With a Little Help from My (Random) Friends:

Success and Failure in Post-Business School Entrepreneurship[*,**]

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How do individuals decide to become entrepreneurs and learn to make optimal entrepreneurial decisions? The concentration of entrepreneurs in regions such as Silicon Valley has stimulated research and policy interest into the influence of peers, but the causal effect is hard to identify empirically. We exploit the exogenous assignment of students into business-school sections to identify the causal effect of entrepreneurial peers. We show that, in contrast to prior findings, a higher share of entrepreneurial peers decreases, rather than increases, entrepreneurship. The decrease is driven by a reduction in unsuccessful entrepreneurial ventures; the effect on successful ventures is significantly more positive.

Introduction

The promotion of entrepreneurship has been a major focus of policymakers in recent years (see Kanniainen 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. Reflecting this interest, the returns to entrepreneurial ventures have become a topic of increasing scrutiny in financial economics, including research on the expected returns of investors in initial public offerings (Ritter [1991]; Brav and Gompers [1997]), venture capital and private equity funds (Kaplan and Schoar [2005]; Phalippou and Gottschalg [2009]; Korteweg and Sorensen [2010]), and angel investors (Kerr, et al [forthcoming]).

What are, then, the determinants of entrepreneurial returns? The concentration of entrepreneurs in regions such as Silicon Valley has triggered speculation that the interaction of high-skilled individuals with similar interests lead to powerful peer effects among entrepreneurs. For instance, individuals who work at recently formed, venture-backed firms are particularly likely to become entrepreneurs (Gompers, et al. [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, consistent with findings on peer effects in other arenas of finance such as the interaction among stock analysts and mutual fund managers (Cohen, et

al. [2008, 2010]). However, the inability of these studies to fully control for unobserved heterogeneity or sorting of individuals into firms and locations means that our interpretation of the results must be cautious.

A second issue with prior findings on the determinants of entrepreneurship, and on peer effects in particular, is its failure to distinguish between successful and unsuccessful entrepreneurial ventures. Calculations using both individual and aggregate data suggest that returns to entrepreneurship may be quite poor (Hamilton [2000]; Moskowitz and Vissing-Jorgensen [2002]; Hall and Woodward [2010]). An emerging literature on "behavioral entrepreneurship" finds that individuals tend to pursue new ventures even if the expected returns are predictably meager (Camerer and Lovallo [1990]; de Meza and Southey [1996]; Arabsheibani, et al. [2000]; Landier and Thesmar [2009]). Such self-selection of overconfident individuals into entrepreneurship may benefit society (Bernardo and Welch [2001]), but the high failure rates of entrepreneurial ventures (see, for instance, Davis, et al. [1998]) raise caution.[2] 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 ventures and make methodological progress in identifying peer effects in entrepreneurship. We exploit the exogenous assignment of 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

[2] 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 an entrepreneur—grow less, die sooner, and are less profitable, despite the fact that these owners tend to put in more effort.

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 likely be seen. We exploit the fact that the representation of students with entrepreneurial backgrounds varies considerably across sections: We analyze the effect of students with prior entrepreneurial experience on the rate of post-MBA entrepreneurship among their sectionmates (without such prior experience). 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. Our novel data set combines 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 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 an entrepreneurial background (evaluated at the mean of all independent variables) reduces the predicted share of the other students going into entrepreneurship 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 effect on successful post-MBA entrepreneurs is indistinguishable from zero, and significantly more positive than the effect on unsuccessful entrepreneurs.

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. Such intra-section learning may occur through several possible channels. First, students with entrepreneurial backgrounds may provide direct counsel to their peers and help identifying which business ideas are worth pursuing (selection of business ideas), or which students are able to run a business successfully (selection of individuals with business skills).[3] 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 elective entrepreneurship classes. We find no effect of the presence on entrepreneurial peers on enrollment in such classes, ruling out the third explanation. (This finding also casts doubt on the second explanation, since a more general discouragement would suggest lower 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 under the second channel. Since the success rate among prior entrepreneurs at HBS is unusually high (42%), our data provides the necessary variation. We do not find any such correlation. Hence, while the lack of micro-data on individual student-level interactions

[3] Entrepreneurial peers might also introduce section-mates with promising ideas to venture capitalists or other sources of financing.

limits our ability to test the causal role of direct student interaction, 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 more 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.

Our analysis fills several gaps in the literature on the determinants of and returns to entrepreneurship. In addition to the above-mentioned appeal of the exogenous assignment and the availability of success measures, our setting overcomes some of the data limitations of the primary sources used in previous entrepreneurship research, such as Census data, Internal Revenue Service data, and the Panel Study of Entrepreneurial Dynamics. As highlighted by Parker [2004], those data capture a specific type of entrepreneurial activity, typically 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 carefully trace the entrepreneurial histories of students who start a company.

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 us-

ing 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 $3.2 billion in August 2012) and SupplierMarket (acquired by Ariba for $581 million). In other words, this paper analyzes a particular and talented subset of the overall population, in contrast to 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. Our results suggest that, in this sample, much of the benefit from exposure to entrepreneurship does not to come from encouragement of more entrepreneurship but from help in weeding out ventures that are likely to fail.

I. 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 of students with prior entrepreneurial experience, which allows us to distinguish between students who 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 ven-

tures.

I.A. Challenges in Identifying Peer Effects

The identification of peer effects is a major challenge in economics. In the context of entrepreneurship, earlier papers measure peer effects by 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 where to work or otherwise interact with their peers, it is difficult to separate selection from peer effects. In fact, several studies in the economics show that peer effects found in settings with endogenous sorting disappear once the analysis is redone exploiting exogenous assignment, regardless of how extensively observables were controlled for in the settings *with* endogenous sorting.[4] In this paper, we move beyond the limitations of endogenous sorting by exploiting exogenous variation in the exposure to entrepreneurial peers.

Another confounding issue in the literature on peer effects is the distinction between the effect of one peer on others and common shocks affecting the entire peer group.[5] 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 versus the individual's own prior inclinations. In the context of entrepreneurship, the question is wheth-

[4] 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 samples of randomly assigned and self-selected roommates. Duflo and Saez [2002] analyze the influence of co-workers on the decision to invest in a retirement account in a setting with endogenous sorting. When they re-analyze the effect in a randomized experiment (Duflo and Saez [2003]), they find significantly smaller (if any) peer effects.

[5] In the context of school outcomes, Sacerdote [2001] finds a significant correlation in the GPAs of randomly assigned college roommates but little evidence that roommates' pre-college academic background (SAT scores and high-school performance) matter. Hence, common shocks due to dorm room characteristics, infections, or joint class choices might explain part of the results (Kremer and Levy [2008]).

er one can distinguish between the influence of entrepreneurial peers versus an individual's own predisposition to become an entrepreneur, as well as interaction effects. To illustrate the identification problem, suppose we would like to identify the effect of how "entrepreneurial" the average peer is, separately from the effect of how "entrepreneurial" an individual herself is, on the individual's decision to become an entrepreneur. A simple individual-level regression model can be written as follows:

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

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 allows for a different peer effect on individuals who are entrepreneurial themselves versus those who are not. Summing the individual-level data by group (j) and dividing by group size, we obtain the group-level regression model:

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

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

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 entrepreneurial influence of peers (β) and an individual's own en-

trepreneurial disposition (γ). Instead, we are measuring the combined effect (β + γ). In addition, the interactive effect $\overline{X}_j \overline{X}_{j-1}$ complicates the estimation.

Our empirical approach avoids this confound since we identify individuals who are likely to exert entrepreneurial peer influence ex ante, using prior entrepreneurial experience as a proxy. At the same time, we exclude pre-MBA entrepreneurs from the outcome variable. In such a reduced sample, the individual-level regression (1) becomes:

$$Y_{i_0,j} = \alpha + \beta \overline{X}_{-i_0,j} + other\ effects \tag{4}$$

where i_0 indicates an individual student in peer group j who has no prior entrepreneurial experience, $i_0 \in \{i \mid X_{i,j} = 0\}$. Here, the peer effect $\overline{X}_{-i_0,j}$ is the share of pre-MBA entrepreneurs in group j excluding student i_0. Since none of the students in the reduced sample has prior entrepreneurial experience, $\overline{X}_{-i_0,j}$ is identical for all i_0 and amounts to the fraction of pre-MBA entrepreneurs relative to the size of section j minus 1:

$$\overline{X}_{-i_0,j} = \sum_i X_{i,j} / (N_j + M_j - 1) = N_j / (N_j + M_j - 1) \equiv \overline{X}_{-1,j}\,.$$

Finally, the third term and the fourth (interaction) term of equation (1) disappear in (4) since $X_{i_0,j}$ = 0 for all i_0. Summing 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:

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

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

I.B. Sections at Harvard Business School

We also exploit Harvard Business School's long-established section system to address the above-mentioned identification challenges. MBA students spend their entire first year in a set group of 80 to 95 students in a single classroom, taking a fixed slate of classes (e.g., accounting, finance, and marketing). 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. The social ties established in the first year appear to remain extremely strong, even after graduation. For instance, at the 25th alumni reunions, 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, which we report in more detail in the Appendix.

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. In the contests between 1998 and 2004, 33% of student teams consisted of section-mates, even though students were free to choose partners across their entire class.[6] Were the selection of partners random across sections, the expected share of section-mates would be 9% for 1998 to 2003 and 10% for 2004.

[6] 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. There were 277 student teams consisting of 566 pairs of second-year students, and 185 of those pairs, or 33%, consisted of section-mates.

A second reason why the HBS section environment is a promising path to explore entrepreneurial peer effects is the professional experience of the students. Unlike other professional schools, HBS students have considerable work experience, between three and five years for the typical student in the classes under study.[7] Moreover, there is considerable diversity of backgrounds, in particular in terms of entrepreneurial experience, which allows us to exploit the differences across sections empirically.

I.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 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): gender; ethnicity; 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; quantitative and verbal skills, in particular, whether the student's admission was conditional on a re-

[7] http://www.hbs.edu/about/mba.html (accessed September 16, 2011) and unpublished tabulations.

medial 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; home region (distinguishes ten US regions, most major European countries, Japan, China, India, and everywhere else); industry in which the student worked in his or her most recent job (e.g., consulting, finance, telecommunications, etc.); age; whether the student attended one of the major "feeder" colleges (Harvard, Yale, West Point, etc.); function in the student's last job (e.g., sales or finance, etc., but there is no function for entrepreneurs); marital status; college major; whether the student worked for one of 49 major companies in their last job.[8] Once a section fills up, the assignments are only made to the remaining sections. Finally, the registrar staff "hand-adjust" these assignments to correct for two considerations: One is 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. The other is 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 that 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 es-

[8] 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." 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.

timation 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.

Most importantly, the administrators do not identify and balance out students who were entrepreneurs prior to HBS. Instead of the detailed textual analysis we undertake (see below), their assignment software uses only the subset of the class card information that can be readily sorted by the computer. Commonly, entrepreneurs are classified as "general management," but this function is very broad and includes a wide range of other backgrounds.[9] Overall, 52.5% of the students with an entrepreneurial experience and 15.2% of all other students are classified as general management. 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 10^{th} percentile to 10% at the 90^{th} percentile, which allows us to gain empirical identification.

The broad definition of the "general management" function also ensures that the number of entrepreneurs in a section is not negatively correlated with other types of "general management" experience. 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

[9] Examples include leadership positions at non-profits (e.g., an associate at a foundation), at for-profit organizations (e.g., the program director at a sports training academy, the general manager of a number of restaurants, or the senior manager of new business development at a heath-care firm), and in the military, e.g., junior officers.

general management background (and year dummies). We find that the relationship is statistically insignificant (with a *t*-statistic of -0.35) and economically negligible (with a coefficient of -0.04). Nevertheless, as an added control, we include "share of students without an entrepreneurial background who worked in a general management function" in all the regression analyses below.

II. The Data

Our analysis draws on four primary sets of data. First, we collect data on the characteristics of students from their class cards. Class cards are initially filled in by school administrators based on students' applications.[10] Students can update their class cards while enrolled at HBS. We obtain the class cards for 6,129 students graduating between 1997 and 2004. 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. We extract information on gender, nationality (in particular, sole or joint U.S. citizenship), age, family status, work experience, and educational background. 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.[11] For family status, we use whether they had a partner, as well as whether they indicated children among their interests or other descriptive material. For work ex-

[10] The fact that the class card information is drawn from applications alleviates concerns that students exaggerate their accomplishments. 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: 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]).

[11] 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.

perience, we use the industry students had worked in after college.[12] For educational background, we use college and college major. We classify whether their primary degrees are from an Ivy League school or, alternatively, an "Ivy Plus" school.[13]

Going beyond the 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].[14] 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 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

[12] We use a sixty-industry scheme of the hiring and compensation database at HBS Career Services. Students who worked in multiple industries are coded as having participated in all of them. The results are robust to assigning each student to a single field—the one in which he or she spent the most time or, if the student worked an equal amount of time in two fields, the area in which he or she worked most recently.

[13] Ivy Plus is an association of administrators of leading schools, which includes the Ivy League schools plus CalTech, University of Chicago, Duke, MIT, Stanford, 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.

[14] 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 are too vague (for instance, "athletics" or "all sports").

mean plus two standard deviations (0.58). Again, the results are little different.

Finally, we use the class cards to construct the key variable for our analysis: prior entrepreneurial experience. We identify students who (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.[15] 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.
- 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

[15] 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.

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 spill-overs 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.[16] Unlike the identification of the pre-MBA entrepreneurs, which is entirely based on official class card records, or the identification of post-business success, where we have multiple, highly consistent information sources, our identification here is only approximate. In addition to the class cards, we use social networking sites such as Facebook and LinkedIn, and direct contacts with the students. In total, we classify 42% of the businesses as successful, 19% as unsuccessful, and the remainder as unknown.

A success rate of 42% is unusually high compared to broader samples of entrepreneurs. Apparently, pre-MBA 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 this selection of entrepreneurs, we conducted interviews with MBAs who had been entrepreneurs prior to business school. They all emphasized their need for skill development and the intention to go onto new and larger ventures. Many had been technically trained prior to business school and highlighted that their lack of business training or insights into marketing, finance, etc. had become increasingly problematic as their businesses grew and they interacted with individual angel investors and venture capitalists. The other main motivation mentioned was

[16] 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.

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 was posed by the failure of HBS to archive class cards prior to 2000. We obtained cards for the years 1997 to 1999 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 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 that class. As a result, the completeness of our information 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 (all or almost all class cards), the cards are 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. To prevent such selection biasing our result, the main analyses in the paper only employ sections where we have been able to gather at least seventy class cards. We undertake supplemental analyses with all sections, with a less restrictive, and with a more restrictive sub-sample (sections with at least 40, 75, or 80 class cards).[17]

[17] 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

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 class size remained approximately constant, around 900 across all sections, but 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 the average section size shrank in conjunction with an added experimental accelerated MBA program, to 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 provided annually in the initial and in all financing rounds of new firms. 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]).

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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.

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. 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, 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 with at least seventy class cards. In terms of control variables, the data reveals the heavy representation of students in investment banking and consulting.[18] We also single out the share of students 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 children and graduates of elite schools. The differences between the 10^{th} and 90^{th} percentiles narrow 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. The average is around 5%, though the 10^{th}-90^{th} percentile range is quite large, between 0 and 10 percent. The scatter plot in Appendix Figure 1 shows the full range of variation by plotting the year-section data points, ordered by section.

To distinguish time-series from cross-sectional variation, we graph the full distribution of entrepreneurs in a section, both the raw count (left graph in Figure 2A) and ad-

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

justed for year effects, i.e., the share divided by the average share in that year (right graph in Figure 2A). 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, shown in Panel B, is smaller, ranging from shares of 3.7% in 1998 to 6.3% in 1997.

Our second data set contains the class choices in the second year. We determine all elective classes students enrolled in, as well as the fraction of such classes the course prospectus listed as (co-)sponsored by the Entrepreneurial Management unit. We compute the share of entrepreneurship classes for students without prior entrepreneurial experience. On average, non-entrepreneurs 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 about the 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.[19] The survey offers multiple categories for the post-graduation industry of employment, for cases where the student is still looking for employment and for students who have founded or are planning to imminently found a new venture. The survey responses are anonymous to ensure candid responses. As the survey only reflects students' intentions at graduation, it is possible that some would-be entrepreneurs abandon their quests later, or, vice versa, students decide to start a company later. Our measure of post-MBA entrepreneurship is unbiased if this inexacti-

[19] The survey does not capture 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.

tude only introduces random noise; it is precise for the stated entrepreneurial intentions.

We obtained access to the number of students starting an entrepreneurial venture, aggregated on the section level. We then separate out 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 aggregate, section-level placement data. 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 identify students with prior entrepreneurial experience and research if they took an entrepreneurial position after HBS. The main sources 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

$$\sum_{\{i|X_i,j=0\}} Y_{i,j} = \sum_i Y_{i,j} - \sum_{\{i|X_{i,j}=1\}} Y_{i,j} .$$

Another difficulty is that, for some sections, we do not have all class cards. 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 number of pre-not-post-MBA entrepreneurs, M_j, by simply subtracting the *number* of "identified" pre-MBA entrepreneurs from the size of section *j*, we would overestimate M_j and hence

underestimate the outcome variable $\bar{Y}_{M_j}$. We correct this potential bias by subtracting, instead, the *proportion* of pre-MBA entrepreneurs calculated in the sample of available class cards. That is, 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, we calculate M_j as

$$M_j = (N_j + M_j)(1 - \frac{\tilde{N}_j}{\tilde{N}_j + \tilde{M}_j}).$$

Hence, $\bar{Y}_{M_j}$ becomes $\dfrac{\sum_i Y_{i,j} - \sum_{\{i|X_i=1\}} Y_{i,j}}{(N_j + M_j)(1 - \frac{\tilde{N}_j}{\tilde{N}_j + \tilde{M}_j})}$ or, in words,

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

The second potential bias due to missing class cards is that, by missing out on some pre-MBA entrepreneurs, we might underestimate the number of pre-and-post-MBA entrepreneurs, $\sum_{\{i|X_i=1\}} Y_{i,j}$. This issue is similar to the one of missing that a pre-MBA entrepreneur became a post-MBA entrepreneur even though he or she (anonymously) indicated entrepreneurship in the placement survey. This bias leads us to overestimate the number of "post-not-pre" entrepreneurs, which is the numerator of $\bar{Y}_{M_j}$, and hence to overestimate $\bar{Y}_{M_j}$. To check the robustness of our results to this bias, we re-do each analysis assuming a set percentage of pre-and-post entrepreneurs.[20]

Finally, we collect data on the success of firms established by students while at HBS or within one year of graduation. An objective threshold criterion of "success" is

[20] We use a 30% rate in the results reported in the paper, based on the Rock Center survey described below. In unreported analyses, we also use other rates, e.g., 23% as suggested by our class card data (see Panel B of Table II), and find little impact.

hard to find. We define a successful business as one that, as of July 2011, (a) had gone public, (b) had been acquired for more than $5m, or (c) had, then or at the time of the sale of the company, at least 50 employees or $5m in annual revenues.[21] The $5m cut-off is 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 to Gompers, et al. [2005], the typical venture-backed firm has 3.0 founders. Assuming a valuation-to-revenue ratio of one,[22] a $5m 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), namely $25 million or even $100 million.

We use three sources. First, we obtain access to research of the HBS External Relations (Development) Office into its entrepreneurial alumni. Second, we obtain access to the online survey of the Rock Center for Entrepreneurship that collects information about students who participated in the business plan contest as well as other early-career entrepreneurs.[23] Third, we conducted interviews with the three 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

[21] 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.

[22] According to Thomson Reuters SDC data, the median multiple of valuation to the 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

[23] 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]).

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 information on a confidential basis.

In total, 26 entrepreneurs (associated with a total of 19 firms) qualified for the lowest success hurdle, amounting to a success rate of only 13%. 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 lower ($5 million) hurdle for success. The temporal pattern of success is less pronounced, but, generally, the years that saw the greatest number of successful entrepreneurs were earlier.

III. 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 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.

III.A. Test of Stratification and Randomization

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

The raw results for all 68 characteristics variables in our data are presented in Appendix Table A1. Out of all job-related characteristics (20 types of last job, 17 types of job functions), demographics (gender, US citizenship, children, partner, age, ethnicity), our risk score measure, and education (major, attendance of an Ivy League or Ivy League Plus college), six are significantly different at the five-percent confidence level: sections with more entrepreneurs are *less* likely to have students who worked in entertainment (3.2% vs. 4.3%), who attended elite schools (22.7% vs. 25.2% for Ivy League and 32.7% vs. 35.7% for Ivy League plus), who majored in history (2.9% vs. 4.2%), and who had a function in human resources (0.2% vs. 0.4%) and are *more* likely to have students who had a function in medical services (0.7% vs. 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 16 significant characteristics). In order to identify the most relevant variables, we use two forward-selection procedures. 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[24]: 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, controlling for year effects. As shown in Table III, this leads to the identification of three additional independent variables—students having a background in agriculture and health care, and majoring in engineering. Second, we use 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 addition to the time dummies, in our analyses. 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.) In all regressions, we also control for the "share of students without an entrepreneurial background who worked in a general management function" to ensure that our results do not reflect negative sorting on this background category as discussed above.[25] Finally, we

[24] See, e.g., Evans and Leighton [1989] and Landier and Thesmar [2009].

[25] An alternative approach would have been to define all variables only for individuals with general management experience. We cannot implement the alternative specification since we do not have outcome variables by individual, or for the subset of individuals with general management experience.

add interactions between the independent variables as further controls. Given the stratification procedure employed for the section assignment, we would ideally include all possible interactions between all stratification variables. Because of the modest number of observations, this is not possible to implement. Instead, we include pairwise interactions between the following significant explanatory variables: the share of section that is male, that are U.S. citizens, with a partner, and with investment banking background.

III.B. Univariate Comparisons

We begin the analysis of entrepreneurial peer effects by plotting the basic relationship between the representation of entrepreneurial students and the rates of post-MBA entrepreneurship, both in total and separating out unsuccessful and successful entrepreneurs. Panel A of Figure 3 relates the share of pre-MBA entrepreneurs to the share of post-MBA entrepreneurs (without prior entrepreneurial experience).[26] 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 post-MBA entrepreneurs.

We then distinguish between unsuccessful and successful post-MBA entrepreneurs. We define the rate of unsuccessful entrepreneurship as the difference between the rates of total and of successful entrepreneurship.[27] Panel B reveals the same pattern for the share of unsuccessful post-MBA entrepreneurs as in Panel A for all post-MBA entrepreneurs. Meanwhile, the pattern for successful post-MBA entrepreneurs, in Panel C, is less pronounced and relatively flat, with the exception of one section with a high number

[26] This is calculated by subtracting out the number of pre-and-post-MBA entrepreneurs (the first of the two possible corrective methodologies described in Section II).

[27] While we believe that we identified a virtually comprehensive list of successful HBS entrepreneurs from the classes in our sample, a similar approach is not feasible for unsuccessful entrepreneurs. Unsuccessful ventures are much less visible after failure, and participants are often unwilling to disclose their failure (e.g., in response to a survey request).

of successful entrepreneurs and a high 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 only 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, there is a significantly 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, consistent with the pattern observed in Figure 3. This negative correlation provides another piece of suggestive evidence speaking to our main research question.

Columns 2 and 3 reveal that this negative correlation is entirely driven by the share of unsuccessful post-MBA entrepreneurs, again consistent with Figure 3: The correlation with unsuccessful entrepreneurship is significantly negative, while the correlation with successful 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 – the only significant correlates are having a partner and the risk aversion score (negative correlation) and the measures of entrepreneurial finance activity (positive). 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 sam-

ple is simply the small number of successful post-MBA entrepreneurs. If we compare the fraction of successful entrepreneurs (among all post-not-pre entrepreneurs[28]) 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.

III.C. Regression Analyses

We test whether the suggestive univariate patterns hold up in a controlled regression framework. As before, the units of observation are section-years, and the main dependent variable is the section share without prior entrepreneurial background who became entrepreneurs after graduation, either overall or divided into successful and unsuccessful. As derived in Section I.A, we control for the characteristics of these same students without prior entrepreneurial experience, using the variables selected in Section III.A.

Table V presents the first main result, the analysis of entrepreneurial peer effects on the propensity of their section-mates without entrepreneurial experience to become entrepreneurs afterwards. Since the left-hand side variable is censored at zero, we first estimate a Tobit specification. The Tobit specification does not allow us to employ year dummy variables (the estimates do not converge), and we use the volume of venture financing and IPOs as controls. Alternatively, we estimate OLS coefficients with the inclusion of year dummies. In those specifications we can also add pairwise interactions between significant explanatory variables as additional controls, as discussed above. We use the two methods discussed in Section II to correct the overall post-MBA entrepreneurship rate for prior entrepreneurial experience: In the first three columns, we subtract the number of identified pre-and-post-MBA entrepreneurs; in the last three columns, we

[28] The calculation of the success rate excludes sections with no post-MBA entrepreneurship.

subtract an average pre-and-post-MBA entrepreneurship rate of 30%.

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. Even using the low coefficient estimate from the OLS regression in the second column, 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 negative estimate for pre-MBA entrepreneurs, may reflect that this category is dominated by buyout firms with little exposure to young firms, rather than 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.

We then distinguish between unsuccessful and successful entrepreneurs. Table VI presents the same set of regression specifications as in the previous table but with different dependent variables: 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). In Panel C, we test whether the peer effects estimated for unsuccessful and for successful entrepreneurs in Panels A and B are the same.

The results for unsuccessful entrepreneurship (Panel A) are very similar to those for overall entrepreneurship. The section share with prior entrepreneurial background is significantly negatively associated with unsuccessful post-MBA entrepreneurship among their peers. In fact, the coefficient estimates of all independent variables are quite similar in terms of significance and size. As expected, given the high likelihood of failure, a reduction in unsuccessful ventures drives the overall negative peer effect.

The economic magnitude of the peer effect is somewhat larger for unsuccessful entrepreneurs than in the baseline, given the smaller baseline. Using again the coefficient estimate from the first OLS regression (column 2), a one-standard deviation increase in the pre-MBA entrepreneurship rate translates into a decrease of 30%, namely, more than one percentage point [-0.36×0.029] out of 3.5% unsuccessful post-not-pre entrepreneurs.

The results of the regressions explaining successful entrepreneurship (Panel B) are rather different: The coefficient on the share of pre-MBA entrepreneurs are much smaller and always positive, ranging from 0.02 to 0.16. They are never statistically significant, nor are any of the other variables that are important in Table V consistently significant. The goodness of fit is also considerably lower.

The lack of significance is not surprising, given the limited representation of successful entrepreneurs (0.4% of all students without prior entrepreneurial experience) and left-censoring. However, the consistently positive coefficient estimates point suggest the *possibility* that entrepreneurial peers are less discouraging, or even encouraging, when

confronted with promising, and hence ultimately successful business ideas.

We perform two tests to explore this possibility. First, we test 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: We estimate a pooled regression on observations from both regressions and then examine the significance of the interaction between the pre-MBA entrepreneur share and the dummy variable denoting successful outcomes. This amounts to performing 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. 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, peers with entrepreneurial experience tend to deter students without an entrepreneurial background from undertaking unsuccessful ventures, but their influence on would-be successful entrepreneurs is significantly more positive.

We perform a second test to ensure that the significant difference estimated in Panel C is not merely a reflection of the lower (absolute) rate of successful entrepreneurs. That is, a potential concern is that the magnitude of a hypothetical negative peer effect on successful ventures is limited because the rate of successful ventures cannot fall below zero. For example, if the shares of both successful and unsuccessful ventures were to drop by the same percentage in response to peer interaction, we might still estimate a positive interaction coefficient given the higher baseline rate of unsuccessful ventures.

To address this concern, we repeat the analysis in Table V using as a dependent variable the ratio of the number of failed to the number of total ventures. If the insignifi-

cantly positive coefficient estimated for successful entrepreneurs concealed a negative effect identical to the one on unsuccessful would-be entrepreneurs, then peers should have no effect on the ratio. If the effect is significantly more positive for successful would-be entrepreneurs, the coefficient estimate should be negative. We deal with the cases of “no new ventures” in a section (zero denominator) in several alternative ways: dropping those observations; coding those ratios as “zero”; adding a small number to both the numerator and denominator in all observations. We re-estimate all six regression models of Table V with each approach. We find that the coefficient on the number of pre-MBA entrepreneurs is negative in all cases: the peer effect is more negative on unsuccessful ventures. Since both the counts of unsuccessful and total ventures are likely to be noisily measured, it might be anticipated that the ratio would be particularly noisy. Nonetheless, the coefficient is significant at conventional significance levels in the majority of cases. For example, when we calculate the ratio dropping cases of zero ventures and when we calculate the ratio coding cases of zero ventures as zero, the coefficient estimate is significant in nine out of twelve cases (marginally significant in the other cases).

Taken together, our results imply that experienced peers are serving a positive role in disproportionately weeding out bad ventures.

We perform a number of robustness checks. First we test whether our results are robust to employing higher thresholds for “success.” As discussed above, we chose the \$5 million threshold for “success” in order to guarantee equity worth about \$1 million or more per founder. In some cases, this cut-off may be too low. 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 the parties involved regarded this as a success.[29] To address this concern, we use \$25 million and \$100 million as alternative cutoffs, 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 super-successful" versus "super-successful") are significantly different at the one-percent confidence level in both cases.

Another robustness check addresses the concerns that, as revealed in Figure 2.C, the class of 2000 had an extraordinary high post-MBA entrepreneurship rate and might explain all of our results. We reran the regressions without the observations from the class of 2000. The results were little changed.

We also repeat the analyses in Tables V and VII, adding additional control variables suggested by the literature on the determinants of entrepreneurship, in particular, Eesley, et al. [2007] and Evans and Leighton [1989]. For instance the results were robust when we added, among other variables: section share (excluding prior entrepreneurs) that is white; section share (excluding prior entrepreneurs) that is Asian; section share (excluding prior entrepreneurs) that is Hispanic; section share (excluding prior entrepreneurs) that are races other than white, black, Asian, and Hispanic; section share (exclud-

[29] The information on Guru.com was obtained from http://www.venturexpert.com (accessed September 16, 2011), Factiva, and other on-line sources.

ing prior entrepreneurs) that is aged 30 or over at matriculation; section share (excluding prior entrepreneurs) with a college major in natural science; section share (excluding prior entrepreneurs) with a college major in medical science; section share (excluding prior entrepreneurs) with a college major in computer science.

Finally, the reported analyses focus on the 60 sections with at least 70 class cards. As additional robustness checks, we repeat the analyses using only sections with a minimum of 75 or 80 class cards (a total of 57 and 40 sections respectively). When we reproduce the analyses in Tables V and VI using these higher cut-off points, the results are generally robust, despite the smaller sample sizes. Hence, the results are not a consequence of any assumptions regarding missing observations.

III.D. Interpretation

As noted in the introduction, we can offer a variety of explanations for the observed intra-section learning. A first possible channel is direct interaction of pre-MBA entrepreneurs with aspiring entrepreneurs in their section and their counsel about what constitutes a good business idea. As argued by the alumni and students we interviewed, 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." Aspiring entrepreneurs with less promising ideas abandon or at least

postpone their plans 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 section-mates to take additional entrepreneurship classes as electives, which may help 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 classes under the sponsorship of the Entrepreneurial Management unit that students without 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. With the exception of two significant time dummies (the classes of 2000 and 2001 had the greatest enrollment in entrepreneurship classes), none of the coefficient estimates are significant at the five-percent confidence level, and only the coefficient estimate for gender is marginally significant but varies depending on the regression specification. Most importantly, the impact of peers with an entrepreneurial background is very small and never significant.[30] Hence, we find no support for the explanation that entrepreneurial peers induce others to take entrepreneurship classes.

It is harder to distinguish between the remaining two explanations, "direct counsel" (channel 1) and "mere presence" (channel 2), though the finding on enrollment in

[30] 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.

entrepreneurship classes points towards channel 1: If the mere presence of entrepreneurial peers discourages start-up activities, we might also expect it to dampen interest in entrepreneurship classes, and hence a negative coefficient.

Relatedly, the second interpretation would be more plausible if pre-MBA entrepreneurs tended to be failed entrepreneurs, whose previous experiences diminish the enthusiasm of their peers about entrepreneurship. 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.

Still, it is possible that prior entrepreneurial experiences color the influence that pre-MBA entrepreneurs exert on the entrepreneurial ambitions of their peers: 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).

For *unsuccessful* post-MBA entrepreneurs, we find a negative peer effect both of successful prior entrepreneurs and of unsuccessful prior entrepreneurs (Panel A). 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.) Only the Tobit specification suggests a stronger peer effect of unsuccessful entrepreneurs, but the differences in coefficients are insignificant in all cases.

Panel B shows the effect on *successful* entrepreneurs. As in Table VI.B, the good-

ness 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 pre-MBA entrepreneurs is always positive while the effect of failed pre-MBA entrepreneurs is either negative or very close to zero. The differences are never significant.

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. If intra-section learning relies on direct interaction, then the effect will be noisier when there are few pre-MBA entrepreneurs present and, hence, interaction and productive feedback are less likely. With a large number of entrepreneurs, instead, one of them will be critical and experienced enough to detect the "flaw" in a business plan. Hence, sections with fewer pre-MBA entrepreneurs should display greater variance in their post-MBA entrepreneurship rates, particularly for unsuccessful entrepreneurs.

Table IX reports the variance in post-MBA entrepreneurship, separately for sections with below-median and above-median shares of pre-MBA entrepreneurs. We find that sections with more prior entrepreneurs have 44% less variance in the overall entrepreneurship rate, a pattern entirely driven by unsuccessful entrepreneurs. However, at least part of the reduction in variance may be mechanistic, due to the reduced likelihood of becoming entrepreneur when many pre-MBA entrepreneurs are present. To alleviate this concern, we repeat the analysis restricted to sections with a minimum number of students becoming entrepreneur: at least three, five, or seven. In all cases, the results are directionally similar: the variance in the rate of unsuccessful (and overall) post-MBA en-

trepreneurship is always higher in sections with below-median numbers of experienced entrepreneurs than in section with above median numbers, and the reverse holds for the rate of successful post-MBA entrepreneurship. Most of the differences in variance become insignificant, likely due to the small sample size when we impose the double-restriction of a minimum number of class cards (70+) and of a minimum number of post-MBA entrepreneurs. The results are significant when we only use the restriction of at least three, five, or seven post-MBA entrepreneurs, regardless of the class-card count.

The robust (and non-mechanistic) reduction in variance is another piece of suggestive evidence, pointing to the role of direct interaction with entrepreneurial peers.

IV. Conclusions

This paper tests how social interactions with peers affect an individual's decision to become an entrepreneur and, hence, the aggregate returns to entrepreneurship. We examine the decision to become entrepreneur among recent graduates of the Harvard MBA program. This setting is empirically attractive due to the exogenous assignment of students to sections, the ability to distinguish success and failure in terms of 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 a significantly lower rate of (ultimately) unsuccessful entrepreneurs. The influence on (ultimately) successful post-MBA entrepreneurs, instead, is indistinguishable from zero, and significantly more positive than the effect on unsuccessful entrepreneurship. Whether former entrepreneurs were successful or unsuccessful themselves has, at best, a weak directional effect. 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.

Our analysis of peer effects in entrepreneurship is relevant to policy-makers, business school faculty, and administrators, given the emphasis they are placing on the promotion of entrepreneurship. During the 1990s and early 2000s, for example, U.S. business schools created over 300 endowed chairs in entrepreneurship, typically paying salaries significantly above those in other business disciplines (Katz [2004]). Hundreds of business plan contests were launched during these years, and entrepreneurial activities often benefitted from public subsidies. 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 attracting more people into entrepreneurship, schools and policy-makers may want to provide support to would-be entrepreneurs in critically evaluating their most promising business ideas.

We see two avenues for future research. First, this paper suggests a richer role for peer effects in entrepreneurship. Most prior studies have implicitly assumed a "contagion effect," where the decision of one individual to begin a firm leads others to do so likewise. Our analysis suggests that the mechanism is more complex: feedback of experienced entrepreneurs may encourage or discourage would-be entrepreneurs. Uncovering the exact 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 for phenomena other than entrepreneurship. Shue's [2011] analysis of executive compensa-

tion and acquisition strategies of companies headed by HBS graduates represents one such analysis, and points to the breadth of research topic possible with these data. 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.

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Appendix: The HBS Section System

Our paper exploits the section system of Harvard Business School to address several challenges to identification present in previous literature. The key feature is the exogenous assignment into sections discussed in the paper. Another advantage of the empirical setting is that section-mates form extremely close ties, and are a setting where peer effects—if they are empirically observable at all—would likely be seen.

The social ties established in the first year appear to remain extremely strong, even after the second-year, when student take elective classes together with the entire student body, and long after graduation. We provide two examples of the numerous journalistic accounts and academic studies analyzing the social experience engendered by HBS sections. First, 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.

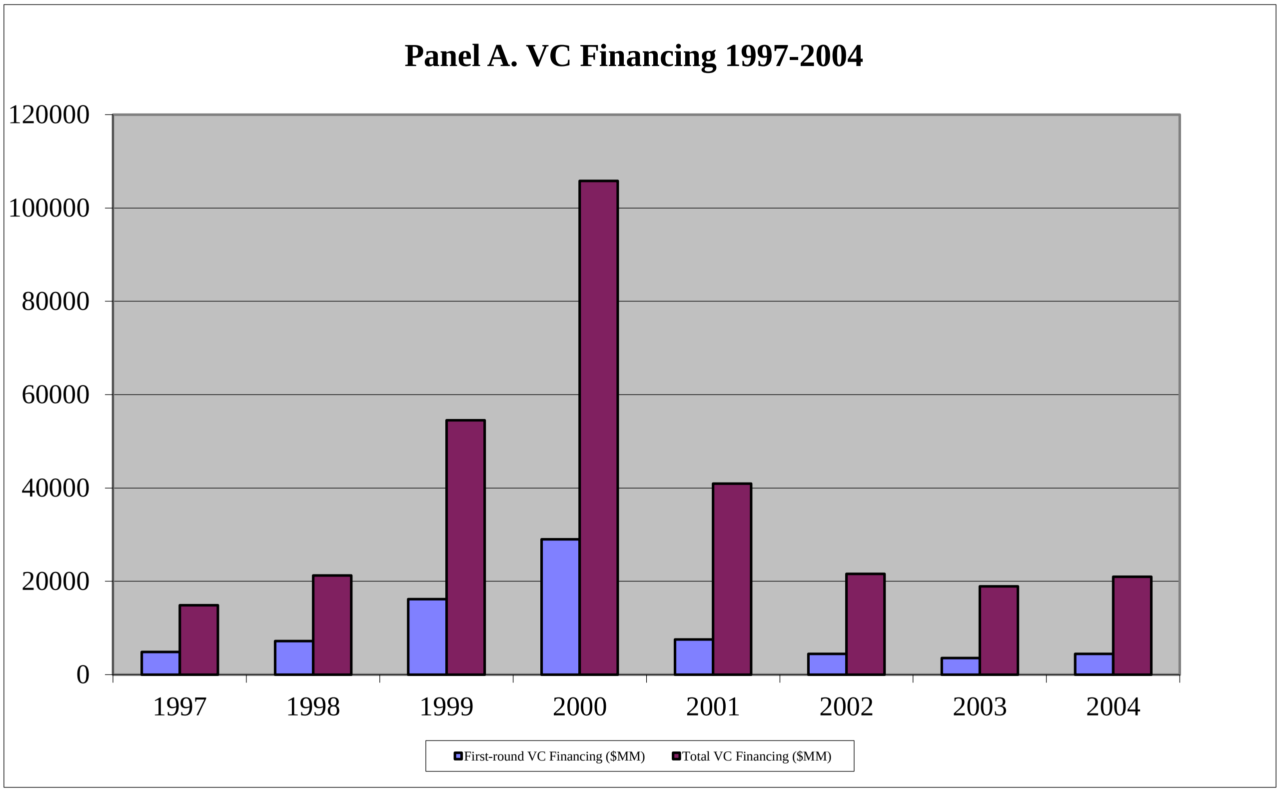
Similarly, in a field-based analysis of the first-year HBS experience, Orth [1963] highlights that section-mates, "in order to insure feelings of safety and, if possible competence in a situation that is initially perceived to them to be threatening," adopt "norms" that affect study patterns, social 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.”

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



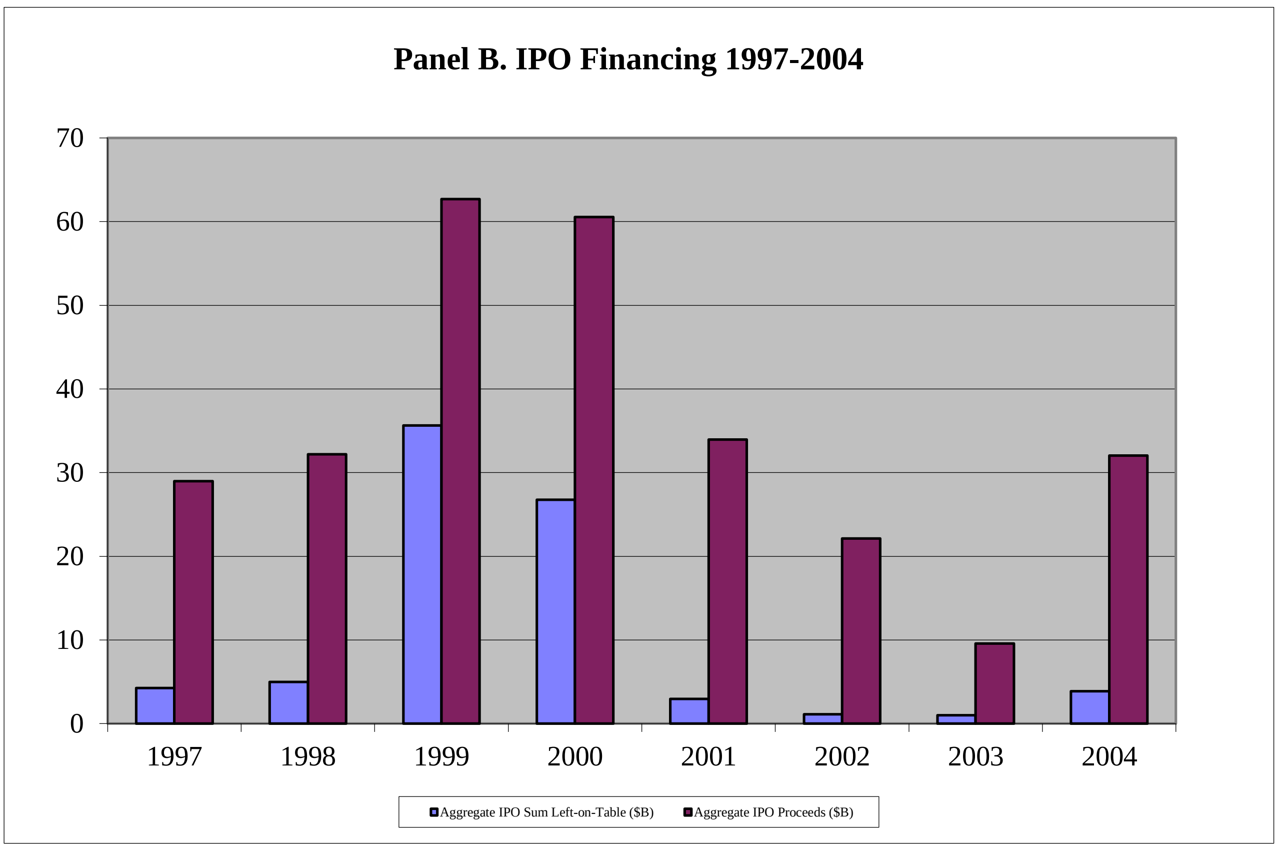


Table II. Section Characteristics

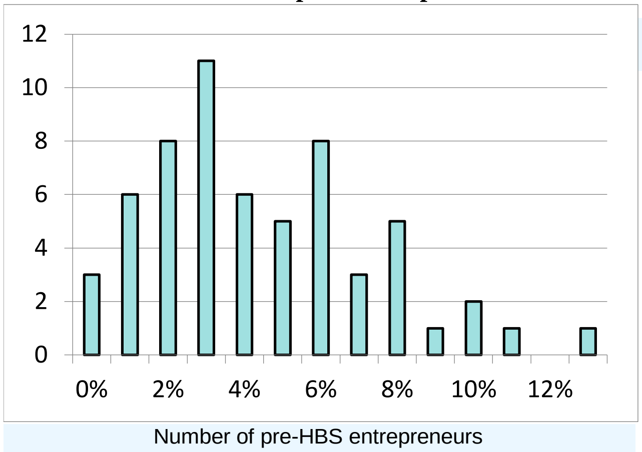
Panel A. Full Sample (86 sections)	*Mean*	*Median*	*St. Dev.*	*10th Percentile*	*90th Percentile*
Share of section that worked					
… as an entrepreneur	5.0%	4.7%	3.4%	0.0%	9.8%
… in consulting	22.9%	23.5%	5.3%	16.3%	29.0%
… in investment banking	19.3%	19.0%	5.7%	12.8%	25.0%
… in private equity	4.7%	4.2%	3.0%	1.1%	8.9%
… in agricultural business	2.4%	2.6%	1.9%	0.0%	4.2%
… in health care	3.2%	2.7%	2.3%	0.0%	5.4%
… in hardware manufacturing	1.3%	1.2%	1.5%	0.0%	3.2%
… in general management	15.6%	15.1%	4.7%	10.0%	20.7%
Share of section that is male	69.4%	67.9%	7.1%	62.8%	82.5%
… has USA citizenship	66.9%	65.8%	6.7%	59.0%	76.9%
… has children	4.9%	4.6%	3.2%	1.3%	9.1%
… has a partner	41.3%	42.1%	7.4%	31.6%	50.6%
Share of section older than 30	6.1%	5.8%	3.8%	1.3%	10.7%
Average maximum risk score	38.4%	38.9%	3.2%	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%

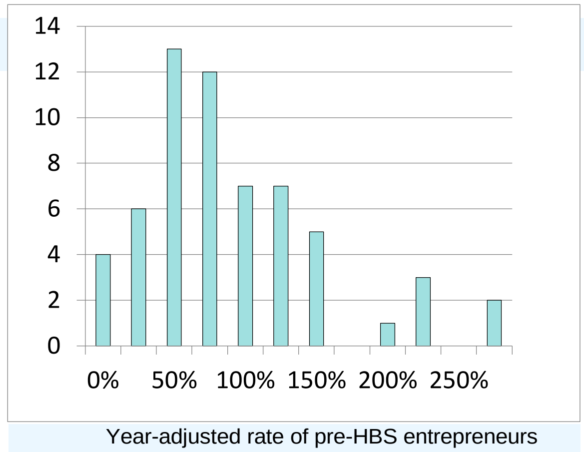
Panel B. Sections with at least 70 class cards (60 sections)	*Mean*	*Median*	*St. Dev.*	*10th Percentile*	*90th Percentile*
Share of section that worked					
… as an entrepreneur	4.8%	4.6%	2.9%	1.3%	8.6%
… in consulting	24.2%	24.0%	4.0%	19.6%	28.8%
… in investment banking	18.7%	18.7%	3.7%	14.1%	22.6%
… in private equity	5.1%	4.6%	3.1%	1.3%	9.4%
… in agricultural business	2.7%	2.6%	1.6%	1.2%	4.1%
… in health care	3.3%	3.3%	1.6%	1.2%	5.3%
… in hardware manufacturing	1.0%	1.2%	1.0%	0.0%	2.4%
… in general management	14.8%	14.5%	3.7%	9.7%	19.9%
Share of section that is male	66.5%	66.2%	3.2%	62.7%	70.6%
… has USA citizenship	65.3%	64.5%	5.6%	58.8%	71.8%
… has children	4.6%	4.1%	2.9%	1.4%	9.0%
… has a partner	42.6%	43.0%	7.1%	33.7%	51.7%
Share of section older than 30	5.0%	4.9%	2.5%	1.3%	8.2%
Average maximum risk score	38.8%	39.3%	2.8%	35.4%	42.1%
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

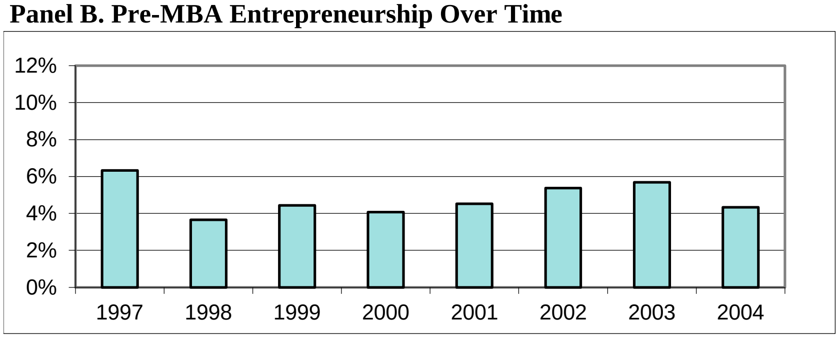
Panel A. Pre-MBA Entrepreneurship Across Sections





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 the 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 the 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).

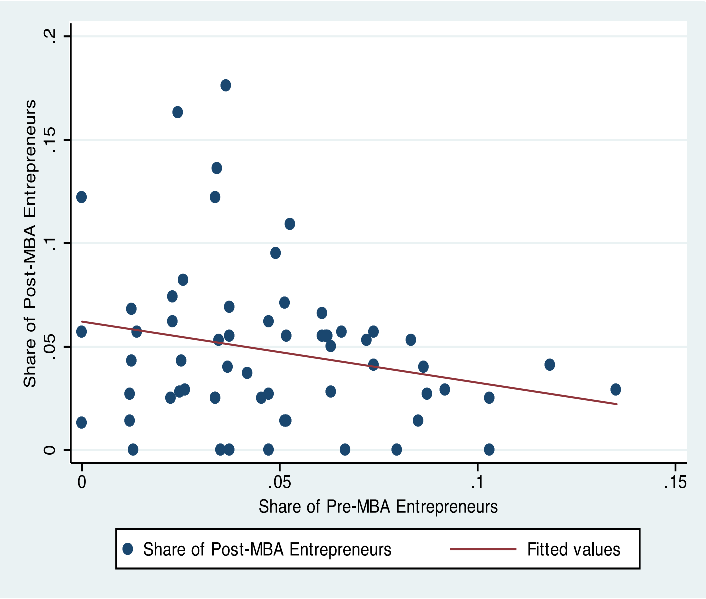
Table III. Predicting the Share of Pre-MBA Entrepreneurs

	Baseline	Alternative
Share that worked pre-MBA in consulting	-0.11	-0.11
	[0.08]	[0.05]**
… in investment banking	0.02	
	[0.07]	
… in private equity	-0.17	
	[0.14]	
… in agricultural business	-0.59	-0.54
	[0.16]***	[0.15]***
… in health care	0.39	0.45
	[0.13]***	[0.11]***
… in hardware manufacturing		0.36
		[0.16]**
… in telecommunications		-0.20
		[0.10]**
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, 7)

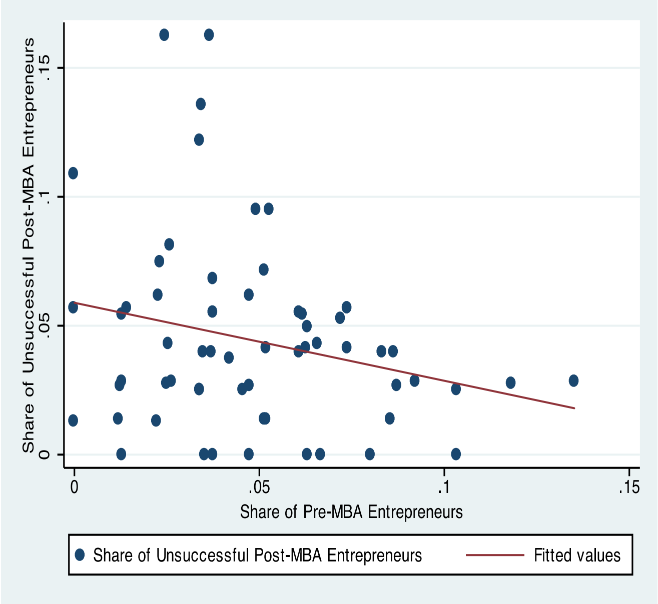
Notes. All section-level measures include pre-MBA entrepreneurs. The additional controls (and alternative sets of additional controls) are discussed in the text. We report the F-statistic for the joint significance of all control variables excluding year effects (and, in parentheses, the p-value and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

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

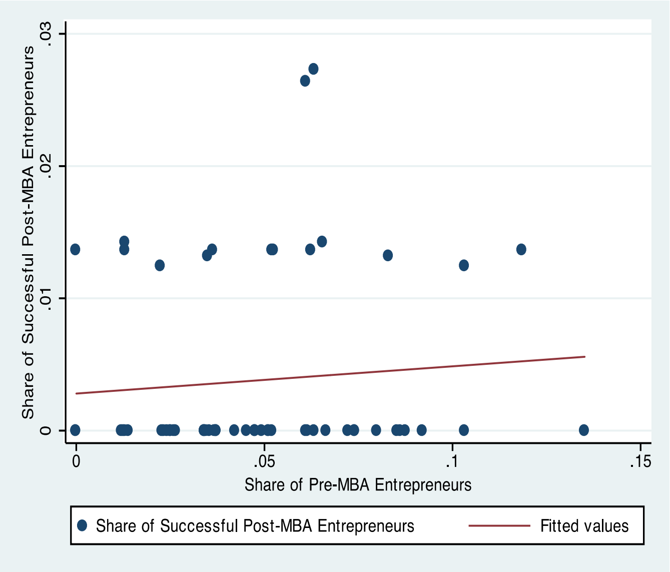
Panel A. All Post-MBA Entrepreneurs



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

	Share of post-MBA entrepreneurs	*Share of unsuccessful post-MBA entrepreneurs*	*Share of successful post-MBA entrepreneurs*
Share of post-MBA entrepreneurs	1.00		
Share of successful post-MBA entrepreneurs	0.17		1.00
	(0.20)		
Share of unsuccessful post-MBA entrepreneurs	0.95	1.00	0.03
	(0.00)		(0.82)
Share that worked pre-MBA			
… as an entrepreneur	-0.33	-0.24	0.12
	(0.01)	(0.07)	(0.35)
… in consulting	-0.13	-0.14	-0.06
	(0.33)	(0.30)	(0.63)
… in investment banking	-0.13	-0.11	-0.14
	(0.32)	(0.40)	(0.30)
… in private equity	-0.08	-0.12	-0.02
	(0.56)	(0.37)	(0.89)
… in agricultural business	0.33	0.35	0.06
	(0.01)	(0.01)	(0.67)
… in health service	0.24	0.31	0.03
	(0.07)	(0.02)	(0.80)
… in general management	-0.01	0.00	-0.05
	(0.93)	(0.70)	(0.98)
Share that is male	0.25	0.21	0.11
	(0.06)	(0.11)	(0.43)
… has USA citizenship	-0.13	-0.22	-0.06
	(0.33)	(0.09)	(0.64)
… has children	-0.04	-0.06	0.14
	(0.76)	(0.65)	(0.27)
… has a partner	-0.04	-0.04	-0.26
	(0.76)	(0.75)	(0.05)
Average maximum risk score	-0.06	-0.07	-0.25
	(0.63)	(0.60)	(0.06)
Share that attended an Ivy League college	-0.21	-0.25	-0.06
	(0.12)	(0.06)	(0.65)
Share that attended an Ivy Plus college	0.14	0.17	0.08
	(0.28)	(0.18)	(0.52)
Share that majored in Engineering in college	0.04	0.05	-0.06
	(0.79)	(0.72)	(0.65)
IPO proceeds in graduation year ($ trillion)	0.57	0.56	0.20
	(0.00)	(0.00)	(0.12)
Total venture funding in graduation year ($ trillion)	0.70	0.69	0.21
	(0.00)	(0.00)	(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

Dependent Variable:	Share of post-MBA entrepreneurs net of …					
	identified share of pre-&-post-MBA entrepr			av. estim. share of pre-&-post-MBA entrepr.		
Share of section with entrepreneurial background	-0.46	-0.35	-0.36	-0.54	-0.43	-0.45
	[0.13]***	[0.11]***	[0.11]***	[0.12]***	[0.12]***	[0.10]***
Share of non-entrepreneurs with consulting background	-0.11	-0.08	-0.1	-0.04	-0.08	-0.06
	[0.10]	[0.09]	[0.10]	[0.09]	[0.07]	[0.08]
... with investment banking background	-0.05	-0.18	0.02	-0.04	-0.16	0.04
	[0.09]	[0.09]*	[0.19]	[0.09]	[0.09]*	[0.17]
... with private-equity background	0.29	0.05	0.03	0.25	0.03	0.03
	[0.14]**	[0.16]	[0.15]	[0.11]**	[0.13]	[0.12]
... with agricultural-business background	-0.36	-0.54	-0.49	-0.35	-0.54	-0.5
	[0.26]	[0.29]*	[0.32]	[0.21]	[0.23]**	[0.24]**
... with health-care background	0.58	0.56	0.56	0.54	0.53	0.55
	[0.28]**	[0.26]**	[0.30]*	[0.25]**	[0.20]**	[0.23]**
... with general management background	0.08	0.01	0.04	0.08	-0.02	-0.03
	[0.10]	[0.10]	[0.10]	[0.08]	[0.03]	[0.03]
Share of non-entrepreneurs that are male	0.53	0.81	0.84	0.47	0.76	0.82
	[0.12]***	[0.21]***	[0.26]***	[0.11]***	[0.18]***	[0.20]***
... that are U.S. citizens	0.05	0.18	0.21	0.07	0.18	0.18
	[0.07]	[0.12]	[0.20]	[0.06]	[0.09]*	[0.15]
... with children	0.01	0.2	0.1	0.03	0.19	0.14
	[0.16]	[0.19]	[0.20]	[0.14]	[0.14]	[0.17]
... with a partner	-0.11	-0.18	-0.12	-0.17	-0.21	-0.17
	[0.06]*	[0.09]**	[0.16]	[0.05]***	[0.07]***	[0.14]
Share of non-entrepreneurs who attended Ivy League college	0.1	0.22	0.22	0.06	0.18	0.14
	[0.15]	[0.14]	[0.19]	[0.13]	[0.12]	[0.15]
... that attended an Ivy Plus college	-0.01	-0.09	-0.08	-0.02	-0.13	-0.12
	[0.12]	[0.12]	[0.15]	[0.10]	[0.09]	[0.11]
… that majored in engineering in college	0.07	-0.03	-0.02	0.09	0	0
	[0.08]	[0.10]	[0.10]	[0.07]	[0.08]	[0.08]
Mean maximum risk score of section	-0.22	-0.26	-0.19	-0.17	-0.2	-0.14
	[0.14]	[0.16]	[0.21]	[0.12]	[0.12]	[0.18]
Total IPO proceeds in graduation year ($ trillions)	-1.38			-1.35		
	[0.54]**			[0.46]***		
Total venture financing in graduation year	1.32			1.24		
	[0.28]***			[0.23]***		
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		0.74	0.78		0.82	0.84

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

Dependent Variable:	Share of *unsuccessful* 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	-0.47	-0.36	-0.36	-0.57	-0.42	-0.43
	[0.14]***	[0.11]***	[0.10]***	[0.14]***	[0.10]***	[0.09]***
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		0.74	0.80		0.82	0.84

Panel B. Successful Entrepreneurship

Dependent Variable:	Share of *successful* 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	0.14	0.03	0.02	0.16	0.03	0.02
	[0.11]	[0.03]	[0.03]	[0.10]	[0.03]	[0.02]
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		0.36	0.59		0.45	0.62

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)

Dependent Variable:	Share of post-MBA entrepreneurs (net of identified pre-and-post-MBA entrepreneurs) who were …				Enrollment in entrepreneurship classes by **non-**pre-MBA entrepreneurs
	not *"very successful"*	*"very successful"*	***not*** *"super-successful"*	*"super-successful"*	
	(1)	(2)	(3)	(4)	(5)
Share of section with entrepreneurial background	-0.36	0.04	-0.36	0.04	0.02
	[0.13]***	[0.03]	[0.13]***	[0.03]	[0.08]
Share of non-entrepreneurs ...					
… with consulting background	-0.07	-0.02	-0.08	-0.02	0.09
	[0.11]	[0.03]	[0.11]	[0.03]	[0.09]
... with investment-banking background	-0.18	-0.01	-0.18	-0.01	-0.10
	[0.13]	[0.03]	[0.13]	[0.03]	[0.07]
... with private-equity background	0.04	0.02	0.05	0.02	-0.04
	[0.17]	[0.04]	[0.17]	[0.04]	[0.10]
... with agricultural-business background	-0.59	0.06	-0.56	0.06	-0.32
	[0.31]*	[0.07]	[0.31]*	[0.07]	[0.21]
... with health care background	0.62	-0.09	0.59	-0.09	-0.17
	[0.29]**	[0.07]	[0.28]**	[0.07]	[0.20]
... with general management background	0.04	-0.04	0.02	-0.04	0.01
	[0.12]	[0.03]	[0.11]	[0.03]	[0.08]
Share of non-entrepreneurs that are male	0.83	-0.03	0.81	-0.03	-0.27
	[0.25]***	[0.06]	[0.25]***	[0.06]	[0.16]*
... that are U.S. citizens	0.24	-0.06	0.21	-0.06	-0.12
	[0.14]*	[0.03]*	[0.14]	[0.03]*	[0.09]
... with children	0.14	0.07	0.18	0.07	0.10
	[0.17]	[0.04]*	[0.17]	[0.04]*	[0.11]
... with a partner	-0.17	-0.02	-0.17	-0.02	-0.06
	[0.07]**	[0.02]	[0.07]**	[0.02]	[0.05]
... that attended an Ivy League college	0.32	-0.09	0.26	-0.09	0.12
	[0.17]*	[0.04]**	[0.17]	[0.04]**	[0.14]
... that attended an Ivy Plus college	-0.14	0.05	-0.11	0.05	-0.07
	[0.12]	[0.03]*	[0.12]	[0.03]*	[0.07]
… with major in engineering in college	-0.04	0.03	-0.03	0.03	0.01
	[0.10]	[0.02]	[0.10]	[0.02]	[0.08]
Mean maximum risk score of section	-0.3	0.04	-0.28	0.04	0.13
	[0.17]*	[0.04]	[0.17]	[0.04]	[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	0.73	0.45	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

Dependent Variable:	Share of *unsuccessful* 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	-0.31	-0.39	-0.36	-0.45	-0.41	-0.43
	[0.29]	[0.27]	[0.32]	[0.21]**	[0.19]**	[0.23]*
Share of section with unsuccessful entrepreneurial background	-0.60	-0.33	-0.36	-0.65	-0.43	-0.43
	[0.22]***	[0.21]	[0.22]	[0.21]***	[0.19]**	[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		0.74	0.80		0.83	0.86
F-statistic, test of successful and unsuccessful entrepeneurs	0.45	0.02	0.00	0.35	0.00	0.00
P-value	[0.50]	[0.88]	[0.99]	[0.55]	[0.96]	[0.99]

Panel B. Effects on Successful Post-MBA Entrepreneurship

Dependent Variable:	Share of *successful* 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	0.08	0.05	0.31	0.06	0.03
	[0.20]*	[0.07]	[0.05]	[0.18]*	[0.06]	[0.05]
Share of section with unsuccessful entrepreneurial background	-0.04	-0.01	0.00	0.03	0.00	0.01
	[0.21]	[0.06]	[0.06]	[0.19]	[0.06]	[0.05]
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		0.38	0.60		0.46	0.62
F-statistic, test of successful and unsuccessful entrepeneurs	1.37	0.74	0.48	0.85	0.34	0.03
P-value	[0.24]	[0.39]	[0.49]	[0.36]	[0.56]	[0.86]

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

	For sections with below median number of students with entrepreneurial background	*For sections with above median number of students with entrepreneurial background*	*p-Value, test of null hypothesis of no difference*
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 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%	2.4%	7.8%	[0.00]***
	(3.4%)	(1.6%)	(2.6%)	
Share of non-entrerprenurs that worked most recently				
… in computer hardware	1.4%	1.4%	1.4%	[0.98]
	(1.5%)	(1.5%)	(1.5%)	
… in computer software	3.7%	3.7%	3.5%	[0.81]
	(2.9%)	(3.1%)	(2.6%)	
… in computer-related services	2.3%	2.3%	2.1%	[0.58]
	(2.3%)	(2.4%)	(2.1%)	
… in other high-tech sectors	1.1%	1.3%	0.8%	[0.07]*
	(1.4%)	(1.6%)	(1.0%)	
… in telecommunications	3.2%	3.5%	3.0%	[0.24]
	(2.2%)	(2.1%)	(2.3%)	
… in diversified manufacturing	1.4%	1.2%	1.6%	[0.15]
	(1.4%)	(0.5%)	(1.6%)	
… in banking	15.4%	15.3%	15.5%	[0.86]
	(5.6%)	(0.3%)	(6.5%)	
… in financial services	6.1%	5.5%	6.7%	[0.06]*
	(2.9%)	(2.7%)	(3.0%)	
… in consulting	18.7%	18.7%	18.6%	[0.94]
	(4.6%)	(3.8%)	(5.2%)	
… in venture capital/private equity	8.0%	8.5%	7.5%	[0.35]
	(4.7%)	(4.4%)	(5.0%)	
… in military	3.3%	3.4%	3.2%	[0.72]
	(2.3%)	(1.9%)	(2.7%)	
… in non-profit organizations	4.3%	4.0%	4.5%	[0.41]
	(2.6%)	(2.6%)	(2.7%)	
… in accounting	1.1%	0.8%	1.4%	[0.08]*
	(1.6%)	(1.4%)	(1.8%)	
… in law	0.9%	0.8%	1.0%	[0.61]
	(1.4%)	(1.2%)	(1.5%)	
… in retail	4.0%	4.3%	3.6%	[0.15]
	(2.7%)	(2.9%)	(2.4%)	
… in advertising/marketing	2.1%	2.4%	1.8%	[0.16]
	(2.3%)	(2.2%)	(2.2%)	
… in entertainment	3.8%	4.3%	3.2%	[0.02]**
	(2.3%)	(2.0%)	(2.4%)	
… in agricultural business	2.4%	2.7%	2.0%	[0.09]*
	(1.8%)	(2.0%)	(1.6%)	
… in health services	3.2%	2.8%	3.7%	[0.06]*
	(2.3%)	(1.8%)	(2.6%)	
… in other industries	1.4%	1.4%	1.3%	[0.57]
	(1.5%)	(1.5%)	(1.5%)	

Appendix-Table A1 (*continued*)

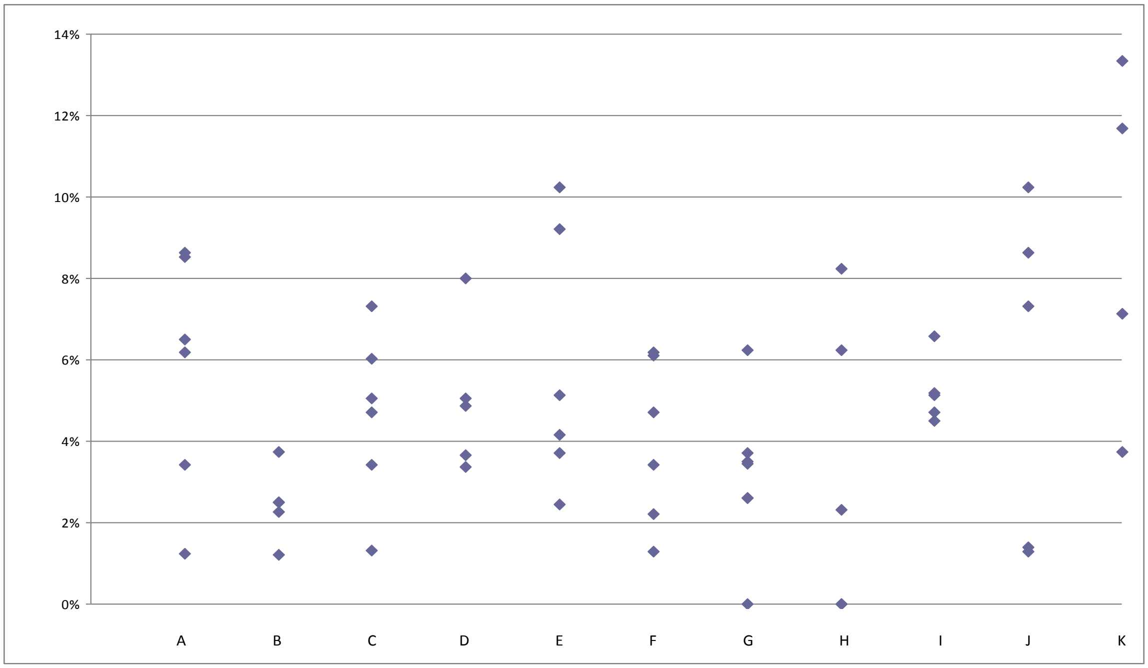
	Full Sample	# of pre-MBA Entrepreneurs below median	# of pre-MBA Entrepreneurs above median	p-values
Share that attended an Ivy League college	24.0%	25.2%	22.7%	[0.02]**
	(5.3%)	(5.0%)	(5.3%)	
… an Ivy Plus League college	32.3%	35.7%	32.7%	[0.02]**
	(6.3%)	(5.7%)	(6.6%)	
Share that is male	69.4%	69.6%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

Appendix-Table A1 (*continued*)

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

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 comparisond exclude pre-MBA entrepreneurs except for the first row.

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.