the proportion of high-type students relative to other universities in the region. This is not easily transformed into a reduced-form specification. For simplicity, to capture this intuition, I consider the university’s regional rank based on the proportion of high-type students. Regional rank does not capture that recruiting outcomes depend on the exact number and proportion of high-quality students 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

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26 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.

27 These methods are explained in the online appendix.

28 Explained in the online appendix.

29 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.
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 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. 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. Table 1, Panel C presents further evidence of regional labor markets for recent graduates, based on B&B data. The percentage of students living in the same region as their university one

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30Most 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.

31The 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 the Dallas and Houston offices suggests regional hiring.
year after graduation is very high, ranging from 77% in the South to 88% in the West. Using university data on post-college geographic mobility, Appendix Table A10 shows little evidence that firms heavily recruit their home-state students studying in other regions.\textsuperscript{32} Importantly, my reduced-form specification is a joint test for the presence of screening costs and regional markets. If regional markets are unimportant, regional rank will not significantly affect recruiting.

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.\textsuperscript{33} For robustness, I exogenously define labor markets as the universities in the same Bureau of Economic Analysis (OBE) region as the firm.\textsuperscript{34} For seven universities, the closest office of every firm was not in their region. Excluding these leaves 342 universities in the dataset.

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.\textsuperscript{35} For universities without these data, $p$ is predicted using test score.

\textsuperscript{32}Western firms do recruit in the East, but this is not a large distortion. The regional nature of these labor markets may seem surprising given previous findings of higher elasticity of local labor supply with respect to wages for high-skill individuals, and that high-skill workers are more responsive to local labor demand shocks (Bound and Holzer (2000), Busso, Gregory, and Kline (2013), Glaeser and Gyourko (2005), Notowidigdo (2013), Topel (1986), Wozniak (2010)). While college graduates may be more mobile than non-college graduates, Wozniak (2010) notes that 55% of college graduates live in their birth state. This is consistent with low levels of regional mobility found here.

\textsuperscript{33}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.

\textsuperscript{34}I combine New England and Mideast. Online appendix has algorithm and region details.

\textsuperscript{35}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
percentiles from IPEDS. The prediction is based on universities with both the Common Data Set and IPEDS, and follows Papke and Wooldridge (1996). I construct an analogous variable denoting the share of students scoring \([700, 800]\) on SAT Verbal or \([30, 36]\) on ACT English.\(^{36}\)

**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 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 graphically shows the identifying variation for the reduced-form analysis. For given \(p\), regional rank is worse in the East than other regions. Consider four universities in different regions: Penn State (\(p = .171\)), Miami University in Ohio (\(p = .163\)), Texas A&M (\(p = .165\)), University of Georgia (\(p = .161\)). Despite similar 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. Appendix Figure A2 in the online appendix shows there are universities across region with both similar number and proportion of high-scoring students (\(p\)).

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 verbal scores would dramatically affect the results. Clearly the definition of students who are high-types for these firms is more complicated than simply SAT scores. The assumption is that the proportion of high SAT score students is positively correlated with the true proportion of high-type students.\(^{36}\) See the online appendix for a detailed description of the calculation of \(p\).
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 $p \in [0.2, 0.4)$, 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**

The model suggests two reasons that universities with worse regional rank may attract fewer firms, holding constant university size and selectivity: screening costs and differences in supply of students. The model shows that without screening costs, firms allocate across universities based on the number of high-type students relative to the market total. The number of high-type students in the East is larger than in other regions. If two universities have the same number of high-types, the university in the East will attract fewer firms because it has a smaller proportion of the region’s high-types. I identify the screening effect versus the supply effect by including the number of high-types at the university divided by the number of high-types in the region.

As is evident from Figure 3, for a given university quality the difference in regional rank varies dramatically over the distribution of university quality. For $p \approx 0$, the regional rank difference between the East and West is about 100, close to 40 when $p = .2$, and less than 20 when $p = .6$. To account for these nonlinearities, I allow for the effect of regional rank to vary with $p$. For given values of $p$ I then evaluate the coefficient at relevant differences in regional rank. The interactive effect between regional rank and $p$ may be correlated with the interactive effects between absolute quality variables and $p$. To mitigate these concerns, I interact the principal explanatory variables with $p$ : $p$, number of high-type students, and number of high-type students relative to the market.$^{37}$

$^{37}$Interacting every explanatory variable with $p$ would clearly result in loss of power. For
Observations are (university, firm) pairs, e.g., (Penn State, Bain). I estimate:

\[
recruit_{sf} = X_s \beta + \gamma_1 RegRank_s + \gamma_2 RegRank_s \times p_s + \gamma_3 FirmsinRegion_s + \\
\gamma_7 Distance_{sf} + \delta_f + \epsilon_{sf}
\] (7)

\(Recruit_{sf}\) indicates whether firm \(f\) recruits at university \(s\). \(X_s\) is a vector of university characteristics. \(Distance_{sf}\) denotes the distance between university \(s\) and firm \(f\)'s closest office. \(FirmsinRegions_s\) is the total number of offices for the firms in my sample located in the same region as university \(s\). I include firm fixed effects, and cluster standard errors at the university level since \(p_s\) 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. Because the model implies no effect for universities below \(p_{cutoff}\), I include only those universities with \(p\) greater than the minimum \(p\) attracting a firm (\(p = .0078\)). I do not include universities with \(p > .7\) since there is very limited overlap across regions.

Financial firms recruit for some positions that may place less value on Math scores, implying that regional rank may have a heterogeneous effect across industry. I interact the regional rank variables, as well as the other variables

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\[^{38}\text{These include } p; \text{number of students } \times p; \text{number of students } \times p \text{ divided by the region total of this variable}; 25\text{th and 75\text{th percentiles of Math and Combined SAT/ACT, weighted by proportion reporting each exam}; percentage scoring [700, 800] on SAT Verbal/ACT English (calculated in same way as } p); \text{percentage in top tenth of High School Class}; \text{US News Ranking}; \text{in-state and out-of-state tuition}; \text{percent of applicants admitted}; \text{indicators for public institution, location in a large city, small or mid-sized city, and offering more than a BA}. \(X_s\) also includes interactions between \(p\) and the following variables: \(p\); number of students \(\times p\); number of students \(\times p \text{ divided by the region total of this variable.}\)

\[^{39}\text{I include only universities with second lowest } p \text{ and higher to mitigate any randomness associated with a firm recruiting at the lowest } p. \text{ The results are robust to including the lowest } p \text{ attracting firms.}\]

\[^{40}\text{In addition, the model implies there should not be a large effect for these universities, since they all have similar regional ranks and low screening costs.}\]
interacted with \( p \), with an indicator denoting a consulting firm.\(^{41}\)

6 Reduced-Form Estimation Results

Column 1 of Table 2 shows that regional rank has a statistically significant effect on recruiting decisions, holding university selectivity, size, and size relative to the region constant. The 25th percentile of \( p \) based on the full sample is approximately .06. A university in Texas with this value of \( p \) has a regional rank of 56, while a university in the East with this \( p \) has a regional rank of 120. For this \( p \), and the corresponding regional rank difference of 64, universities in the East are 1.8 percentage points less likely to attract a firm than universities in Texas. This effect is large, given recruiting in only 6.2% of (university, firm) pairs in the regression sample. I find a smaller effect of approximately .007 percentage points for universities with the median value of \( p \) (.14), where the corresponding difference in regional ranks is about 50 places. The online appendix presents coefficients on all variables.

The specification in Column 2 includes interactions between the key explanatory variables, \( p \), and an indicator for consulting firms. The coefficients on regional rank are jointly significant at the 1% level, as are the coefficients on regional rank interacted with \( \text{Consult} \). The results suggest stronger effects for consulting firms relative to finance firms. For universities with \( p \) at the 25th percentile, a university in Texas is 3 percentage points more likely to attract a consulting firm than a university in the East. The effect is similar in size for universities with the median \( p \).\(^{42}\)

The effect of regional rank on recruiting decisions is large, though not as large as some absolute quality variables. For comparison, among universities

\(^{41}\)For robustness, I estimate the regression including triple interactions between every variable and \( p \times \text{Consult} \), along with the interactions with \( p \) and \( \text{Consult} \) separately. Unsurprisingly given the loss of power, the results are similar, though less statistically significant. See online appendix for results.

\(^{42}\)I estimate the specifications in columns 1 and 2 further allowing for interactions between regional rank and firm rank (as well as firm rank and the other key explanatory variables). These interactions are not jointly statistically significant; however, the magnitudes suggest better-ranked firms are more sensitive to a university’s regional rank (not shown).
with the median $p$, increasing the number of high-types by one standard deviation (462 students) increases the probability of attracting a consulting firm by 5.5 percentage points (the effect of regional rank was 3 percentage points). Among universities with $p$ at the 25th percentile, the effect is 4.2 percentage points (the effect of regional rank was 3 percentage points).\footnote{These estimates were obtained using the linear combination of the coefficients on number of high-types, and number of high-types relative to the region.}

The results support the model’s prediction that regional rank should matter if screening costs are present and labor markets are regional. If screening costs were not important, firms would choose campuses based only on the number of students relative to the market total. If labor markets were not regional, firms would choose campuses based on their national, not regional, rank.

The results provide support for the theoretical prediction: regional rank affects recruiting decisions, holding constant university characteristics, as well as the number of high types divided by the region total, and the number of firms in the region. However, when making decisions about college choice, students should not hold regional characteristics constant. There are more firms in the East. Excluding this variable may suggest benefits of attending university in the East, despite the worse regional rank. To address this question, I obtain the predicted values from the regression allowing for industry heterogeneity. I then estimate a lowess regression of the predicted values on $p$ for consulting firms. These predicted values account for the effect of attending university in a region with more firms.

The plots are shown in Figure 5. In the West, for universities with $p \leq .05$, the smoothed predicted probability of attracting a consulting firm reaches as high as .029. In the East, only universities with $p \geq .125$ attract consulting firms with equivalent probability.\footnote{This is the minimum $p$ associated with a smoothed predicted probability of attracting a consulting firm within .005 of .029.} For universities with $.19 \leq p \leq .21$ in the West, the smoothed predicted probability of attracting a consulting firm reaches .10. The only universities in the East with smoothed predicted probability this high are those with $p \geq .36$. Finally, for universities in the West with $.27 \leq p \leq .28$ (University of Texas at Austin), the smoothed predicted
probability of attracting a consulting firm reaches as high as .186. In order to attend a university with an equivalent probability, a student would need to choose a university with \( p \geq .56 \) (Tufts University).

Robustness

For robustness, I estimate the specifications using probit and logit. The results for consulting firms are smaller in magnitude and statistical significance, though the magnitudes still suggest nontrivial negative effects of a worse regional rank (Appendix Table A7, online appendix).

Using Bureau of Economic Analysis (OBE) regions for robustness, there are many more observations for which the university and the closest firm office are not in the same region. As a result, they are dropped from the analysis. Both the data and common sense suggest these observations should be classified as the same labor market, highlighting the benefit of using a community detection algorithm.\(^45\) In addition to being a smaller sample, it is also likely biased because of the observations excluded. The results using OBE regions show large effects of regional rank for the least selective universities (Appendix Table A9, online appendix). However, the effects for the median university are smaller. While the coefficients on regional rank are jointly significant, the combinations at the 25th and 50th percentile of \( p \) are not statistically significant.

Selection on Unobservables

While the regressions control for many measures of university quality, universities with worse regional rank may attract fewer firms due to unobservable differences. Based on the insight formalized in Altonji, Elder, and Taber (2005), I use selection on observables to learn about potential bias from selection on unobservables. Specifically, Altonji, Elder, and Taber (2005) measure how much stronger selection on unobservables

\(^{45}\)For example, Chicago is the closest office of many firms to Washington University in St. Louis. While Missouri and Illinois are in the same community detection region (the Midwest), the OBE region for Missouri is the Plains and for Illinois is the Great Lakes. Many Chicago firms recruit at Washington University in St. Louis and it seems very reasonable that they should be in the same region.
must be relative to selection on observables in order to explain away the estimated effect. I use the extension of this strategy for a linear model developed in Bellows and Miguel (2009).46

Given these tests assume no treatment heterogeneity (see Altonji, Elder, and Taber 2002, 2008 for a discussion), I estimate a specification including regional rank without its interaction with \( p \). Because differences in regional rank vary nonlinearly with \( p \), I restrict the regression to universities with \( p \) in the interquartile range, where regional rank differences are more constant.47 I use the sample of consulting firms since results were strongest for this sample. This results in a sample of 3115 firm, university pairs.

As derived in Bellows and Miguel (2009), the selection on unobservables relative to observables needed to explain away the effect can be obtained from the following ratio: \( \frac{\hat{\gamma}_F}{\hat{\gamma}_R - \hat{\gamma}_F} \). The coefficient \( \hat{\gamma}_F \) is the coefficient on \( \text{RegRank} \) from a regression including the full set of controls and \( \hat{\gamma}_R \) is the coefficient on \( \text{RegRank} \) from a regression with a restricted set of controls (\( p \), number of high-scoring students, number of high-scoring students relative to the region, number of offices in the region, and distance between firm and university).48 Assuming the control variables are representative of all possible controls, a high ratio implies a large amount of selection on unobservables relative to observables to explain away the effect.

The coefficient on \( \text{RegRank} \) in the full regression is -.049, which is slightly smaller than in the restricted regression (-.051).49 This suggests limited selection on observables. The ratio is equal to 18.84, which suggests that if the entire effect was due to differences in unobservables, selection on unobservables would have to be at least 18.84 times larger than selection on observables. This

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46 The strategy is also implemented and further described in Nunn and Wantchekon (2011). Altonji, Elder, and Taber (2005) consider a bivariate normal structure.

47 I use the interquartile range for the sample restricted to consulting recruiting: \( p = .06 \) to \( p = .27 \). Intuition also suggests no effect for the least and most selective universities.

48 The restricted set of controls was chosen to ensure the implementation of the basic identification strategy: comparing the probability of recruiting at universities of equivalent quality, controlling for the number of firms in the region and distance between the firm and university. I include the percent, number, and number of high-scoring students relative to the region to separate the screening cost mechanism from supply mechanisms.

49 See results in online appendix, Appendix Table A5.
seems unlikely given the richness of the controls in the full regression.\textsuperscript{50}

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 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 limit the sample to graduates of universities with national rank (based on $p$) 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. Among this sample, I only include individuals with adjusted earnings (defined below) greater than or equal to the 5th percentile (approximately $17,630). University characteristics pertain to Freshmen in Fall 2004, as the sample is college graduates in Spring 2008. The online appendix presents summary statistics.

The recruiting regressions allowed the effect of regional rank to vary with university selectivity. The model also predicts high test score students will

\textsuperscript{50}For comparison, Altonji, Elder, and Taber (2005) obtain a ratio of 3.55, Bellows and Miguel (2009) obtain ratios ranging from 5 to 17, and Nunn and Wantchekon (2011) obtain a median ratio of 4.1.
be hurt most by attending a university with worse regional rank, since these students could be hired by finance and consulting firms. This effect should be more pronounced at less selective universities, where the regional rank is much worse in the East. Because of the smaller sample size, and the loss of power from including a triple interaction, I estimate regressions including $\text{RegRank} \times SAT$. I also include interactions between the student’s SAT score and key explanatory variables ($p$, number of high-scoring students, and number of high-scoring students divided by the region total).\footnote{For robustness, I estimate the specification with interactions between the student’s SAT score and each university characteristic.} I then estimate separate regressions for universities with $p \leq 75$th percentile (approximately .17) and $p > 75$th percentile.\footnote{Based on the 2004 data, $p$ for Texas A&M is about .12 and for Penn State is about .11.}

I cluster standard errors at the university level and estimate:

$$
\text{LogEarnings}_{isl} = X_s \beta + Z_i \rho + \gamma_1 \text{RegRank}_s + \gamma_2 \text{RegRank}_s \times SAT_i \\
+ \gamma_6 \text{Avg Wage BAGrad}_l + \epsilon_{isl}
$$

(8)

$\text{LogEarnings}$ are from the primary job in 2009, calculated on an annual basis, for individual $i$, who graduated from university $s$, and lives in state $l$. I adjust for earnings differences across states using 2006 US Bureau of Economic Analysis state price parities (Aten and D’Souza, 2008).\footnote{The closest year to 2009 with price parity data was 2006. I adjust earnings using the price parity for their 2009 state of residence.} Using the American Community Survey, I also control for average earnings of college graduates aged 25-34 in state $l$, adjusted using state price parities.

$X_s$ includes university characteristics, including numerous measures of university quality.\footnote{Variables include the proportion ($p$), and the number of high math scoring students at the university, the number of high math scoring students divided by the total in the region, the percent of students admitted, the 25th and 75th percentiles of the combined math and verbal SAT score or the composite ACT converted to an SAT score, the 25th and 75th percentile of the Math SAT or ACT score converted to an SAT score, whether the university is public, offers more than a bachelor’s degree, is located in a large or mid-sized city, the US News ranking in 2008, and in- and out-of-state tuition. Because some universities were not ranked by US News, and some did not have data on the degree of urbanization or the tuition, I also include indicators for whether these variables are nonmissing. If universities reported...} \(Z_i\) includes individual-level demographics and SAT/ACT...
I also include interactions between the student’s SAT score and the following three variables: \( p \), the number of high scoring students at the university, and this variable divided by the region total. I do not include region fixed effects as these would eliminate the identifying across-region variation.

The coefficient on \( \text{RegRank} \times SAT \) in Column 1 of Table 3 implies that graduating from a university with a worse regional rank has a differentially negative effect on earnings for higher SAT students, holding university size and quality constant, (statistically significant at the 5% level). For students scoring 1400 on the SAT, the coefficients suggest earnings are 8% lower if her university’s regional rank is worse by 50 places. These effects are much smaller for a student scoring 1000 on the SAT. The coefficients on regional rank are jointly significant at the 5% level. Controlling for the number of high-scoring students, and the number relative to the total in the region helps to identify that these effects are due to screening costs. Column 7 shows the results are robust to including interactions between all, rather than just key, university characteristics and the student’s SAT score.

As predicted, Column 2 shows the effects are larger for students attending university with \( p \leq 75th \) percentile. For a student with an SAT score of 1400, earnings are 9% lower if her university’s regional rank is worse by 50 places. The effects are approximately half the size for students with an SAT score of

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55Variables include 2006 income (parental for dependent students), combined SAT score or the composite ACT score converted to an SAT score, 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 academic year. 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. Approximately 30 individuals did not take either exam. I include an indicator for whether the individual has test score data.

56The coefficients on regional rank are jointly significant at the 10% level, and the magnitudes are fairly similar, when weighting observations by the survey’s sampling weights (normalized so the sum of the weights equals the number of observations). For students scoring 1400 on the SAT, earnings are 11.5% lower if the university’s regional rank is worse by 50 places, holding university size and quality constant. The effect for students with an SAT score of 1000 is approximately 0 (though not statistically significant).
The regional rank coefficients are jointly significant at the 10% level. As expected, column 3 shows the regional rank coefficients are not jointly significant at more selective universities.

While the regressions control for the student’s SAT score, and many measures of university quality, graduates of worse regionally-ranked universities may earn less due to unobservable differences. I again use the strategy based on Altonji, Elder, and Taber (2005), and Bellows and Miguel (2009), to learn about potential bias from selection on unobservables.

I first estimate the main specification with only the key explanatory variables. Column 4 shows the magnitudes of the effects are largely unchanged. Second, to implement the Bellows and Miguel (2009) strategy (which assumes no treatment heterogeneity) I do not include interactions between regional rank (and other variables) and student SAT score. Since the predicted effect is among high SAT score students at less selective universities, it will not be captured without this interaction. Instead, I restrict the regression to a more relevant sample: universities with \( p \leq 90\text{th} \) percentile (approximately \( p = .35 \)), and SAT score greater than or equal to the 25th percentile (approximately 1040). Restricting more significantly would increase the relevance, but becomes problematic given the small sample size.

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

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57 These include the regional rank variables, student SAT score, \( p \), number of high-type students, number of high-type students divided by region total, and interactions of these last three variables with student SAT score.

58 The restricted set of controls includes \( p \), number of high scoring students, number of high scoring students relative to the region, student’s SAT score, and whether they have SAT score data. These were chosen to implement the basic identification strategy: comparing earnings of students with equivalent SAT scores and university quality. I include the percent, number, and number of high scoring students relative to the region to separate the screening cost mechanism from supply mechanisms.
8 Alternative Mechanisms

Regional rank affects recruiting decisions, controlling for university quality. Given that I control for regional differences in supply of high-scoring students, I attribute this effect to ranking in the distribution of regional selectivity. While this may be evidence of screening costs, it may also be evidence of the importance of regional prestige, separate from screening costs. For example, clients of finance and consulting firms may prefer working with employees who attended regionally prestigious universities. Alternatively, office culture might depend on regional prestige of alma mater, and this may yield complementarities. I test whether these alternative mechanisms explain the results by using differences in personnel practices across consulting firms.

Consulting firms often use global or local staffing models. With a global model, location of case assignments does not depend on the consultant’s “home” office. With a local model, consultants work on cases close to their home office. For firms utilizing a global staffing model, regional prestige should not matter for client relations or office culture, since consultants are not working within the region. Importantly, firms with global models may still need to recruit regionally since consultants return to their home office by Friday. I identify whether firms use local or global staffing policies based on the careers section of firms’ websites, which contain useful information about the nature of the work and travel.59

Given regional prestige should not matter for global-staffing firms, the university with worse regional rank should only attract fewer of these firms because of screening costs, controlling for the number and proportion of high-type students at the university. Column 3 of Table 2 shows that there is still a large effect of regional rank on recruiting decisions for consulting firms utilizing global staffing models. The coefficients on regional rank are also jointly significant with a p-value of .033. While the regional rank coefficients are not

59I confirmed this coding with someone working at one of the firms in my sample.
jointly significant for local-staffing firms (Column 4), the magnitude of the effects are fairly similar, though they are larger for universities with higher $p$.

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 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. Including these variables does not dramatically change the effect of regional rank (see online appendix).

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

## 9 Structural Estimation and Counterfactuals

The reduced-form analysis suggests strong support for the presence of screening costs. 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).\footnote{Appendix Table A11 (online) shows parameter estimates for various $\gamma$.} 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:

$$\pi = (1 - e^{-p_1\lambda(s_{1N_1})})(v - \frac{(\lambda s_{1N_1})(p_1v - c)}{N_1(e^{p_1\lambda(s_{1N_1})} - 1)} - \frac{c}{p_1})$$ (9)

The parameters $c$ and $v$ are also unknown, though they are not separately identified.\footnote{Doubling $v$ and $c$ doubles profits at each university in the profit equality conditions. This implies that the profit-equalizing values of $N_i$ are the same for $(v, c)$ and $(2v, 2c)$.} The productivity parameter, $v$, is normalized to 1, leaving two unknown parameters $c$ and $\lambda$. Put differently, I estimate $\frac{c}{v}$.
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 (reservation wage) 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 $p_t \geq c$. 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.\footnote{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.} I check the solution equalizes profits at all universities.\footnote{I require that the squared norm of the profit equality equations is $\leq 1e-10$.}

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...
λ by finding the values minimizing the difference between the model’s predictions and the data, using GMM. Moments include the difference between the predicted and observed proportion of firms recruiting at each university 
\[ \left( \frac{N_t^{\text{Predicted}}}{NTot^{\text{Predicted}}} - \frac{N_t^{\text{Observed}}}{NTot^{\text{Observed}}} \right) \], \text{64} this error multiplied by } p_t, \text{and by } log(S_t). \text{65} 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 λ from .05 to .35 at intervals of .05, and over c from .01 to .2 at intervals of .01.\text{66} 

The parameter c is identified by explaining firms’ preference for universities with higher proportion, but identical number, of H-type students. Non-zero estimates of c reject a simple supply and demand story, which predicts firm allocation based only on the number of H-type students. The parameter λ is identified by explaining firms’ preference for universities with larger number, but identical proportion, of H-type students. Consider two universities with equal proportion, but different number, of H-types. If the larger university does not attract more firms, the proportion of students interested in the firms (λ) 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.\text{67} 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 γ from \( \gamma = 10 \), they do not dramatically change when increasing γ from \( \gamma = 15 \), when \((c, \lambda) = (.07, .3)\).\text{68} Panel A also shows high estimated profits in the Midwest, due to low screening

\[ \text{64}NTot^{\text{Predicted}} = \gamma \times TotalFirmOffices \text{ and } NTot^{\text{Observed}} = \sum_{t=1}^{T} N_{t,\text{Observed}} \]

\[ \text{65}\]Given that \( p_t \) and \( log(S_t) \) are exogenous to this error, they can be interacted with the error to yield additional moment restrictions as in Berry, Levinsohn, and Pakes (1995).

\[ \text{66}\]I check the solution is not occurring at one of the grid bounds. I also check that the objective function looks smooth around the solution. For example, for a given value of the screening cost parameter, the objective function is decreasing in \( \lambda \) until the solution, and after the solution is increasing in \( \lambda \).

\[ \text{67}\]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.

\[ \text{68}\]Estimates of c are relatively similar, yet \( \lambda \) estimates are higher, when \( \gamma = 15 \). See Appendix Table A11 (online). 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.

35
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 fit, I compare the predicted and observed distributions of the proportion of firms recruiting at the university. Appendix Figure A1 (online) shows the model fits the data reasonably well in each region.

**Impact of Search Frictions on Student Outcomes**

Few papers have quantified the impact of search frictions on wages. 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 per firm 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 per-applicant screening costs of .09 (9% of worker productivity $v$) in the East, the cut-off $p$ below which recruiting is unprofitable is approximately .14. There are 85 universities in the East with $p < p_{\text{cutoff}}$ and 83 with $p \geq p_{\text{cutoff}}$.

Panel B of Table 4 shows the effect of removing screening costs for various universities in the East. A wage of zero can be understood as the reservation wage, for example the wage offered by a firm outside finance and consulting. Analogously, $v$ can be understood as the additional productivity of a high-type worker at a finance or consulting firm relative to firms in other industries. Screening costs have a very negative impact on high-type students at less selective universities. With per-applicant screening costs that are 9%...

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69 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.
of worker productivity $v$, 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, students receive the reservation wage. However, this university does attract 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 the reservation wage plus 37% of the additional worker productivity ($v$) at these firms.

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

With per-applicant screening costs that are 9% of productivity $v$, over 2.5% of firms recruit at Massachusetts Institute of Technology (MIT), which has the highest $p$ in the East (.86).\textsuperscript{70} The many competing firms at MIT creates upward pressure on wages, yielding high-type student wages equal to the reservation wage plus 45% of the additional worker productivity at these firms. Without screening costs firms recruit more heavily at less selective universities, reducing the number of firms at MIT from 72 to 51, and the wage to the reservation wage plus 37% of the additional productivity at these firms.

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

**Cost per Hired Worker**

Having estimated screening cost per applicant, I calculate screening cost per hire: expected number of applicants reviewed (eq. (1)) multiplied by screening cost per applicant. I report these costs for worker productivity $v$ of $100,000. At less selective universities, firms on average review more applicants, so cost

\textsuperscript{70} 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.
per hire is greater. Expected number of applicants reviewed at MIT \((p=.86)\)
is \(.77\), and the screening cost per hire is about $6900. Expected number of applicants reviewed at Fordham \((p=.14)\) is about \(3.2\), and the screening cost per hire is $28,700. Differences in cost per hire are equilibrated through the wage and number of H-type applicants. Firms paying more in screening costs have more H-type applicants in their pool and pay lower wages.

10 Discussion and Conclusion

This paper analyzes labor market matching in the presence of search and informational frictions, through studying the immensely prevalent, though largely unexplored, phenomenon of on-campus recruiting. I incorporate relevant search frictions into a directed search model of the campus recruiting market, and present reduced-form and structural evidence that 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 less selective universities.

The results highlight possible equity and efficiency consequences of elite universities. With elite universities, students at non-elite universities have reduced access to prestigious firms (if firms would choose differently than an elite university). Thus, elite universities may obstruct equal access to firms for students equally likely to be hired by those firms. If initial jobs affect career paths, equity effects are amplified. However, by incurring screening costs, and reducing these costs for firms, elite universities may increase efficiency.\(^71\) Higher screening costs for firms in the absence of elite universities

\(^{71}\)This is just a transfer unless screening costs are lower for universities than for firms.
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 9% less at universities of equal size and selectivity, but worse regional rank by 50 places. This may reflect the value of attending college, and living in, the Northeast.

References


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

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 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

Figure 1b: Bain Recruiting Page for Penn State

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 3: Differences in Regional Rank for a Given University Selectivity](image1)

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

![Figure 4: Recruiting at the University Attracting the Most Firms, by University Selectivity Bin and Region](image2)

Figure 5: Lowess Predicted Probability of Recruiting on University Selectivity

![Figure 5: Lowess Predicted Probability of Recruiting on University Selectivity](image3)

Note: See text for details. In Figure 4, I show four university selectivity bins: Proportion of students scoring at least 700 on the Math SAT or 30 on the Math ACT ∈ [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. In Figure 5, the predicted probability that Recruit=1 is obtained from the regression allowing for heterogeneity across industry (Column 2 of Table 2). I estimate a lowess regression of these predicted values on p for consulting firms (bandwidth .1), and plot the lowess fitted values.
Table 1: Summary Statistics by Region

Panel A: Number of Firms

<table>
<thead>
<tr>
<th></th>
<th>East</th>
<th>Midwest</th>
<th>South</th>
<th>West</th>
</tr>
</thead>
<tbody>
<tr>
<td># Consulting Firms</td>
<td>21</td>
<td>19</td>
<td>13</td>
<td>20</td>
</tr>
<tr>
<td># Banking Firms</td>
<td>17</td>
<td>13</td>
<td>10</td>
<td>16</td>
</tr>
<tr>
<td>Total Firms</td>
<td>38</td>
<td>32</td>
<td>23</td>
<td>36</td>
</tr>
<tr>
<td># Consulting Firm Offices</td>
<td>152</td>
<td>94</td>
<td>40</td>
<td>141</td>
</tr>
<tr>
<td># Banking Firm Offices</td>
<td>128</td>
<td>55</td>
<td>44</td>
<td>94</td>
</tr>
<tr>
<td>Total Firm Offices</td>
<td>280</td>
<td>149</td>
<td>84</td>
<td>235</td>
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</table>

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

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<th>Regional Rank</th>
<th>National Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
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<td>3</td>
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</tr>
<tr>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
</tr>
</tbody>
</table>

Panel C: Post-College Geographic Mobility

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

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

<table>
<thead>
<tr>
<th>Dependent Variable: Recruit</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional Rank (hundreds)</td>
<td>-0.038***</td>
<td>-0.039***</td>
<td>-0.035**</td>
<td>-0.021</td>
</tr>
<tr>
<td></td>
<td>[0.012]</td>
<td>[0.015]</td>
<td>[0.015]</td>
<td>[0.017]</td>
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<tr>
<td>Regional Rank (hundreds) * p</td>
<td>0.187</td>
<td>0.633***</td>
<td>0.099</td>
<td>-0.132</td>
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<tr>
<td></td>
<td>[0.185]</td>
<td>[0.205]</td>
<td>[0.282]</td>
<td>[0.233]</td>
</tr>
<tr>
<td>Regional Rank (hundreds) * Consult</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>[0.012]</td>
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<td></td>
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<tr>
<td>Regional Rank (hundreds) * p * Consult</td>
<td>-0.778***</td>
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<tr>
<td></td>
<td>[0.179]</td>
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</table>

P-value, Joint Test of Coefficients on Regional Rank

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<th>All Firms</th>
<th>Consulting</th>
<th>Global</th>
<th>Local</th>
</tr>
</thead>
<tbody>
<tr>
<td>Universities with $p = .06$</td>
<td></td>
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<td></td>
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<tr>
<td>Texas (Regional Rank 56)</td>
<td>-0.015</td>
<td>-0.026***</td>
<td>-0.017</td>
<td>-0.016</td>
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<tr>
<td></td>
<td>[.01]</td>
<td>[.01]</td>
<td>[.014]</td>
<td>[.013]</td>
</tr>
<tr>
<td>East (Regional Rank 120)</td>
<td>-0.033</td>
<td>-0.056***</td>
<td>-0.035</td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td>[.02]</td>
<td>[.021]</td>
<td>[.03]</td>
<td>[.027]</td>
</tr>
<tr>
<td>Universities with $p = .14$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Texas (Regional Rank 32.5)</td>
<td>-0.004</td>
<td>-0.019*</td>
<td>-0.007</td>
<td>-0.013</td>
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<tr>
<td></td>
<td>[.009]</td>
<td>[.01]</td>
<td>[.015]</td>
<td>[.012]</td>
</tr>
<tr>
<td>East (Regional Rank 82)</td>
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<td>-0.048*</td>
<td>-0.018</td>
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<td></td>
<td>[.024]</td>
<td>[.026]</td>
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Firms

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<th>Global</th>
<th>Local</th>
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<td>N</td>
<td>10,730</td>
<td>10,730</td>
<td>1,958</td>
<td>4,090</td>
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<tr>
<td>Mean(Recruit)</td>
<td>0.062</td>
<td>0.062</td>
<td>0.031</td>
<td>0.074</td>
</tr>
</tbody>
</table>

Note: *** p-value ≤ .01, ** p-value ≤ .05, * p-value ≤ .1. See text and online appendix for details on variable and sample construction, and a full list of variables in the regressions. Regressions include firm fixed effects; standard errors are clustered at the university level. States comprising each region are listed in the online appendix. All columns include interactions between key explanatory variables and $p$; column 2 includes triple interactions between key explanatory variables, $p$, and an indicator for consulting firm (as well as the necessary two-term interactions). Key explanatory variables include $p$, number of high-scoring students, and number of high-scoring students divided by the region total of this variable.
### Table 3: Effect of Regional Rank on Earnings After Graduation

<table>
<thead>
<tr>
<th></th>
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<th>(2)</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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<tbody>
<tr>
<td><strong>Regional Rank (hundreds)</strong></td>
<td>0.189</td>
<td>0.152</td>
<td>-0.012</td>
<td>0.224*</td>
<td>-0.137**</td>
<td>-0.145***</td>
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<td>[0.052]</td>
<td>[0.180]</td>
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<tr>
<td>*<em>Regional Rank (hundreds)<em>SAT</em></em></td>
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<td>-0.028**</td>
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<td>[0.012]</td>
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<td>[0.070]</td>
<td>[0.012]</td>
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<tr>
<td><strong>SAT Score (hundreds)</strong></td>
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<td>0.043*</td>
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<td>[0.011]</td>
<td>[0.009]</td>
<td>[0.010]</td>
<td></td>
</tr>
</tbody>
</table>

#### Linear Combination of Regional Rank Coefficients for:

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1400 SAT</td>
<td>-0.162***</td>
<td>-0.183**</td>
<td>-0.185</td>
<td>-0.17***</td>
<td></td>
<td>-0.16**</td>
<td></td>
</tr>
<tr>
<td>1000 SAT</td>
<td>-0.062</td>
<td>-0.088*</td>
<td>-0.136</td>
<td>-0.057</td>
<td></td>
<td>-0.072</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[.045]</td>
<td>[.05]</td>
<td>[.273]</td>
<td>[.04]</td>
<td></td>
<td>[.044]</td>
<td></td>
</tr>
</tbody>
</table>

#### P-value on Joint Test of Regional Rank Coefficients

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Universities</strong></td>
<td>0.031</td>
<td>0.092</td>
<td>0.617</td>
<td>0.013</td>
<td></td>
<td>0.066</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less Selective</td>
<td>More Selective</td>
<td>All</td>
<td>SAT ≥ 25th percentile (1040)</td>
<td>All</td>
<td></td>
</tr>
<tr>
<td>Full Set of Student and University Controls</td>
<td>All</td>
<td>Selective</td>
<td>Selective</td>
<td>All</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interactions of University Controls, student SAT</td>
<td>Key</td>
<td>Key</td>
<td>Key</td>
<td>Key</td>
<td>Key</td>
<td>Key</td>
<td>All</td>
</tr>
<tr>
<td>N</td>
<td>2120</td>
<td>1600</td>
<td>520</td>
<td>2120</td>
<td>1380</td>
<td>1380</td>
<td>2120</td>
</tr>
</tbody>
</table>

| R-squared                     | 0.168  | 0.154  | 0.246  | 0.085  | 0.161  | 0.073  | 0.180 |

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the university level. The dependent variable is the natural log of the respondent’s earnings in 2009, adjusted for state price parity based on the state of residence in 2009. Sample excludes those with earnings below the 5th percentile, adjusted for state price parities ($17,630). Key interactions include those between SAT score and the following variables: proportion of high-scoring students, number of high-scoring students, and number of high-scoring students divided by the region total of this variable. Less selective universities in column 2 include those with p ≤ 75th percentile (.17), and more selective universities in column 3 include those with p > 75th percentile. Sample sizes are rounded to the nearest ten to preserve confidentiality. See text and online appendix for list of explanatory variables, region definitions and details on variable and sample construction.
Table 4: Structural Estimation Results

Panel A: Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>East</th>
<th>Midwest</th>
<th>South</th>
<th>West</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c)</td>
<td>0.09</td>
<td>0.03</td>
<td>0.1</td>
<td>0.12</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>0.1</td>
<td>0.3</td>
<td>0.25</td>
<td>0.15</td>
</tr>
<tr>
<td>Profit</td>
<td>0.32</td>
<td>0.84</td>
<td>0.38</td>
<td>0.22</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>2800</td>
<td>1490</td>
<td>840</td>
<td>2350</td>
</tr>
</tbody>
</table>

Note: The cost of screening 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

<table>
<thead>
<tr>
<th>University</th>
<th>(p)</th>
<th>(c) (Screening cost)</th>
<th>% of Firms</th>
<th># Firms</th>
<th>Wage</th>
<th>H-type Applicants per Firm</th>
<th>Students’ Expected Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>University of New Hampshire</td>
<td>0.05</td>
<td>0.09</td>
<td>0.00%</td>
<td>0.00</td>
<td>0.00</td>
<td>N/A</td>
<td>0.00</td>
</tr>
<tr>
<td>Fordham University</td>
<td>0.14</td>
<td>0.09</td>
<td>0.22%</td>
<td>6.08</td>
<td>0.02</td>
<td>4.20</td>
<td>0.0007</td>
</tr>
<tr>
<td>MIT</td>
<td>0.86</td>
<td>0.09</td>
<td>2.58%</td>
<td>72.27</td>
<td>0.45</td>
<td>1.25</td>
<td>0.22</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Banking Firms</th>
<th>Consulting Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>4  JP Morgan Investment Bank</td>
<td>McKinsey</td>
</tr>
<tr>
<td>6  Credit Suisse</td>
<td>Boston Consulting Group</td>
</tr>
<tr>
<td>8  Barclays Investment Banking</td>
<td>Bain</td>
</tr>
<tr>
<td>11 Evercore</td>
<td>Booz and Company</td>
</tr>
<tr>
<td>13 Perella Weinberg</td>
<td>Mercer</td>
</tr>
<tr>
<td>14 Jefferies</td>
<td>Monitor</td>
</tr>
<tr>
<td>20 Deloitte Corporate Finance</td>
<td>Oliver Wyman</td>
</tr>
<tr>
<td>22 Royal Bank of Scotland</td>
<td>AT Kearney</td>
</tr>
<tr>
<td>31 Piper Jaffray</td>
<td>Parthenon</td>
</tr>
<tr>
<td>32 BNY Mellon</td>
<td>Towers Watson</td>
</tr>
<tr>
<td>41 Miller Buckfire</td>
<td>Navigant</td>
</tr>
<tr>
<td>46 Gleacher</td>
<td>ZS Associates</td>
</tr>
<tr>
<td>48 Susquehanna</td>
<td>NERA</td>
</tr>
<tr>
<td></td>
<td>Huron</td>
</tr>
</tbody>
</table>

**Investment Management Firms**

| 8  The D. E. Shaw Group              | Aon Hewitt                 |
| 9  Wellington Management             | Cornerstone                |
| 13 Fidelity                          | Cambridge Group            |
| 19 Vanguard                          | Charles River Associates   |
|                                      | Corporate Executive Board  |
|                                      | Advisory Board             |
|                                      | Analysis Group             |
|                                      | First Manhattan Group      |

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