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EXPLORATION FOR HUMAN CAPITAL:
EVIDENCE FROM THE MBA LABOR MARKET

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ABSTRACT

We empirically investigate the effect of uncertainty on corporate hiring. Using novel data from the labor market for MBA graduates, we show that uncertainty regarding how well job candidates fit with a firm's industry hinders hiring, and that firms value probationary work arrangements that provide the option to learn more about potential full-time employees. The detrimental effect of uncertainty on hiring is more pronounced when firms face greater firing and replacement costs, and when they face less direct competition from other similar firms. These results suggest that firms faced with uncertainty use similar considerations when making hiring decisions as when making decisions regarding investment in physical capital.

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1 Introduction

Human capital is a critical asset for firms, yet the process by which companies decide whom to hire is still not well understood. The decision to hire people is similar to the decision to invest in physical assets, as both types of investments are generally made under uncertainty regarding their future productivity. Here we combine insights from the investments literature in finance and from the labor and personnel economics literature to conduct an empirical analysis of the process by which firms select employees.[1]

Studying the MBA hiring market, we find that uncertainty regarding the productivity of potential employees, which we capture through a lack of prior experience in a hiring firm's industry, has a negative effect on firms' hiring. We document that corporations value temporary employment arrangements that provide the option to learn about the productivity of workers before making long-term hiring decisions. The hindering effect of uncertainty on corporate hiring is more pronounced when firing and replacement costs are lower (as they are in the case of summer interns), and when firms face less competition from other firms in their industry. The patterns in hiring that we document here are similar in many ways to those shown by the literature studying the effects of uncertainty on corporate investment in physical assets.[2]

Our empirical setting is the labor market for students at a large and prestigious MBA program. In our sample, a large fraction of job applicants have unknown industry fit, which creates uncertainty regarding their future productivity. We find that firms prefer to make offers to candidates characterized by low uncertainty – namely, those individuals who have worked in the firms' industry. These applicants' odds of success at getting a job offer are 1.71 times higher than those of applicants characterized by more uncertainty regarding their industry fit.

We document that employers value the option to learn about candidates lacking industry experience by making significant use of cheap probationary employment – namely, summer intern positions after the students' first year in the MBA program – which allow the termination of revealed poor matches at low cost. We document that separation rates at the

[1]See Oyer and Schaefer (2011) for a review of the successes and limitations of the economics literature on employer-employee matching. For empirical evidence on the selection of senior executives, see Bandiera, Guiso, Prat and Sadun (2010), Graham, Harvey and Puri (2010) and Kaplan, Klebanov and Sorensen (2012).

[2]See Grenadier (2002), Bloom, Bond and Van Reenen (2007) and references therein.

end of the summer are 19% higher for interns without industry expertise relative to their more experienced peers, indicating that probationary employment is used to learn about candidates' industry fit.

Consistent with the idea that exploration of riskier workers is costlier past the probationary employment stage, we show that the preference that firms have toward hiring less uncertain applicants is significantly stronger at the full-time recruiting stage, compared to the internship stage. At the full-time stage, a low uncertainty candidate has 2.38 times better odds of getting an offer relative to a higher uncertainty applicant. At the internship stage, the odds are only 1.66 times better for the low uncertainty applicants relative to the rest. We also document that the preference towards certainty when hiring is particularly high for firms that are less prestigious or smaller, and when firms face fewer competitors recruiting from the same pool of applicants.

Overall, these results suggest that uncertainty hinders hiring, and that this effect is magnified by the costs that firms face for firing poor matches or finding replacements, and diminished by the degree of competition for talent that they face.

Probationary or temporary employment arrangements similar to the summer internships we consider are widespread and continue to gain importance. This type of employment has been shown to be a stepping stone to permanent employment, accounting for a significant percentage of jobs across the world: for example, 10% in the U.K. (Booth, Francesconi and Frank (2002)) and 35% in Spain (Guell and Petrongolo (2007)). Using U.S. survey data, Houseman (2001) reports that temporary and part-time workers are employed by 46% and 72% of business establishments, respectively. While providing firms with flexibility to weather changes in the economic environment (Segal and Sullivan (1997), Levin (2002)), temporary and contract employment is also valued for offering firms the option to learn about the quality of workers. In the U.S. survey sample constructed by Houseman (2001), 21% of employers using temporary workers from agencies and 15% using part-time workers cite screening as an important reason for using these types of work arrangements.

In this paper we focus on a specific form of employee uncertainty – the unknown degree to which an individual will be a good fit for a firm's industry. There are other characteristics of workers that may be uncertain, including general ability traits that cannot be fully determined in the hiring process and the degree to which a potential hire fits the specific firm that considers hiring her. We focus on industry fit uncertainty because we can measure the degree to which a candidate's fit with a particular industry is known by firms, and because we observe significant variation in the data regarding industry fit uncertainty.

In human capital investments, concerns about the inherent heterogeneity of human capital add to those brought by uncertainty regarding product market demand. Our data allow us to focus on firms' option to learn as they determine the value of these assets (i.e., the employees) over time rather than on the option to wait for information revelation in the product market.[3]

As documented by Oyer and Schaefer (2011), few prior papers have studied firms' strategic choice about how much risk to take when hiring, and most of this work is theoretical. One paper in this area is Lazear (1998), which presents a model of the option to learn in a labor market context, and states conditions under which hiring risky workers can be a profit-maximizing strategy for firms. Given the institutional context we study empirically, our setting differs from that in Lazear (1998) in a few key ways. We focus on industry-specific productivity and study an environment where firms post and pay the same wage to all employees. While few empirical papers have studied how much and why firms choose to hire workers with uncertain productivity (see Bollinger and Hotchkiss (2003) and Hendricks, DeBrock and Koenker (2003) for examples from sports markets), much of the extant labor literature takes it as a given that firms take substantial risks when hiring workers. For example, our work builds on the large literatures regarding matching and employer learning. However, while most prior work focuses on firms learning about an employee's ability or the quality of the match to the firm, we focus on workers' match to an industry. Our work is inspired by the classic Jovanovic (1979) matching model, the learning models in Waldman (1984), Greenwald (1986), and Farber and Gibbons (1996), and the idea in Prescott and Visscher (1980) that organization capital is enhanced by the ability to learn more about workers' characteristics, before assigning them to specific production tasks, by observing their performance in an apprenticeship-like endeavor.

[3]Stein and Stone (2013) show empirically that product demand-side uncertainty depresses aggregate hiring. Also, Kahn and Lange (2014, forthcoming) point out a type of employee heterogeneity that is more analogous to the option to wait in real option models of physical capital by considering the fact that workers' productivity is constantly changing and that these changes differ across people. This suggests that firms might value both the option to learn and the option to wait on employees as they do with other assets (see Grenadier and Malenko (2010)), so that they can see how a given worker's productivity develops. However, because our empirical analysis focuses (due to data availability) on the initial firm/worker match, we cannot analyze this form of option value.

Getting a better understanding of the matching process in high-skill environments such as the one studied here is important, given the increasing prevalence of graduate degrees and the significant role of high-skill and professional labor markets in the economy. The process of matching firms and employees early in their career is also particularly interesting to study, in light of the strong impact of these initial matches on long-term employment and compensation (Oyer (2008)). Our empirical results provide some guidance on what employers are searching for in at least one high-talent market.[4]

Our paper complements the emerging finance literature regarding the role of workers on corporate decisions and outcomes. For example, the firms' workforce characteristics have been shown to influence capital structure choices, theoretically and empirically (e.g., Berk, Stanton and Zechner (2010), Agrawal and Matsa (2011), Schmalz (2013)), as well as the cost of capital (Eisfeldt and Papanikolaou (2013)). The acquisition of productive labor, not just physical assets, is an important driver of M&A decisions (Ouimet and Zarutskie (2011)).

We discuss the underlying conceptual framework that motivates our empirical analysis in Section 2 of the paper. We describe the data set and the key features of our empirical setting in Sections 3 and 4. Section 5 contains the empirical results, and Section 6 concludes.

2 Conceptual framework

We now motivate the empirical work to follow by laying out an intuitive conceptual framework to match the setting we analyze. Our data come from a two-year full-time MBA program. The vast majority of students have a work history from before their time in the MBA program, do an internship in the summer between the two years of the program, and take a full-time job upon graduation. Internships give summer employers an opportunity to learn about the students before making a commitment for full-time employment.

Following Lazear (1998), we consider a market where potential hires vary in both predictable and unpredictable ways. Specifically, a potential hire's productivity at a firm is

[4]Data on MBA graduates has recently been used in other economics and finance research. For example, Shue (2011) finds that networking through MBA education leads executives to exhibit commonalities in firm policies. Bertrand, Goldin and Katz (2010) document a rising gap in earnings between men and women after graduation from business school. Kaniel, Massey and Robinson (2010) find that optimistic MBA students receive job offers faster than their peers. Ahern, Duchin and Shumway (2013) find positive peer effects in risk aversion among MBA students, while Malmendier and Lerner (forthcoming) document MBA peer effects in entrepreneurial pursuits.

increasing in each of three attributes. First, the person will be more productive if his general ability, which we will measure through grades, is higher. Second, the person will be more productive if his skills and interests are a good match for the industry in which the firm operates. Finally, there is an idiosyncratic firm-worker match component driven, for example, by how well the person fits with the other workers of the firm or with the firm's strategies. Employers can learn important things along all these dimensions during an internship. However, given that firms already have a significant amount of information about the person's academic success, which is our proxy for general ability, internships are especially likely to be informative about industry and idiosyncratic match quality. Learning along both these dimensions during the summer internship is certainly valuable to firms. However, we only have the ability to empirically study learning about industry fit, and hence we focus our analysis on this dimension.[5] Specifically, our data allow us to quantify the uncertainty regarding the fit between a potential employee and a firm's industry. We observe the pre-MBA jobs of the students in our sample, and hence we can measure the degree of experience that a job candidate has with the industry of the firm to which he is applying.

A simple way to capture this setting is to have the productivity of candidate i working for firm j in industry k be: $Productivity_{ijk} = General\ Ability_i + Firm\text{-}Specific\ Fit_{ij} + Industry\ Fit_{ik}$, where $Industry\ Fit_{ik} = 1$ with probability p or 0 with probability $(1-p)$. In other words, the industry fit of a candidate could be high or low. Upon receiving a job application from a candidate, the firm knows the probability p that the industry fit will be high, but not the actual value of $Industry\ Fit_{ik}$. It is easy to show that the expected value, as well as the variance of $Industry\ Fit_{ik}$ depend on the probability p. Specifically, $E[Industry\ Fit_{ik}] = p$ and $\sigma^2_{IndustryFit_{ik}} = p - p^2$.

The Expected value of industry fit will be increasing in p and, as long as p is at least 0.5, the variance of industry fit will be decreasing in p. In the setting we study, we believe a lower bound of 0.5 is reasonable for p. Conditional on the applicant wanting a job and

[5]There is no variation in our sample in terms of the uncertainty in the firm-specific fit of each applicant-firm pair, since for each such pair there is no prior employment relationship (i.e., there is a high level of uncertainty about the firm-specific fit for each of these pairs). The variation that we can observe, and relate to hiring outcomes, comes from uncertainty in the industry fit of these candidates, as given by their industry experience. Hence, the paper focuses on the importance of learning about industry fit, and documents that this aspect of the candidates productivity is important for firms hiring decisions. However, firm-specific fit could also be very important, and we leave it to future work, based on data where there is measurable variation in firm-specific fit, to cleanly identify this effect.

surviving several rounds of interviews, firms will have a pretty good (but far from perfect) sense for industry fit. As we show below, just over forty percent of those with no relevant industry experience at the start of a Summer Internship receive an offer to return to a full-time position. Given that many firms cannot make an offer for budgetary reasons or because a better candidate comes along, we believe that 0.5 is a reasonable lower bound for p.[6]

Now compare two job candidates: for one of them, it is equally likely that the industry fit will be high or low. In other words, the firm has the least amount of information about this person's fit. This corresponds to p near $\frac{1}{2}$. A natural case in which this may happen is when the job candidate is somebody who never worked in the industry of the firm before. For this person, the expected value of the industry fit is low and the variance of industry fit is relatively high: $E[Industry\ Fit_{ik}]\ \frac{1}{2}$ and $\sigma^2_{IndustryFit_{ik}}\ \frac{1}{4}$. For the other candidate, the firm assigns a very high probability that the industry fit will be high, $p\ 1$. A natural case in which this may happen is when the job candidate is somebody who worked in the exact, narrow industry of the firm before. This candidate therefore has high industry fit, as well as low variance of his industry fit: $E[Industry\ Fit_{ik}]\ 1$ and $\sigma^2_{IndustryFit_{ik}}\ 0$.

Empirically, the industry experience of a candidate will be our proxy for the probability p that the person has a high value for $Industry\ Fit_{ik}$. The lowest degree of industry experience corresponds to a value of p close to $\frac{1}{2}$. The highest degree of industry experience corresponds to a value of p close to 1. Therefore, as the industry experience of the candidate increases, p will increase, which means that the expected value of $Industry\ Fit_{ik}$ increases and the variance, or uncertainty, of $Industry\ Fit_{ik}$ decreases. This implies that learning more about the candidate is particularly useful to firms when they consider the high uncertainty applicants, which are those people with the least amount of industry experience.

In the analysis, we label the uncertainty about the candidates' industry fit as either low, medium or high. Uncertainty is low in the case of people who have worked in the specific, narrowly-defined industry of the firm. For these people, the probability p that $Industry\ Fit_{ik}$ is high is close to 1. For example, this would be the case of a student previously employed by an investment bank who applies for a job with another investment bank recruiting on campus. Uncertainty is high in the case of candidates who have not worked in organizations

[6] An alternative framework, which would be somewhat more complicated, but would lead to similar predictions, is to let $Industry\ Fit_{ik}$ follow a distribution where its mean is increasing, and its variance is decreasing, in relevant pre-MBA experience.

that, broadly speaking, belong to the same industry as that of the firm they are applying to. For these applicants, p is relatively low (and possibly close to $\frac{1}{2}$). This would be the case of somebody whose entire work experience is in consulting, but is now applying to a job in investment banking. Finally, uncertainty is medium when the candidate has previously worked in the same broadly-defined industry. In these cases, p is between $\frac{1}{2}$ and 1. For example, this would happen when a candidate previously employed by a commercial bank now applies to an investment banking position. In other words, we can classify each applicant to a particular job as being characterized by either low, medium or high uncertainty regarding their fit with the industry of the firm posting that job. The main empirical prediction we test is whether the odds that an application results in a job offer are higher for candidates characterized by low uncertainty about industry fit, relative to candidates characterized by either medium or high uncertainty about industry fit.

Our predictions regarding the effect of general ability on a student's job market prospects are straight-forward: we expect students with better grades to be more attractive in the job market. This should be true at both the summer internship and permanent hiring stages. Hence we expect better academic performance to have a positive effect on the probability of an interested student getting a job offer from a given firm.

As we proceed empirically, we assume that it is detrimental for a firm to hire a person who is a poor industry fit because the employee will be unproductive and firing and replacing the person will be costly. Moreover, the cost of hiring a bad fit is likely lower for summer interns than for permanent hires because the firm can simply choose not to continue the employment relationship at the end of the summer. Perhaps most controversially, we assume that firms offer the same wage to all people to whom they offer jobs. This is a strong assumption in that it precludes the labor market clearing through wage competition. As we show below, we can justify this in our context, as employers generally offer the same wage to all new MBA hires, and post these wages prior to observing the candidate pool.

Under these assumptions, consider a firm deciding to whom it should make offers. At either the summer internship or full-time hiring stage, the firm will always prefer higher general ability candidates and will prefer industry stayers (i.e., low uncertainty applicants) to industry switchers (i.e., higher uncertainty ones). We expect firms to be less concerned about the uncertainty in the candidate's industry fit in situations when firing or replacing a revealed poor match is easier, and when firms face the risk that waiting before making offers may lead them to face a worse pool of available candidates. Hence, we expect to find that firms will take more risks in summer hiring. That is, the lack of industry experience will be less of a factor for summer hiring than for full-time hiring. Moreover, like Lazear (1998), we expect to find firms to be less risk-tolerant when they face higher firing or replacement costs. In our setting, higher costs of this type will induce firms to value industry experience relatively highly. Since firms do not own employees' human capital, we expect that the negative effect of uncertainty on hiring is not reduced for candidates with high levels of general ability, or redeployability. Finally, we expect that when firms face many competitors, they should be more inclined to hire riskier workers, rather than wait for the resolution of uncertainty but likely face a pool of candidates of lower quality during later stages of recruiting.

Our empirical analysis tests these predictions about the role of uncertainty regarding job applicants' industry fit on the decisions of firms to hire.

3 Data

We use a novel dataset describing detailed aspects of the recruiting process conducted by a large number of globally-known firms at a top business school in the United States. The data span three MBA cohorts during 2007-2009, encompassing 1,482 job applicants and 383 firms, covering both internship and full-time recruiting. The data include details regarding the firms' identity and industry, job openings posted, as well as the candidates' personal and work background, MBA coursework completed, applications sent during both recruiting stages, and offers received. Importantly, we also know the grade point average (GPA) of these individuals while in business school, which provide us with a proxy for their general ability.[7] Table 1 provides basic summary statistics for these job candidates and firms.

We describe firms using various measures of industry, size, and prestige. We use a broad breakdown of industry, putting firms into one of six categories – consulting, finance, general corporations, technology, government/non-profit and other services (mainly law firms), as well as a narrow classification scheme, based on the 60-industry breakdown used by the business school providing the data. We measure firm size based on annual revenues or the number of employees. These figures are collected from Compustat in the case of publicly-traded firms, and from databases compiled by Hoovers, Manta.com, and Vault.com in the

[7]See Kuhnen (2011) for more details regarding the dataset.

case of private firms. We classify a firm as prestigious if it is listed in the *Fortune MBA 100* annual rankings during 2007-2009.[8] Fortune constructs this list by asking MBA students at various business schools where they would most like to work. Companies that are included on this list are labeled as "Top 100 MBA Employers".

The recruiting process at the business school providing the data for this study is well structured. It unfolds in a series of steps. 1) The recruiting process begins during the first-year of the two-year MBA program when students submit resumes (at no cost) to companies that will offer on-campus recruiting for summer internships, indicating they would like the company to interview them. 2) Employers select some of these students, known as the "closed" interviewing list. 3) Then an "open" or "bidding" phase takes place. Students bid points from their annual endowment of 800 to obtain an interview slot. Given the scarcity of bid points, getting an open interview is costly. 4) The firm interviews those chosen on the closed list and those who bid enough points to get on the open list, and after these interviews, the firm makes offers to some students. 5) Each student then accepts or rejects the offer. 6) At some point after the summer internship, the firm may make the student an offer to return to a full-time position upon graduation.

Steps 1-5 repeat for the second-year students applying for full-time post-MBA positions. Those who participate in the full-time recruiting stage include most students who did not get an offer to return to their summer employer (at least not as of the start of the on-campus recruiting season) and those who got an offer but want to continue to explore alternatives.

The data we have on this process include which students applied to which openings through both the open and closed systems, how many points each student bid when applying for an open interview, whether or not the person got an offer from each job to which they applied, which offer the student accepted, and whether each summer internship led to a full-time offer. Unfortunately, we do not see data on intermediate steps such as whether a student was selected for a closed interview or how many rounds of interviews a student completed.

On-campus recruiting for summer internships occurs from January to March of the first year in the program. On-campus recruiting for full-time positions begins near the start of the second year of the MBA program, in October. For the students in the cohorts studied here we observe 2286 internship offers, 68% of which are obtained through the on-campus internship

[8] The rankings for 2007-2009 are available at: http://money.cnn.com/magazines/fortune/mba100/2007.

recruiting system during the students' first year in the MBA program, 1% are summer positions with their pre-MBA employer, and 31% are obtained through other, off-campus channels. Also, we observe 1676 full-time job offers. Among these, 34% are the result of a successful summer internship, 35% are obtained through the on-campus full-time recruiting stage in the students' second year of the MBA program, 9% are offers from their pre-MBA employer, and 22% come through other, off-campus channels. Our analysis is focused on the on-campus hiring activity, because for firms that post either internship or full-time positions using the on-campus recruiting system, we know the complete set of applications received for each position, as well as which applications resulted in offers. The resulting sample consists of 30783 applications, of which 21683 are for internships and come from 1249 unique students and 9100 are for full-time positions and come from 968 unique students. 100% of the students in the three cohorts studied here used the on-campus recruiting process, either for internships or full-time jobs.

4 Key features of the empirical setting

4.1 Wages are set prior to hiring

The first key feature in the data is that firms offer a single wage for any given position. This implies that wages offered to candidates do not depend on individual characteristics such as general ability or industry experience. An institutional detail driving this feature is that employers that recruit on campus are required to post details such as the job title, location, and salary at the very beginning of the recruiting season, before seeing any candidates. As shown in the regression model in Table 2, the data confirms that starting salaries for full-time positions, which characterize the first year of employment after graduate school, are specific to the position available and do not depend on characteristics of the person who receives the employment offer.[9] Specifically, controlling for class, industry, job location and

[9]We only have data concerning starting salaries. It is likely that after working for a company for a while, an employee will be compensated based on proven performance. The flexibility to give lower raises and bonuses to poor performers lowers adjustment costs for firms and therefore may ease the hiring of risky workers. Signing bonuses are also not included in our dataset. It is possible that firms offer a signing bonus commensurate with the industry experience of the candidate receiving the offer. If firms make significant changes in compensation on this margin, this would make it less likely for us to observe that industry experience is positively related to the likelihood of application success. This is because people with more industry experience, who might be offered high signing bonuses, become relatively more expensive relative

company-job title fixed effects, we find no evidence that the GPA, quality of undergraduate institution attended, industry experience, age, gender, or international student status of the person receiving the full-time offer are related to the offered wage (either in logs or levels). Furthermore, in the data only 10.8% of starting full-time wages are renegotiated, and the corresponding figure for internships is 1.72%. As a result, it is unlikely that wages are used in this setting as a means for selecting, screening, or bargaining with candidates with specific characteristics (e.g., a high or a low level of uncertainty regarding their productivity). This feature of the setting eases the interpretation of our empirical results concerning firms' hiring decisions and their dependence on the uncertainty regarding candidates' industry fit.

4.2 Hiring firms face uncertainty

The second key data feature for our analysis is that many applicants have unknown industry fit, because they have not worked in the exact industry of the hiring firm, creating uncertainty regarding their future productivity. We observe that among all applications sent for jobs, the fraction coming from individuals who have not worked in the broadly defined industry of the hiring firm is 68% at the internship stage and 65% at the full-time stage. The fraction of applications that come from individuals who have not worked in the narrowly defined (i.e., using the 60-category classification scheme created by the school) industry of the hiring firm is 89%. For full-time jobs, the corresponding fraction is 86%.

Hence, when considering the majority of potential candidates, firms face medium or high levels of uncertainty regarding these individuals' industry-specific fit. Importantly, while candidates lacking either narrowly or broadly defined industry experience are not as successful in securing offers, as the rest of the analysis will show, they are represented in the pool of people that firms end up making offers to. Specifically, across internships and full-time jobs, high uncertainty (i.e., lacking even broadly defined industry experience) candidates represent 67% of the applications pool and 58% of the offer pool. Medium uncertainty (i.e., lacking narrowly defined, but not broadly defined industry experience) candidates represent 21% of the applicant pool and 24% of the offer pool. Finally, low uncertainty (i.e., possessing

to those with less industry experience and hence more uncertainty about industry fit, which would make the latter category of applicants more attractive. The fact that we still see in the data a very strong connection between industry experience and odds of application success indicates that signing bonuses likely do not vary much with industry experience.

narrowly-defined industry experience) candidates represent 12% of the applicant pool and 18% of the offer pool.

4.3 Uncertainty is reduced by learning during internships

In our setting, we interpret a lack of industry experience as an indication that firms are uncertain about a candidate's fit in their industry. However, an alternative interpretation is that lack of industry experience is simply a lack of useful, industry-specific human capital. Thus, observing that firms are reluctant to hire industry switcher may not indicate that firms dislike uncertainty, but that they dislike candidates with lower skill levels. According to this alternate account, there is no learning involved, since the level of industry-specific fit or skill is known by the firm when it considers a candidate's application. While this could certainly be happening (i.e., candidates with lots of experience in a particular industry already possess certain skills that firms in that industry find valuable), in the data we observe patterns that strongly indicate that firms do learn about the candidates industry fit – in particular, during the summer internship period.

Assume that learning is not important to firms – perhaps because the level of industry-specific fit is known by firms with certainty when the candidate applies for the job. Consider two people who both received internship offers at a firm and both accepted and completed these internships. One of these people had no industry experience when he was offered the internship and the other had significant industry experience. If industry experience is a perfect indicator of industry fit, then the hiring firm would know that the first person has low industry fit and the second person has high industry fit, at the moment when the internship offers are made. In other words, the summer internships of these two people will not provide the firm with any new information about the industry fit of these two interns.

Therefore, when the firm has to decide whether these summer interns get full-time job offers at the end of the internship, the probability that each intern gets the full-time offer should not depend on the industry experience of that person. In particular, the person with no industry experience should have an equal chance to convert the internship into a full-time offer as the person with a high level of industry experience. This is because the firm had known from the beginning the degree of industry fit of each of these people and did not learn anything more about this aspect of the candidate during the summer.

However, as shown by the statistics in Table 3, the data do not support this scenario where firms do not learn about industry fit during the internship. For all categories of firms in our sample, large, small, prestigious or non-prestigious, we observe a very large difference in the probability that a summer internship results in a full-time offer, depending on whether the intern is somebody with low or high levels of industry experience. Specifically, summer interns who had worked in the narrow industry of the firm before business school (these are people we referred to as low uncertainty candidates) have between 14%-27% higher probabilities of converting the internship into a full-time job, relative to interns with lower levels of industry experience (these are the people with medium or high uncertainty about industry fit). These differences – driven by industry experience – in the likelihood of having an internship resulting in an offer for long-term employment are economically large and statistically significant ($p < 0.01$). In a world where firms would not use the summer internship to learn about industry fit, these differences would not exist. That is, in that world with no learning occurring over the summer, industry switchers should not be disadvantaged relative to industry stayers, in terms of their success at obtaining full-time offers at the end of internships.

Therefore, by observing these patterns in the conversion of internships into full-time jobs, we can infer that learning about industry fit – that is, reducing uncertainty about this aspect of an employees productivity – is important to firms.

5 Results

5.1 Uncertainty hinders hiring

We find that uncertainty hinders hiring. Figure 1 shows that the success rate of job applications decreases monotonically with the level of uncertainty regarding the industry fit of the candidates. The fraction of applications for internships and full-time jobs that result in offers is 7.77% among low uncertainty candidates, 5.65% among medium uncertainty candidates, and 4.39% among high uncertainty candidates. These sample frequencies are different from each other at $p < 0.001$, indicating that firms' hiring decisions may differ across applicant types in a systematic way. Specifically, Figure 1 suggests that employers prefer to make offer to applicants characterized by less uncertainty regarding their productivity, namely, those individuals with more experience in the particular industry of the hiring firm.

A natural measure of the firms' preference towards certainty can be obtained by comparing the odds that applications result in offers across various types of candidates, where odds are defined in the usual way as the probability of success (i.e., offer) divided by the probability of failure (i.e., no offer). In our sample the odds of application success are 8.42%, 5.99%, and 4.59% for applications coming from low, medium and high uncertainty candidates, respectively. Comparing these odds of success across candidate subsamples, we observe that firms' interest in making offers is 1.83 times stronger among low uncertainty candidates relative to high uncertainty ones, and 1.30 times stronger among medium uncertainty candidates versus high uncertainty ones. The preference for low uncertainty applicants is 1.71 times stronger than for the other two categories (i.e., medium and high uncertainty) combined. These ratios of odds of success in getting offers are summarized in Figure 2. An odds ratio equal to 1 would indicate that firms' hiring decisions do not differ across different types of job candidates. However, Wald chi-square tests show that all these odds ratios are significantly different from 1 at $p < 0.001$, implying that firms prefer less uncertainty to more when they decide to whom jobs should be offered.

While these univariate results suggest that uncertainty hinders hiring decisions, other interpretations are possible and must be investigated. For example, people with less experience in the industry of the firm to which they apply, whom we have so far referred to as higher uncertainty candidates, may have lower general ability or other characteristics that make them less desirable to employers. It is also possible that there are more industry switching (i.e., higher uncertainty) candidates in particular cohorts graduating at times when firms do not hire as much, for example during recession years. Moreover, industry switching candidates may tend to apply to industries with fewer jobs available, or, within an industry, to firms with a lower capacity to hire, or to those faced with a higher number of applicants.

We account for these potential confounds in the econometric models in Table 4. There, we estimate three models predicting the likelihood that a job application results in an offer: a linear probability model, a logistic regression showing odds ratios effects, and a GLM model indicating risk ratios effects, with the goal of identifying the effect of the candidates' uncertainty about industry fit on their likelihood of success. As control variables, we include the candidates' GPA, which is our proxy for their general ability, as well as indicator variables for gender and international student status (the latter may influence hiring decisions due to work-visa concerns). We also include cohort fixed effects, as well industry fixed effects.

Moreover, we control for the number of interview slots available to applicants for each specific job opening, as a way to account for the firms' capacity to hire. Finally, to account for the possibility that different organizations may face different numbers of applicants, we control for firm size (as measured by sales) and prestige, as well as for the number of competing companies in the same industry that are recruiting concurrently.

As shown by the results in Table 4, even after accounting for these confounding factors in hiring decisions, we continue to observe a very strong negative effect of industry fit uncertainty on the likelihood that an application will result in the firm making an offer. Using the logistic regression specification, which is the easiest to interpret, we find that low uncertainty and medium uncertainty candidates have odds of receiving an offer that are 1.90 times and 1.24 times higher, respectively, as those candidates characterized by high uncertainty about industry fit. These estimates are very close to the univariate results shown in Figure 2, and illustrate yet again that firms prefer certainty when they make hiring decisions. These effects are significant at $p < 0.01$ and are common across all three empirical specifications in the table.

The control variables included in the model in Table 4 have the expected effects. Specifically, the odds of application success are higher for candidates with higher GPA during business school, those who are not international students, women, those applying to larger or to less prestigious firms, as well as to job openings with more interview slots. Applications are also significantly more likely to result in offers at the internship stage compared to the full-time recruiting stage. Specifically, the odds of an application resulting in an offer are 1.38 times higher for internships than for full-time jobs ($p < 0.01$).

The results in Table 4 indicate that, controlling for other firm and applicant characteristics that may be important for hiring decisions, higher uncertainty regarding the applicants' industry fit lessens the chance that firms will hire them. In other words, uncertainty about productivity hinders corporate investment in people, similar to the effect previously documented in the case of investment in physical assets. We now turn to analyzing whether differences in the adjustment costs or competition faced by firms impact the effect of uncertainty on hiring in ways that also parallel the effects documented in the context of physical investments.

5.2 Adjustment costs magnify the effect of uncertainty on hiring

5.2.1 Firing costs

To understand whether uncertainty is more detrimental to hiring when firms face higher firing costs we analyze whether the lack of information about a candidate's industry fit reduces the odds of success of their application more at the full-time recruiting stage, when the costs of dissolving a poor match are high, than at the internship recruiting stage, when these costs are relatively small.

The logistic regression in Table 5 presents evidence consistent with this hypothesis. The goal of the econometric model is to identify the differences in the odds that an application results in a job offer across different levels of uncertainty about industry fit, and across the two recruiting stages.

The analysis includes the same set of firm and job applicant controls as used in Table 4. The reference category refers to applications coming from individuals characterized by medium or high uncertainty about industry fit. Our prior results suggest that this category of applications should have lower odds of success compared to low uncertainty candidates, and the results in the table confirm that is indeed the case. At the internship stage, the odds of success of a low uncertainty applicant are 1.66 times as high as those of other candidates ($p < 0.01$), while at the full-time recruiting stage, the odds of success of a low uncertainty applicant are 2.38 times as high as those of the other, more uncertain, candidates ($p < 0.01$). These two effects are significantly different from each other, as well as significantly different from 1 (i.e., the indifference threshold), at $p < 0.05$. Therefore, the preference of firms to hire people characterized by low uncertainty about industry fit is particularly pronounced at the full-time recruiting stage, when the costs of firing and replacing a poor match are much higher than at the internship stage.

Note that the estimation method in Table 5 allows us to avert two potential confounding effects. First, perhaps there are more industry switchers (i.e., less experienced and thus higher uncertainty candidates) in the applicant pool at the internship stage relative to the full-time stage, so even if firms have equally strong reservations about hiring more uncertain candidates at the two stages, they would mechanically end up making more offers to such applicants at the internship stage. To account for this, the logistic models in Table 5 compare at each recruiting stage the odds of application success for the subset of low uncertainty candidates to the odds of success in the subset of more uncertain candidates, and this comparison does not depend on the difference in the prevalence of low uncertainty applicants between the two recruiting stages. Second, perhaps the pool of industry switchers (i.e., higher uncertainty candidates) at the internship stage is better somehow – for example, they may have higher general ability – than the pool of switchers still looking for a job at the full-time stage. This should lead to firms being more likely to make offers to higher uncertainty people at the internship stage compared to the full-time stage. However, this cannot drive the wedge in the firms' preference for low uncertainty people between these two recruiting stages that we document in Table 5, since there we control for candidate characteristics, including their general ability as measured by their GPA.

Another potential confound in the interpretation of the difference in the effect of the low uncertainty indicator on the odds of application success at the internship and the full-time stage (1.66 vs. 2.38) is that perhaps people whom we label as low uncertainty candidates at the full-time recruiting stage may in fact be characterized by lower uncertainty about their industry fit, relative to people whom we label as low uncertainty candidates at the internship recruiting stage. This can happen if people who apply to jobs in a particular industry at the full-time stage tend to have already done internships in that same industry. In such a scenario, firms recruiting for full-time positions would assess that the probability of these industry-experienced candidates of having high industry fit is greater than the probability they would assign for a similar applicant at the internship stage.

To check whether or not this alternative mechanism explains our finding that the odds of success for low uncertainty people vs. the others are significantly better at the full-time stage relative to the internship stage (i.e., 2.38 vs. 1.66), in unreported analyses we estimated the same logistic model for the probability that an application results in an offer at the full-time stage, as in the last column of Table 5. We did this, however, only for full-time job applications coming from individuals who at the internship stage took a summer job in a broad industry different from that they were in before coming to business school. If the alternative account is correct, then the coefficient on the low uncertainty variable in this logistic regression should be equal to that obtained in the logistic regression estimated at the internship stage, which is in column 1 of Table 5 (i.e., 1.66). This is because the degree of uncertainty is the same for the people in these two analyses, since for both samples of applicants the only information about their industry fit is conferred by the identity of their pre-MBA industry. However, what we find is that the coefficient in this logistic regression is 2.45, which is close to, and statistically not distinguishable from, the 2.38 coefficient in the logistic model estimated for the full-time stage, for all those applying for jobs at that stage, irrespective of their internship industry. This implies that the difference in the impact of the low uncertainty variable on the odds of application success that we see between the internship and the full-time stage is not related to a change in the degree of uncertainty of what we label as low uncertainty candidates.

Overall, these results suggest that there exists a strengthening in firms' preference to hire workers with less uncertain industry fit from the probationary to the full-time recruiting stage, consistent with the idea that at the full-time stage it is more costly to fire an employee who has been revealed to be a poor match.

5.2.2 Replacement costs

We now turn to examining whether firms that face lower costs of hiring a replacement for a revealed poor match will be less concerned about candidates' uncertainty regarding industry fit, and hence, more likely to hire riskier workers. Two categories of firms are likely to face relatively low replacement costs for poor matches: prestigious and large organizations. First, firms that are widely regarded as prestigious places to work are likely to receive numerous applications through many recruiting channels, and hence can find suitable candidates with ease. Second, large firms have dedicated human resources departments and can tap into numerous recruiting venues (including internal staff, see Tate and Yang (2011)) to find new candidates for a particular position. Hence we expect that the firms that will be the least concerned about candidate uncertainty will be the prestigious and large ones.

In the logistic regressions in Table 6, we estimate the effect of uncertainty on hiring decisions as a function of firm prestige. A firm is labeled as prestigious if it was included in the *Fortune MBA 100* annual rankings during 2007-2009. The analysis includes the same set of firm and job applicant controls as used in Table 4. We find that the preference of firms for low uncertainty candidates is stronger for non-prestigious firms compared to prestigious ones, as predicted. Specifically, low uncertainty candidates have odds of getting an offer that are 2.58 times higher than those of riskier candidates when applying for positions at non-prestigious firms, but only 1.57 times higher when applying for positions at prestigious firms. These odds ratio estimates are significantly different at $p < 0.01$.

A natural concern is that these differences in the odds ratios across the two different types of firms do not indicate differences across firms in their dislike for uncertainty, but rather, differences in the composition of the pool of applicants faced by prestigious and non-prestigious firms. Our choice to use odds ratios to measure firms' hiring propensities allows to us alleviate this concern. Note that in a world where the uncertainty in the candidates' fit did not matter for firms' hiring decisions, the ratio of odds of success (where odds are defined, as usual, as the probability of success, i.e., that the an application will result in an offer, divided by the probability of failure, i.e., that the application will not result in an offer) of the low uncertainty candidates vs. the rest would be equal to 1. This is not what the data show. We consistently find this odds ratio to be significantly higher than 1, meaning that the odds of success in getting job offers are better for low uncertainty applicants. Since the odds ratios we estimate in Table 6 are 1.57 for prestigious firms and 2.58 for non-prestigious ones, the difference between these numbers indicates that, for reasons independent of the composition of the applicant pools faced by these two types of firms, low uncertainty candidates are particularly successful in getting offers at non-prestigious firms. Or equivalently, prestigious firms are those where higher uncertainty applicants have better odds of success.[10]

The discrepancy in the preference for certainty between these two types of firms is particularly large at the full-time recruiting stage. At that stage, low uncertainty candidates have 3.57 times higher odds of getting offers, relative to the other candidates, when applying to non-prestigious firms, whereas for prestigious ones, the corresponding increase in odds is only 1.74 times. These effects are significantly different at $p < 0.01$. This suggests that when firms face both high firing costs, as well as high replacement costs, they are particularly reluctant to make offers to candidates characterized by higher uncertainty about industry fit.

Turning to our other source of variation in replacement costs, in the logistic regression in Table 7 we estimate the effect of uncertainty on hiring decisions as a function of firm size, measured by sales. Conducting the same analysis using the number of employees as our

[10]It is also possible that the most prestigious firms attract the best overall candidates, for whom prior knowledge about the firms industry may be less important. That is, industry switchers hired by prestigious firms may have better ability. In our analysis we try our best to control for general ability – we use the students' GPA while in business school as our proxy for general ability, as well as the students' GMAT scores, in alternate specifications unreported here for brevity. That being said, there may be complementarities between industry expertise and general ability, or non-linear effects, that differ between prestigious and non-prestigious firms, which our empirical specification may not capture.

measure of firm size yields very similar results in terms of both magnitude and significance levels, so we omit them here for brevity. The analysis includes the same set of firm and job applicant controls as used in Table 4. The results support the idea that small firms (i.e., with below-median sales) are more inclined to hire low uncertainty applicants than large firms (i.e., with above-median sales), in general as well as at each of the two recruiting stages.[11] For example, across both internship and full-time recruiting, the odds of success of low uncertainty candidates are 2.19 times higher than those of riskier candidates in the case of small firms, but only 1.69 times higher in the case of large firms. This difference, however, is not statistically significant at conventional levels.

The estimates in Table 7 show an interesting interaction of the effects of replacement costs as indicated by firm size with those of firing costs as indicated by the recruiting stage. The biggest difference in firms' preference for certainty can be seen when comparing the relative odds of success of low uncertainty candidates across two scenarios: when applying for full-time jobs at small firms, and when applying for internships at large firms (odds ratio estimates of 2.71 vs. 1.55, significantly different at $p < 0.05$). In the first scenario, the recruiting firms face a high firing cost, as well as a high replacement cost. In the second scenario, recruiting firms can easily fire a revealed bad match and also face lower costs of finding a suitable replacement for a revealed poor match. Hence, high firing and high replacement costs appear to induce firms to prefer certainty more in the first scenario relative to the second.

5.2.3 General ability

As a final dimension of adjustment costs, we now examine the general ability of a candidate. Thinking in terms of option value, we would expect people who are of higher ability to be easier to redeploy if their initial employment arrangement does not work out for some reason. Also, it is possible that high ability candidates can compensate through on-the-job learning for lack of industry fit. This is potentially analogous to the option value of physical assets that can be more easily redeployed. Firms are not reluctant to invest in physical capital with uncertain productivity if those assets can be easily sold or put to another use. This would

[11] While we argue that large firms likely face lower costs of finding a replacement for a revealed bad match, they may also face lower costs of dissolving that bad match by reassigning the person to a different division. Both these channels are very much in line with our thinking, that is, with the idea that firing and replacement costs modulate the effects of uncertainty regarding industry fit on firms hiring decisions.

suggest that in the case of candidates with high general ability, the relationship between their industry expertise and their odds of receiving job offers may be weak or non-existent.

Note, however, that there is an important difference from a companys perspective between human capital and physical assets. Firms capture the rents of valuable physical assets whether those rents occur with the intended use of those assets or, if the firm finds the assets not valuable, through resale or redeployment. But, while the rents from human capital are shared between the firm and the worker if the match lasts, the worker captures all the rents if he leaves the firm. This suggest that, while firms are not as concerned about uncertainty regarding physical assets' future productivity if they are characterized by higher redeployability (Bloom et al. (2007)), higher general ability will not influence the negative effect of uncertainty about industry fit on the firms' willingness to make job offers. In other words, the negative effect of industry-fit uncertainty on the odds of application success will be equally strong for either low general ability, or high general ability job applicants.

The data, as shown in Table 8, suggest that this second mechanism may be more important than the first, as we find that the strength of the preference that firms have towards low uncertainty workers is similar across candidates with high or low general ability. We measure general ability using the person's grades while in the MBA program. We characterize each student as having either a high or a low GPA, depending on whether their GPA is above or below the median. The results in Table 8 show that the odds of an application resulting in an offer for low uncertainty candidates are 1.81 times as high as for the other applicants in the subset of low GPA students, and 1.83 times as high in the subset of high GPA students. Hence, as predicted, in general the strength of the preference that firms have towards low uncertainty workers is similar across candidates with high or low general ability. The estimates in Table 8 do suggest that at the full-time recruiting stage firms' preference for low uncertainty may be stronger among the low GPA candidates relative to the high GPA ones, but the two odds ratios estimates (3.27 vs. 1.96) for these subsamples are only weakly statistically different ($p < 0.09$).

Overall, these results suggest that adjustment costs – in particular, firing and replacement costs, and to a much lesser extent, the value of the person in alternative jobs – strengthen the preference of hiring firms towards less risky candidates. These effects parallel those concerning the interaction between uncertainty and adjustment costs in the context of physical investments when the firm can capture the option value. However, in the case of general ability, where employees capture the value of the (human) capital if it is put to an alternate use, the parallel to physical capital is not as strong.

5.3 Competition diminishes the effect of uncertainty on hiring

The investments literature has shown that firms faced with more competition are less concerned by project uncertainty because waiting for its resolution may lead to more limited opportunities later on. In our setting this argument implies that we should observe a lower impact of candidate uncertainty on firms' decisions to make offers for those firms that have more competitors recruiting at the same time from the same pool of students. We find evidence consistent with this hypothesis, as illustrated by the results in Table 9. There, we estimate the effect of uncertainty on the odds that applications result in offers separately for firms that face below or above median competition, as measured by the number of firms in the same industry that are concurrently recruiting in the same pool of MBA students. For the typical, narrowly defined industry in the sample, the median number of firms recruiting on campus at any given stage (internship or full-time) is 10. Hence, for example, if there are 10 or more firms from the investment banking industry recruiting on campus for full-time positions in 2007, we label each of these organizations at this particular point in time as facing high competition – or, for sake of clarity, facing many competing firms.[12]

The results in Table 9 show that the preference for certainty is particularly strong among recruiters that face few competitors. For these firms, low uncertainty applicants have 2.49 times higher odds of getting offers compared to the riskier applicants. For firms faced with many competitors, the odds of success for low uncertainty applicants are only 1.63 times higher than for the rest. These odds ratios are significantly different ($p < 0.05$). The estimates in Table 9 also show an interesting interaction of the effects of competition with those of firing costs. Specifically, the biggest difference in firms' preference for certainty can be seen when comparing the relative odds of success of low uncertainty candidates across two scenarios: when applying for full-time jobs to firms that face few competitors, and when applying for internships at firms that face many competitors (odds ratio estimates of 2.90

[12]Indicating that firms with more industry peers recruiting at the same time indeed face more competition for talent, we find that with each additional competitor, the number of applications a firm receives per interview slot decreases by 0.02 ($p < 0.05$). The median number of applications per interview slot in our sample is 1.42.

vs. 1.60, significantly different at $p < 0.05$). In the first scenarios, the recruiting firms face a high firing cost, and also, can afford to be selective, since applicants do not have much choice. In the second scenario, recruiting firms can easily fire a revealed bad match and also do not have the luxury of delaying hiring, since applicants have many choices of employers in that same industry that are present on campus at the same time. Hence both competition effects and firing costs effects lead firms to prefer certainty more in the first scenario relative to the second.

These results indicate that the concerns that firms have regarding employee uncertainty indeed diminish with the intensity of competition for talent, in a similar way as found in the context of physical investments.[13]

6 Conclusion

We conduct an empirical study of the role of uncertainty in corporate hiring decisions. We find that firms are less inclined to make job offers to candidates characterized by higher uncertainty regarding their industry fit. The preference of firms for certainty when hiring is magnified when they are more likely to face higher firing and replacement costs, and when they face less competition for talent. Our analysis is based on a unique dataset covering MBA recruiting activity at a top U.S. business school.

We should note the data have limitations that lead to caveats about the internal and external validity of our results. First, even though the career office at the school that provided the data works hard to encourage students to report all of their offers, it is possible that students do so with some error. Second, a substantial amount of the job search by students at this school is done through channels other than on-campus recruiting. In these cases, we do not have any information about firms' preferences because we do not observe who applies to these firms. While we do not think that these issues bias our results substantially (if anything, the measurement error would imply any relationships in the data are likely to be stronger than our analysis suggests), we do not know for sure. Third, the external validity

[13] A necessary condition for competition to speed up hiring and lessen the delaying effect of uncertainty is that firms that wait longer before making offers will be faced with a lower quality pool of potential workers. We observe this effect in our sample, as better candidates leave the available pool sooner. For example, when examining how the applicant pool changes from the internship stage to the full time stage, we observe a decrease in average GPA of a quarter standard deviation, and a 5% decrease in the prevalence of low uncertainty candidates.

of our analysis is limited by the fact that our data set covers job seekers at one school and the particular firms that choose to conduct recruiting activities there.

While these limitations are important, high-skill labor markets such as the one we study are growing in importance world-wide. Also, there has been limited empirical work analyzing the matching process between firms and workers. Therefore, we believe our analysis makes a useful contribution by showing that considerations similar to those used in the context of physical investments are also significant determinants of corporate hiring decisions.

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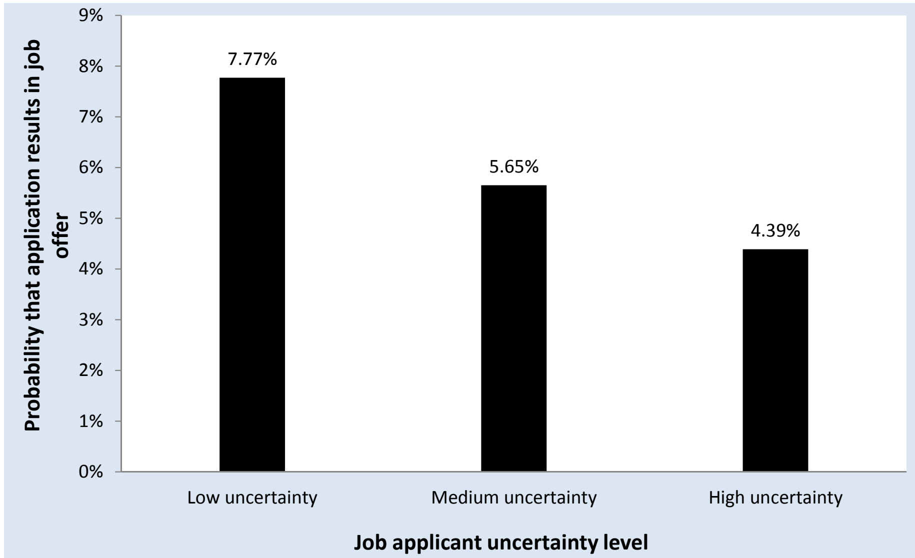

Figure 1: Fraction of applications that result in job offers, by the level of uncertainty in candidates' productivity as indicated by their industry experience.

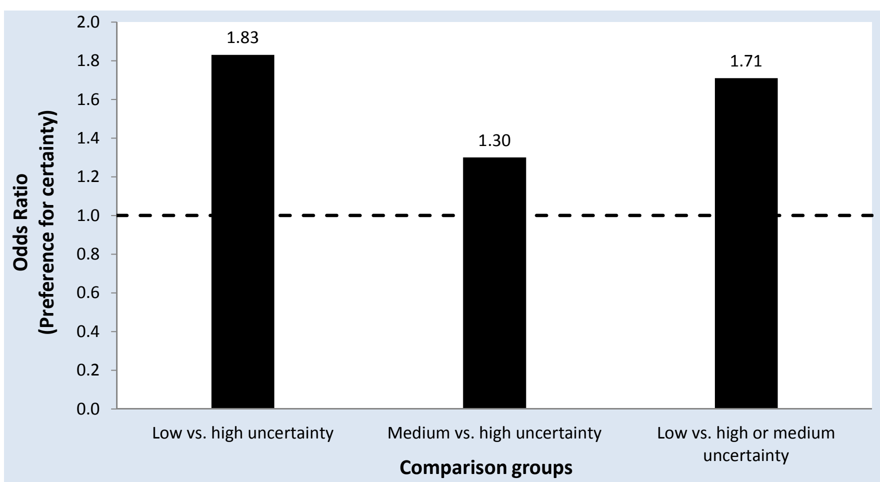

Figure 2: Firms' preference for certainty, as measured by the ratio of the odds of application success (i.e., resulting in offer) for different types of candidates: low vs. high uncertainty candidates, medium vs. high uncertainty candidates, and low vs. either high or medium uncertainty candidates. All odds ratios are significantly different than 1 at $p < 0.01$. An odds ratio equal to 1 would indicate that firms' hiring decisions do not differ across different types of job candidates.

Table 1: Summary statistics for job candidates and firms.

Panel A: Job candidates ($N = 1482$)	
Male	65.80%
International student	39.13%
Attended Top 100 college	48.33%
GPA	Mean: 3.45; St. Dev.: 0.28; Median:3.46
Age (years)	Mean: 30.11; St. Dev.: 2.19; Median: 30.00

Panel B: Firms ($N = 383$)	
Industry	General Coporations: 33.94%
	Finance: 29.50%
	Technology: 17.23%
	Consulting: 15.93%
	Other services: 2.09%
	Government/Non-Profit: 1.31%
On *Fortune MBA 100* list	24.28%
Publicly traded	58.49%
Annual sales ($ billions)	Mean: 22.56; St. Dev.: 43.52; Median: 6.03.
Employees (thousands)	Mean: 54.63; St. Dev.: 135.20; Median: 15.40.
Posted jobs located in the U.S.	98.10%

Table 2: OLS wage regression. Keeping the company and job characteristics fixed, salaries for full-time job offers do not depend on the ability of the person receiving the offer.

Dependent variable	$Wage_i$	$Ln(Wage)_i$
GPA_i^{MBA}	–1011.57	–0.01
	(–1.01)	(–1.04)
$Top100Undergrad_i$	332.39	0.00
	(0.73)	(0.53)
$Low\ uncertainty_i$	–201.90	–0.01
	(–0.38)	(–0.92)
$InternationalStudent_i$	–293.09	–0.00
	(–0.54)	(–0.40)
$Male_i$	522.53	0.01
	(1.03)	(1.02)
Age_i	–30.89	–0.00
	(–0.24)	(–0.40)
$Constant$	93878.65	11.45
	(9.28)***	(98.05)***
Class FEs	Yes	Yes
Industry FEs	Yes	Yes
Job Source FEs	Yes	Yes
Job Location FEs	Yes	Yes
Company-Job title FEs	Yes	Yes
R^2	0.48	0.40
Observations	1676	1676

Table 3: Across all firm categories, industry experience has a significant and positive impact on the probability that a summer internship results in a full-time offer. *** indicates differences significant at $p < 0.01$.

	Probability that a summer internship results in a full-time job offer		
	Low uncertainty interns (those at firms in same narrow industry as their pre-MBA employers)	Mid/high uncertainty interns (those at firms not in same narrow industry as their pre-MBA employers)	Difference between low uncertainty interns and the rest
All firms	63.22%	40.19%	23.03% ***
Prestigious firms	75.36%	48.54%	26.82% ***
Non-prestigious firms	43.53%	29.23%	14.30% ***
Large firms	63.53%	46.29%	17.24% ***
Small firms	79.45%	52.13%	27.30% ***

Table 4: The effect of uncertainty regarding job applicants' industry fit on the firms' decision to make offers. The dependent variable across the three models estimated in the table is an indicator equal to 1 for each application that resulted in an offer. The three panels report the results of a linear probability model, a logistic regression, and a GLM model. Candidate i to job j is characterized as having low, medium or high uncertainty regarding industry fit if they have worked in the same narrowly defined industry as that of the firm offering job j, if they have worked in the same broadly (but not narrowly) defined industry as that of the firm offering job j, and, respectively, if they have not worked in the broadly defined industry to which the firm belongs. For example, candidates applying to a job j in investment banking have high uncertainty regarding industry fit if they never worked in any finance-related industry before; if they previously worked in commercial banking, for example, they would have a medium level of uncertainty regarding industry fit; whereas candidates who worked in investment banking before have a low level of uncertainty regarding industry fit for job j. The reference (thus omitted) category in all three models is $High\ uncertainty_{ij}$. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer		
	Linear probability model	Logistic regression Odds ratios effects	GLM model Risk ratios effects
$Low\ uncertainty_{ij}$	0.03	1.90	1.81
	(6.95)***	(8.32)***	(8.77)***
$Medium\ uncertainty_{ij}$	0.01	1.24	1.22
	(2.68)***	(3.02)***	(3.26)***
GPA_i	0.05	3.19	2.96
	(9.93)***	(10.23)***	(10.99)***
$InternationalStudent_i$	-0.03	0.53	0.55
	(–10.27)***	(–9.76)***	(–10.09)***
$Male_i$	-0.02	0.69	0.71
	(–5.53)***	(–6.24)***	(–6.70)***
$Interview\ slots_j$	0.0003	1.01	1.01
	(2.26)**	(2.51)**	(3.25)***
$Ln(Firm\ sales_j)$	0.003	1.09	1.08
	(3.58)***	(3.20)***	(4.14)***
$Prestigious_j$	-0.01	0.78	0.80
	(–2.63)***	(–2.63)***	(–3.20)***
$Many\ Competitors_j$	0.01	1.08	1.07
	(1.40)	(0.99)	(1.17)
$Internship\ stage$	0.01	1.38	1.35
	(4.11)***	(4.09)***	(4.81)***
Class FEs	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
R^2	0.02	0.05	0.05
Observations	30783	30783	30783

Table 5: The effect of uncertainty on hiring decisions for each of the two recruiting stages: internship and full-time hiring. The internship recruiting stage applications in our dataset are the applications sent to firms that come to campus to recruit when students are in their first year of the MBA program. The full-time recruiting stage applications are the applications sent to firms that come to campus to recruit when students are in their second year of the MBA program. The dependent variable is an indicator equal to 1 for each application of a candidate i to job j that resulted in an offer. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer	
	Internship recruiting stage	Full-time recruiting stage
$Low\ uncertainty_{ij}$	1.66	2.38
	(5.83)***	(6.07)***
GPA_i	3.31	2.88
	(9.11)***	(4.76)***
$InternationalStudent_i$	0.57	0.44
	(–7.77)***	(–6.31)***
$Male_i$	0.70	0.63
	(–5.13)***	(–3.78)***
$Interview\ slots_j$	1.01	0.99
	(3.14)***	(–1.65)*
$Ln(Firm\ sales_j)$	1.08	1.11
	(2.37)**	(2.40)**
$Prestigious_j$	0.78	0.81
	(–2.28)**	(–1.26)
$Many\ Competitors_j$	1.17	0.92
	(1.87)*	(–0.43)
Class FEs	Yes	Yes
Industry FEs	Yes	Yes
R^2	0.04	0.07
Observations	21683	9100

Table 6: The effect of uncertainty on hiring decisions, as a function of firm prestige. The dependent variable is an indicator equal to 1 for each application of a candidate i to job j that resulted in an offer. A firm is labeled as prestigious if it was included in the *Fortune MBA 100* annual rankings during 2007-2009. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer					
	Non-Prestigious Firms	Prestigious Firms	Non-Prestigious Firms Internship stage	Non-Prestigious Firms Full-time stage	Prestigious Firms Internship stage	Prestigious Firms Full-time stage
$Low\ uncertainty_{ij}$	2.58	1.57	2.16	3.57	1.54	1.74
	$(7.18)^{***}$	$(5.01)^{***}$	$(4.72)^{***}$	$(5.87)^{***}$	$(4.19)^{***}$	$(3.01)^{***}$
GPA_i	2.95	3.31	3.43	2.14	3.28	3.62
	$(5.70)^{***}$	$(8.51)^{***}$	$(5.16)^{***}$	$(2.44)^{**}$	$(7.54)^{***}$	$(4.16)^{***}$
$InterntnlStudent_i$	0.50	0.55	0.63	0.29	0.53	0.59
	$(-5.83)^{***}$	$(-7.91)^{***}$	$(-3.37)^{***}$	$(-5.57)^{***}$	$(-7.21)^{***}$	$(-3.29)^{***}$
$Male_i$	0.71	0.68	0.75	0.66	0.68	0.60
	$(-3.27)^{***}$	$(-5.40)^{***}$	$(-2.28)^{**}$	$(-2.19)^{**}$	$(-4.64)^{***}$	$(-3.20)^{***}$
$Interview\ slots_j$	1.01	1.01	1.02	0.98	1.01	1.00
	(1.33)	$(2.02)^{**}$	$(2.00)^{**}$	(–0.93)	$(2.27)^{**}$	(–0.61)
$Ln(Firm\ sales_j)$	1.06	1.06	1.07	1.08	1.02	1.24
	$(1.76)^{*}$	(1.22)	(1.46)	(1.50)	(0.37)	$(2.97)^{***}$
$ManyCompetitors_j$	0.94	1.12	1.00	1.04	1.23	0.77
	(–0.43)	(1.21)	(0.02)	(0.12)	$(2.02)^{**}$	(–1.14)
Internship stage	1.25	1.41				
	$(1.75)^{*}$	$(3.41)^{***}$				
Class FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.04	0.04	0.11	0.04	0.06
Observations	10608	20175	6682	3849	14949	5174

Table 7: The effect of uncertainty on hiring decisions, as a function of firm size, as measured by sales (small vs. large firms, depending on whether their sales are below or above median). The dependent variable is an indicator equal to 1 for each application of a candidate i to job j that resulted in an offer. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer					
	Small Firms	Large firms	Small firms Internship stage	Small firms Full-time stage	Large firms Internship stage	Large firms Full-time stage
Low uncertainty$_{ij}$	2.19	1.69	2.02	2.71	1.55	2.28
	(5.56)***	(5.67)***	(4.14)***	(4.59)***	(4.13)***	(4.26)***
GPA_i	3.52	3.04	3.68	3.25	3.17	2.76
	(5.35)***	(8.63)***	(4.46)***	(2.98)***	(7.83)***	(3.75)***
$InternationalStudent_i$	0.54	0.53	0.61	0.41	0.55	0.46
	(–4.90)***	(–8.43)***	(–3.46)***	(–3.82)***	(–7.04)***	(–5.00)***
$Male_i$	0.63	0.71	0.66	0.60	0.72	0.64
	(–3.61)***	(–4.99)***	(–2.70)***	(–2.38)**	(–4.27)***	(–2.99)***
Interview slots$_j$	1.01	1.01	1.01	0.99	1.01	1.00
	(1.16)	(3.35)***	(1.69)*	(–0.94)	(3.64)***	(–0.29)
$Prestigious_j$	1.01	0.75	1.11	0.91	0.69	0.90
	(0.06)	(–3.17)***	(0.53)	(–0.19)	(–3.49)***	(–0.57)
Many Competitors$_j$	0.95	1.11	0.95	1.17	1.22	0.79
	(–0.28)	(1.30)	(–0.25)	(0.43)	(2.25)**	(–1.10)
Internship stage	1.39	1.32				
	(2.09)**	(3.20)***				
Class FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.04	0.04	0.10	0.03	0.06
Observations	10266	20517	6665	3525	15018	5499

Table 8: The effect of uncertainty on hiring decisions, as a function of the candidate's general ability measured by their GPA while in business school. The dependent variable is an indicator equal to 1 for each application of a candidate i to job j that resulted in an offer. *High GPA* and *Low GPA* are indicators for whether a candidate's GPA is above or below median. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer					
	Low GPA applicants	High GPA applicants	Low GPA applicants Internship stage	Low GPA applicants Full-time stage	High GPA applicants Internship stage	High GPA applicants Full-time stage
$Low\ uncertainty_{ij}$	1.81	1.83	1.47	3.27	1.81	1.96
	$(5.07)^{***}$	$(6.15)^{***}$	$(2.59)^{***}$	$(6.00)^{***}$	$(5.48)^{***}$	$(3.11)^{***}$
$InternationalStudent_i$	0.44	0.56	0.47	0.36	0.58	0.48
	$(-7.86)^{***}$	$(-7.24)^{***}$	$(-6.29)^{***}$	$(-4.88)^{***}$	$(-5.99)^{***}$	$(-4.20)^{***}$
$Male_i$	0.75	0.75	0.79	0.63	0.75	0.73
	$(-3.28)^{***}$	$(-3.83)^{***}$	$(-2.43)^{**}$	$(-2.43)^{**}$	$(-3.33)^{***}$	$(-1.96)^{**}$
$Interview\ slots_j$	1.00	1.01	1.00	0.98	1.01	1.00
	(–0.01)	$(3.20)^{***}$	(0.62)	$(-2.40)^{**}$	$(3.53)^{***}$	(–0.56)
$Ln(Firm\ sales_j)$	1.06	1.11	1.05	1.10	1.11	1.11
	(1.34)	$(3.55)^{***}$	(0.87)	$(1.69)^{*}$	$(2.99)^{***}$	$(1.89)^{*}$
$Prestigious_j$	0.93	0.68	0.97	0.83	0.66	0.80
	(–0.50)	$(-3.58)^{***}$	(–0.20)	(–0.81)	$(-3.36)^{***}$	(–1.03)
$Many\ Competitors_j$	1.12	1.06	1.29	0.65	1.08	1.18
	(1.03)	(0.63)	$(2.05)^{**}$	$(-1.78)^{*}$	(0.74)	(0.64)
Internship stage	1.36	1.41				
	$(2.89)^{***}$	$(3.57)^{***}$				
Class FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.03	0.09	0.03	0.06
Observations	15358	15425	10448	4850	11228	4175

Table 9: The effect of uncertainty on hiring decisions, as a function of the degree of competition for talent faced by firms, as measured by the number of competing firms in the same industry that are concurrently recruiting on-campus (few vs. many, depending on whether the number of competitors is below or above the median). The dependent variable is an indicator equal to 1 for each application of a candidate i to job j that resulted in an offer. Standard errors are clustered at the job level and are robust to heteroskedasticity.

Dependent variable	Indicator equal to 1 if candidate i's application to job j resulted in an offer					
	Few competing firms	Many competing firms	Few competing firms Internship stage	Few competing firms Full-time stage	Many competing firms Internship stage	Many competing firms Full-time stage
$Low\ uncertainty_{ij}$	2.49	1.63	2.12	2.90	1.60	1.98
	(7.18)***	(5.43)***	(4.42)***	(5.47)***	(4.56)***	(3.54)***
GPA_i	2.61	3.86	2.61	2.42	3.98	3.99
	(5.66)***	(8.97)***	(4.57)***	(3.03)***	(8.31)***	(3.96)***
$InternationalStudent_i$	0.55	0.51	0.56	0.53	0.56	0.30
	(–6.41)***	(–7.55)***	(–5.16)***	(–3.80)***	(–6.09)***	(–5.43)***
$Male_i$	0.67	0.68	0.75	0.54	0.65	0.85
	(–4.62)***	(–4.78)***	(–2.76)***	(–3.75)***	(–4.80)***	(–0.94)
$Interview\ slots_j$	1.00	1.01	1.01	0.99	1.01	1.00
	(0.87)	(1.74)*	(1.78)*	(–1.27)	(1.70)*	(–0.44)
$Ln(Firm\ sales_j)$	1.02	1.13	1.00	1.08	1.13	1.19
	(0.66)	(3.71)***	(0.02)	(1.68)*	(3.47)***	(2.28)**
$Prestigious_j$	0.79	0.78	0.71	0.95	0.87	0.46
	(–1.95)*	(–1.84)*	(–2.39)**	(–0.25)	(–1.02)	(–2.17)**
Internship stage	1.21	1.60				
	(1.85)*	(3.84)***				
Class FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.06	0.03	0.07	0.05	0.09
Observations	14110	16673	9219	4891	12464	4209