

**With a Little Help from My (Random) Friends:
Success and Failure in Post-Business School Entrepreneurship^{*}**

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To what extent do peers affect our occupational choices? This question has been of particular interest in the context of entrepreneurship, but the causal effect of entrepreneurial peers is hard to identify empirically. We exploit the exogenous assignment of students into business school sections that have varying numbers of peers with an entrepreneurial background. We find that the presence of entrepreneurial peers strongly predicts subsequent entrepreneurship among students without an entrepreneurial background, but in a more complex way than the previous literature suggests: A higher share of entrepreneurial peers leads to a decrease rather than an increase in entrepreneurship among the other students. However, the decrease is entirely driven by a significant reduction in unsuccessful entrepreneurial ventures. The effect on successful post-MBA entrepreneurship is instead indistinguishable from zero, and significantly more positive than the effect on unsuccessful entrepreneurship. In addition, sections with few prior entrepreneurs have a considerably higher variance in their rates of unsuccessful entrepreneurs. The results are consistent with intra-section learning, where the close ties between section-mates lead to insights about the merits of business plans.

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I. Introduction

The promotion of entrepreneurship has been a major focus of policymakers in recent years (see Kannianen and Keuschnigg [2004]). Thousands of national and local initiatives have been launched to foster entrepreneurship in the belief that entrepreneurial activity is associated with the creation of wealth, technological innovation, and increased social welfare. Consistent with this assertion, cross-national studies (e.g., Djankov, et al. [2002]) suggest that nations with greater barriers to entry of new firms also have poorer-functioning and more corrupt economies.

The concentration of entrepreneurs in regions such as Silicon Valley have triggered speculation that interactions among high-skilled individuals with similar interests lead to large social multipliers in the “entrepreneurial production function,” or, put another way, that there are powerful peer effects among entrepreneurs. Studies have shown that individuals who work at recently formed, venture-backed firms are particularly likely to become entrepreneurs (Gompers, Lerner and Scharfstein [2005]), as are those who work at companies where colleagues become entrepreneurs (Nanda and Sorensen [2010]) and in regions where many others opt for entrepreneurship (Giannetti and Simonov [2009]). These studies suggest that peer effects are important determinants of entrepreneurial activity. However, their inability to fully control for unobserved heterogeneity or sorting of individuals into firms and locations means that our interpretation of these results must be cautious.

A bigger, more conceptual issue is that the putative benefits to entrepreneurship are only likely to occur if ventures are successful. An emerging literature on “behavioral entrepreneurship” suggests that individuals may pursue new ventures even if the returns are predictably meager (Camerer and Lovallo [1990]; de Meza and Southey [1996]; Bernardo and Welch [2001]; Arabsheibani, et al. [2000]). This behavioral literature

argues that entrepreneurs may start ventures even if the decision is not individually rational, consistent with the high failure rates of entrepreneurial ventures (see, for instance, Davis, Haltiwanger, and Schuh [1998]).¹ The returns to society of attracting talented people into unsuccessful ventures are unlikely to be high. Despite this concern, much of the previous research, including the work on peer effects in entrepreneurship, has focused on what induces entrepreneurship rather than asking what increases the rate of successful but decreases the rate of unsuccessful ventures.

In this paper, we distinguish between successful and unsuccessful entrepreneurship and make methodological progress in identifying peer effects in entrepreneurship. We exploit the exogenous assignment of entrepreneurial peers among Masters of Business Administration (MBA) students at Harvard Business School (HBS) into sections. At HBS, school administrators exogenously assign students into sections that spend the entirety of their first year in the program studying and working together. These sections form extremely close ties, and are a setting where peer effects—if they are empirically observable at all—would be likely to be seen. We exploit the fact that the representation of students with entrepreneurial backgrounds varies considerably across sections to evaluate the impact of peers on the decision to become an entrepreneur. Moreover, we collect detailed data about the students' entrepreneurial ventures, which allow us to differentiate between successful and unsuccessful start-ups and to relate peer effects to entrepreneurial success.

In addition to the appeal of the exogenous assignment and the availability of success measures, this setting is attractive since it overcomes several limitations of the primary data sources used in previous entrepreneurship research, such as Census data,

¹ Landier and Thesmar [2009] find that firms run by optimists—a characteristic that has been shown by Evans and Leighton [1989] to be associated with the decision to become entrepreneurs—grow less, die sooner, and are less profitable, despite the fact that these owners tend to put in more effort.

Internal Revenue Service data, and the Panel Study of Entrepreneurial Dynamics. Those data allow only a specific type of entrepreneurial activity to be observed. As highlighted by Parker [2004], most empirical studies have focused on the self-reported decision to become self-employed (e.g., as a groundskeeper or consultant) rather than the founding of an entrepreneurial firm. In fact, in many databases, founders of entrepreneurial companies cannot be distinguished from employees of established firms. In our setting, we can carefully trace the entrepreneurial histories of the students.

A second challenge facing much of the earlier empirical work is that the importance of entrepreneurial entities varies tremendously. While the bulk of entrepreneurial ventures simply replicate other entities and have limited growth potential (Bhide [2000]; Hurst and Pugsley [2012]), a small number of ventures create enormous wealth and have a profound economic impact. Our paper complements previous research in using data that include a significant number of high-potential start-ups. Historically, Harvard Business School students have been instrumental in founding leading firms in a variety of industries (e.g., the Blackstone Group, Bloomberg, LLP, and the modern Xerox Corporation; for many more examples, see Cruikshank [2005]). Even within our relatively recent sample, we encounter early-career entrepreneurs founding highly successful firms, such as athenahealth (publicly traded, with a market capitalization of \$1.5 billion in March 2011) and SupplierMarket (acquired by Ariba for \$581 million). In other words, this paper analyzes a particular and talented subset of the overall population, differently from much of the prior literature mentioned above.

The differences in samples preclude comparisons with previous findings. Any differences in the sign and magnitude of peer effects in our analysis, relative to prior literature, may either reflect the improved identification or sample differences. However, given the highly skewed nature of entrepreneurial outcomes, the occupational choices and

peer effects in this subset of individuals are particularly relevant and important.

We analyze the effect of students with prior entrepreneurial experience on the rate of post-MBA entrepreneurship among their section-mates (without prior experience). Using data from the official class card records of 5,897 students of the classes 1997 to 2004, section-level post-MBA placement data, and hand-collected data on the success of entrepreneurial ventures, we create a novel data set to test for entrepreneurial peer effects.

We find a striking pattern: exposure to a higher share of peers with a pre-MBA entrepreneurial background leads to *lower* rates of entrepreneurship post-MBA. A one standard deviation increase in the share of peers with a pre-MBA entrepreneurial background in a section (evaluated at the mean of all independent variables) reduces the predicted share of the other students going into an entrepreneurial role after graduation by about one percentage point, a reduction of more than twenty-five percent.

When we differentiate between successful and unsuccessful ventures, however, we find that the negative peer effect is exclusively driven by a decrease in unsuccessful entrepreneurship. The share of students who start ventures that do not achieve critical scale or other measures of success is significantly and negatively related to the presence of pre-MBA entrepreneurs in the same section. Meanwhile, the effect on the share of successful post-MBA entrepreneurs is indistinguishable from zero (insignificantly positive), and the differences between the peer effect on the successful versus unsuccessful post-MBA entrepreneurship rates are significantly positive.

Our results are consistent with the presence of intra-section learning. An extensive literature, beginning with Jovanovic [1982], has highlighted the fact that entrepreneurs learn about their abilities through running their businesses. The close ties between students in the same section may accelerate the learning process about prospective business ideas. It is also consistent with the “cascade” model of Bernardo and Welch

[2001], which suggests that absent accurate signals of project quality (which experienced peers may provide), there may be excessive entry into entrepreneurship by overconfident individuals.

There are several possible channels for such intra-section learning, which we explore in further empirical tests. First, students seeking to start new ventures could be benefitting from the direct counsel of their peers. Students with entrepreneurial backgrounds may help in identifying which business ideas are problematic and which ones are worth pursuing. Second, the mere presence of entrepreneurial peers and their reports about their experiences may help other students to realize the challenges involved in starting a company. That is, even without individual advice, pre-MBA entrepreneurs may inject realism into other students and discourage all but the best potential entrepreneurs from pursuing their ventures. Third, the presence of entrepreneurial peers may not affect individual decisions directly, but encourage students to take more elective entrepreneurship classes, which in turn lead to better decisions.

We address the third mechanism by examining the enrollment in second-year entrepreneurship classes. We find that, in sections with more entrepreneurial peers, students without a prior entrepreneurial background are neither more nor less likely to enroll in elective entrepreneurship classes, ruling out the third explanation. This finding also casts doubt on the second explanation, since a discouraging “mere-presence effect” would suggest less enrollment.

In addition, we test whether prior entrepreneurs’ own (prior) success or failure is related to the sign or strength of the peer effect, as one would expect if mere exposure to the reports of prior entrepreneurs explains our findings. We do not find any such correlation. Hence, while the lack of micro-data on individual student-level interactions limits our ability to test the causal role of direct student interaction (channel 1), the

empirical patterns seem most consistent with this interpretation.

This first channel is also consistent with our last finding: the variance of post-MBA entrepreneurship rates is significantly lower when relatively many entrepreneurs are present in the section. One interpretation of the reduction in variance is that, with a large enough number of entrepreneurial peers, it becomes more likely that at least one of them has the expertise to detect the flaw in a given business idea.

In addition to helping understand peer effects in entrepreneurship, our analysis is relevant to policy-makers, business school faculty, and administrators.² Business schools are putting significant energy and resources into the promotion of entrepreneurial activities, often with public subsidies. For instance, during the 1990s and early 2000s, U.S. business schools created over 300 endowed chairs in entrepreneurship, typically paying salaries that were significantly higher than those in other business disciplines (Katz [2004]). Several hundred business plan contests for business school students were also launched during these years. The results of this paper suggest a slight redirection in educational and policy initiatives. Much of the benefit from exposure to entrepreneurship appears not to come from encouragement of more entrepreneurship but from help in weeding out ventures that are likely to fail. Rather than focusing on the attraction of more people into entrepreneurship, schools and policy-makers may want to provide support to would-be entrepreneurs in critically evaluating and identifying their most promising ideas.

II. Identification

Our identification strategy exploits three unique features of the data we collected. The first is the exogenous assignment of students to sections. The second is the identification

² Other papers examining entrepreneurial choices among MBAs are Lazear [2005] and Eesley, Hsu and Roberts [2007]; both have quite different focuses.

of students with and without prior entrepreneurial experience, which allows us to distinguish between students who will likely exert an entrepreneurial influence and those who are less likely to do so. And, third, we obtain information about the scale and success of the entrepreneurial ventures. Hence, our paper provides not only a clean (and different) answer to the question whether exposure to entrepreneurial peers increases entrepreneurship, but also addresses the question whether entrepreneurial peers help in making the “right” decision.

II.A. Challenges in Identifying Peer Effects

The appropriate identification of peer effects is a major challenge in economics. In the context of entrepreneurship, earlier papers measured peer effects by using observational data and regressing entrepreneurship outcomes on entrepreneurship among peers. There are several difficulties in interpreting coefficients estimated with this approach (Manski [1993], Sacerdote [2001]).

The most important issue is self-selection. If individuals choose the firm or other location of interaction with their peers, it is difficult to separate out selection effects from actual peer effects. In fact, several studies in the economics of education show that peer effects found in settings with endogenous sorting tend to disappear once the analysis is redone exploiting exogenous assignment, regardless of how extensively observables are controlled for in the settings with endogenous sorting. Kremer and Levy [2008], for example, study the peer effects of college students who frequently consumed alcohol prior to college on the GPA of their roommates and find systematically different effects in the sample of randomly assigned and in the sample of self-selected roommates. Another example is the decision to invest in a retirement account. Duflo and Saez [2002] analyze the influence of co-workers in a setting with endogenous sorting. When they re-analyze the effect in the context of a randomized experiment (Duflo and Saez [2003]),

they find significantly smaller (if any) peer effects.

In this paper, we are able to move beyond the limitations of endogenous sorting by exploiting exogenous variation in the exposure to entrepreneurial peers, as discussed in more detail in the next subsection.

Another confounding issue in the literature on peer effects is the distinction between the effect of one peer on others, on the one hand, and common shocks affecting the entire peer group, on the other hand. In the context of school outcomes, for example, Sacerdote [2001] finds a significant correlation in the GPAs of randomly assigned college roommates but little evidence that students are affected by their roommate’s pre-college academic background (SAT scores and high-school performance). Hence, as discussed in Kremer and Levy [2008], common shocks due to dorm room characteristics, infections, or joint class choices might be influencing both roommates and explain part of the results. Focusing on pre-determined characteristics, such as entrepreneurial activities prior to graduate school, avoids this problem.

A related issue is the distinction between the influence of peers on an individual versus the individual’s own prior inclinations and interaction effects. In the context of entrepreneurship, the question is whether one can cleanly distinguish between the influences of entrepreneurial peers versus an individual’s own predisposition to become an entrepreneur as well as possible interaction effects. To illustrate the identification problem, suppose we would like to identify the effect of how “entrepreneurial” the average peer is as well as the effect of how “entrepreneurial” individuals themselves are. A simple individual-level regression model can be written as follows:

$$Y_{i,j} = \alpha + \beta \bar{X}_{-i,j} + \gamma X_{i,j} + \delta X_{i,j} \times \bar{X}_{-i,j} + \text{other effects} \quad (1)$$

where i indicates the individual, j the group of peers, and $Y_{i,j}$ is an indicator equal to 1 if individual i becomes an entrepreneur. $\bar{X}_{-i,j}$ is the average peer effect, i.e., the share of

entrepreneurial peers in group j excluding individual i , and $X_{i,j}$ is an indicator equal to 1 if individual i is entrepreneurial herself. The interaction term accounts for a possibly different peer effect on individuals who are entrepreneurial themselves versus those who are not. Summing up the individual-level data by group (j) and dividing by group size, we obtain the group-level regression model:

$$\bar{Y}_j = \alpha + \beta \bar{X}_j + \gamma \bar{X}_j + \delta \cdot \frac{N_j}{N_j + M_j} \cdot \frac{N_j - 1}{N_j + M_j - 1} + \text{other effects} \quad (2)$$

$$\Leftrightarrow \bar{Y}_j = \alpha + (\beta + \gamma) \bar{X}_j + \delta \cdot \bar{X}_j \bar{X}_{j-1} + \text{other effects} \quad (3)$$

where \bar{Y}_j is the share of individuals in group j who become entrepreneurs; \bar{X}_j is the share of entrepreneurial peers in group j ; \bar{X}_{j-1} is the share of entrepreneurial peers in group j after removing one entrepreneurial individual (and is equal to 0 if there is no entrepreneurial peer); N_j is the number of entrepreneurial peers in group j ; and M_j is the number of non-entrepreneurial peers in group j .

Equation (3) illustrates that we cannot separately estimate the peer effect of others' entrepreneurial influence (β) and an individual's own entrepreneurial disposition (γ). Instead, we are measuring the combined effect ($\beta + \gamma$). In addition, the interactive effect $\bar{X}_j \bar{X}_{j-1}$ complicates the estimation.

Our empirical approach to identification has the advantage that, differently from the typical setting in the entrepreneurial peer effects literature, we can distinguish between individuals who are likely to exert entrepreneurial peer influence and those who are not, namely, students with and without prior entrepreneurial experience. By using prior entrepreneurial experience as a proxy, on the one hand, and excluding such pre-MBA entrepreneurs from the sample in which we measure the influence of entrepreneurial peers in the same group (section), on the other hand, we can estimate peer effects independently of the effect of individuals' own entrepreneurial inclination, i.e., independently of the effects of pre-MBA entrepreneurs on themselves. In such a reduced

sample, the above individual-level regression (1) becomes:

$$Y_{i_0,j} = \alpha + \beta \bar{X}_{-i_0,j} + \text{other effects} \quad (4)$$

where i_0 indicates an individual student in peer group j who has no prior entrepreneurial experience, $i_0 \in \{i \mid X_{i,j} = 0\}$. As in the notation before, $Y_{i_0,j}$ is an indicator equal to 1 if student i_0 of group j became an entrepreneur post-MBA, and the peer effect $\bar{X}_{-i_0,j}$ the share of pre-MBA entrepreneurs in group (section) j excluding student i_0 . Since none of the students in the reduced sample has prior entrepreneurial experience, $\bar{X}_{-i_0,j}$ is identical for all i_0 and amounts to the fraction of pre-MBA entrepreneurs relative to the size of section j minus 1: $\bar{X}_{-i_0,j} = \sum_i X_{i,j} / (N_j + M_j - 1) = N_j / (N_j + M_j - 1) \equiv \bar{X}_{-1,j}$. Finally, the third term and the fourth (interaction) term of equation (1) disappear since $X_{i_0,j} = 0$ for all i_0 in the new sample. Summing up over all non-prior entrepreneurs i_0 by section j and dividing by their total number M_j , we obtain the new section-level model:

$$\bar{Y}_{M_j} = \alpha + \beta \bar{X}_{-1,j} + \text{share of other controls (in reduced sample)} \quad (5)$$

where \bar{Y}_{M_j} indicates the fraction of students becoming entrepreneurs among all students without prior entrepreneurial experience, $\bar{Y}_{M_j} = \sum_{i_0 \in \{i \mid X_{i,j} = 0\}} Y_{i_0,j} / M_j$. We use model (5) for our regression analysis.

II.B. Sections at Harvard Business School

We exploit Harvard Business School's long-established section system to address the above-mentioned identification challenges. MBA students spend their entire first year in groups of 80 to 95 students in a single classroom, taking a fixed slate of classes (e.g., accounting, finance, and marketing) with a set group of peers. There is no provision for switching between sections. And while administrators ensure that each section is taught by a mixture of junior and senior faculty, no effort is made to match faculty and section characteristics. In their second year of the program, students take elective courses with the entire student body. The social ties established in the first year appear to remain

extremely strong, even after graduation. For instance, at 25th reunions of HBS alumni, fundraising and many activities are arranged on a section-by-section basis.

The power of the social experience engendered by HBS sections has been observed upon in both journalistic accounts and academic studies. For instance, in his account of Harvard Business School life, Ewing [1990] observes:

If the Harvard Business School has a secret power, it is the section system. A first-year section has a life of its own, bigger than any student, more powerful than any instructor... All first-year instructors I know agree about the awesome power of the section. They may not like the way it works in all cases—who does—yet it drives B-school students to learn, influencing them in countless ways.

Similarly, in a field-based analysis of the first-year HBS experience, Orth [1963] highlights the extent to which students in sections, “in order to insure feelings of safety and, if possible competence in a situation that is initially perceived to them to be threatening,” adopt “norms” that affect study patterns, social interactions, and even choices regarding employers with which to interview. He notes that “some norms appeared to be common to all first-year sections and others appeared to develop as a result of a particular section’s pattern of adaptation to the conflicts and pressures of the first year.”

Given the profound influence of the section experience, it seems conceivable that section-mates affect their peers’ decisions to become entrepreneurs. Cruickshank [2005] offers a number of illustrations where section-mates began businesses or refined business ideas together. Another place to see the impact of the section relationships on entrepreneurial choices is the HBS business plan contest. This contest, started in 1997, was open in its initial years only to second-year students. Many of the entries were the foundation for post-MBA ventures. Despite their freedom to choose partners across their entire class, students disproportionately chose partners who had been in their first-year

sections. In the contests between 1998 and 2004, there were 277 student teams consisting of 566 pairs of second-year students, and 185 of those pairs, or 33%, consisted of section-mates.³ Were the selection of partners random across sections, the expected share of section-mates would be 9% for the classes of 1998 through 2003 and 10% for 2004.

A second reason why the assignment to varying section environments is a promising path to explore entrepreneurial peer effects is the professional experience of the students prior to entering business school. Unlike many other professional schools, HBS students have considerable work experience prior to matriculation. In the classes under study, the typical student had between three and five years of post-college work experience.⁴ Moreover, there is a considerable degree of diversity in terms of the backgrounds of the students across sections, in particular in terms of their entrepreneurial experience, which allows us to exploit the differences across sections empirically.

II.C. Assignment to Sections

Students are assigned into sections by a computer program developed by HBS administrators. The assignment procedure is a mixture of randomization and stratification. It is based on the information about students on the official forms that all entering students fill out and that are also the basis of the class cards that we analyze.

The assignment program has undergone slight modifications over the years, but worked as follows during the period under study: First, approximately 200 students are randomly chosen out of all entering students and randomly assigned to sections. Then, additional students are considered one at a time in random order and assigned to a section based on a stratification score. This score is a weighted average of the Herfindahl index

³ Students were allowed in these years to involve students from other schools but not first-year students. In our calculations, we consider all pairwise combinations, ignoring non-HBS students. For example, a team consisting of three students, hailing from sections A, B, and B, was regarded as involving three pairs, one of which consisted of students in the same section and two of which did not.

⁴ <http://www.hbs.edu/about/mba.html> (accessed September 16, 2011) and unpublished tabulations.

of each stratification criterion. The program computes which assignment would make the weighted average Herfindahl index lowest, and assigns the student to that section. The stratification criteria are, in order of priority (and hence weight):

- a. Gender.
- b. Ethnicity.
- c. Whether the student went to the remedial analytics course in August prior to matriculation, and if so, what (remedial) section the student was assigned to.
- d. Quantitative and verbal skills, in particular, whether the student's admission was conditional on a remedial analytics course, supplemental work on quantitative skills, or work on verbal skills, and whether the student's quantitative or verbal GMAT score was high, medium, or low.
- e. Home region. (The system distinguishes ten US regions, most major European countries, Japan, China, India, and elsewhere.)
- f. Industry in which the student worked in his or her most recent job (e.g., consulting, finance, telecommunications, etc.).
- g. Age.
- h. Whether the student attended one of the major "feeder" colleges (Harvard, Yale, West Point, etc.).
- i. Function in the student's last job (e.g., sales or finance). Note that there is no function for entrepreneurs.
- j. Marital status.
- k. College major.
- l. Whether the student worked for one of 49 major companies in their last job. Due to software limitations (the program requires an exact match), this category works very poorly. For instance, it recognizes "McKinsey & Co." or "McKinsey &

Company,” but not “McKinsey” or “McKinsey Chicago.” For example, out of approximately 450 admits in the class of 2010 that we examined, the program only recognized the firms for about 10%. All others were bunched together in “other,” along with former entrepreneurs and students who worked for smaller firms.

Once a section fills up (reaches capacity), the assignments are only made to the remaining sections. Finally, the registrar staff “hand-adjust” these assignments to correct for two considerations the program misses:

- Students born to expatriate parents. For example, a student born in the U.S. with French citizenship (which suggests French parents) may be switched to a section with fewer French people.
- Students with a military background whom the program missed because of a brief stint on Wall Street or in consulting before going to business school. Students will be swapped to ensure the military component in each section is about even.

Hence, the primary dimensions along which students are sorted are orthogonal to the ones of interest of our study. Some of the secondary considerations in assigning students to sections, such as the undergraduate institution—e.g., Ivy League vs. state university graduates—are not orthogonal to the variable of interest. However, while stratification along these dimensions may lower the power of our analysis, it does not bias our estimation given the exogenous assignment and our ability to control for the stratification categories. We had access to all information used about the students in the sectioning process (or approximations of that information) with the exception of that on test scores and conditional admissions (items c and d).

Most importantly, because the administrators do not undertake the detailed textual analysis we do (see below) and their assignment software uses only the subset of the class card information that can be readily sorted by the computer, they do not identify and

balance out students who were entrepreneurs prior to HBS. Instead, entrepreneurs are commonly grouped into the function “general management” – but so is a broad range of other types of previous jobs. Examples include leadership positions at non-profits (e.g., an associate at a foundation), at for-profit organizations (e.g., a program director at a sports training academy, general managers of restaurants, or the senior manager of new business development at a health-care firm), and in the military, e.g., junior officers.⁵ As a result of the coarse classification, sections vary widely in the number of entrepreneurs. The section share of entrepreneurial peers ranges from 0% at the 10th percentile to 10% at the 90th percentile, which allows us to gain empirical identification.

The broad definition of the “general management” function entails a second advantage for our identification strategy: It ensures that the number of entrepreneurs in a section is not negatively correlated with other types of “general management” experience. In other words, a possible threat to identification could have been that sections with more entrepreneurs would have significantly fewer other students in the general management category and that the presence of more entrepreneurs therefore affects the types of non-entrepreneurial students in a section. To address this concern, we regress the share of pre-MBA entrepreneurs on the share of non-entrepreneurs with a general management background (and year dummies). We find that the relationship is both statistically insignificant (with a *t*-statistic of -0.35) and economically negligible (with a coefficient of -0.04).

III. The Data

Our analysis draws on four primary sets of data. These data sources characterize the incoming student body and their first-year sections, elective course choices in the second

⁵ Overall, 52.5% of the students with prior entrepreneurial experience and 15.2% of all other students are classified as general management.

year, career choices upon graduation, and the ultimate outcomes of entrepreneurial ventures, respectively.

First, we collect data on the characteristics of students in the classes graduating between 1997 and 2004 from their class cards. The starting date was dictated by data availability; the end date by the need to have several years after graduation in order to identify which entrepreneurs were successful. The class cards are initially filled in by school administrators based on students' applications.⁶ Students can update their class cards while enrolled at HBS.

We obtain the class cards for 6,129 students and extract information on gender, nationality (in particular, sole or joint U.S. citizenship), age, family status, educational background, and work experience. Due to inappropriately classified students (e.g., cross registrants) and missing data, the usable data amounts to 5,897 students. For age, we use 21.5 years plus the time elapsed since college graduation.⁷ For family status, we use whether they had a partner, as well as whether they indicated children among their interests or other descriptive material.

In terms of work experience, we identify the industry students had worked in after college. Students who worked in multiple industries (e.g., investment banking and private equity) are coded as having participated in all of them.⁸ In terms of educational

⁶ The fact that the information in the class cards is drawn from applications helps address concerns that students exaggerate their accomplishments on the cards to impress peers. Lying on one's application is a very high-risk strategy, as it can lead to expulsion from the school or even the voiding of a degree. HBS takes ethics during the application process very seriously: for instance, several years ago, some accepted students who had checked the status of their application on a web site earlier than allowed had their offers rescinded (Broughton [2008]).

⁷ This calculation is based on estimates by school administrators. While U.S. Census data suggests that the average graduate of an undergraduate program is considerably older, the majority of the school's enrollees complete their undergraduate programs faster. The primary exceptions are Mormon students, who frequently take two years off from college to serve as missionaries.

⁸ We use a sixty-industry scheme employed in the hiring and compensation database of HBS Career Services. In an unreported analysis, we explore the robustness of the results to assigning each student to a single field—the one in which he or she spent the most time. (If a student worked an equal amount of time in two fields, we choose the area in which he or she worked most recently before entering business school, as they are likely to have had more responsibility there.) The results are little changed.

background, we use their college and their college major. We classify whether their primary degrees are from an Ivy League school or, alternatively, from an “Ivy Plus” school (an association of administrators of leading schools, which includes the Ivy League schools as well as the California Institute of Technology, the University of Chicago, Duke University, the Massachusetts Institute of Technology, Stanford University, and the Universities of Cambridge and Oxford). In unreported analyses, we also use a classification that adds the top non-U.S. schools, as defined by the Times Higher Education Supplement, in addition to Cambridge and Oxford: the Ecole Polytechnique and the London School of Economics. These changes make little difference to the results.

Going beyond the baseline characteristics used by HBS for stratification, we also attempt to characterize risk attitudes, given suggestive evidence in the literature on lower risk-aversion among entrepreneurs (Parker [2004]). As an imperfect proxy, we exploit the riskiness of the activities listed by the students based on the injury data from American Sports Data [2005].⁹ We employ their compilation of “Total Injuries Ranked by Exposure Incidence,” which gives the number of injuries per 1000 exposures for each sport. The most risky activity (boxing) causes 5.2 injuries per 1000 exposures and gets a risk score of 1. Other activities are scaled accordingly. Lacrosse, for example, causes 2.9 injuries per 1,000 exposures and gets a risk score of $2.9/5.2 = 0.558$. We average the top risk score for each student in the section. In unreported robustness checks, we employ the average across all activities listed by each student. We also calculate the share of students

⁹ The data is based on a survey of 25,000 households in 2003 (62% response rate). Several injury measures are provided, e.g., total injuries, injuries resulting in an emergency room visit, etc., which tend to be quite correlated. For sports not included in the American Sports Data, we substitute the closest sport (e.g., baseball for cricket, day hiking for orienteering). If there is no comparable listing, we assign the top ranking if they appear to be very high risk (e.g., motorcycle racing) and the median ranking if they are more moderate (for instance, fencing). We exclude activities that do not involve physical exertion (e.g., fantasy football and pigeon racing) or that were too vague to be classified (for instance, “athletics” or “all sports”).

in each section whose top risk scores are higher than certain thresholds – higher than the mean (0.38), higher than the mean plus one standard deviation (0.48), and higher than the mean plus two standard deviations (0.58) – as the risk-seeking students are the ones who might be more likely to become entrepreneurs. Again, the results are little different.

Finally, we use the class cards to construct the key variable for our analysis of entrepreneurial peer effects: prior (pre-MBA) entrepreneurial experience. We identify students who founded or co-founded an entrepreneurial venture prior to entering business school. We do this by searching for terms such as “co-founded,” “started,” or “launched.” We include ventures which are spun-off from another firm, but eliminate corporate ventures, e.g., starting up and heading a division within a company.¹⁰ Unlike the calculation of industry experience (which focused on post-college employment), we include businesses begun before graduating from college, on the grounds that these experiences also provide insights into the planning and implementation of entrepreneurial ventures.

Overall, the prior entrepreneurial endeavors were quite diverse, but most fell into three broad categories:

- Businesses geared toward a limited market. Frequent examples included campus-oriented services (e.g., a bottled water delivery service to dorm rooms at local college campuses) and food service facilities (e.g., a 14-unit retail bagel chain in Hungary).
- Businesses that were acquired due to economies of scale or scope, such as a chain of eight bike shops sold to a larger competitor, or an Internet consulting firm that was sold to a more generally focused consulting firm after a failed IPO.

¹⁰ Freelance consulting is not counted as starting a business unless there are other consultants working for that person. We also do not include a small number of cases where students operated franchises as entrepreneurs since operating a franchise is more similar to running a corporate unit.

- Ventures where the entrepreneurial founder was eventually shunted into a narrower functional role (e.g., chief technology officer) as the firm grew and professional management was recruited, e.g., in a security software firm.

For supplemental analyses, we also assess the success of those prior entrepreneurial ventures. (This information is only used in Table VIII.) If there are entrepreneurial peer effects, the influence of successful entrepreneurs may be more encouraging than that of unsuccessful entrepreneurs. Moreover, while the core of our analysis focuses on spillovers from entrepreneurial experience rather than entrepreneurial skills, this measure allows us to approximate the latter.

Our primary cut-off point for success is whether the business achieved a million dollars in annual revenues.¹¹ Unlike the identification of the pre-HBS entrepreneurs (which is done entirely using the official class card records) or the identification of post-business success (where we have multiple, highly consistent information sources, as discussed below), here our identification is only approximate. In addition to descriptions in the class cards, we use social networking sites such as Facebook and LinkedIn, and direct contacts with the students. In total, 42% of the businesses were classified as successful, 19% as unsuccessful, and the remainder as unknown.

Note that a success rate of 42% is unusually high compared to broader samples of entrepreneurs. Apparently, pre-HBS entrepreneurs often sold their businesses at a profit. We encountered descriptions such as “grew business from start-up to \$6 million per year in revenues—my brother is managing now,” or “took \$2 million in profits out of business in three years before wrapping it up.”

To better understand the selection of entrepreneurs entering the MBA program,

¹¹ Note that the cut-off is lower than in the definition of the success for post-business school entrepreneurship discussed below. The lower hurdle reflects that students engaging in pre-business school entrepreneurship had a lower opportunity cost.

we conducted a number of interviews with MBAs who had been entrepreneurs prior to business school. They all emphasized their need for skill development and explained that they chose to enter an MBA program with the intention to go for new and larger ventures. Many had been technically trained prior to business school and had little by way of business training or insights into marketing, finance, etc. That deficiency, they highlighted, had become increasingly important as their businesses grew and they interacted with individual angel investors and venture capitalists. The other main motivation they mentioned was the desire for more contacts. Several respondents expected ties with venture investors, corporate development specialists, and wealthy people in general to result from enrollment at HBS, which would increase the probability of success of future ventures.

A difficulty in the data collection process was posed by the failure of HBS to archive class cards prior to 2000. For the period between 1997 and 1999, we obtained the cards from HBS professors who had saved the class cards of the classes they had taught. Some of these instructors had taught first-year classes, in which case they had information on all the students in a given section. Others had taught second-year classes, in which case the class cards covered students from various sections who had chosen the respective elective class. As a result, the completeness of our information about sections in the early years varies.

Missing class cards reduce the precision with which we can characterize the features of sections and raise concerns about response bias. In high-count sections, for which we have all or almost all class cards, the cards are either provided by HBS or by first-year instructors, who are assigned randomly to sections. Thus, there is little potential for bias. In low-count sections, instead, the cards come from second-year instructors. Only a minority of instructors saves the cards of former students, and these are typically

professors of management practice (successful practitioners who become instructors after their business careers) and professors in more practically minded fields such as entrepreneurship. Hence, the class cards available in low-count sections characterize the selected set of students who, in their second year, choose to register in classes with these professors. In order to prevent such selection biasing our result, the main analyses reported in the paper only employ sections where we have been able to gather at least seventy class cards. In addition, we undertake supplemental analyses with all sections and with a less restrictive sub-sample (sections with at least 40 class cards).¹²

Tables I and II show the summary statistics. Unlike in the rest of the paper, Table I displays aggregate data on the entire student body, including students for whom we are missing class cards. The year-by-year statistics reveal that, while class size remained approximately constant, around 900 across all sections, the composition changed: female, minority, and non-U.S. students were increasingly represented. In addition, the share of students with a technical or science background increased markedly. The average section size is stable, around 80 students, from the class of 1998, when an additional section was added and the average section size shrank in conjunction with an experimental accelerated MBA program, until the class of 2004, when the number of sections was reduced from 11 to 10 after elimination of the accelerated program.

The lower half of Table I shows measures of macro-economic financing conditions, which we use to control for the U.S. economic environment for entrepreneurship. One measure is the amount of U.S. venture capital financing. Venture capital is an important mechanism for funding new growth firms, including many of the ventures begun by Harvard MBAs. We compile the amounts provided annually in the

¹² In the more expansive samples (all sections or all sections with 40+ class cards), we also replicated our analyses weighting the observations by the number of class cards. All of our main results are robust to all of these alternative approaches, though in some cases the levels of statistical significance are lower – consistent with underlying selection bias. All replication tables are available from the authors.

initial and in all financing rounds. The information is taken from National Venture Capital Association [2005], based on the records of Venture Economics.

Another measure, compiled from Securities Data Company and the website of Jay Ritter, is the number and dollar volume of initial public offerings in United States, as well as the amount “left on the table” in these offerings (the difference between the closing price on the first day and the offer price, multiplied by the number of shares sold). Even though IPOs are typically confined to firms that have several years of operations, they provide a useful proxy of the financing available to new ventures in the same industry, possibly reflecting investment opportunities in this industry (Gompers, et al. [2008]).

The year-by-year tabulation in the lower half of Table I highlights the acceleration of activity during the “bubble years” of the late 1990s. This pattern is also illustrated in Figure 1. In our regression analysis, we employ both a VC and an IPO measure of financing conditions. (The results are robust to the choice of measures.) Alternatively, we include year dummies.

Table II shows detailed characteristics for those students for whom we have class card information. We aggregate by section to make the data compatible with the outcome data, post-MBA entrepreneurship, which is available only by section (as described below). Panel A shows the summary statistics for all 86 sections, and Panel B for the 60 sections where we were able to gather at least seventy class cards. In terms of control variables, the data reveals the heavy representation of students in investment banking and consulting.¹³ We also single out the share of students working in private equity (which we define here to include both venture capital and buyout funds), since these students may be particularly well prepared to provide counsel to would-be entrepreneurs. Sections differ on a variety of personal characteristics, including the presence of students with

¹³ The variation in the share of investment bankers (10th versus 90th percentile) reflects in large part time-series variation, i.e., the ebb-and-flow of these admits across classes, rather than inter-section differences.

children and graduates of elite schools. The differences between the 10th and 90th percentiles narrow somewhat when we require data on at least 70 students (Panel B), which reflects the fact that the distribution becomes less noisy.

The key variable of interest is the share of students who previously worked as entrepreneurs. In both panels, the average is around 5%, though the 10th-90th percentile range is quite large, between zero and ten percent. The scatter plot in Appendix Figure 1 shows the full range of variation for our main sample (sections with at least 70 class cards) by plotting the year-section data points, ordered by section.

To distinguish time-series from cross-sectional variation, we graph the full distribution of the shares of entrepreneurs in a section, both on a raw count basis (left graph in Figure 2A) and adjusted for year effects, i.e., divided by the average share in that year (right graph in Figure 2A). The two graphs show that, while some sections have no members with previous entrepreneurial ventures, others have up to 13% (12 pre-MBA entrepreneurs) and, year-adjusted, a rate nearly three times the rate of the other sections in that year. The year-by-year variation, instead, is somewhat smaller. As shown in Panel B, the share of students that have had entrepreneurial experience varies between 3.7% in 1998 and 6.3% in 1997.

Our second data set contains the students' elective class choices in their second year. As noted above, the different possible explanations for the patterns of peer effects have differing implications for enrollment in the elective entrepreneurship classes in the second year. We determine all elective classes students enrolled in, as well as the fraction of such classes listed as (co-)sponsored by the Entrepreneurial Management unit in the course prospectus. We compute the share of entrepreneurship classes for all the students without prior entrepreneurial experience. On average, non-entrepreneurs in a given section devote 19% of their elective classes to entrepreneurship. The ratio varies from as

low as 9% to as high as 27% across sections and years.

Our third data set provides information related to the choice of careers post-graduation including the key outcome variable, post-MBA entrepreneurship. We use the annual HBS “exit survey.” Since HBS makes the picking of a cap and gown for graduation conditional on survey completion, participation is almost perfect. The survey offers multiple choice categories to characterize the post-graduation employment (i.e., for industry of employment), as well as for cases where the student is still looking for employment and where the student has founded or is planning to imminently found a new venture. The survey responses are anonymous, in order to ensure candid responses. We identify all cases where students had or were beginning an entrepreneurial venture. We obtained access to this data aggregated on the section level.

Note that the survey only reflects students’ intentions at the time of graduation. It is possible that some would-be entrepreneurs abandon their quests later, maybe due to receiving an attractive job offer. And, vice versa, graduates may decide to start a company later. Thus, the actual number of students beginning companies may be either larger or smaller. Our measure of post-MBA entrepreneurship is unbiased if this inexactitude only introduces random noise; it is precise for the stated entrepreneurial intentions.¹⁴

The survey also does not characterize the career choices of students who drop out without completing a degree. This (very small) fraction, typically considerably under 1%, overwhelmingly represent students who leave the program involuntarily due to poor academic performance. Even at the peak of the Internet boom, only a handful of students permanently left school before graduation to pursue an entrepreneurial opportunity.

¹⁴ We cannot characterize those who began entrepreneurial companies later in their careers. Given the substantial evidence of the greater likelihood of former entrepreneurs to become entrepreneurs again (e.g., Evans and Leighton [1989], Gompers, et al. [2007]), these individuals are likely to be over-represented among those making such decisions later in their careers.

The final element of preparing the post-graduation data involved separating out, among those who became entrepreneurs post-MBA, the shares of students who also were entrepreneurs pre-MBA. As discussed above, we need to exclude “pre-and-post-MBA” entrepreneurs from the estimation of peer effects to obtain identification and to distinguish the estimated peer effect from the effect of own prior experience. Our desired outcome variable \bar{Y}_{M_j} is the fraction of students in section j who become entrepreneurs post-MBA among all students with no prior entrepreneurial experience in that section: $\bar{Y}_{M_j} = \sum_{i_0 \in \{i|X_{i,j}=0\}} Y_{i_0,j} / M_j$. The empirical difficulty lies in the anonymity of the placement data. As noted above, we obtain those data compiled by section. To create the desired ratio, we need to identify, for all sections j , the number of students with prior entrepreneurial experience who also started a (new) company post-MBA.

We use our individual-level class card data to extract information on each of the students with prior entrepreneurial experience and research if they took an entrepreneurial position after HBS. The main sources of additional information were social networking sites, Google, and direct contacts. This data allows us to calculate the numerator of the outcome variable, $\sum_{\{i|X_{i,j}=0\}} Y_{i,j}$, as $\sum_i Y_{i,j} - \sum_{\{i|X_{i,j}=1\}} Y_{i,j}$.

A second difficulty is that we do not have all the class cards for some of the sections. In those sections, our measure of the fraction of post-MBA entrepreneurs among non-pre-MBA entrepreneurs, \bar{Y}_{M_j} , could be biased in two ways. First, if we calculated the denominator, the number of non-pre-MBA entrepreneurs M_j , by simply subtracting the number of “identified” pre-MBA entrepreneurs from the size of section j , we would overestimate the denominator. We correct this potential source of bias by applying the pre-MBA entrepreneurship rate calculated on the sample of available class cards to the full section size, $N_j + M_j$, i. e., if $\tilde{N}_j + \tilde{M}_j$ is the sample of available class cards and $\tilde{N}_j / (\tilde{N}_j + \tilde{M}_j)$ the pre-MBA entrepreneurship rate in that sample, we calculate M_j as

$$(N_j + M_j) \left(1 - \frac{\tilde{N}_j}{\tilde{N}_j + \tilde{M}_j}\right). \text{ Hence, } \bar{Y}_{M_j} \text{ becomes } \frac{\sum_i Y_{i,j} - \sum_{\{i|X_{i,j}=1\}} Y_{i,j}}{(N_j + M_j) \left(1 - \frac{\tilde{N}_j}{\tilde{N}_j + \tilde{M}_j}\right)} \text{ or,}$$

$$\frac{\# \text{ of post-MBA entrepreneurs in section } j - \# \text{ of pre-and-post entrepreneurs in section } j}{\text{section size} \times (1 - \text{section's pre-MBA entrepreneurship rate})}$$

A second potential source of bias due to missing class cards is that, by failing to account for some pre-MBA entrepreneurs, we might underestimate the number of pre-and-post-MBA entrepreneurs, $\sum_{\{i|X_i=1\}} Y_{i,j}$. Relatedly, we might simply miss that a (pre-MBA entrepreneurial) student became an entrepreneur even though he or she (anonymously) indicated entrepreneurship in the placement survey. Both biases would lead us to overestimate the number of “post-not-pre” entrepreneurs, which is the numerator of \bar{Y}_{M_j} . To check the robustness of our results to this potential bias, we re-do each analysis assuming that a set percentage of the students who were entrepreneurs prior to entering the MBA program also chose this career upon graduation.¹⁵

Finally, we collect data on the success of firms established by students while at HBS or within one year of graduation. It is hard to find an objective threshold criterion of “success.” For the bulk of the paper, we define a successful business as one that, as of July 2011, (a) had gone public, (b) had been acquired for more than \$5 million, or (c) had, then or at the time of the sale of the company, at least 50 employees or \$5 million in annual revenues.¹⁶ The \$5 million cut-off is somewhat arbitrary, and our results are robust to a wide range of alternative cut-offs (see below). We chose to report the analyses using \$5 million based on the following rationale: Hall and Woodward [2010] estimate the mean equity stake of entrepreneurial teams at the time of exit at 53%, and, according

¹⁵ The share of prior entrepreneurs who become entrepreneurs after business school can be estimated in various ways. The Rock Center survey described below suggests a rate of 30%. Using the class card data (see Panel B of Table II), we obtain a rate of 23%: the difference stems from the fact that the class cards includes individuals who did not respond to the survey, and we do not have class card data from some survey respondents. We use a 30% rate in the results reported in the paper, but in unreported analyses, we also use other rates and find they had little impact.

¹⁶ While we would have liked to determine the success as of a set time after graduation (e.g., three years after degree completion), this information proved infeasible to gather.

to Gompers, Lerner and Scharfstein [2005], the typical venture-backed firm has 3.0 founders. Assuming a valuation-to-revenue ratio of one,¹⁷ a five million dollar valuation at exit guarantees that the equity per founder is (approximately) worth at least one million dollars. In supplemental analyses, we employ higher hurdles for criteria (b) and (c), requiring acquisition payments and revenues of \$25 million or even \$100 million.

We determine this information from three sources. First, we obtained access to the research of the HBS External Relations (Development) Office into its entrepreneurial alumni. Second, we obtained access to the online survey of entrepreneurial alumni conducted by the Rock Center for Entrepreneurship. The survey collects information about students who participated in the above-mentioned business plan contest as well as others known to have undertaken early-career entrepreneurial ventures.¹⁸ Third, we conducted interviews with the three key faculty members in the HBS Entrepreneurial Management unit, who are intimately involved with most alumni ventures – whether as sponsors of the independent studies where the initial business plans are drawn up, or as directors, advisory board members, or investors in subsequently established ventures – and who often stay in touch with alumni entrepreneurs even without a formal role. As a result, they have extensive knowledge about the performance of these ventures. In cases where none of the three sources revealed the revenues, public status, or acquisitions of our sample firms, we consulted a wide variety of business databases, such as CorpTech, EDGAR, Factiva, and Orbis. We also contacted entrepreneurs directly to obtain this information on a confidential basis.

¹⁷ According to Thomson Reuters SDC data, the median multiple of valuation to last twelve months revenues in all U.S. IPOs between 1997 to 2004 was 1.55; when excluding the “bubble years” of 1999 and 2000, it was 0.99

¹⁸ The survey used a “viral” approach, whereby known entrepreneurs were asked to identify other entrepreneurs among their classmates, and encourage them to complete the survey. Alumni were initially contacted via e-mail in January 2005. Non-respondents were contacted three times via e-mail and telephone. Overall, 41% of all contacted students participated. This rate is consistent with or above the level of responses typical in social science studies of this cohort (Baruch [1999]).

In total, we identified 26 entrepreneurs (associated with a total of 19 firms) who qualified for the lowest success hurdle, amounting to a success rate of only 13% among post-MBA entrepreneurs. Of these, 14 entrepreneurs were identified by the Development Office and 16 through the Rock Center survey (for a total of 22). The three faculty members identified respectively 19, 25, and 22 of the entrepreneurs. Given the high degree of overlap across these various sources, we are confident we have captured the universe of successful post-MBAs in our sample.

After compiling this information on individual ventures, we again aggregate it on the section level. We compute the share of the class who became entrepreneurs after graduation, as well as those who became successful entrepreneurs, both for the entire graduating class and only for those who were not entrepreneurs prior to graduation. (The latter is the dependent variable in our regression analyses.)

Figure 2, Panel C, summarizes some key patterns of the outcomes data. (Because we have placement data for virtually all students, we report the data here for all sections.) Entrepreneurial activities vary over time, with the peak in entrepreneurial entry occurring around 2000. More than 10% of the class began entrepreneurial ventures upon graduating in 2000. The rate of successful entrepreneurship is low, even when using the first, less demanding definition of successful entrepreneurship. The temporal pattern of success is less pronounced, but, generally, the years that saw the greatest number of successful entrepreneurs were earlier (suggesting that less suited students may have been drawn into entrepreneurship by their predecessors' successes).

IV. Empirical Analysis

Our analysis proceeds in several steps. First, we perform several tests of stratification and (conditional) randomization in section assignment. Then, we present our main result, the analysis of peer effects on the rate of students in each section becoming

entrepreneurs, as well as differential peer effects on the rate of successful versus unsuccessful entrepreneurs. Finally, we explore possible channels for entrepreneurial peer effects, including an effect of prior entrepreneurs' own previous success or failure and an effect on enrollment in elective entrepreneurship classes.

IV.A. Test of Stratification and Randomization

We saw already that the distribution of pre-MBA entrepreneurs across sections appear to be random (e.g., in Appendix Figure 1). We now compare the distribution of the students without an entrepreneurial background in sections with more (above median) and fewer (below median) pre-MBA entrepreneurs. We test whether the students display significant differences in any of their demographics or other characteristics.

The raw results for all 68 characteristics variables in our data are presented in Appendix Table A1. Out of all job-related characteristics (last job in consulting, investment banking, private equity), demographics (gender, US citizenship, children, partner, age range), our risk score measure, and education (attendance of an Ivy League or Ivy League Plus college, and major), we find that six sets of differences are significant at the five-percent confidence level: sections with more entrepreneurs are *less* likely to have students who worked in entertainment (3.2% versus 4.3%), who attended elite schools (22.7% versus 25.2% for Ivy League and 32.7% versus 35.7% for Ivy League plus), who majored in history (2.9% versus 4.2%), and who had a function in human resources (0.2% versus 0.4%) and are *more* likely to have students who had a function in medical services (0.7% versus 0.3%). Many of the differences, however, are in categories with a very small number of positive respondents, and the differences range only from 0.2 to 3.0 percent. Another ten variables differ at the ten-percent level.

We aim to control for these differences in our main analysis. Given that we have sixty sections with at least seventy class cards, we cannot use all 68 characteristics (nor

even the 14 significant characteristics). In order to identify the most relevant variables, we used two forward-selection procedures, reported in Table III.

First, we start with a number of variables that are commonly viewed as being particularly influential in determining the propensity of students to become entrepreneurs: having consulting, investment banking, and private equity backgrounds, gender, nationality, the presence of partners and children, attendance at an Ivy League or Ivy Plus college, risk appetite, and year of graduation. We then conduct a forward stepwise selection to identify which additional student characteristics have significant explanatory power (at the 5% level) in predicting the share of pre-MBA entrepreneurs in a section using a linear regression framework and controlling for year effects. This leads to the identification of three additional independent variables—students having a background in agriculture and health care, and those majoring in engineering. Second, we used a forward step-wise approach, with only year dummies preset, and include all additional variables significant at the 5% level. In this case, we identify five variables in addition to the year dummies.

We use both sets of control variables in our analyses, and we report the analyses with the first set of variables in the main tables. (All replications with the second set of independent variables are available from the authors.)

Overall, these results suggest that a relatively small number of demographic and other characteristics have significant explanatory power and help identify the non-random variables to be controlled for in the final regression analysis.

IV.B. Univariate Comparisons

We begin by analyzing the basic relationship between the representation of students with previous entrepreneurial experience in a given section and the rates of post-MBA entrepreneurship, both in total and separating out unsuccessful and successful

entrepreneurs.

Figure 3 presents the patterns graphically. Panel A relates the share of pre-MBA entrepreneurs in a section and the share of total post-MBA entrepreneurs (without prior entrepreneurial experience).¹⁹ The panel suggests that sections with more pre-MBA entrepreneurs have, on average, *lower* rates of post-MBA entrepreneurs. Moreover, these sections have considerably less variation in the share of entrepreneurs after graduation. Panel B shows the same pattern for the share of unsuccessful post-MBA entrepreneurs. Meanwhile, the pattern in Panel C, which looks at the share of successful post-MBA entrepreneurs, is less pronounced and relatively flat, with the exception of one section with a high number of successful entrepreneurs and a high normalized pre-MBA entrepreneurship rate. Certainly, no sign of a negative relationship, as identified in the other two panels, appears here.

Table IV examines the correlation coefficients between various characteristics of the sections and the share of students without an entrepreneurial background who became entrepreneurs after finishing the program. In Column 1, we see that sections with more males, U.S. citizens, and students with children have higher rates of entrepreneurship. (Again, all variables are computed using just the students who were not pre-MBA entrepreneurs.) Both venture capital funding and IPO activity in the year of graduation are highly correlated with post-MBA entrepreneurship. Most importantly, the correlation with the section share of students with prior entrepreneurial experience provides suggestive evidence speaking to our main research question: Consistent with the pattern observed in Figure 3, there is a statistically significant, negative relationship between the section share of pre-MBA entrepreneurs and the share of those who were not prior entrepreneurs but began ventures after their MBA.

¹⁹ This is calculated by subtracting out the number of pre-and-post-MBA entrepreneurs (the first corrective methodology described in Section III).

Columns 2 and 3 reveal that this negative correlation is entirely driven by the share of unsuccessful post-MBA entrepreneurs. While the correlation with unsuccessful post-MBA entrepreneurship is significantly negative, the correlation with successful post-MBA entrepreneurship is insignificant (and has a positive sign). More generally, the correlations with unsuccessful entrepreneurship in Column 2 mirror those of Column 1, while the correlations with successful entrepreneurship in Column 3 are much weaker. For successful entrepreneurship, the only significant correlates are the measures of entrepreneurial finance activity in the year of graduation, and even these are not consistently significant at the five-percent confidence level. One reason for the lack of significance in the sample of successful entrepreneurs—as well as for the close resemblance of correlation coefficients in the full and in the unsuccessful sample—is the small number of successful post-MBA entrepreneurs. If we compare the fraction of successful entrepreneurs (among all post-not-pre entrepreneurs²⁰) in sections with above and below-median numbers of pre-MBA entrepreneurs, 18.0% versus 7.5%, the difference is not significant (p -value = 17.1%), but economically large.

These patterns are, of course, simply suggestive. Our main analysis, in the next subsection, controls for a number of features of the sections simultaneously.

IV.C. Regression Analyses

We now turn to the regression analyses of post-MBA entrepreneurship. The units of observation are section-years. The main dependent variable is the share of the section without prior entrepreneurial background who became entrepreneurs immediately after graduation, either overall or divided into successful and unsuccessful. As derived in Section II.A, we control for the characteristics of these same students. That is, the independent variables in the regressions are calculated using only those students who

²⁰ The calculation of the success rate excludes sections with no post-MBA entrepreneurship.

were not entrepreneurs prior to entering business school (with the exception, of course, of the share of prior entrepreneurs in the section).

Table V presents the first main result, the analysis of entrepreneurial peer effects on the propensity of students who were not entrepreneurs prior to entering business school but to become entrepreneurs afterwards. Because the left-hand side variable is censored at zero, we first estimate a Tobit specification. Since the Tobit specification does not allow us to employ year dummy variables (the estimates do not converge), we use the volume of venture financing and IPOs as controls. Alternatively, we show OLS specifications with the inclusion of year dummies. In those specifications we can also add pairwise interactions between significant explanatory variables as additional controls. The variables we use for the interactions are the share of section that is male, that are U.S. citizens, with a partner, and with investment banking background.

As discussed in Section III, we use the two methods to correct the aggregate post-MBA entrepreneurship rate for prior entrepreneurial experience: In the first three columns, we subtract out the number of identified pre-and-post-MBA entrepreneurs; in the last three columns, we subtract an average post-MBA entrepreneurship rate of 30% among pre-MBA entrepreneurs.

All regressions confirm the pattern found in the raw data: The coefficient on the share of the section with an entrepreneurial background is always significantly negative. The effect is not only statistically significant, but also economically meaningful. In the first OLS regression specification, a one-standard deviation increase in the pre-MBA entrepreneurship rate translates into a decrease of 26% in the predicted rate of entrepreneurship after business school: the share of post-not-pre entrepreneurs drops by one percentage point (-0.35×0.029), from 3.9% to 2.9%. The second set of regressions suggests declines of even larger magnitudes.

In addition to our main result, we observe several interesting patterns. The share of students with a private equity background is positive but insignificant (after the inclusion of year dummies). The difference in sign, relative to the pre-MBA entrepreneurship coefficient estimate, may reflect the fact that this category is dominated by students who have worked for buyout firms that have little exposure to young firms, rather than for venture capitalists. We also see that the coefficient on the share of the section that is male is always positive and typically statistically significant, while the share that has a partner is always negative and (at least marginally) significant. The coefficient on the mean risk tolerance of the section is generally insignificant. Finally, more entrepreneurial activity in the economy is associated with periods of more venture activity. When we employ class dummies, those for 1999 and 2000 have the greatest magnitude and significance. When we employ the venture and IPO dummies, the relationship is consistently positive and significant at the one-percent level.

We then distinguish between the rates of unsuccessful and successful post-MBA entrepreneurs. We define the rate of unsuccessful entrepreneurship as the difference between the total rate of entrepreneurship and the successful entrepreneurship rate in each section.²¹ Table VI presents regressions with the same set of specifications as in the previous table. The dependent variable is the share of post-MBA entrepreneurs who were not previously entrepreneurs and whose post-graduation ventures ultimately failed (in Panel A) or whose ventures were successful (in Panel B).

The results of the regressions explaining unsuccessful entrepreneurship (Panel A) are very similar to those for overall entrepreneurship in Table V. The share of the section with prior entrepreneurial background is significantly negatively associated with

²¹ While we believe that we identified a virtually comprehensive list of successful HBS entrepreneurs from the classes in our sample, a similar approach would not have worked for unsuccessful entrepreneurs. Unsuccessful ventures are frequently much less visible, and participants may not be willing to disclose their failure (e.g., in response to a survey request).

unsuccessful post-MBA entrepreneurship among their peers. The coefficient estimates are almost identical to those in the baseline analysis. Also the coefficient estimates of the other independent variables are quite similar in terms of significance and size.

The estimation results imply that the economic magnitude of the peer effect is even somewhat larger for unsuccessful entrepreneurs than in the baseline estimation, given that the rate of unsuccessful entrepreneurs is slightly lower (3.6%). Using again the coefficient estimate from the first regression specification, a one-standard deviation increase in the pre-MBA entrepreneurship rate translates into a decrease of 36%, namely, more than one percentage point [-0.46×0.029] out of 3.6% unsuccessful post-not-pre entrepreneurs.

The results of the regressions explaining successful entrepreneurship (Panel B), instead, are rather different: The coefficient on the share of pre-MBA entrepreneurs are much smaller, ranging from 0.03 to 0.12, and always positive, while the standard errors remain similar to those in Panel B. As a result, the coefficients are never statistically significant. Nor are any of the other variables that are important in the Table V regressions consistently significant. The goodness of fit is also considerably lower. Given the low average rate of successful entrepreneurs (0.3% of those without prior experience) and left-censoring, the representation of successful entrepreneurs is much more difficult to predict.

In Panel C, we test formally whether the peer effects estimated for unsuccessful and for successful entrepreneurship in Panels A and B are the same. We employ the standard econometric approach to estimate a pooled regression using observations from both regressions and to then perform a *t*-test of the null hypothesis that the coefficients on the pre-MBA entrepreneurial share variable are not different in the successful and unsuccessful entrepreneurship regressions. In other words, we examine the significance

of the interaction between the pre-MBA entrepreneur share and the dummy variable denoting successful outcomes. We also undertake an F -test comparing all coefficients in the two regressions.

As shown in Panel C, the null hypothesis of no difference is always rejected at the one-percent confidence level. Thus, the presence of peers who have had entrepreneurial experience tends to deter students without an entrepreneurial background from undertaking unsuccessful ventures, but does not deter those students who will launch successful ventures. Indeed, entrepreneurial peers may even have a slightly positive effect on would-be successful entrepreneurs.

Our results are robust to employing higher thresholds for “success.” As discussed above, we chose the \$5m threshold in order to guarantee equity worth about \$1m or more per founder, but this cut-off may be too low in some cases. For example, Guru.com, an online marketplace for freelance talent in our sample, was sold for approximately \$5 million to rival Unicru in 2002. Given that Guru.com raised over \$62 million in venture capital financing in 1999 and 2000, it is doubtful whether any of the key parties associated with the firm regarded this as a success.²² In order to address this type of concern, we repeat the above analyses using the \$25 million and \$100 million cutoffs defined above, which we term “very successful” and “super-successful” respectively.

Columns 1 through 4 of Table VII show results akin to those in the specifications of Column 2 of Table VI, Panels A and B. The coefficient estimates closely resemble those using our original success measure, not only in terms of sign and significance but also in terms of economic magnitude. Moreover, the coefficients on the share of pre-MBA entrepreneurs in the regressions predicting unsuccessful versus successful post-MBA entrepreneurship (i.e., “not very successful” versus “very successful,” and “not

²² The information on Guru.com was obtained from <http://www.ventureexpert.com> (accessed September 16, 2011), Factiva, and other on-line sources.

super-successful” versus “super-successful”) are significantly different at the one-percent confidence level in both cases.

Another robustness check addresses possible concerns related to the HBS class of 2000. As Figure 2, Panel C, revealed, the class of 2000 had an extraordinary high post-MBA entrepreneurship rate. In an unreported analysis, we reran the regressions without the observations from the class of 2000. The results were little changed.

IV.D. Interpretation

As noted in the introduction, we can offer a variety of explanations for the results seen above. A first channel for intra-section learning is direct interaction with pre-MBA entrepreneurs and their counsel about what constitutes a good business idea. Intra-section learning of this type is most consistent with the views offered by the alumni and students we interviewed, who argue that students who were entrepreneurs prior to business school play a critical if informal knowledge dissemination role: would-be entrepreneurs approach these individuals and receive help evaluating their potential business plans and understanding their strengths and weaknesses. While others in the section may have the same analytical skills, the personal experience of prior entrepreneurs gives them a credibility others do not have.

A second interpretation is that the mere presence of former entrepreneurs and their reports about their prior entrepreneurial ventures discourage all but the best “would-be entrepreneurs” and lead them to abandon or at least postpone their plan to start a company, even without direct interaction and specific counsel. This explanation is particularly plausible if the entrepreneurial peers had negative experiences, given that we estimated the peer effect to be significantly negative.

A third interpretation is that entrepreneurs do not affect other students directly, but raise interest in entrepreneurship and induce their sectionmates to take additional

entrepreneurship classes as electives, which may lead them to subsequently make better decisions about pursuing new ventures.

The third hypothesis is directly testable. We use our additional data on enrollment in elective entrepreneurship classes to test whether there is a positive relationship with the presence of prior entrepreneurs in a section. We employ the share of second-year classes under the sponsorship of the Entrepreneurial Management unit that the students without an entrepreneurial background took in their second year as the new outcome variable, and repeat the prior regression analyses. Column 5 of Table VII displays the regression specification that mirrors Column 2 of Table V. None of the coefficient estimates are significant at the five-percent confidence level, and the coefficient estimate for gender is marginally significant but varies depending on the regression specification. (The exceptions are two time dummies: the classes of 2000 and 2001 had the greatest enrollment in entrepreneurship classes.) Most importantly, the impact of peers with an entrepreneurial background is very small and never significant.²³ Hence, we find no support for the explanation that entrepreneurial peers induce others to take entrepreneurship classes.

It is harder to distinguish between the first two explanations, “mere presence” versus “direct counseling,” though the finding on enrollment in entrepreneurship classes is hard to reconcile with the second explanation. Under this interpretation, i.e., the interpretation that entrepreneurial peers dampen interest in entrepreneurship, we would have expected a negative coefficient. Relatedly, the second interpretation would be more plausible if pre-MBA entrepreneurs tended to be failed entrepreneurs, whose previous experiences dampen the general enthusiasm about entrepreneurship among their peers.

²³ Because the number of electives shifted over time, and the number of sections with seventy or more class cards is not evenly distributed, we repeated these analyses for all sections and for the set of the sections with forty or more class cards. We use weighted and unweighted data. The results are the same.

However, as we saw already, pre-MBA entrepreneurs in our sample have been quite successful, with some even having sold companies for tens of millions of dollars.

It is possible, though, that the outcome of prior entrepreneurial ventures colors the influence that pre-MBA entrepreneurs exert on the entrepreneurial ambitions of their section-mates: A successful entrepreneur may be more encouraging, and a failed entrepreneur may be more discouraging.

We test the latter hypothesis using our hand-collected data on the outcomes of prior ventures of MBA students. In Table VIII, we present the same regression specifications as in Table VI, but split the share of pre-MBA entrepreneurs into those who were successful and those who failed (total rate minus successful rate).

Panel A estimates the effect of previously successful and unsuccessful entrepreneurs on *unsuccessful* post-MBA entrepreneurs. We find a negative peer effect both for successful prior entrepreneurs and for unsuccessful prior entrepreneurs. Both coefficients are similar in magnitude to our previous estimations, though estimated less precisely. (The loss of significance is not surprisingly given that we are splitting the already small number of pre-MBA entrepreneurs into two groups.) In other words, the peer effect of failed entrepreneurs is not systematically stronger than the effect of successful peers. Even directionally, only the Tobit specifications point in the direction of stronger peer effects of unsuccessful entrepreneurs in discouraging unsuccessful entrepreneurship, but the OLS regressions show the reverse. And, in all cases, the differences in coefficients are insignificant.

Panel B shows the effect on *successful* entrepreneurs. As in Table VI.B, the goodness of fit is considerably lower, and only two out of the twelve coefficients of interest are even marginally significant. Directionally, the peer effect of successful entrepreneurs is always positive while the peer effect of failed entrepreneurs is either

negative or very close to zero. The differences are never significant (Column 1).

Overall, we have at best very weak evidence that the specific prior experience of entrepreneurial peers is central in explaining our results. Again, it is possible that the lack of significant results reflects the lack of power.

As a final piece of evidence, we examine the variance, rather than the mean rate of entrepreneurship. As hypothesized above, sections with fewer students with an entrepreneurial background are likely to display a greater variance in their post-MBA entrepreneurship rates, particularly in the share of unsuccessful entrepreneurs. If intra-section learning relies on direct interaction, then, the fewer pre-MBA entrepreneurs are in a section, the less likely it is that one of them finds the flaw in the business plan.

Table IX reports the variance in the rate of post-MBA entrepreneurship separately for sections with a below-median and with an above-median share of pre-MBA entrepreneurs. We find that sections with more entrepreneurs have 44% less variance in the overall entrepreneurship rate, a pattern entirely driven by unsuccessful entrepreneurs.

At least part of the reduction in variance may be mechanistic and due to the reduction in the likelihood to become entrepreneur when many pre-MBA entrepreneurs are present. The remainder, however, points to the channel of intra-section learning: if the impact of pre-MBA entrepreneurs comes from their interaction with aspiring entrepreneurs among their section-mates, the effect will be noisier when there are fewer pre-MBA entrepreneurs present and, hence, interaction and productive feedback are less likely. With a large enough number of entrepreneurs present, instead, one of them will be critical and experienced enough to detect the “flaw” in a business plan.

V. Conclusions

This paper studies a topic of increasing scholarly and practical interest, the impact of peer effects on the decision to become an entrepreneur. We examine the decision to undertake

entrepreneurial activities among recent graduates of the Harvard MBA program. This setting is an attractive one for a study of these issues due to the exogenous assignment of students to sections, the ability to distinguish firm outcomes, and the potentially high economic impact of these ventures.

We find that a higher share of former entrepreneurs in a given section reduces entrepreneurship rates among students without an entrepreneurial background. This effect is driven by the rate of (ultimately) unsuccessful entrepreneurs: students in sections with more entrepreneurial peers are less likely to start unsuccessful ventures. The relationship between the share of pre-MBA entrepreneurs and (ultimately) successful post-MBA entrepreneurs is indistinguishable from zero, and significantly more positive than the peer effect on (ultimately) unsuccessful post-MBA entrepreneurship. The presence of former entrepreneurs does not affect enrollment in entrepreneurship classes, and whether former entrepreneurs were successful or unsuccessful themselves has, at best, a weak directional effect. Finally, sections with few prior entrepreneurs have a considerably higher variance in their rates of unsuccessful post-MBA entrepreneurship.

Our results are consistent with intra-section learning, where the close ties between students in a section lead to an enhanced understanding of the merits of proposed business ideas.

We highlight two avenues for future research. First, this paper suggests a richer role for peer effects in entrepreneurship than what has been described in the prior literature. Most of the empirical studies of peer effects in entrepreneurship, for instance, have implicitly assumed a “contagion effect,” where the decision of one individual to begin a firm leads others to do so likewise. This analysis suggests that there are more subtle dynamics at work, with specific feedback on business ideas might play a larger role. Understanding these effects in more detail and uncovering the channels of

interaction would be worthwhile also beyond the business school setting, e.g., for the design of business incubators.

A second avenue for future research is exploiting section assignments at HBS to look at phenomena other than entrepreneurship. The differing educational, national, religious, and experiential mixtures of the various sections should make this a fertile testing ground for a variety of network and peer effects. Shue's [2011] analysis of executive compensation and acquisition strategies of companies headed by HBS graduates represents one such important analysis, and points to the breadth of research topic possible with these data.

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Table I. Background Variables

	Class of ...							
	1997	1998	1999	2000	2001	2002	2003	2004
MBA Enrollment	898	913	903	880	865	917	898	898
MBA Applications	6,973	8,053	7,496	8,061	8,476	8,124	8,893	10,382
Profile								
Female	27%	24%	29%	30%	31%	33%	36%	35%
Minorities	19%	18%	18%	19%	18%	20%	21%	25%
International	24%	25%	26%	26%	35%	32%	33%	32%
Undergraduate Majors								
Humanities & Social Science	50%	46%	47%	42%	41%	41%	45%	40%
Engineering & Sciences	22%	26%	29%	34%	31%	31%	30%	32%
Business Administration	24%	25%	20%	21%	24%	24%	20%	20%
Other	5%	3%	4%	3%	4%	4%	5%	8%
Average Section Size	90	83	82	80	79	83	82	90
IPOs in Graduation Year								
Number of IPOs	432	267	457	346	76	67	62	179
Aggregate Proceeds (\$ billion)	29	32	63	61	34	22	10	32
Aggregate Sum Left-on-Table (\$ billion)	4	5	36	27	3	1	1	4
Venture Financing in Graduation Year								
First-Round Financing (\$ million)	4,844	7,199	16,201	28,979	7,512	4,452	3,577	4,438
Total Financing (\$ million)	14,897	21,270	54,480	105,832	40,943	21,615	18,924	20,993

Figure 1. Macroeconomic Conditions over Time

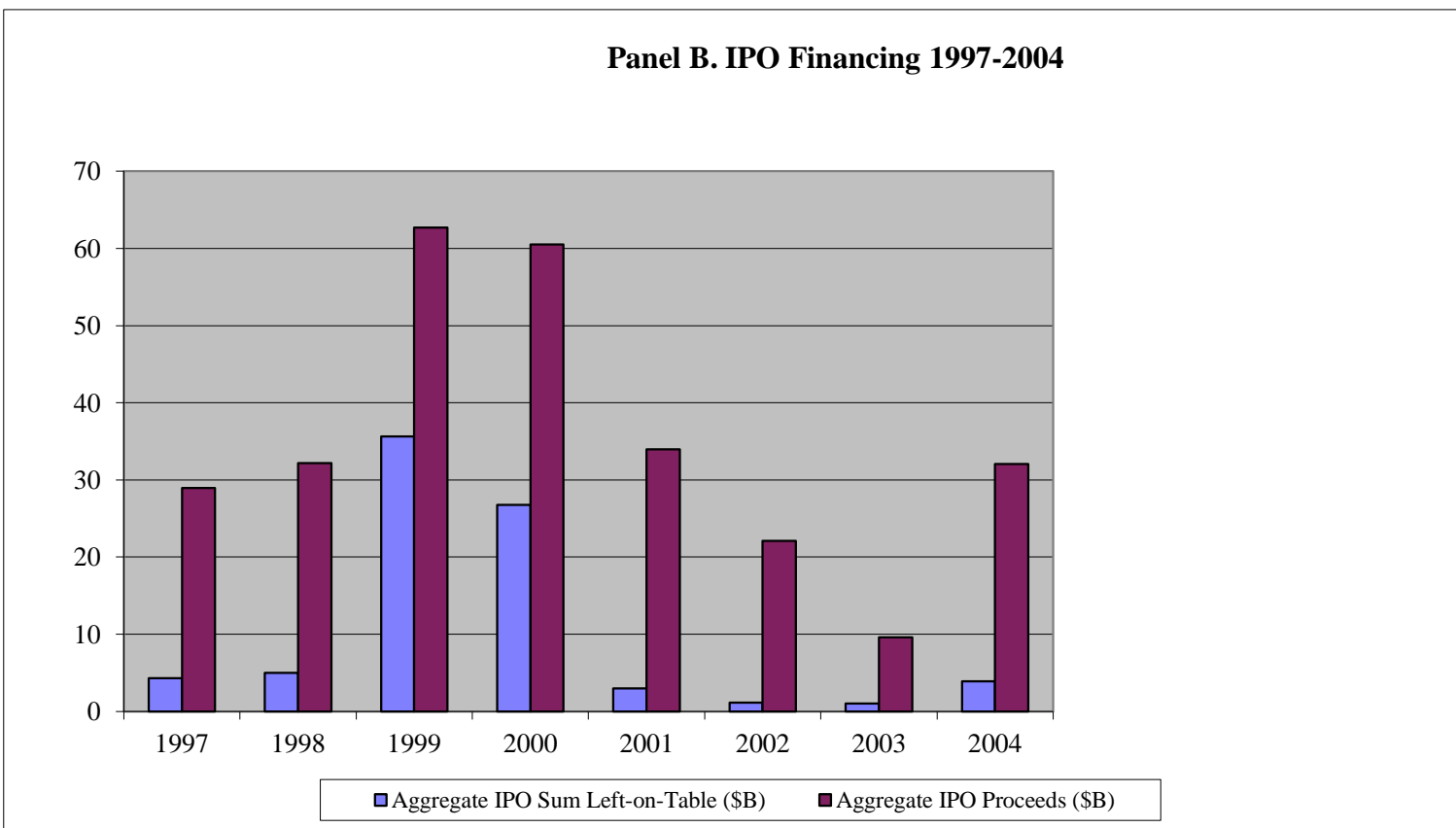
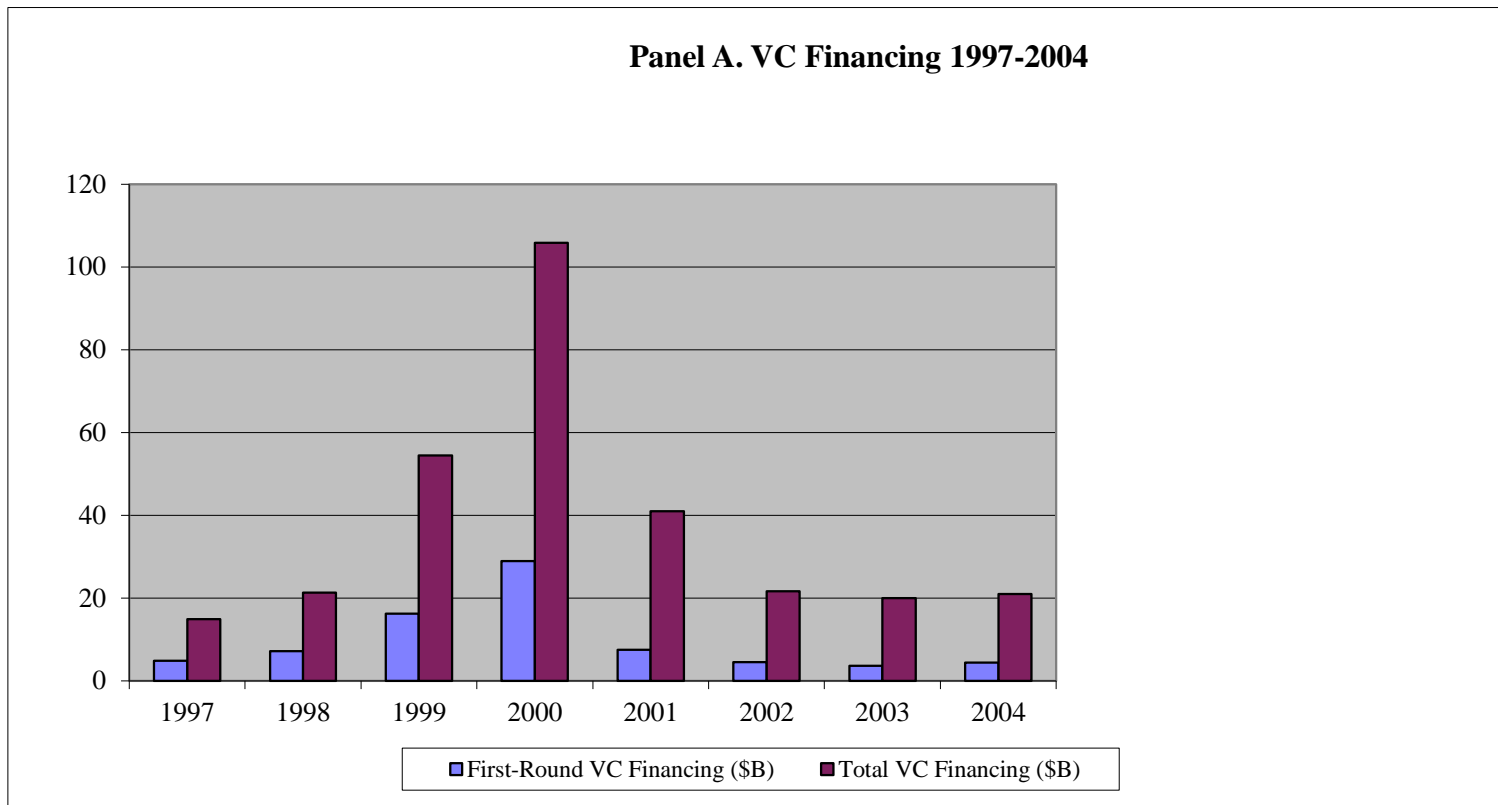


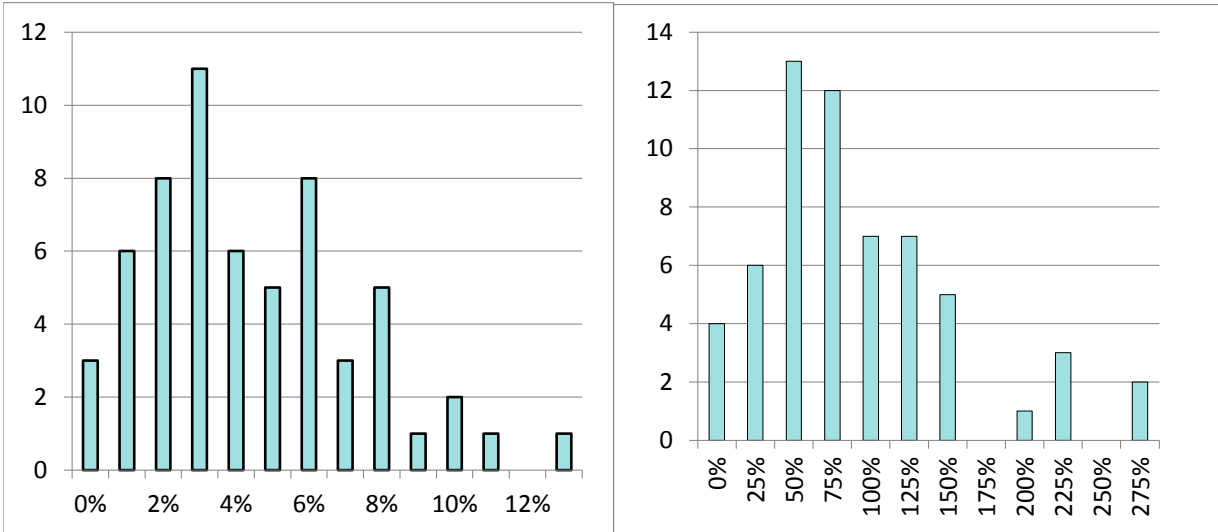
Table II. Section Characteristics

Panel A. Full Sample (86 sections)	<i>Mean</i>	<i>Median</i>	<i>St. Dev.</i>	<i>10th</i>	<i>90th</i>
				<i>Percentile</i>	<i>Percentile</i>
Share of section that worked					
... as an entrepreneur	5.0%	4.7%	3.4%	0.0%	9.8%
... in consulting	22.5%	22.9%	5.4%	16.0%	28.4%
... in investment banking	18.7%	18.6%	5.5%	12.8%	25.0%
... in private equity	4.6%	4.0%	3.0%	1.1%	8.6%
... in agricultural business	2.4%	2.5%	1.8%	0.0%	4.2%
... in health care	3.2%	2.7%	2.3%	0.0%	5.4%
... in hardware manufacturing	1.3%	1.2%	1.4%	0.0%	3.2%
Share of section that is male	70.2%	68.5%	7.0%	63.9%	82.5%
... has USA citizenship	66.6%	65.9%	6.5%	58.2%	75.9%
... has children	5.1%	4.9%	3.3%	1.3%	9.7%
... has a partner	41.5%	42.0%	7.7%	31.7%	50.7%
Share of section older than 30	6.1%	5.8%	3.8%	1.3%	10.7%
Average maximum risk score	38.6%	39.0%	3.1%	34.4%	42.2%
Share of section having attended an Ivy League college	24.2%	24.1%	5.5%	18.1%	31.8%
Share of section having attended an Ivy Plus college	34.4%	34.4%	6.5%	25.3%	42.7%
Share of section with an Engineering major in college	22.6%	22.6%	5.7%	15.9%	29.4%
Share of post-MBA entrepreneurs	4.5%	4.2%	3.5%	0.0%	7.9%
Share of successful post-MBA entrepreneurs	0.6%	0.0%	1.0%	0.0%	1.4%
Share of post- but not pre-MBA entrepreneurs	3.7%	2.9%	3.7%	0.0%	8.4%
Share of successful post-but not pre-MBA entrepreneurs	0.6%	0.0%	1.0%	0.0%	1.5%
<hr/>					
Panel B. Sections with at least 70 class cards (60 sections)	<i>Mean</i>	<i>Median</i>	<i>St. Dev.</i>	<i>10th</i>	<i>90th</i>
				<i>Percentile</i>	<i>Percentile</i>
Share of section that worked					
... as an entrepreneur	4.8%	4.6%	2.9%	1.3%	8.6%
... in consulting	24.0%	23.6%	4.1%	19.5%	28.3%
... in investment banking	18.3%	18.4%	3.7%	13.5%	23.0%
... in private equity	5.1%	4.3%	3.1%	1.3%	9.4%
... in agricultural business	2.4%	2.5%	1.8%	0.0%	4.1%
... in health care	3.2%	3.3%	1.5%	1.2%	5.2%
... in hardware manufacturing	1.0%	1.1%	1.0%	0.0%	2.3%
Share of section that is male	67.2%	67.3%	3.1%	63.5%	71.0%
... has USA citizenship	64.9%	64.7%	5.4%	58.2%	72.6%
... has children	4.7%	4.4%	3.0%	1.3%	9.1%
... has a partner	42.7%	43.3%	7.3%	33.3%	51.3%
Share of section older than 30	5.0%	4.9%	2.5%	1.3%	8.2%
Average maximum risk score	38.9%	39.6%	2.7%	35.4%	42.0%
Share of section having attended an Ivy League college	24.0%	24.1%	4.1%	19.4%	29.1%
Share of section having attended an Ivy Plus college	34.7%	34.3%	5.5%	27.4%	42.2%
Share of section with an Engineering major in college	22.2%	22.3%	4.5%	16.2%	28.2%
Share of post-MBA entrepreneurs	4.8%	4.2%	3.8%	0.0%	10.2%
Share of successful post-MBA entrepreneurs	0.4%	0.0%	0.7%	0.0%	1.4%
Share of post- but not pre-MBA entrepreneurs	3.9%	2.8%	4.1%	0.0%	10.6%
Share of successful post-but not pre-MBA entrepreneurs	0.4%	0.0%	0.8%	0.0%	1.4%

Notes. The sample contains the classes of 1997-2004.

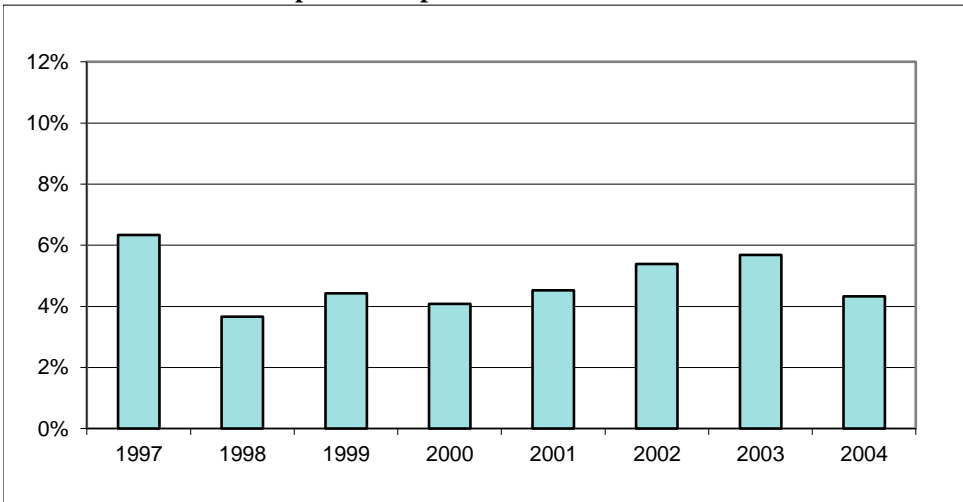
Figure 2. Variation in Entrepreneurial Activity

Panel A. Pre-MBA Entrepreneurship Across Sections



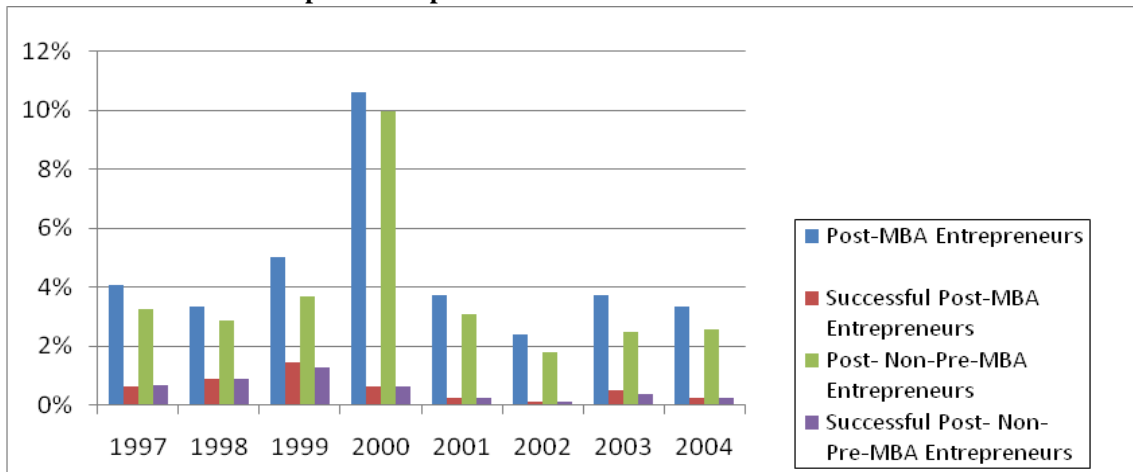
Notes. The left graph shows the histogram of the fraction of students (in percent) with entrepreneurship experience prior to entering the MBA program (relative to section size). The right graph shows the histogram of the number of entrepreneurs normalized by the number of class cards available for the section, divided by the average rate in the same year across sections. The sample contains 60 sections with 70 or more available class cards.

Panel B. Pre-MBA Entrepreneurship Over Time



Notes. The graph shows rates of students with entrepreneurship experience prior to entering the MBA program. The sample contains 60 sections with 70 or more available class cards.

Panel C. Post-MBA Entrepreneurship



Notes. The graph shows the rate of post-HBS entrepreneurship and the rate of successful post-HBS entrepreneurship for all graduates of the MBA program (two leftmost bars in each year) and the same two rates for students who were not entrepreneurs prior to entering the MBA program (two rightmost bars in each year).

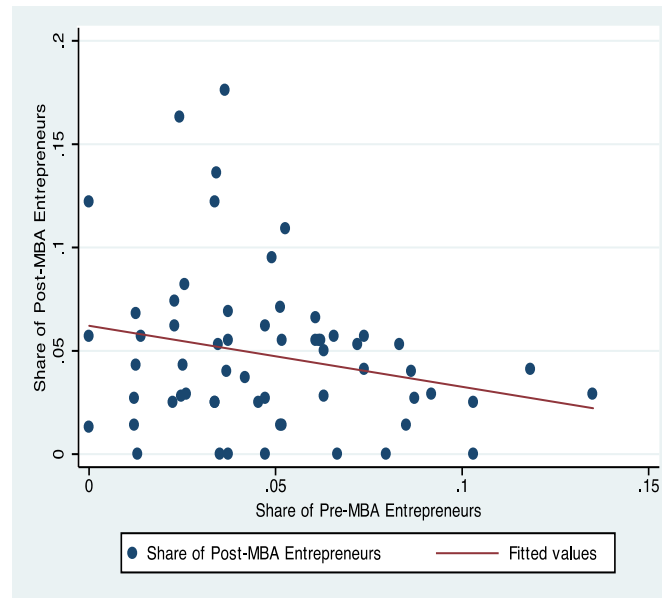
Table III. Predicting the Share of Pre-MBA Entrepreneurs

	Baseline	Alternative
Share that worked pre-MBA in consulting	-0.11 [0.08]	-0.11 [0.05]**
... in investment banking	0.02 [0.07]	
... in private equity	-0.17 [0.14]	
... in agricultural business	-0.59 [0.16]***	-0.54 [0.15]***
... in health care	0.39 [0.13]***	0.45 [0.11]***
... in hardware manufacturing		0.36 [0.16]**
Share that is male	0.19 [0.08]**	
... has US citizenship	-0.02 [0.07]	
... has children	-0.11 [0.12]	
... has a partner	0.07 [0.07]	
Share older than 30		0.25 [0.09]***
Average maximum risk score	0.08 [0.13]	
Share that attended an Ivy League college	-0.1 [0.12]	
Share that attended an Ivy Plus college	-0.04 [0.10]	
Share that majored in Engineering in college	-0.18 [0.07]**	
Year fixed effects	yes	yes
Observations	60	60
R-squared	0.46	0.47
F-test (excluding year effects)	4.10 (0.00, 13)	11.63 (0.00, 6)

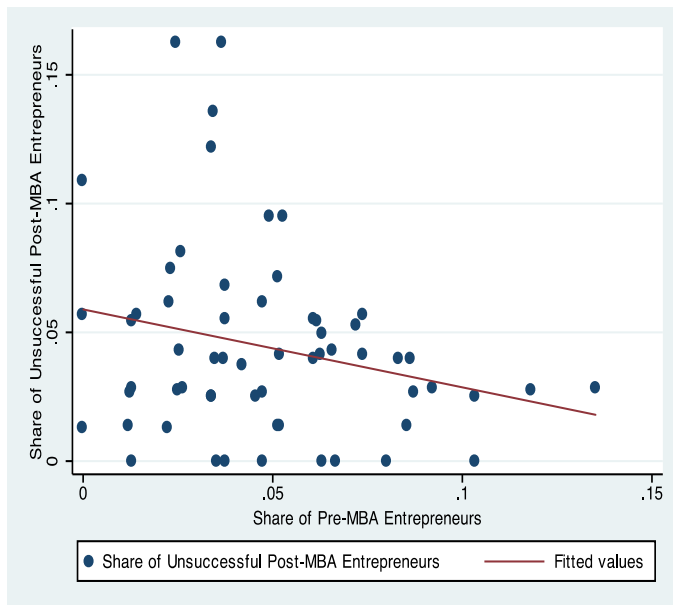
Notes. All section-level measures include pre-MBA entrepreneurs. The additional controls (and alternative sets of additional controls) are discussed in the text. We report the F -statistic for the joint significance of all control variables excluding year effects (and, in parentheses, the p -value and the number of constraints). Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Figure 3. Relationship between Pre- and Post-MBA Entrepreneurship

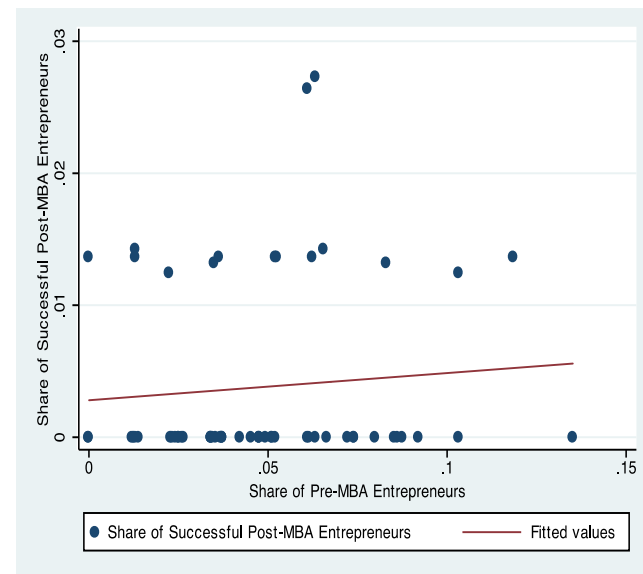
Panel A. All Post-MBA Entrepreneurs



Panel B. Unsuccessful Post-MBA Entrepreneurs



Panel C. Successful Post-MBA Entrepreneurs



Notes. In all three panels, the sample consists of all sections with at least 70 class cards.

Table IV. Correlation Coefficients

	<i>Share of post-MBA entrepreneurs</i>	<i>Share of unsuccessful post- MBA entrepreneurs</i>	<i>Share of successful post-MBA entrepreneurs</i>
Share of post-MBA entrepreneurs	1.00		
Share of successful post-MBA entrepreneurs	0.17 (0.20)		1.00
Share of unsuccessful post-MBA entrepreneurs	0.95 (0.00)	1.00	0.03 (0.82)
Share that worked pre-MBA			
... as an entrepreneur	-0.33 (0.01)	-0.24 (0.07)	0.12 (0.35)
... in consulting	-0.13 (0.33)	-0.14 (0.30)	-0.06 (0.63)
... in investment banking	-0.13 (0.32)	-0.11 (0.40)	-0.14 (0.30)
... in private equity	-0.08 (0.56)	-0.12 (0.37)	-0.02 (0.89)
... in agricultural business	0.33 (0.01)	0.35 (0.01)	0.06 (0.67)
... in health service	0.24 (0.07)	0.31 (0.02)	0.03 (0.80)
Share that is male	0.25 (0.06)	0.21 (0.11)	0.11 (0.43)
... has USA citizenship	-0.13 (0.33)	-0.22 (0.09)	-0.06 (0.64)
... has children	-0.04 (0.76)	-0.06 (0.65)	0.14 (0.27)
... has a partner	-0.04 (0.76)	-0.04 (0.75)	-0.26 (0.05)
Average maximum risk score	-0.06 (0.63)	-0.07 (0.60)	-0.25 (0.06)
Share that attended an Ivy League college	-0.21 (0.12)	-0.25 (0.06)	-0.06 (0.65)
Share that attended an Ivy Plus college	0.14 (0.28)	0.17 (0.18)	0.08 (0.52)
Share that majored in Engineering in college	0.04 (0.79)	0.05 (0.72)	-0.06 (0.65)
IPO proceeds in graduation year (\$ trillion)	0.57 (0.00)	0.56 (0.00)	0.20 (0.12)
Total venture funding in graduation year (\$ trillion)	0.70 (0.00)	0.69 (0.00)	0.21 (0.10)

Notes. The sample includes all sections with at least 70 class cards. All section-level measures (except the share that worked pre-MBA as an entrepreneur) exclude pre-MBA entrepreneurs. *P*-values in parentheses.

Table V. Determinants of Post-MBA Entrepreneurship

<i>Dependent Variable:</i>	Share of post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. estim. share of pre-and-post-MBA entrepr.		
Share of section with entrepreneurial background	-0.46 [0.13]***	-0.35 [0.11]***	-0.34 [0.12]***	-0.55 [0.12]***	-0.44 [0.11]***	-0.44 [0.12]***
Share of non-entrepreneurs with consulting background	-0.11 [0.11]	-0.06 [0.09]	-0.04 [0.10]	-0.03 [0.09]	-0.07 [0.07]	-0.05 [0.08]
... with investment banking background	-0.07 [0.10]	-0.19 [0.10]*	-0.19 [0.11]*	-0.06 [0.09]	-0.18 [0.09]**	-0.16 [0.09]*
... with private-equity background	0.30 [0.14]**	0.03 [0.16]	0.02 [0.16]	0.26 [0.11]**	0.01 [0.13]	0.01 [0.13]
... with agricultural-business background	-0.46 [0.25]*	-0.64 [0.30]**	-0.43 [0.62]	-0.45 [0.21]**	-0.63 [0.22]***	-0.54 [0.44]
... with health-care background	0.53 [0.28]*	0.58 [0.25]**	0.62 [0.28]**	0.51 [0.24]**	0.56 [0.20]***	0.60 [0.23]**
Share of non-entrepreneurs that are male	0.54 [0.12]***	0.84 [0.21]***	0.90 [0.22]***	0.49 [0.11]***	0.79 [0.17]***	0.85 [0.18]***
... that are U.S. citizens	0.05 [0.07]	0.19 [0.11]*	0.23 [0.12]*	0.08 [0.06]	0.19 [0.08]**	0.22 [0.09]**
... with children	0.03 [0.16]	0.22 [0.17]	0.19 [0.17]	0.05 [0.14]	0.21 [0.13]	0.18 [0.14]
... with a partner	-0.11 [0.06]*	-0.19 [0.08]**	-0.19 [0.08]**	-0.17 [0.05]***	-0.22 [0.06]***	-0.23 [0.07]***
Share of non-entrepreneurs that attended an Ivy League college	0.09 [0.14]	0.22 [0.14]	0.19 [0.17]	0.06 [0.12]	0.18 [0.12]	0.13 [0.14]
... that attended an Ivy Plus college	-0.01 [0.12]	-0.09 [0.12]	-0.07 [0.14]	-0.02 [0.10]	-0.13 [0.09]	-0.10 [0.11]
... that majored in engineering in college	0.08 [0.08]	-0.03 [0.10]	-0.02 [0.10]	0.10 [0.07]	0.00 [0.08]	0.00 [0.08]
Mean maximum risk score of section	-0.22 [0.14]	-0.28 [0.15]*	-0.25 [0.16]	-0.17 [0.12]	-0.22 [0.11]*	-0.20 [0.12]*
Total IPO proceeds in graduation year (\$ trillions)	-1.52 [0.50]***			-1.51 [0.42]***		
Total venture financing in graduation year	1.35 [0.27]***			1.26 [0.22]***		
Year dummies		X	X		X	X
Selected interactions of stratification variables			X			X
Regression type	Tobit	OLS	OLS	Tobit	OLS	OLS
Observations	60	60	60	60	60	60
R-squared		0.75	0.76		0.83	0.83

Notes. The sample consists of all sections with at least 70 available class cards. All section-level measures (except for pre-MBA entrepreneurs) exclude pre-MBA entrepreneurs. The selected set of stratification variables included as interactions contains the share of section that is male, that are U.S. citizens, with a partner, and with investment banking background. Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table VI. Determinants of Unsuccessful versus Successful Post-MBA Entrepreneurship

Panel A. Unsuccessful Entrepreneurship

<i>Dependent Variable:</i>	Share of <i>unsuccessful</i> post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. est. share of pre-and-post-MBA entrepr.		
Share of section with entrepreneurial background	-0.46 [0.14]***	-0.36 [0.11]***	-0.36 [0.11]***	-0.58 [0.13]***	-0.43 [0.10]***	-0.43 [0.11]***
Controls for other professional backgrounds of non-entrepreneurs	X	X	X	X	X	X
Controls for demographic characteristics and education of non-entrepreneurs	X	X	X	X	X	X
Controls for total IPO proceeds and total venture financing in graduation year	X			X		
Year dummies		X	X		X	X
Selected interactions of stratification variables			X			X
Regression type	Tobit	OLS	OLS	Tobit	OLS	OLS
Observations	60	60	60	60	60	60
R-squared		0.75	0.76		0.84	0.85

Panel B. Successful Entrepreneurship

<i>Dependent Variable:</i>	Share of <i>successful</i> post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. est. share of pre-and-post-MBA entrepr.		
Share of section with entrepreneurial background	0.11 [0.10]	0.03 [0.03]	0.04 [0.04]	0.12 [0.10]	0.03 [0.03]	0.04 [0.03]
Controls for other professional backgrounds of non-entrepreneurs	X	X	X	X	X	X
Controls for demographic characteristics and education of non-entrepreneurs	X	X	X	X	X	X
Controls for total IPO proceeds and total venture financing in graduation year	X			X		
Year dummies		X	X		X	X
Selected interactions of stratification variables			X			X
Regression type	Tobit	OLS	OLS	Tobit	OLS	OLS
Observations	60	60	60	60	60	60
R-squared		0.30	0.40		0.38	0.47

Panel C. Test of Differences

	Share of post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. estim. share of pre-and-post-MBA entrepr.		
p-Value, test of difference in successful and unsuccessful regressions:						
Share of section with entrepreneurial background	0.000	0.000	0.000	0.000	0.000	0.000
Joint test of all variables	0.000	0.000	0.000	0.000	0.000	0.000

Notes. The sample consists of all sections with at least 70 class cards. Controls for other professional backgrounds of non-entrepreneurs and Controls for demographic characteristics and education of non-entrepreneurs include all control variables shown in Table V. The selected set of stratification variables included as interactions contains the share of section that is male, that are U.S. citizens, with a partner, and with investment banking background. Robust standard errors are in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table VII. Alternative Success Measures and Alternative Outcome (Elective Courses)

<i>Dependent Variable:</i>	Share of post-MBA entrepreneurs (net of identified pre-and-post-MBA entrepreneurs) who were ...				Enrollment in entrepreneurship classes by non-pre-MBA entrepreneurs
	<i>not "very successful"</i>	<i>"very successful"</i>	<i>not "super-successful"</i>	<i>"super-successful"</i>	
	(1)	(2)	(3)	(4)	(5)
Share of section with entrepreneurial background	-0.37 [0.13]***	0.04 [0.03]	-0.36 [0.12]***	0.03 [0.02]*	0.02 [0.08]
Share of non-entrepreneurs ...					
... with consulting background	-0.07 [0.11]	-0.01 [0.03]	-0.06 [0.11]	0.00 [0.01]	0.10 [0.09]
... with investment-banking background	-0.19 [0.13]	0 [0.03]	-0.20 [0.13]	0.00 [0.02]	-0.09 [0.08]
... with private-equity background	0.04 [0.17]	0.02 [0.04]	0.03 [0.17]	0.01 [0.02]	-0.04 [0.10]
... with agricultural-business background	-0.63 [0.29]**	0.09 [0.07]	-0.67 [0.28]**	0.05 [0.03]	-0.32 [0.21]
... with health care background	0.62 [0.28]**	-0.09 [0.07]	0.61 [0.28]**	-0.05 [0.03]	-0.18 [0.20]
Share of non-entrepreneurs that are male	0.84 [0.24]***	-0.04 [0.06]	0.85 [0.24]***	-0.02 [0.03]	-0.27 [0.15]*
... that are U.S. citizens	0.24 [0.14]*	-0.06 [0.03]*	0.22 [0.13]	-0.03 [0.02]*	-0.12 [0.09]
... with children	0.15 [0.17]	0.06 [0.04]	0.19 [0.16]	0.03 [0.02]	0.11 [0.11]
... with a partner	-0.16 [0.07]**	-0.02 [0.02]	-0.18 [0.07]**	-0.02 [0.01]**	-0.06 [0.05]
... that attended an Ivy League college	0.32 [0.17]*	-0.1 [0.04]**	0.26 [0.16]	-0.04 [0.02]*	0.12 [0.15]
... that attended an Ivy Plus college	-0.15 [0.12]	0.06 [0.03]*	-0.11 [0.12]	0.01 [0.01]	-0.08 [0.07]
... with major in engineering in college	-0.04 [0.10]	0.03 [0.03]	-0.03 [0.10]	0.01 [0.01]	0.01 [0.08]
Mean maximum risk score of section	-0.31 [0.16]*	0.05 [0.04]	-0.29 [0.16]*	0.02 [0.02]	0.13 [0.10]
Year dummies		X	X	X	X
Regression type	OLS	OLS	OLS	OLS	OLS
Observations	60	60	60	60	60
R-squared	0.73	0.43	0.75	0.44	0.88

Notes. OLS regressions on the sample of all sections with at least 70 class cards. All section-level measures (except the share with entrepreneurial background) do not include pre-MBA entrepreneurs. Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table VIII. Effects of Successful and Unsuccessful Pre-MBA Entrepreneurship

Panel A. Effects on Unsuccessful Post-MBA Entrepreneurship

<i>Dependent Variable:</i>	Share of <i>unsuccessful</i> post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. est. share of pre-and-post-MBA entrepr.		
Share of section with successful entrepreneurial background	-0.32 [0.29]	-0.39 [0.26]	-0.39 [0.30]	-0.48 [0.21]**	-0.43 [0.18]**	-0.46 [0.21]**
Share of section with unsuccessful entrepreneurial background	-0.61 [0.22]***	-0.33 [0.20]	-0.35 [0.21]	-0.66 [0.21]***	-0.43 [0.19]**	-0.42 [0.18]**
Controls for other professional backgrounds of non-entrepreneurs	X	X	X	X	X	X
Controls for demographic characteristics and education of non-entrepreneurs	X	X	X	X	X	X
Controls for total IPO proceeds and total venture financing in graduation year	X			X		
Year dummies		X	X		X	X
Selected interactions of stratification variables			X			X
Regression type	Tobit	OLS	OLS	Tobit	OLS	OLS
Observations	60	60	60	60	60	60
R-squared		0.75	0.76		0.84	0.85
F-statistic, test of successful and unsuccessful entrepreneurs	0.29	0.29	0.02	0.20	0.20	0.04
P-value	[0.59]	[0.59]	[0.89]	[0.65]	[0.65]	[0.84]

Panel B. Effects on Successful Post-MBA Entrepreneurship

<i>Dependent Variable:</i>	Share of <i>successful</i> post-MBA entrepreneurs net of ...					
	identified share of pre-and-post-MBA entrepr.			av. est. share of pre-and-post-MBA entrepr.		
Share of section with successful entrepreneurial background	0.37 [0.20]*	0.08 [0.07]	0.06 [0.05]	0.32 [0.18]*	0.07 [0.06]	0.04 [0.05]
Share of section with unsuccessful entrepreneurial background	-0.04 [0.22]	-0.01 [0.06]	-0.01 [0.06]	0.02 [0.19]	0.00 [0.06]	0.01 [0.06]
Controls for other professional backgrounds of non-entrepreneurs	X	X	X	X	X	X
Controls for demographic characteristics and education of non-entrepreneurs	X	X	X	X	X	X
Controls for total IPO proceeds and total venture financing in graduation year	X			X		
Year dummies		X	X		X	X
Selected interactions of stratification variables			X			X
Regression type	Tobit	OLS	OLS	Tobit	OLS	OLS
Observations	60	60	60	60	60	60
R-squared		0.32	0.40		0.38	0.47
F-statistic, test of successful and unsuccessful entrepreneurs	1.93	0.68	0.48	1.66	0.34	0.13
P-value	[0.17]	[0.41]	[0.49]	[0.20]	[0.56]	[0.72]

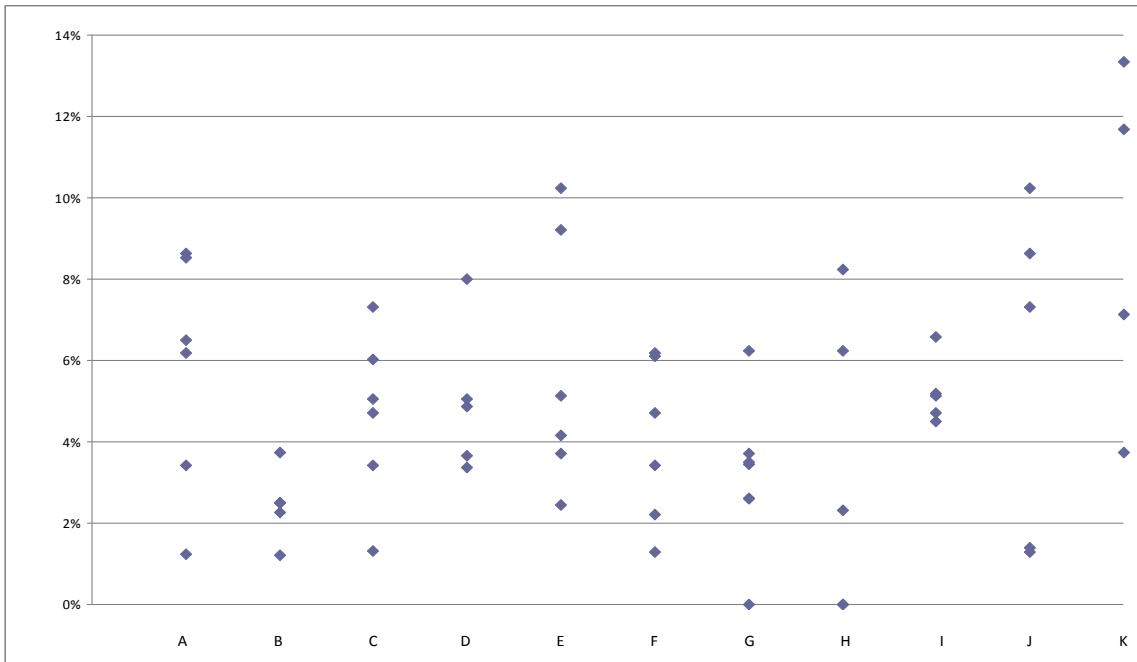
Notes. All section-level measures (except the share with pre-MBA entrepreneurs) do not include pre-MBA entrepreneurs. The sample consists of all sections with at least 70 class cards. The regressions contain all controls used in Tables V and VII. The selected set of interactions of stratification variables include share of section that is male, are U.S. citizens, with consulting background, with investment banking background, with private equity background, and that attended an Ivy Plus college. The F-test reports a test of the null hypothesis that the coefficients on the two entrepreneurial background variables are the same. Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

Table IX. Variance in Post-MBA Entrepreneurship Rates

	<i>For sections with below median number of students with entrepreneurial background</i>	<i>For sections with above median number of students with entrepreneurial background</i>	<i>p-Value, test of null hypothesis of no difference</i>
Standard Deviation of Entrepreneurship Rate			
Total Post-MBA Entrepreneurship	5.30%	4.16%	0.007
Successful Post-MBA Entrepreneurship	0.24%	0.55%	0.010
Unsuccessful MBA Entrepreneurship	5.05%	3.66%	0.005

Notes. The sample consists of all sections with at least 70 available class cards.

Appendix Figure 1. Variation in Entrepreneurial Activity



Notes. The graph plots each section-year observation of the rate of pre-MBA entrepreneurs, ordered by section (A to K). The sample contains the 60 sections with at least 70 available class cards.

Appendix Table A1. Stratification Checks:
Comparing sections with high- and low shares of pre-MBA entrepreneurs

	Full Sample	# of pre-MBA Entrepreneurs		p-values
		below median	above median	
Share that ever worked as an entrepreneur	5.0% (3.4%)	2.4% (1.6%)	7.8% (2.6%)	[0.00]***
Share of non-entrepreneurs that worked most recently				
... in computer hardware	1.4% (1.5%)	1.4% (1.5%)	1.4% (1.5%)	[0.98]
... in computer software	3.7% (2.9%)	3.7% (3.1%)	3.5% (2.6%)	[0.81]
... in computer-related services	2.3% (2.3%)	2.3% (2.4%)	2.1% (2.1%)	[0.58]
... in other high-tech sectors	1.1% (1.4%)	1.3% (1.6%)	0.8% (1.0%)	[0.07]*
... in telecommunications	3.2% (2.2%)	3.5% (2.1%)	3.0% (2.3%)	[0.24]
... in diversified manufacturing	1.4% (1.4%)	1.2% (0.5%)	1.6% (1.6%)	[0.15]
... in banking	15.4% (5.6%)	15.3% (0.3%)	15.5% (6.5%)	[0.86]
... in financial services	6.1% (2.9%)	5.5% (2.7%)	6.7% (3.0%)	[0.06]*
... in consulting	18.7% (4.6%)	18.7% (3.8%)	18.6% (5.2%)	[0.94]
... in venture capital/private equity	8.0% (4.7%)	8.5% (4.4%)	7.5% (5.0%)	[0.35]
... in military	3.3% (2.3%)	3.4% (1.9%)	3.2% (2.7%)	[0.72]
... in non-profit organizations	4.3% (2.6%)	4.0% (2.6%)	4.5% (2.7%)	[0.41]
... in accounting	1.1% (1.6%)	0.8% (1.4%)	1.4% (1.8%)	[0.08]*
... in law	0.9% (1.4%)	0.8% (1.2%)	1.0% (1.5%)	[0.61]
... in retail	4.0% (2.7%)	4.3% (2.9%)	3.6% (2.4%)	[0.15]
... in advertising/marketing	2.1% (2.3%)	2.4% (2.2%)	1.8% (2.2%)	[0.16]
... in entertainment	3.8% (2.3%)	4.3% (2.0%)	3.2% (2.4%)	[0.02]**
... in agricultural business	2.4% (1.8%)	2.7% (2.0%)	2.0% (1.6%)	[0.09]*
... in health services	3.2% (2.3%)	2.8% (1.8%)	3.7% (2.6%)	[0.06]*
... in other industries	1.4% (1.5%)	1.4% (1.5%)	1.3% (1.5%)	[0.57]

Appendix-Table A1 (continued)

	Full Sample	# of pre-MBA Entrepreneurs		p-values
		below median	above median	
Share that attended an Ivy League college	24.0% (5.3%)	25.2% (5.0%)	22.7% (5.3%)	[0.02]**
... an Ivy Plus League college	32.3% (6.3%)	35.7% (5.7%)	32.7% (6.6%)	[0.02]**
Share that is male	69.4% (7.1%)	69.6% (7.3%)	69.2% (6.9%)	[0.82]
... has a partner	41.2% (7.3%)	41.8% (6.6%)	40.6% (8.1%)	[0.42]
... has a male partner	31.8% (5.7%)	32.7% (4.8%)	30.7% (6.5%)	[0.10]*
... has a female partner	9.2% (4.6%)	8.7% (4.3%)	9.6% (4.8%)	[0.44]
Share with business major at college	23.8% (5.8%)	23.5% (5.9%)	24.1% (5.6%)	[0.61]
... with economics major at college	22.7% (5.9%)	22.4% (6.5%)	22.9% (5.1%)	[0.73]
... with engineering major at college	16.6% (4.7%)	17.4% (4.0%)	15.8% (5.5%)	[0.13]
... with computer science major at college	6.0% (3.1%)	5.8% (3.2%)	6.1% (3.0%)	[0.67]
... with mathematics major at college	2.3% (2.0%)	2.1% (1.9%)	2.4% (2.0%)	[0.59]
... with natural science major at college	4.1% (3.0%)	3.9% (2.0%)	4.1% (3.7%)	[0.83]
... with law major at college	0.7% (0.9%)	0.8% (0.9%)	0.6% (0.9%)	[0.52]
... with medical science major at college	0.3% (0.7%)	0.2% (0.6%)	0.4% (0.8%)	[0.29]
... with humanity major at college	4.8% (3.1%)	4.4% (2.8%)	5.1% (3.3%)	[0.32]
... with history major at college	3.6% (2.6%)	4.2% (2.8%)	2.9% (2.2%)	[0.01]**
... with journalism major at college	0.4% (0.8%)	0.4% (0.7%)	0.4% (0.8%)	[0.76]
... with architecture major at college	0.3% (0.9%)	0.1% (0.3%)	0.5% (1.2%)	[0.09]*
... with political science major at college	7.9% (3.8%)	7.4% (3.9%)	8.4% (3.6%)	[0.24]
... with anthropology major at college	4.9% (3.0%)	5.4% (3.0%)	4.3% (2.9%)	[0.06]*
Share that has US citizenship	66.9% (6.7%)	67.4% (6.6%)	66.3% (6.9%)	[0.45]
Share of Caucasians	43.2% (12.2%)	43.7% (12.6%)	42.7% (12.0%)	[0.72]
... of Asians	5.8% (2.9%)	5.7% (2.8%)	5.9% (3.1%)	[0.81]
... of Hispanics	1.8% (1.6%)	1.9% (1.6%)	1.6% (1.5%)	[0.32]
... of other races	3.9% (2.8%)	3.8% (2.6%)	4.1% (3.1%)	[0.69]

Appendix-Table A1 (continued)

	Full Sample	# of pre-MBA Entrepreneurs		p-values
		below median	above median	
Share with age less than 22	0.7% (1.1%)	0.8% (1.1%)	0.7% (1.1%)	[0.64]
... with age 23-25	56.3% (8.7%)	57.3% (8.0%)	55.3% (9.3%)	[0.28]
... with age 26-29	36.9% (7.8%)	36.5% (7.9%)	37.5% (7.8%)	[0.55]
... with age 30 and higher	5.8% (3.6%)	5.2% (3.0%)	6.4% (4.0%)	[0.11]
Share who have ever had a function in general mgmt	15.6% (4.6%)	15.8% (5.0%)	15.4% (4.3%)	[0.67]
... in business consulting	18.6% (5.0%)	18.9% (4.0%)	18.3% (6.0%)	[0.61]
... in strategic planning	4.2% (2.7%)	4.8% (2.5%)	3.7% (2.7%)	[0.05]*
... in corporate finance	28.2% (6.3%)	28.7% (6.0%)	27.8% (6.6%)	[0.50]
... in marketing	9.4% (4.1%)	9.3% (4.0%)	9.4% (4.3%)	[0.89]
... in logistics	8.5% (3.4%)	8.4% (3.0%)	8.5% (3.8%)	[0.87]
... in accounting	1.4% (1.7%)	1.1% (1.3%)	1.8% (2.1%)	[0.05]*
... in assorted other areas	0.5% (0.8%)	0.4% (0.7%)	0.5% (0.9%)	[0.43]
... in engineering	3.2% (2.3%)	3.2% (2.4%)	3.2% (2.1%)	[0.90]
... in fund-raising	0.1% (0.5%)	0.1% (0.4%)	0.1% (0.5%)	[0.85]
... in human resources	0.3% (0.7%)	0.4% (0.8%)	0.2% (0.4%)	[0.05]**
... in legal services	0.9% (1.5%)	0.8% (1.3%)	1.0% (1.8%)	[0.66]
... in medical services	0.5% (0.8%)	0.3% (0.6%)	0.7% (0.9%)	[0.03]**
... in consulting	22.9% (5.3%)	22.7% (5.4%)	23.1% (5.3%)	[0.72]
... in investment banking	19.3% (5.7%)	19.0% (4.8%)	19.6% (6.6%)	[0.62]
... in private equity	4.7% (3.0%)	5.1% (2.9%)	4.0% (3.0%)	[0.12]
... in other sectors	5.6% (3.1%)	5.3% (2.9%)	5.9% (3.3%)	[0.36]
Average maximum risk score	38.4% (3.2%)	38.6% (2.6%)	38.2% (3.8%)	[0.63]

Notes. The tables shows mean percentages (and standard deviations in parentheses). The sample consists of the 60 sections with at least 70 class cards. The last column shows heteroskedasticity-robust p-values for the test of no difference in means between the subsamples with a below-median and an above-median number of entrepreneurs. All section-level comparisons exclude pre-MBA entrepreneurs except for the first row. * significant at 10%; ** significant at 5%; *** significant at 1%