Peer Effects in Entrepreneurship*

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Abstract

We study how exposure to peers with entrepreneurship experience affects new entrepreneurship by exploiting quasi-random student assignment in an MBA program. Successful peers increase, while unsuccessful peers decrease successful entrepreneurship, by 15% each, so that their combined effects cancel. Successful peers decrease unsuccessful entrepreneurship. These findings favor a model where students are uncertain about their business idea and successful peers are effective at screening. We structurally estimate this model and show that a policy of increasing meetings with entrepreneur peers need not affect successful entrepreneurship, but a policy of reallocating meetings to successful peers has large positive effects.

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1 Introduction

Successful entrepreneurship generates enormous social value, but the factors that guide talent towards successful entrepreneurship are not well understood. A natural approach is to provide financial incentives through tax benefits, but such incentives tend to influence only marginal entrepreneurs (Bell, Chetty, Jaravel, Petkova and Van Reenen 2019a). An alternative approach is to encourage interactions with entrepreneur peers, as is done in entrepreneurial clusters or incubators.[1] Randomized evidence about the impact of such interactions on entrepreneurship is scarce. Lerner and Malmendier (2013), exploiting the quasi-random assignment of MBA students at HBS, document a negative effect of entrepreneur peers on entrepreneurship, which is concentrated in unsuccessful entrepreneurship. However, there is an absence of well-identified evidence on peer effects creating *successful* entrepreneurship. The mechanisms behind such peer effects, and the potential for policies to take advantage of them, are also not well understood.

We make progress on these issues by exploiting rich data on quasi-random student allocations in the London Business School (LBS) MBA program. We make two main contributions. First, we document that successful entrepreneur peers increase successful entrepreneurship and decrease unsuccessful entrepreneurship, while unsuccessful entrepreneur peers decrease successful entrepreneurship. These effects, we show, are consistent with a model in which peers screen business ideas and only successful peers are effective at screening, but not with alternative models based on learning or morale effects. The simultaneous presence of positive and negative effects implied by the screening model suggests that the overall sign of peer effects may be context-dependent. At LBS, both the positive effect of successful peers (15%) and the negative effect of unsuccessful peers (-15%) on successful entrepreneurship are large, but they cancel, implying that peers have no aggregate effect on successful entrepreneurship.

The absence of an aggregate effect, in the presence of large positive effects from successful peers, feels like a missed opportunity. In our second main contribution, we study the design of peer interactions to leverage the positive effects. We estimate a structural model of screening peer effects and evaluate two counterfactual policies. We find that a policy of increasing meetings with

[1] See Chatterji, Glaeser and Kerr (2014), Kerr and Robert-Nicoud (2020), and Eesley and Wang (2017).

entrepreneurial peers, depending on the composition of those peers, can have either positive or negative effects on successful entrepreneurship. In contrast, a policy of reallocating meetings from unsuccessful to successful peers (e.g. by pre-screening peers) unambiguously increases successful entrepreneurship and complements the first policy. In the long run, the positive effects are amplified because they improve the pool of entrepreneurs who screen new ideas. The implied effects are sizable, suggesting large societal gains from creating peer groups of successful entrepreneurs.

Our analysis is based on a model of entrepreneurial peer effects we present in Section 2. In the model, an MBA student's decision to pursue an entrepreneurial idea is influenced by interactions with a peer who is a past entrepreneur. We consider three peer effect mechanisms. Knowledge: the peer increases the student's entrepreneurial human capital or social capital. Morale: the peer, by sharing her experience, changes the student's perceived probability of success. Screening: the peer provides information on whether the student's idea is good. A successful entrepreneur peer has a more positive effect in all three mechanisms: she provides more knowledge, a more positive morale boost, and more informative screening. These mechanisms make distinct predictions. The knowledge mechanism predicts that both successful and unsuccessful peers increase entrepreneurship. The morale mechanism predicts that successful peers increase entrepreneurship, while unsuccessful peers decrease it. The screening mechanism predicts that successful peers increase successful and decrease unsuccessful entrepreneurship, whereas unsuccessful peers decrease both.

In Section 3, we present our empirical strategy. We study MBA students attending LBS during 2012-2022. Each year, incoming students are assigned quasi-randomly to 'streams.' Streams are natural peer groups because students in a stream take all their core courses together. LBS collects demographic and employment data about students both pre- and post-MBA, implying that we have self-reported data on both pre-MBA and post-MBA entrepreneurship. We complement these data by matching students to their LinkedIn profiles, and matching the businesses they created to company pages in the Pitchbook startup database. This allows us to classify entrepreneurs into two main categories: those without a digital footprint, for whom we could not identify any record of entrepreneurship online; and those with a digital footprint, for whom some online record exists. Entrepreneurs with a digital footprint have on average 24 employees on LinkedIn. We use the with-versus without-footprint classification to measure successful and unsuccessful entrepreneurship.

Our research design is to exploit the quasi-random allocation of students to streams and evaluate the impact of (randomly) having a higher share of entrepreneur peers in the student's stream. Implementing this design is challenging because the assignment to streams is not purely random, but driven by an algorithm that aims to balance several demographic variables across the streams in a cohort. Past entrepreneurship is not one of the balancing variables, implying that there is meaningful variation in the share of entrepreneurs across streams. Nevertheless, the balancing of demographics may generate correlation between student characteristics and the share of peers who are entrepreneurs.[2] We deal with this problem using an approach, inspired by Borusyak and Hull (2023), which isolates the purely random component of the share of entrepreneur peers. Using the exact algorithm that LBS uses to create stream assignments, we draw many counterfactual stream assignments and compute the share of peers who are entrepreneurs in each assignment. Averaging across these counterfactual assignments gives, for each student, the share of entrepreneur peers that she can expect to have under the LBS assignment process. The difference between the realized and the expected share isolates the random component in the share of entrepreneurial peers. We then conduct our estimation using a 're-centered IV' specification (Borusyak and Hull 2023) in which we instrument the share of entrepreneurial peers with the isolated random component. We validate this strategy with balance tests over students' fixed characteristics, which show imbalance in a 'naive OLS' specification but balance in the re-centered IV.

In Section 4, we present our reduced-form results. We first estimate the overall effect of the share of pre-MBA entrepreneurs on post-MBA entrepreneurship. We find small and insignificant effects on post-MBA entrepreneurship with or without a digital footprint. These results may be consistent either with the absence of peer effects or with opposite-signed peer effects that cancel.

We then separate the pre-MBA entrepreneur peers based on their digital footprint. The results change dramatically. We find that pre-MBA entrepreneurs with a digital footprint have a significant positive effect on post-MBA entrepreneurs with a digital footprint and a significant negative effect on post-MBA entrepreneurs without a digital footprint. In contrast, pre-MBA entrepreneurs

[2]This is a typical problem with estimating peer effects under quasi-random assignment (Jochmans 2023).

Table 1: Patterns of estimated peer effects

	Successful entrepreneurship	Unsuccessful entrepreneurship
Successful peer	$\uparrow$	$\downarrow$
Unsuccessful peer	$\downarrow$	

without a digital footprint have a significant negative effect on successful entrepreneurship and an insignificant effect on unsuccessful entrepreneurship. The signs of the effects, summarized in Table 1, can be used to distinguish between the mechanisms of the model. The negative impact of successful peers on unsuccessful entrepreneurs is inconsistent with the knowledge mechanism and the morale mechanism. However, all of the signs are consistent with the screening mechanism, which predicts that successful peers screen in good ideas and screen out bad ideas, while unsuccessful peers just discourage entrepreneurship. The magnitude of the effects is large: the point estimates imply that each successful peer created 0.41 successful entrepreneurs while each unsuccessful peer destroyed 1.05 successful entrepreneurs. However, given the composition of peers, these effects essentially cancel: in the aggregate, successful peers increased successful entrepreneurship by about 15%, while unsuccessful peers reduced it by about the same amount.

A potential concern with our identification strategy is that peer effects may be driven by some other variable correlated with the share of entrepreneurs, such as a characteristic associated with entrepreneurship like courage. But it is not clear how such a mechanism would explain both the positive and negative peer effects; it may predict impacts on other career choices beyond entrepreneurship, which we do not find in the data. Another concern may be that our measure of successful entrepreneurship is too crude. But we obtain similar results when using an alternative measure based on the presence of the entrepreneur's business in the Pitchbook startup database. We also show that measuring post-MBA entrepreneurship three years after graduation strengthens the results. A third concern may be that streams are too large to capture the relevant peer group. We look at smaller peer groups defined based on seating charts and study groups, and find that entrepreneurial peer effects are not further localized inside the stream.[3]

[3] In this analysis, analogously to our main results, we exploit the random component of the share of entrepreneur peers within the smaller peer group.

The peer effects logic predicts impacts not just on entrepreneurship but also on students' acquisition of entrepreneurial human and social capital. To explore this, we use data on students choice of entrepreneurship electives, which teach skills for starting a business, and students attendance of Entrepreneurship Club events, which enable connections with financiers and founders. We find, paralleling our main results, that entrepreneur peers with a digital footprint increase, while entrepreneur peers without a digital footprint decrease students' choice of entrepreneurial electives and Entrepreneurship Club registrations. These findings provide internal validity to our peer effect results, further support the screening mechanism, and imply that entrepreneurial human and social capital are complementary to having a good business idea.

In Section 5 we study policies that may increase successful entrepreneurship. We start by extending the screening model to incorporate dynamics, which leads to a new mechanism: screening in a given period affects the composition of entrepreneurs who conduct the screening in the next period. We then estimate the model structurally and use the estimates to evaluate two counterfactual policies. In the first policy, we increase the number of meetings an individual has with entrepreneur peers. This policy can represent initiatives such as entrepreneurship clubs or clusters. At the estimated parameter values, such a policy would have negligible short-run and small long-run effects on successful entrepreneurship, because its positive and negative effects cancel. In the second policy, we increase the share of entrepreneurial meetings that are with *successful* entrepreneur peers. This policy can represent initiatives such as mentor selection at incubator programs, or imposing quality standards at entrepreneurial clusters. This policy meaningfully increases successful entrepreneurship. For example, increasing the successful share among entrepreneurial meetings from 70% to 84% increases the creation of successful entrepreneurs by 9% in the short run and 13% in the long run. Moreover, in the presence of the second policy, the first policy has positive effects: e.g., increasing the frequency of meeting an entrepreneur from 2.9% to 3.5% further increases the long-run effect to 17%. Considering that such gains could be directly reflected in economic growth, and given the small cost of the policies, these effects seem large. We conclude that designing high-quality entrepreneurial peer groups has the potential to substantially increase successful entrepreneurship.

Our research builds on work studying the allocation of talent to entrepreneurship. Entrepreneurial talent may be under-provided because of its positive externalities (Smith 1776, Schumpeter 1911, Bloom, Schankerman and Van Reenen 2013), and may be misallocated because of market distortions or limited awareness of entrepreneurship (Murphy, Shleifer and Vishny 1991, Bell, Chetty, Jaravel, Petkova and Van Reenen 2019b). Thus, policies that increase entrepreneurship, perhaps through interactions, may create value. Many papers present evidence consistent with positive peer effects in entrepreneurship, when peers are measured using neighbours (Giannetti and Simonov 2009, Guiso, Pistaferri and Schivardi 2021), worker networks (Nanda and Sørensen 2010, Wallskog 2024), family ties (Hvide and Oyer 2018), or university peers (Kacperczyk 2013). But these studies lack quasi-random variation in peer groups. In contrast, Lerner and Malmendier (2013), using the quasi-random assignment of HBS students, document negative peer effects, which are concentrated in unsuccessful entrepreneurs.[4] Our main contribution to this work is the randomized evidence on positive and negative peer effects in successful entrepreneurship; the evidence supporting the screening mechanism, which helps reconcile the opposite-signed results in the above work; and the evaluation of counterfactual policies to increase successful entrepreneurship.

A related line of research studies the determinants of innovation. This work documents the role of childhood exposure to innovators, perhaps because it provides awareness and role models (Bell et al. 2019a, Bell et al. 2019b); and the role of exposure to the customer base, perhaps because it provides knowledge about customer needs (Einiö, Feng and Jaravel 2023). Our main contribution to this work is to study the choice of entrepreneurship among individuals who are all aware of entrepreneurship, and to document the importance of the screening mechanism.

More broadly, we build on work documenting peer effects in the classroom in different contexts (Sacerdote 2001, Carrell, Fullerton and West 2009, Guryan, Kroft and Notowidigdo 2009, Chetty, Friedman, Hilger, Saez, Schanzenbach and Yagan 2011, Carneiro, Cruz-Aguayo, Salvati and Schady 2024). Our contribution to this literature is to document peer effects in entrepreneurship.[5]

[4] Related work in development economics studies the impacts of firm-to-firm interactions and of training on business performance, generally focusing on existing firms (Cai and Szeidl 2018, McKenzie, Woodruff, Bjorvatn, Bruhn, Cai, Gonzalez-Uribe, Quinn, Sonobe and Valdivia 2021), and the effect of monetary incentives in business competitions (Fafchamps and Quinn 2017, McKenzie 2017).

[5] Another related line of work studies the impact of business education on economic outcomes (Yang, Christensen, Bloom, Sadun and Rivkin 2020, Acemoglu, He and le Maire 2022).

2 A simple model of peer effects in entrepreneurship

An MBA student must decide whether to pursue an entrepreneurial idea. She believes her idea is of high quality, h, with probability $\rho \in (0, 1)$ and of low quality, l, with probability $1 - \rho$. A low quality idea is unsuccessful and creates low returns, L, whereas a high quality idea creates high returns, H. We normalize, without loss of generality, $L = 0$ and $H = 1$. The student can, instead of developing the idea, accept her best outside option $R \geq 0$ (e.g. working for a hedge fund) drawn from distribution Γ. The student observes R and then makes her career choice. Hence, the student becomes an entrepreneur whenever $R \leq \rho$; the likelihood that the student becomes an entrepreneur is $\Gamma(\rho)$.

We are interested in how the student's decision may be affected by interacting with peers who have entrepreneurial experience. Suppose the student interacts with an MBA peer who, before the program, was an entrepreneur. The peer may have had a successful, S, or unsuccessful, U, experience and peer effects may depend on this. The student does not observe whether the peer was successful or unsuccessful.

We consider three mechanisms for peer effects (see Appendix B for formal analysis.) The first mechanism, the *knowledge peer effect*, postulates that peer interaction increases the entrepreneurial human and social capital of the student and, therefore, the private return from implementing a business idea.This effect may vary depending on peer's past success and the underlying idea's quality, but it always increases the likelihood of entrepreneurship. The second mechanism, the *morale peer effect*, assumes that by sharing past entrepreneurial experiences, peers affect the morale of the prospective entrepreneur. A successful peer shares positive stories and boosts morale, increasing the student's beliefs that her idea is of high quality; an unsuccessful peer, in contrast, lowers morale and reduces the student's belief. Thus, a successful peer increases, while an unsuccessful peers reduces the likelihood of both successful and unsuccessful entrepreneurship.

The third mechanism, which we call the *screening peer effect*, postulates that peers screen the idea's quality. A successful peer perfectly screens ideas and tells the student that the project is h when it is high quality and l when it is low quality. In contrast, an unsuccessful peer always tells that the project is l regardless of its true quality. Bayes' rule implies that a l message lowers and a h message increases the student's prior ρ. Hence, successful peers increase the likelihood of successful entrepreneurship and reduce the likelihood of unsuccessful entrepreneurship; unsuccessful peers decrease the likelihood of both successful and unsuccessful entrepreneurship.

2.1 Empirical predictions

We postulate that each student i allocates a total time $\hat{p}$ for interaction within the stream, which is shared equally across all other $n-1$ students, leading to an interaction probability $\hat{p}/(n-1)$ with each student.[6] Let $\gamma_{i,S} = N_S/(n-1)$ and $\gamma_{i,U} = N_U/(n-1)$ be the share of successful and unsuccessful peers in the student i's stream. In Appendix B we show that, regardless of the peer effect channel, student i's probability of becoming a successful entrepreneur and of becoming an unsuccessful entrepreneur can be written, respectively, as:

$$\Pr{}_i(\text{successful entrepreneur}) = c_{i,h} + \beta_{i,h;S}\gamma_{i,S} + \beta_{i,h;U}\gamma_{i,U} \tag{1}$$

$$\Pr{}_i(\text{unsuccessful entrepreneur}) = c_{i,l} + \beta_{i,l;S}\gamma_{i,S} + \beta_{i,l;U}\gamma_{i,U}. \tag{2}$$

The three channels predict different signs for the four coefficients $(\beta_{i,h;S}, \beta_{i,h;U}, \beta_{i,l;S}, \beta_{i,l;U})$.

Prediction A.

1. *Knowledge peer effect.* Exposure to both successful and unsuccessful peers increases successful and unsuccessful entrepreneurship, i.e. $\beta_{i,T;Q} \geq 0$ for all $T \in \{h, l\}$ and $Q \in \{S, U\}$.

2. *Morale peer effect.* Exposure to successful peers increases, exposure to unsuccessful peers decreases both successful and unsuccessful entrepreneurship, i.e. $\beta_{i,T;S} > 0$ and $\beta_{i,T;U} < 0$ for $T \in \{h, l\}$.

3. *Screening peer effect.* Exposure to successful peers increases successful entrepreneurship and decreases unsuccessful entrepreneurship, while exposure to unsuccessful peers decreases successful and unsuccessful entrepreneurship, i.e. $\beta_{i,h;S} > 0$ and all the other coefficients are negative.

[6] When needed, we take first-order approximations of the derived expression under the assumption that the expected number of interactions is small.

3 Context, Data, and Empirical Strategy

3.1 Context

The LBS MBA is a two-year comprehensive degree program designed for mid-career professionals. Each year, incoming students are allocated by LBS into five or six 'streams' which partition the cohort. Students take all core courses, which includes every course in the first six months and the majority of courses in the second six months, with their stream. For these core courses, students are seated in lecture theatres according to seating charts prepared by LBS. In addition, LBS assigns each student to a 'study group' with between four and seven people from their stream. The assignment of students into streams, seats, and study groups is designed by the program office in a way that is quasi-random, conditional on some stratification criteria. We exploit this quasi-random variation in our identification strategy.

During the second year, students have the opportunity to tailor their MBA experience according to their career goals and personal interests. This phase includes elective courses, where students can delve deeper into specific sectors or functional areas; and various career development activities including recruitment events, company presentations, and networking opportunities. During the entire program students also participate in events organised by student clubs, forming social connections and expanding their professional networks.

3.2 Data

We use the following data about LBS students who graduated between 2014 and 2022.

Demographics. Predetermined characteristics for each student, such as gender, English fluency, and nationality, come directly from the LBS School Database (SchoolDB). SchoolDB also includes information related to qualifications for admission, such as GMAT scores and years of work experience, and career aspirations (desired industry and function upon graduating from LBS).

Courses. LBS MBA students are enrolled in a predetermined set of 'core' courses during the first year and select 'electives' in the second. Data extracted from the SchoolDB covers all courses taken by MBA students in our sample period. There are seven subject areas that offer a variety of electives every year. We are primarily interested in electives offered by the Strategy & Entrepreneurship department, and in consultation with professors from that department, we identified nine electives that are relevant for entrepreneurial human capital development.[7]

Clubs. Student clubs provide members of the LBS community with the opportunity to connect over shared professional or personal interests, and are classified as either 'social', 'sports', 'regional' (i.e. geographic), or 'career' clubs. Students register for events organised by clubs by providing their email addresses and, in some cases, paying a registration fee.[8] We obtained student club event registration data for over 7,000 events during the 2014-2022 academic years from the LBS student association.[9] Our primary interest is the Entrepreneurship Club, which organises pitch competitions, guest speakers, and networking events related to entrepreneurship.

Employment. Data on employment history comes from three sources. (1) Pre-MBA employment history is requested during the admissions process. Students can report multiple past jobs, including the company name, industry, position, start/end dates, and location. This information is included in the SchoolDB. (2) Data on post-MBA employment comes from the LBS Career Portal Plus (CPP) platform. After graduation, the career centre runs a survey through CPP to secure a response from all students within 90 days about their job offers (e.g. firm name, industry and position). We define the post-MBA job as the accepted post-graduation job offer with the latest acceptance date. (3) Additional information is gathered from LinkedIn.[10] For every student in the LBS dataset we searched for their LinkedIn profile using first, known-as, and last names, and then verified the results by matching work/education histories with SchoolDB data. We extracted data from LinkedIn about the employment experiences for 93% of students in the 2014 through 2022 cohorts.

Entrepreneurship. We have data on entrepreneurship from all three employment data sources:

[7] They are New Venture Development (E189), Managing the Growing Business (E202), Financing the Entrepreneurial Business (E224), New Technology Ventures (E384), Entrepreneurial Summer School (E400), Entrepreneurship in Emerging Markets (E471), Pathways to Start-up Success (E489), Entrepreneurship through Acquisition (E603), and Entrepreneurial Mindset (E615).

[8] An important caveat is that registration for an event does not guarantee attendance, but it does indicate interest. Some students may also attend events without registering, but this has been described to us as uncommon by student association officials who administer club activities.

[9] This does not cover the first academic year of the first cohort, which finished their first year in 2013.

[10] LinkedIn is a professional networking platform that allows users to create profiles showcasing their professional credentials, form connections with peers, follow companies, and receive messages from recruiters.

SchoolDB, the CPP survey, and LinkedIn. In addition, we have data on entrepreneurial activity from Pitchbook, a company that compiles data on venture capital, private equity, and M&A transactions (including early stage funding deals) as part of a suite of tools for financial analysts. We use these data to define three categories of entrepreneurship.

- *Pre-MBA entrepreneurs* are identified from the SchoolDB data by searching for job titles that include 'founder'/'founded', job function stated as 'entrepreneur', or job type reported as 'self-employed'. We then filtered these jobs to those that began prior to starting the MBA program and were active within one year of arriving at LBS.[11] We use the within-one-year criterion to make sure the pre-MBA entrepreneurship experience is still fresh, but using other cutoffs does not affect our qualitative results.

- *Post-MBA entrepreneurs within 90 days of graduation* are identified from the CPP data as individuals who reported their work status as 'self-employed/starting a business' within 90 days of graduation.

- *Post-MBA entrepreneurs within t years of graduation* further include individuals if in the LinkedIn data they had 'founder' or 'founded' in their job titles and started that job during the t years after graduation.[12]

Within each of these categories, we determined whether the entrepreneur had a digital footprint by (i) checking if they posted to their LinkedIn profile an instance of entrepreneurship (e.g. working as a 'co-founder' for 'Company ABC'); and if not, by (ii) searching for the name of their business online. For students identified as a with-footprint entrepreneur, we searched Pitchbook to see if their company has a Pitchbook page. The distinction of without versus with digital footprint can be considered a signal of entrepreneurial acumen or quality since less capable, potentially failed entrepreneurs are less likely to publicise that aspect of their employment history; having a Pitchbook

[11] Active refers to not having an end date more than one year prior to the start of the program. In the absence of an end date students were assumed to still be active in that role.

[12] We also classified students as entrepreneurs using their LinkedIn profile biographies, but only when there was reference to a specific job with start/end dates.

Table 2: Entrepreneurship data sources

	Pre-MBA	Post-MBA within 90 days	Post-MBA within t years
All entrepreneurs	SchoolDB	CPP	CPP or LinkedIn
With digital footprint		LinkedIn/another website	
Footprint, accomplished		PitchBook	

page is an additional accomplishment that reflects entrepreneurial success. Table 2 summarizes the data sources used for the different definitions.

Merging. Datasets were merged using unique, anonymised identifiers created to comply with GDPR. We reconciled entrepreneurial classifications across the SchoolDB, CPP, and LinkedIn datasets by comparing start dates, locations, and company names of employment experiences.[13] We chose to restrict pre-MBA entrepreneurs to those identifiable through the SchoolDB because the few students who only mentioned starting a business on LinkedIn (i.e. without informing LBS) did not have any other online presence that confirmed their entrepreneurial activities.

Sample definition. We estimate peer effects in a core sample of students defined as follows. We begin with $3,970$ students in the $2014-2022$ cohorts. (1) We exclude 46 students who did not respond to the post-graduation CPP survey. (2) We exclude 219 students for whom we could not find a LinkedIn profile. (3) We exclude 178 students who have missing demographic data. (4) We exclude 102 students who were pre-MBA entrepreneurs, which allows us to focus on peer effects on new entrepreneurship. This leaves us with a core sample of $3,425$ students.

3.3 Summary statistics

Table 3 presents summary statistics for the nine cohorts in our dataset who graduated between 2014 and 2022. The average cohort size was 441, of which on average 392 students are in our core sample. All subsequent statistics are computed for this core sample. Students were on average 29

[13] An independent research assistant working for LBS generated the anonymous identifiers using the master list of MBA students from SchoolDB. Instances of misalignment, such as a student being an entrepreneur in London according to LinkedIn but working in Paris at that time according to SchoolDB, were manually verified by another independent LBS-employed research assistant who was given access to the relevant rows of the raw data to perform the task.

Table 3: Summary statistics

Characteristic	Avg.	Std.	Min.	Max.
Population size				
Cohort size	391.9	31.4	358	435
Stream size	73.5	3.99	66	83
Study group size	5.20	0.87	3	7
Demographics				
Age	28.8	2.36	23.2	39.3
Male	0.641	0.480	0	1
Native English speaker	0.395	0.489	0	1
Asian nationalities	0.294	0.456	0	1
European nationalities	0.318	0.466	0	1
North American nationalities	0.199	0.400	0	1
Other nationalities	0.189	0.391	0	1
Experience				
Years of work experience	5.39	1.95	1	36
Consulting industry	0.237	0.425	0	1
Finance industry	0.210	0.407	0	1
Other industries	0.553	0.497	0	1
GMAT (overall score)	700.6	37.3	530	790
Additional variables				
Aspiring entrepreneur	0.096	0.295	0	1

Note: all variables except "aspiring entrepreneurship" are used as stratification variables in stream and study group allocation.

years old, and almost two thirds of them were men. Within these limits, the student body was quite diverse: only about 40% were native English speakers, and only about half of them came from Europe or North America, with almost 30% coming from Asia. Students had on average five years of work experience prior to starting the program, and almost half of them had a background in consulting or finance. Around 10% of students were aspiring entrepreneurs, defined as having expressed interest in starting a business in the entry survey.

Table 4 focuses on entrepreneurship. The average stream had around 3% of students who were pre-MBA entrepreneurs. Among the remaining students, about 7% became entrepreneurs within one year of graduation. A majority of the post-non-pre-MBA entrepreneurs had a digital footprint (200 of 245, or 82%), a third of whom (68) are classified as accomplished. Appendix Figure A1 presents the share of pre-MBA and post-MBA entrepreneurs with and without a digital

Table 4: Stream-level entrepreneurship averages

Characteristic	Count	(Std. Dev.)	Percent	(Std. Dev.)
Pre-MBA				
All entrepreneurs	2.12	(1.47)	2.93	(2.00)
Without footprint	0.60	(0.87)	0.82	(1.19)
With footprint	1.52	(1.27)	2.10	(1.76)
With footprint, not accomplished	1.31	(1.17)	1.82	(1.64)
With footprint, accomplished	0.21	(0.46)	0.28	(0.62)
Post-non-pre-MBA				
All entrepreneurs	5.10	(2.50)	7.14	(3.46)
Without footprint	0.94	(0.86)	1.30	(1.20)
With footprint	4.17	(2.25)	5.84	(3.14)
With footprint, not accomplished	2.75	(1.76)	3.87	(2.50)
With footprint, accomplished	1.42	(1.35)	1.97	(1.86)

Note: pre-MBA average stream percentages computed in core sample plus the pre-MBA entrepreneurs; post-non-pre-MBA computed in core sample used in regression analysis.

Table 5: Post-non-pre-MBA entrepreneur companies

Category	Number of companies	Active employee connections	(SD)
Footprint, accomplished	85	33	(63.5)
Footprint, not accomplished	116	15	(63.2)
With footprint (total)	201	24	(63.7)

Note: total number of companies differs from the number of post-non-pre-MBA entrepreneurs because some founded multiple companies and others co-founded.

footprint by cohort, which shows that all cohorts have a meaningful share of both pre-MBA and post-non-pre-MBA entrepreneurs.

Table 5 presents statistics on companies founded by with-footprint non-pre-MBA entrepreneurs. There are 201 companies in total, of which 85 or 42% have a page in PitchBook such that their founders are classified are accomplished. On average the firms have 24 active employee connections on LinkedIn, although there is considerable variation in firm size. This relatively large firm size justifies our classification of with-footprint entrepreneurs as successful. Over a quarter of the companies are headquartered in London (56), with the second largest concentration being in New York City (8).

3.4 Student allocation

The stream, study group, and seat assignment process for the LBS MBA program is a quasi-random procedure that produces an allocation which must satisfy specific requirements set by the program office to ensure several characteristics are stratified evenly across all cohort divisions. The characteristics that need to be balanced are age, GMAT score (total), years of work experience, prior industry, previous firm, geographic region, primary nationality, male/female, and native English speaker. The allocation process is quite involved: it solves a binary programming problem subject to integer and range constraints for the different stratification variables, and we describe it in more detail in Appendix A1. Importantly, entrepreneurship is not a stratification criteria at any stage of the process. Thus, stratification does not mechanically ensure that pre-MBA entrepreneurs are evenly distributed across streams, study groups, or in their seating assignments.

Key to our identification strategy is that—based on extensive consultation with the LBS personnel in charge of implementing each stage of the assignment process—we have access to the full algorithm used to create assignments, including all the original code files. This allows us to create counterfactual allocations of the stream, study group, and seating assignments by replicating that process exactly as implemented.

3.5 Empirical strategy

Guided by the theoretical framework in Section 2, our estimating equation for identifying peer effects at the stream level is

$$Y_{isc} = \beta \overline{X}_{-isc} + \theta Z_i + \alpha_c + \varepsilon_{isc}, \tag{3}$$

where i stands for student, s for stream, and c for cohort. The variable Y_{isc} is an outcome of interest, e.g. an indicator variable that takes value 1 if student i has a post-MBA entrepreneurship status. The key term on the right-hand side is $\overline{X}_{-isc}$ which measures the average pre-MBA entrepreneurial experience X of the *other* students in student i's stream. To compute $\overline{X}_{-isc}$, we average over all students in the core sample who are in the stream as well as all pre-MBA-entrepreneurs in the stream (who are not in our core sample); by excluding pre-MBA-entrepreneurs from the sample

$\overline{X}_{-isc}$ is constant across students in the same stream.

To capture time-variation in entrepreneurship, which could be driven by the economic cycle, we include in the regression cohort fixed effects α_c. And to reduce residual variation we include predetermined student-level controls Z_i. We chose these controls using a LASSO procedure to predict post-MBA entrepreneurship, which selected three variables: aspiring entrepreneur, male, and native English speaker.[14] Finally, the error term ε_{isc} represents variation in entrepreneurship unexplained by peer effects, time effects, or predetermined characteristics.

Estimating (3) using OLS assumes that $\overline{X}_{-isc}$ is mean-independent of ε_{isc}. We expect that the identification condition would hold if students were truly randomly assigned to streams. However, the stratification constraints of the LBS procedure can introduce correlations. For example, since in our data entrepreneurs are more likely to be male, a female student, who will have more male peers on average due to the LBS procedure, can expect to have a higher share of pre-MBA entrepreneur peers. One intuitive approach to deal with this issue is to include all the stratification variables as controls in the regression. However, the LBS stratification procedure imposes constraints across the entire cohort and has nonlinear stratification targets, hence it is not clear that including a set of controls in a linear fashion fully eliminates the confounding correlations.

To address this problem, we take advantage of a strategy suggested by Borusyak and Hull (2023) to isolate the random component of $\overline{X}_{-isc}$. Using the original LBS stream-assignment algorithm, we create 200 counterfactual assignments for each cohort. Computing the average $\overline{X}_{-isc}$ for each student across these counterfactuals gives us $\mu_{ic} = E[\overline{X}_{-isc}]$, which is the expectation over all possible realizations of the LBS stream-assignment procedure and thus captures the on-average effects of stratification. The residual $\left(\overline{X}_{-isc} - \mu_{ic}\right)$ should then measure the truly random component of entrepreneurial peer assignment. Following the recommendation of Borusyak and Hull (2023), we use this random component as an instrument for $\overline{X}_{-isc}$ in what they call a 're-centered IV' specification.

[14] Our results are robust to omitting these controls.

In summary, our main specification (4) is a 2SLS version of equation (3):

$$Y_{isc} = \beta\widehat{\overline{X}}_{isc} + \theta Z_i + \alpha_c + \varepsilon_{isc} \tag{4}$$

$$\overline{X}_{isc} = \psi\left(\overline{X}_{-isc} - \mu_{ic}\right) + \phi Z_i + \omega_c + \nu_{isc} \tag{5}$$

where the first stage (5) regresses the share of entrepreneur peers $\overline{X}_{-isc}$ on the random component of the variation, and the predicted values $\widehat{\overline{X}}_{isc}$ are used in the second stage. To account for within-stream correlations in entrepreneurial activity due classroom and social interactions, we cluster standard errors at the stream level and estimate them using the Imbens and Kolesár (2016) variance estimator to adjust for the relatively small number of clusters (48) we have in the data. Later in the paper we estimate analogous models to evaluate peers effects in study groups and seating charts, and we describe those specifications in more detail when we present the results.

3.5.1 Validation of identification strategy

To validate our empirical strategy we conducted balance tests, reported in Appendix Table A1. We used five different measures of entrepreneurial peers: share of stream peers who were pre-MBA entrepreneurs, only those without a digital footprint, only those with a digital footprint, those with a digital footprint but not accomplished, and those with a digital footprint and accomplished. And we used ten predetermined characteristics as outcome variables, all of which were used in the LBS stratification.[15] We estimated these 50 regressions both with OLS and with the re-centered IV. When estimating with OLS, 14% of the coefficients had p-value below 0.1, while with the IV only 8%, which is closer to the rate we would expect by chance. These results suggest that the IV succeeds in correcting for the bias potentially created by the assignment process.[16]

[15]These are: worked in consulting, worked in finance, Asian nationality, European nationality, North American nationality, male, native English speaker, older than cohort average, GMAT above cohort average, and experience above cohort average.

[16] We also replicated the same exercise with standard errors generated using a random inference technique recommended by Borusyak and Hull (2023) and obtained similar results (Appendix Table A2).

Table 6: Peer effects on post-MBA entrepreneurship

	Post-MBA entrepreneur				
	All	Without footprint	With footprint	Footprint, not accomplished	Footprint, accomplished
Panel A	(1)	(2)	(3)	(4)	(5)
All entrepreneurs	−0.181	−0.096	−0.085	−0.036	−0.049
(with or w/o footprint)	(0.223)	(0.075)	(0.227)	(0.185)	(0.156)
Panel B	(6)	(7)	(8)	(9)	(10)
Without footprint	−0.970**	0.115	−1.085**	−0.681**	−0.404*
	(0.410)	(0.183)	(0.457)	(0.325)	(0.237)
With footprint	0.223	−0.204**	0.427**	0.294	0.133
	(0.203)	(0.081)	(0.195)	(0.208)	(0.183)
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Post-MBA entrepreneurs	245	45	200	132	68
Observations	3,425	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

4 Peer effects in entrepreneurship: empirical results

4.1 Main results

Table 6 presents our main results on post-MBA entrepreneurship. In these regressions we measure entrepreneurship one year after graduation. We estimate the re-centered IV regression (4) in the core sample of non-pre-MBA entrepreneur students. In Panel A, our measure of peer effects is the share of stream peers with any entrepreneurial experience, with or without a digital footprint. In column 1 the outcome variable is an indicator for any type of post-MBA entrepreneurship within one year of graduation. The coefficient is insignificant. In columns 2-5 we estimate the same regression using as outcomes entrepreneurship without a digital footprint, with a digital footprint, with a digital footprint but not accomplished (lacks a Pitchbook page), and with a digital footprint and accomplished (has a Pitchbook page). All of these regressions yield insignificant results. Overall, Panel A suggests that the peer share of pre-MBA entrepreneurs have limited impact on post-MBA entrepreneurship on average.

In Panel B we separately measure the impacts of pre-MBA entrepreneurs without versus with a digital footprint. We measure the contribution of these two groups of entrepreneur peers with their shares among stream peers, and instrument the two shares with their re-centered versions. Thus, we estimate a regression analogous to (4) but with two endogenous variables and two instruments. Separately measuring the impacts of peers without and with a digital footprint changes the results dramatically. Column 1 shows that entrepreneur peers without a digital footprint significantly reduce the probability of post-MBA entrepreneurship. Columns 2-5 show that this reduction is concentrated in post-MBA entrepreneurs with a digital footprint, and even affects post-MBA entrepreneurs that have a Pitchbook page. At the same time, pre-MBA entrepreneurs with a digital footprint have an insignificant positive effect on post-MBA entrepreneurship on average (column 1), which however masks important heterogeneity: these peers reduce post-MBA entrepreneurship without a footprint, but increase post-MBA entrepreneurship with a footprint. In summary, these results show that unsuccessful (without footprint) peers reduce successful (with footprint) entrepreneurship, while successful peers reduce unsuccessful and increase successful entrepreneurship.

We now interpret these results using Prediction A of the model in Section 2. The negative impact of successful peers on unsuccessful entrepreneurship is inconsistent with the knowledge mechanism, which does not predict negative peer effects, and with the morale mechanism, which predicts that successful peers increase all entrepreneurship. However, the results are consistent with the screening mechanism, which predicts negative peer effects from unsuccessful peers, while type-dependent (positive for successful, negative for unsuccessful) peer effects from successful peers. The one prediction of the screening mechanism we do not find significant evidence for is that unsuccessful peers should reduce unsuccessful entrepreneurship. Specification 7 of Table 6 reports an insignificant effect with a large standard error, so that we cannot reject that the true effect is quite negative. We conclude that the observed patterns are well explained by the screening mechanism.[17]

The magnitudes of the effects are sizable. Our results imply that one more unsuccessful peer

[17] A variant of the screening mechanism is that successful peers encourage and unsuccessful peers discourage entrepreneurship-related activities, such as taking entrepreneurship electives and participating in entrepreneurship events, and it is these activities that enable students to screen their business idea. In this variant, screening is indirect.

creates about 1.05 fewer successful entrepreneurs in the stream, a reduction of 25%. On the other hand, one more successful peer creates about 0.41 more successful entrepreneurs in the stream, an increase of 10%.[18] Aggregating across our sample, we find that unsuccessful peers destroyed about 30.5 successful entrepreneurs, a reduction of about 15%, while successful peers created about 29.9 successful entrepreneurs, an increase of about 15%.[19] Thus both positive and negative peer effects had large impacts on successful entrepreneurship, but their combined effects ultimately cancelled out.

The result that peer effects do not increase successful entrepreneurship seemingly contradicts our Bayesian screening model. After all, Bayesian learning from peers should make entrepreneurs with a high-quality idea (on average) increase their posterior about their idea. This does hold in our model, but the higher average posterior comes from a mix of very high and low posteriors for those receiving high and low signals. If the distribution function of outside options Γ is sufficiently concave, the increase in entrepreneurship in the former group will be small, while the decrease in entrepreneurship in the latter group will be large. Intuitively, low-quality ideas are dominated by outside options, such that getting a low message has a large effect on exit from entrepreneurship.

Although the positive and negative effects cancel in our setting, they need not cancel in general. In our model, a higher share of successful peers would generate gains in successful entrepreneurship; and a lower share would generate losses.[20] Thus, whether screening peer effects increase successful entrepreneurship depends on the details of the context, raising new questions about welfare and design. Assuming that entrepreneurship has large positive externalities, the social gains from peer effects are mainly driven by the number of successful entrepreneurs, therefore the null effect on this

[18] The effect of an additional unsuccessful peer on successful entrepreneurship is the average number of non-pre-MBA entrepreneurs in a stream (71.35) times the increase in the share of unsuccessful peers (1/73.5) times the estimated effect of the share of unsuccessful peers regression coefficient ($\beta_{hU} = -1.085$). The effect of an additional successful peer can be computed analogously (using $\beta_{hS} = 0.427$). Percent changes are relative to the average number of successful post-MBA entrepreneurs per stream (4.17).

[19] The aggregate effect of unsuccessful peers on successful entrepreneurship is the effect of an additional unsuccessful peer ($\beta_{hU} = -1.085$) times the total number of unsuccessful pre-MBA peers 29. The aggregate effect of successful peers is the effect of an additional successful peer ($\beta_{hS} = 0.427$) times the total number of successful pre-MBA peers 73. The percent changes are relative to the 200 successful post-MBA entrepreneurs in the data.

[20] A caveat is that changing these shares in the model would also change Bayesian updating and the coefficients β_{hS} and β_{hU}. We show in Section 5 that under empirically realistic assumptions we can hold fixed β_{hS} and β_{hU} for small changes in the composition.

outcome suggests small social gains. Given the availability of successful peers for screening, this feels like a missed opportunity. How should we organize entrepreneurial meetings to increase successful entrepreneurship? We return to this research question in Section 5 by evaluating counterfactual policies.

4.2 Remarks about interpretation, robustness, and heterogeneous effects

Interpretation of peer effects. Given that our approach exploits the purely random component of variation, it plausibly identifies a causal effect. However, it does not allow us to exclusively attribute this effect to peer entrepreneurs. In principle, the results could be driven by some other characteristic of the peer group correlated with the share of pre-MBA entrepreneurs. Since the peer group is effectively randomly assigned, this other characteristic needs to be some other attribute of the entrepreneur peers themselves, such as independence or courage.[21] In our setting, there are two reasons to believe that the peer effects are driven by peers being past entrepreneurs. First, the signs of our estimates vary with the success of peers and students, a pattern which can be rationalized by screening but not with attributes such as courage or independence, which plausibly predict same-signed (positive) peer effects. Second, we expect that other attributes may influence not just the choice to become an entrepreneur, but career choice more broadly. For example, peer effects that instill independence may encourage careers in consulting, which is relatively independent work; peer effects that instill courage may encourage a career in technology, which is relatively high risk. Appendix Table A3 presents peer effect regressions in which the outcomes are post-MBA career choices in consulting, finance, and technology. None of the estimates are significant. These results support the view that entrepreneurship drives our peer effect estimates.

Refined definition of successful pre-MBA entrepreneur. In our main specification we use digital footprint as our measure of the success of the pre-MBA entrepreneur. However, we have also tested a more refined measure based on whether that entrepreneur's business has a Pitchbook page. In Appendix Table A6 we report results in which pre-MBA entrepreneurial success is decomposed into two peer effect variables using this distinction (labelled 'accomplished'). Since we now esti-

[21] This identification problem is common with peer effect estimation which is based on random assignment to peer groups (Bramoullé, Djebbari and Fortin 2009).

mate three kinds of peer effects—peers without a footprint, with a footprint but not accomplished, with a footprint and accomplished—we lose some statistical power. Nevertheless, the high-level qualitative lessons remain. Specification 2 shows a significant negative effect of non-accomplished with-footprint peers on post-MBA entrepreneurs without footprint; specification 3 shows a significant positive effect of accomplished peers on post-MBA entrepreneurs with footprint. We conclude that the qualitative findings are robust to using these more refined measures.

Interaction between successful and unsuccessful entrepreneur peers. A natural question is how the positive and negative peer effects interact. For example, the screening model suggests that the presence of successful peers should mitigate the negative effect of unsuccessful peers when the outcome is successful entrepreneurship, and amplify it when the outcome is unsuccessful entrepreneurship. Appendix Table A7 reports the results from estimating regressions that include the interaction between the share of successful and unsuccessful entrepreneur peers. The interaction coefficient is always insignificant: we are underpowered to document such mitigation or amplification effects. A possible interpretation is that each feedback from an entrepreneur peer is a low-probability event, so that receiving multiple feedbacks occurs with negligible probability.

Heterogeneous effects. In our main specification we require post-MBA entrepreneurship to begin within one year of graduation. However, starting a business takes time, and some MBA students may be financially constrained or decide to take a high paying job only to pursue their business idea at a later stage.[22] Moreover, it is possible that peers only influence the speed, but not the presence of entrepreneurial activities. Table 7 presents the results for without-footprint (unsuccessful) and with-footprint (successful) post-MBA entrepreneurship at alternative horizons. The outcome variables are measured at 90 days (using only CPP data), one year (as in Table 6), two years, and three years. The specifications are analogous to those in Table 6 Panel B. The table shows that all of our results are robust, and if anything slightly increasing over time. Thus, exposure seems to have a long-lasting impact on business creation.

We next look at heterogeneity by gender. Existing work shows that women are significantly less likely to become entrepreneurs (Estrin and Mickiewicz 2011, Guzman and Kacperczyk 2019)

[22] Conversations with MBA students and alumni confirm these possibilities.

Table 7: Post-MBA entrepreneurship by horizon

	Post-MBA entrepreneur within			
	90 days	1 year	2 years	3 years
Panel A: without-footprint	(1)	(2)	(3)	(4)
Without footprint	0.115	0.115	0.115	0.149
	(0.159)	(0.183)	(0.183)	(0.185)
With footprint	-0.138^{*}	-0.204^{**}	-0.204^{**}	-0.228^{***}
	(0.081)	(0.081)	(0.081)	(0.075)
Panel B: with-footprint	(5)	(6)	(7)	(8)
Without footprint	-1.186^{***}	-1.085^{**}	-1.099^{**}	-1.232^{**}
	(0.310)	(0.457)	(0.460)	(0.522)
With footprint	0.356^{**}	0.427^{**}	0.574^{***}	0.616^{***}
	(0.180)	(0.195)	(0.191)	(0.216)
Post-MBA without-footprint	41	45	45	46
Post-MBA with-footprint	138	200	234	265
Cohort fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native English speaker. *p<0.1; **p<0.05; ***p<0.01.

or inventors (Hunt, Garant, Herman and Munroe 2012, Kahn and Ginther 2017). We ask whether peer effects contribute to this gender gap. Appendix Table A8 presents regressions in which we interact our measures of peer effects with the gender of the student. Peer effects for men and women are not statistically distinguishable from each other.

But peer effects may depend on the gender of both parties: if same-gender interactions are of higher quality, then they should create stronger peer effects. Appendix Table A9 presents regressions on same-gender peer effects, measured with the share of stream peers who are pre-MBA entrepreneurs and have the same gender as the student. Although we lack sufficient power to document differences between same-gender and different-gender peer effects, the point estimates are consistently larger, and only significantly different from zero, for same-gender effects. Same-gender bad (without footprint) entrepreneurs have a significant negative effect, while same-gender good (with footprint) entrepreneurs have a significant positive effect on good entrepreneurship.[23] These

[23] The table also reports these regressions separately in the subsamples of men and women. Results are noisier but

results suggest that peer effects may contribute to maintaining a gender gap in entrepreneurship: if women entrepreneurs are scarce, then prospective female entrepreneurs will have fewer opportunities to receive feedback on their entrepreneurial ideas.[24]

Peer group definition. In our main results we define the stream as the peer group. We can also explore peer effects in smaller peer groups: study groups and students close in physical space in the classroom. As mentioned previously, students in each stream are allocated to study groups in a quasi-random fashion subject to stratification constraints, and then allocated to seating charts subject to further stratification constraints (see Appendix A1 for details). Our empirical approach isolates the random component of these allocations using the same type of re-centering procedure implemented for streams. For study groups, we define the peer group simply as the study group, which encompasses on average 4.2 peers. For seating, we define the peer group as the set of students within a circle around each student in the classroom map. The radius of the circle was chosen so that on average 25% of students (19.9 students) are included.[25] For both peer groups, we measure peer effects with the share of pre-MBA entrepreneurs among peers in the group.

Appendix Table A10 presents the results for study groups. We find no evidence of peer effects in entrepreneurship in the study group. Appendix Table A11 presents the results for seating charts. In these regressions we separately measure peer effects from inside and outside the circle of students that constitute the peer group. We find that peer effects from inside and from outside the circle are not statistically distinguishable (specifications 1-3). We conclude that peer effects do not appear to be localized by study groups or distance in the classroom. Thus, conversations about business ideas do not seem to be strongly affected by the study groups or the seating allocation.

Contrasting effects in prior work. Our results may help explain why part of the prior work documents (correlational evidence on) positive peer effects, while Lerner and Malmendier (2013)document negative peer effects. Because the screening model features both positive and negative effects, different model parameters, such as the optimism of would-be entrepreneurs or the composition of

the negative effects of same-gender bad entrepreneurs continue be significant in these subsamples.

[24] In related work, Bell et al. (2019b) find that childhood exposure to female inventors has a positive effect on girls' propensity to become inventors.

[25] The results are robust to different definitions of radius, and alternative measures of 'distance', like being next to each other.

entrepreneur peers, determine whether the positive or negative effects dominate. In particular, the negative effects of Lerner and Malmendier (2013) are consistent with the screening mechanism; their lack of positive effects may be explained by HBS entrepreneurs being very optimistic about their idea, in which case negative screening has a meaningful effect but positive screening effects are only negligible. The positive effects in other studies may be explained by would-be entrepreneurs being relatively pessimistic, so that negative screening has a negligible effect while positive screening effects are more meaningful. Other ways of reconciling the evidence may be possible too; the key is that by generating both positive and negative peer effects the screening model makes it easier to explain the opposing effects in prior work.

4.3 Peer effects in acquiring entrepreneurial capital

We next turn to study the impacts of peers on the acquisition of entrepreneurial human and social capital, which we measure with the selection of entrepreneurial elective courses and participation in entrepreneurial events. Appendix B extends the framework developed in Section 2 by allowing students to invest in entrepreneurial capital. These investments are costly and increase the private return from the implementation of a successful idea.[26] This extension leads to new predictions on investment in entrepreneurial capital:

Prediction B.

1. *Knowledge peer effect.* Exposure to both successful and unsuccessful peers increases investment in entrepreneurial capital.[27]

2. *Morale peer effect.* Exposure to successful peers increases investment in entrepreneurial capital, while exposure to unsuccessful peers decreases it.

3. *Screening peer effect.* Exposure to successful peers increases investment in entrepreneurial capital for successful entrepreneurs and decreases it for unsuccessful entrepreneurs and, in

[26] When these returns do not change with the student's investment we obtain the model presented in Section 2.

[27] This prediction relies on the assumption that peer knowledge complements individual knowledge; in the case where these two are substitutes we obtain the opposite prediction.

Table 8: Entrepreneurship clubs and courses

	Entrepreneurship courses		Entrepreneurship club	
	Count	Share	Count	Share
Panel A	(1)	(2)	(3)	(4)
All entrepreneurs	0.171	−0.001	2.782	−0.008
(with or w/o footprint)	(1.211)	(0.105)	(4.115)	(0.064)
Panel B	(5)	(6)	(7)	(8)
Without footprint	-3.617^{***}	-0.346^{***}	-11.397^{*}	-0.254^{**}
	(1.386)	(0.121)	(6.762)	(0.106)
With footprint	2.113^{**}	0.176^{**}	10.051^{**}	0.119^{**}
	(1.065)	(0.086)	(3.986)	(0.058)
Cohort fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

the aggregate, increases investment if there are enough high quality business ideas. Exposure to unsuccessful peers decreases investment in entrepreneurial capital.

Table 8 presents the results of our empirical analysis. The first two columns show regressions in which the outcome is either the number of entrepreneurial electives taken by the student, or the share out of the total electives taken by the student. The patterns we document are very similar to those in our main results. Specifications 1 and 2 in Panel A show that entrepreneur peers on average have no significant effect on these outcomes. But specifications 5 and 6 in Panel B reveal that once we decompose peers by their business success, the pattern changes: unsuccessful peers (without a digital footprint) reduce, while successful peers increase the taking of entrepreneurial electives. The point estimates imply that having one more unsuccessful peer in a stream reduces aggregate enrollment across all entrepreneurial electives by 4.5 courses, while having one more successful peer increases aggregate enrollment by 1.1 courses.

The latter two columns of the table report regressions in which the outcome is either the number of registrations in entrepreneurial club events or the share out of the total club registrations of the student. Here too, the results have the same pattern. Pre-MBA entrepreneur peers have no significant effect on average; unsuccessful peers decrease, while successful peers increase, registration. The estimates imply that one more unsuccessful peer in a stream reduces the total number of registrations across all entrepreneurial club events by 13.2 events, while having one more successful peer increases total registrations by 7.6 events.

Taken together, the results on electives and clubs support the evidence for peer effects on post-MBA entrepreneurship by showing that entrepreneur peers also influence the acquisition of entrepreneurial human and social capital. They also provide evidence on the mechanism.[28] According to Prediction B the type-dependent peer effects we document here are inconsistent with the knowledge peer effect, which predicts positive effects for both types, but can be consistent with the morale and the screening mechanisms. In summary, the results about entrepreneurial capital acquisition are consistent with our main results about entrepreneurial peer effects and the potential importance of the screening mechanism.[29]

5 Structural estimation and counterfactuals

In this section we structurally estimate the screening peer effect model to evaluate the short-run and long-run implications of counterfactual policies.

5.1 Model for estimation

We extend the screening model introduced in Section 2 by modelling the supply of entrepreneurs and peers. Assume there is a unit mass of potential peers, containing a mass n_S of successful entrepreneurs and a mass n_U of unsuccessful entrepreneurs, with $n_S + n_U \leq 1$. A subset of these individuals are selected to a peer group. The selection process depends on two parameters r_1 and r_2, which govern the share and the composition of entrepreneur peers relative to the population.

[28] Appendix Table A4 shows that there are no peer effects on registering for club events related to finance or consulting, or for events organized by social clubs in general. The null effects for these placebo outcomes support our identification strategy. Similarly, Appendix Table A5 shows that there are no peer effects on attendance of strategy electives which are not entrepreneurial, accounting electives or economic electives; we find a significant effect from peers with footprint on the selection of finance courses.

[29] We consider peer effects on entrepreneurship capital in study groups or using seating charts. Specification (4) and (5) of Appendix Table A10 and Table A11 show that peer effects on entrepreneurial capital are not further localized.

First, the peer group consists of a share $r_1(n_S + n_U)$ of entrepreneurs and a share $1 - r_1(n_S + n_U)$ of non-entrepreneurs. Second, among entrepreneur peers, the share of successful entrepreneurs is $r_2 n_S/(n_S + n_U)$. Hence, within the peer group, the shares of successful peers, γ_S, and unsuccessful peers, γ_U, are

$$\gamma_S = r_1 r_2 n_S \quad \text{and} \quad \gamma_U = r_1[n_S(1 - r_2) + n_U], \tag{6}$$

while the share of non-entrepreneur peers is $1 - \gamma_S - \gamma_U$. When $r_1 = r_2 = 1$, the peer group is representative of the population. When $r_1 < 1$ the peer group is biased in favour of non-entrepreneurs. When $r_2 < 1$ the composition of entrepreneur peers is biased towards unsuccessful entrepreneurs. These biases may result from the choice of potential peers to apply to or enroll in the program, or the choice of the institution organizing the program to overweight particular groups.

As in our basic model, there is a mass 1 of potential new entrepreneurs, a fraction q has a high quality business idea, h, and a fraction $(1-q)$ has a low quality idea, l. The former, if implemented, always pays 1, and the latter, if implemented, always pays 0. Each potential entrepreneur meets k peers chosen from the peer group in an i.i.d. and random fashion: for each meeting, the probability of meeting a successful peer is γ_S, an unsuccessful peer is γ_U and a non-entrepreneur $1 - \gamma_S - \gamma_U$.

We assume that a successful peer sends message h to an individual with a high-quality idea, and message l to an individual with a low-quality idea, whereas an unsuccessful peer always sends l. Communication is not perfect: conditional on meeting, a message is sent with probability $\hat{p}/k$. An individual with an idea of quality $y = h, l$, who receives x_h h-messages and x_l l-messages updates the prior belief according to Bayes' Rule to $\rho_y(x_h, x_l)$. Thus, the individual who implements the idea will earn, in expectation, $\rho_y(x_h, x_l)$.[30] The individual can always get an outside option whose value is known to her and it is a draw from a distribution with CDF Γ. Thus, the probability that the individual becomes an entrepreneur is $\Gamma(\rho_y(x_h, x_l))$.

Note that $\rho_y(x_h, x_l)$ depends on the distribution of signals, and thus depends on the peer composition (γ_S, γ_U). Our assumption that a positive message reveals the quality of the idea with

[30] Note that $\rho_y(0, 0)$ is the prior belief of an individual with business idea $y = h, l$. Prior belief may be different between an individual with a high and low quality idea, capturing possible individual investments in information acquisition about their business idea.

certainty implies that $\rho_h(x_h, x_l) = 1$ for all $x_h \geq 1$ regardless of (γ_S, γ_U).[31] In contrast, $\rho_y(0, x_l)$ for $x_l > 0$ depends on (γ_S, γ_U). The following assumption ensures that this dependence does not matter for outcomes, which is the reason we do not account for it in our notation.

Assumption 1. We consider a range of values of (γ_S, γ_U) such that $\Gamma(\rho_y(0, x_l)) = 0$ for all $x_l \geq 1$.

This assumption states that an individual receiving only negative messages will always take the outside option. We show below that our structural estimates support this assumption. We denote the share of individuals who become successful and unsuccessful entrepreneur by $\hat{n}_S$ and $\hat{n}_U$.

Overlapping generations. In a dynamic setting, the composition of new entrepreneurs $(\hat{n}_S, \hat{n}_U)$ will screen the next generation of potential entrepreneurs. As a result, the short-run peer effect on entrepreneurship can accumulate over time. To explore these long term effects, we extend the static model to an overlapping generation model by assuming that in every period there is a new generation of potential entrepreneurs and that the peer group of period t is determined by selecting entrepreneur peers in the population of individuals who made decisions in period $t-1:\ (n_{St}, n_{Ut}) = (\hat{n}_{St-1}, \hat{n}_{Ut-1})$.[32]

5.2 Predictions

We formulate the model's predictions that will guide the structural estimation and the counterfactuals. The model is particularly simple to analyze under a first-order approximation in the probability that a meeting results in active communication $\hat{p}/k$. We derive predictions and estimate the model under this assumption, and then show that under the estimated parameters the approximation is valid. In Appendix C we derive all the relevant expressions without the first order approximation; we will use these more general expressions when we conduct our counterfactual analysis.

[31] More precisely, this holds as long as $\gamma_S > 0$. If $\gamma_S = 0$ then the event that a student receives a positive message has zero probability, and we can choose any belief.

[32] A caveat with this extension is that Assumption 1 becomes stronger. Suppose we consider a range of values $(\gamma_{S,t}, \gamma_{U,t})$ *for all* t such that $\Gamma(\rho_y(0, x_l)) = 0$ for all $x_l \geq 1$. We can check the restrictiveness of this assumption for the counterfactual as follows. Since only successful peers provide informative feedback, Bayes' rule implies that $\rho_y(0, x_l)$ is decreasing in the share of successful peers $\gamma_{S,t}$ and increasing in the share of unsuccessful peers $\gamma_{U,t}$. Hence, we can check whether the assumption remains plausible by verifying that at every period $t \geq 1$, $\gamma_{S,t} \geq \gamma_{S,0}$, and $\gamma_{U,t} \leq \gamma_{U,0}$, where $(\gamma_{S,0}, \gamma_{U,0})$ is matched to the data.

Under this assumption, the share of individuals who become successful entrepreneurs and the share of individuals who become unsuccessful entrepreneurs are, respectively:

$$\hat{n}_S = c_h + \beta_{hS} \cdot \gamma_S + \beta_{hU} \cdot \gamma_U \tag{7}$$

$$\hat{n}_U = c_l + \beta_{lS} \cdot \gamma_S + \beta_{lU} \cdot \gamma_U. \tag{8}$$

These are essentially the regression specifications, analogous to equations (1) and (2), which express the probability that an individual becomes a successful or unsuccessful entrepreneur as a function of the composition of peers. The constants are $c_h = q\Gamma(\rho_h(0,0))$ and $c_l = (1-q)\Gamma(\rho_l(0,0))$, and the regression coefficients are

$$\beta_{hS} = q\hat{p}\left[\Gamma(\rho_h(1,0)) - \Gamma(\rho_h(0,0))\right] \tag{9}$$

$$\beta_{hU} = q\hat{p}\left[\Gamma(\rho_h(0,1)) - \Gamma(\rho_h(0,0))\right] \tag{10}$$

$$\beta_{lU} = (1-q)\hat{p}\left[\Gamma(\rho_l(0,1)) - \Gamma(\rho_l(0,0))\right]. \tag{11}$$

The constant captures that absent entrepreneurial peers the share of good ideas q, the prior $\rho_X(0,0)$, and the distribution of outside options Γ determine entrepreneurship. The intuition for β_{hS} is that for an individual with a high quality idea (q), being exposed to a higher share of successful peers increases the probability of entrepreneurship by increasing the probability of receiving a h signal ($\rho_h(1,0)$ versus $\rho_H(0,0)$), an effect mediated by the opportunity cost of entrepreneurship (Γ) and the probability that communication is successful ($\hat{p}$). The intuition for the other coefficients can be understood similarly. Observe that these formulas only compare receiving zero versus one feedback: this is the consequence of our first-order approximation, which abstracts away from receiving multiple messages. Finally, note that $\beta_{lS} = \beta_{lU}$ because an entrepreneur with a low-quality idea will get a message of l from both a successful and an unsuccessful peer.[33]

In the special case when there are no successful or unsuccessful entrepreneur peers in the

[33] We will not use β_{lS} in our GMM estimation below because we obtained a noisy and insignificant value for that coefficient in the reduced form analysis.

population, the formulas simplify to

$$\hat{n}_S(\gamma_S = 0, \gamma_U = 0) \;\; = \;\; c_h \tag{12}$$

$$\hat{n}_U(\gamma_S = 0, \gamma_U = 0) \;\; = \;\; c_l. \tag{13}$$

We can use the equations presented thus far to estimate all the deep parameters except for the policy parameters r_1 and r_2. To estimate those parameters as well, we need to know the shares of successful and unsuccessful entrepreneurs in the population, from which the shares in the peer group are selected. For simplicity, we assume that the population shares equal the shares that would be implied by the model absent peer effects, i.e. that society is in the steady state of the no-peer-effects model. Hence, $n_S = c_h$ and $n_U = c_l$ and the peer group composition is

$$\gamma_S \;\; = \;\; r_1 r_2 c_h \tag{14}$$

$$\gamma_U \;\; = \;\; r_1[c_h(1 - r_2) + c_l]. \tag{15}$$

Overlapping generation model. The formulas are intuitive to adjust to the overlapping generations model. The law of motion is given by equations (7) and (8) where: (i) (γ_S, γ_U) becomes $(\gamma_{St}, \gamma_{Ut})$, (ii) $(\gamma_{St}, \gamma_{Ut})$ are determined by equation (6), where (n_S, n_U) becomes $(n_{S,t}, n_{U,t})$. The state at period t is $(n_{S,t}, n_{U,t})$ and $(\hat{n}_S, \hat{n}_U)$ becomes $(n_{S,t+1}, n_{U,t+1})$ which represents the new state at period $t + 1$. A steady state is (n_S, n_U) such that $n_{S,t} = n_{S,t+1} = n_S$ and $n_{U,t} = n_{U,t+1} = n_U$.

5.3 GMM estimation

We use the predictions derived in Section 5.2 to estimate the deep parameters of the model using GMM. We map our MBA setting to the model as follows. First, we assume that each MBA stream constitutes the population in the model. Students without entrepreneurial experience play the role of the potential entrepreneurs, and all students, including those with and without entrepreneurial experience, play the role of the peer group. Thus, each student without entrepreneurial experience is both a potential entrepreneur receiving feedback and a peer (without entrepreneurial experience) that can be asked for feedback. Second, we assume that the first-order approximations used to derive the model predictions are valid. We will verify this assumption once we obtain our estimates.

Under these assumptions, we can use equations (9)–(11), (12)–(13) and (14)–(15) as seven moment conditions to estimate seven deep parameters. The moments corresponding to equations (9)–(11) are the regression coefficients measuring the effect of entrepreneurial peers in the data, as estimated in specification (7) and (8) in Table 6. The moments corresponding to equations (12)–(13) are the shares of successful and unsuccessful post-MBA entrepreneurs in streams with no pre-MBA entrepreneurs. The moments corresponding to equations (14)–(15) are the shares of successful and unsuccessful pre-MBA entrepreneurs in streams. The seven deep parameters are $\theta = \{q, \hat{p}, \Gamma(\rho_h(1,0)), \Gamma(\rho_h(0,0)), \Gamma(\rho_l(0,0)), r_1, r_2\}$.

We estimate this system using GMM. There are three implementation details worth noting. Since our empirical design is an IV, we use moment conditions that express orthogonality with the instruments for matching the regression coefficient moments. In other words, to estimate these regression coefficients with GMM while accounting for our control variables, we residualize both the outcome and the treatment variables by the cohort fixed effects and controls. For the regression where the outcome is unsuccessful entrepreneurship, we further residualize by the unsuccessful-pre-share (estimated as an IV) because that coefficient is not a moment condition. Finally, we compute standard errors and 95% confidence intervals using 500 bootstrapped simulations by sampling streams with replacement.

5.4 Estimation results

Table 9 summarizes the point estimates for the deep parameters. Our estimate for the communication time budget $\hat{p}$ implies, given the average stream size and the average share of peers who are pre-MBA entrepreneurs, that the expected number of messages the individual receives is 0.55. This is sufficiently low that our first-order approximation, which effectively assumes that the individual gets at most one informative message, performs well. The neglected event under which an individual gets more than one message occurs only with probability 0.11.[34]

[34] The expected number of messages is $(\gamma_S + \gamma_U)\hat{p}$. The probability that the student receives zero or one message is the sum of $(1 - (\gamma_S + \gamma_U)p)^{n-1}$ and $(n-1)(\gamma_S + \gamma_U)p(1 - (\gamma_S + \gamma_U)p)^{n-2}$, respectively, where $p = \hat{p}/(n-1)$ and n is the stream size. The above numbers follows from noticing that the average stream size is 76 and that, given the estimates, $\gamma_S = 2.05\%$ and $\gamma_U = 0.85\%$.

Table 9: GMM deep parameter estimates

Parameter	Estimate (SE)	[95% CI]
$\hat{p}$	19.88	
	(2.249)	[15.743, 25.495]
q	0.36	
	(0.123)	[0.131, 0.679]
$\Gamma(\rho_h(1,0))$	0.21	
	(0.066)	[0.123, 0.339]
$\Gamma(\rho_h(0,0))$	0.15	
	(0.039)	[0.056, 0.227]
$\Gamma(\rho_l(0,0))$	0.02	
	(0.009)	[0.002, 0.037]
r_1	0.45	
	(0.166)	[0.671, 1.303]
r_2	0.84	
	(0.231)	[0.229, 1.093]

Notes: parameter estimates from fitting GMM on core sample, standard errors (SE) and the 95% confidence interval (CI) computed using 500 bootstrapped simulations where streams were sampled with replacement.

We estimate the share of high-quality ideas q at about 36% : this is the share of non-pre-MBA entrepreneur students who have an idea that could be turned into a successful business. This is a high share, but seems plausible given the sample of MBA students at a leading business school. Yet, many of these ideas do not get converted into successful businesses. One reason is our estimate of $\Gamma(\rho_h(1,0)) = \Gamma(1) = 0.21$: an individual who gets positive feedback and thus *knows* that the idea is good only becomes an entrepreneur with about 21% probability. Consistent with our understanding of the context, the MBA students in our sample seem to have excellent outside options, so that many of them choose not to realize their business ideas. If all individuals with a good idea knew the quality of their idea, the share of successful entrepreneurs would be about $36\% \cdot 0.21 = 7.5\%$. This the 'first best' in our context.

The share of successful entrepreneurs absent peer effects is $q \cdot \Gamma(\rho_h(0,0)) = 5.4\%$. According to equation (12), positive peer effects increase this by about $\beta_{hS}\gamma_S = 0.9$ percentage points, while negative peer effects reduce it by about $-\beta_{hU}\gamma_U = 0.9$ percentage points. That is, consistent with the reduced form results, we estimate that positive and negative peer effects on successful entrepreneurship essentially cancel out.[35] It follows that there is room to close the gap between the share of successful entrepreneurship absent peer effects 5.4% and the first-best share 7.5%.

The model-implied shares of successful and unsuccessful entrepreneurs absent peer effects, $q \cdot \Gamma(\rho_h(0,0)) = 5.4\%$ and $(1-q) \cdot \Gamma(\rho_l(0,0)) = 1\%$, determine, by assumption, the population shares of successful and unsuccessful entrepreneurship. Comparing these shares with the composition of successful and unsuccessful peers at LBS, as given in Table 4, imply $r_1 = 0.45$ and $r_2 = 0.84$. That is, LBS peers are less likely to be entrepreneurs, especially successful entrepreneurs, relative to the composition we expect from LBS graduates (absent peer effects). Biases in this direction seem realistic as young entrepreneurs may not have financial resources for an MBA program and successful entrepreneurs may have limited time and incentives to apply. More broadly, young entrepreneurs, and in particular young successful entrepreneurs, may have limited time to interact with peers.

The prior probability of becoming an entrepreneur when the individual has a low-quality idea and high-quality idea, about 2% and 15% respectively, are quite low, which lends support to our assumption that conditional on receiving some negative signals but no positive signals, the individual never becomes an entrepreneur, i.e. that $\Gamma(\rho_x(0,1)) = 0$ for $x = h, l$. Finally, it is reassuring to note that $\Gamma(\rho_h(1,0)) > \Gamma(\rho_h(0,0)) > \Gamma(\rho_l(0,0))$, that is, the probability of becoming an entrepreneur is higher for a high-quality-idea and a high signal than for a high-quality idea and no signal, which in turn is higher than for a low-quality-idea and no signal. This is not a mechanical effect but an implication of the moments in the data.

5.5 Counterfactuals

We use the deep parameter estimates to evaluate the short-run and long-run effects of counterfactuals capturing possible interventions. We focus on two types of interventions. The first is increasing the share of entrepreneur peers, and thus the likelihood of receiving feedback from an entrepreneur (r_1). In the context of business schools, increasing r_1 may correspond to launching entrepreneur

[35] Since peer effects cancel, one might expect that the share of successful entrepreneurs in the data also equals 5.4%. As Table 4 shows, that share is 5.8%. The difference is due to the average stream with no pre-MBA entrepreneurs, which is what our moment equations (12) and (13) match, having slightly different demographics and hence slightly different values for the control variables.

mentoring programmes or organizing pitch competitions where experienced entrepreneurship practitioners interact with attendees.[36] At a higher level, it could correspond to incentivizing the co-location of entrepreneurs, through business clusters, research parks, tax breaks for startups in specific locations, and policies supporting networking among entrepreneurs, e.g. by creating venues for socialization.[37] The second intervention we study is increasing the share of successful entrepreneur peers among entrepreneur peers (r_2). This increases the likelihood, conditional on receiving feedback, of receiving informative feedback. In the context of business schools, this could represent mentor selection in mentoring programs. More broadly, incentives to co-locate entrepreneurs could be contingent on screening business performance.[38]

Because new businesses creating desirable products and jobs have a large social value, our main outcome in the counterfactuals is the creation of successful businesses. The short-run peer effect is computed as the one-period impact of activating the screening peer effect on the share of successful entrepreneurs. The long-run peer effect is computed as the steady-state impact on the share of successful entrepreneurs. We evaluate impacts relative to the share of successful entrepreneurs in the benchmark of no peer effects, which, based on the estimated model, is 5.4%. This is the same share we observe in the data for streams that have no pre-MBA entrepreneurs.[39] We also confirm that our Assumption 1 holds (both for the short and long run) when we do the counterfactual analysis.

Table 10 reports our results. At the estimated value of $r_1 = 0.45$ and $r_2 = 0.84$, the short-run peer effects are essentially zero, reflecting the empirical fact at LBS that positive and negative peer effects cancel out. Long-term peer effects are marginally positive as they increase the successful share from 5.4% to 5.7%. This is because peer effects weed out some unsuccessful entrepreneurs, improving the composition of entrepreneurs that screen future generations. Increasing the share of entrepreneurs in the peer group to $r_1 = 0.55$, which corresponds to an increase in the chance of

[36] See Eesley and Wang (2017).

[37] See Chatterji et al. (2014) and Kerr and Robert-Nicoud (2020) for surveys of such interventions and clusters and Choi, Guzman and Small (2024) for the impact of Starbucks on startups.

[38] Joining research parks or business clusters are often contingent on passing a screening review that may include a business plan review, financial assessment, and evaluation of past performance.

[39] We compute the counterfactuals exactly, without relying on the first order approximation, using equations (A1) and (A2) in Appendix C1. We set $k = 76$, which is the average stream size in our sample, but we note that any choice of $k > \hat{p} \approx 20$ would lead to very similar quantitative results.

Table 10: Counterfactual share of successful entrepreneurs (percent)

	Peer Effects			
	Short-run	Long-run	Short-run	Long-run
	$r_1 = 0.45$		$r_1 = 0.55$	
$r_2 = 0.84$	5.5	5.7	5.6	5.8
$r_2 = 1$	5.9	6.1	6	6.3

Notes: We set $k = 76$ and use the estimates of Table 9 to compute $n_{S,t}$ and $n_{U,t}$ from equations (A1) and (A2) in Appendix C1 for different levels of r_1 and r_2. We report the share of successful entrepreneur in the short-run and in the long run)steady state value). Recall that the share of successful entrepreneurs without peer-effects is 5.4%.

meeting an entrepreneur from about 2.9% to 3.5% (a 20 percentage point increase), only changes these results slightly. Intuitively, meeting more entrepreneurs—to a first-order approximation—just scales up both the positive and the negative peer effects, but these effects continue to cancel. Overall, the first row of the table paints a less-than-encouraging picture: neither long-term peer effects, nor increasing the share of entrepreneurial meetings appears to have large effects on entrepreneurship in settings similar to LBS.

In the second row we evaluate the impact of eliminating the bias towards selecting more unsuccessful entrepreneurs, i.e., we set $r_2 = 1$. The increase to $r_2 = 1$ means that we increase the share of successful entrepreneurs from 2.05% to 2.4% and we decrease the share of unsuccessful peers from 0.85% to 0.5%. This implies that, conditional on meeting an entrepreneur, the likelihood of meeting a successful peer has increased from 70% to 84%. We see that peer effects in the short run increase successful entrepreneurship by half a percentage point, which is a 9% increase relative to the baseline 5.4%. Increasing r_2 generates relatively more meetings with successful peers, which results in more informative feedback that encourages successful entrepreneurship. The long-run impact of peer effects is even higher, about 0.7 percentage points or 13%. The improved composition of entrepreneurs evaluating future generations has large long-run effect on successful entrepreneurship. Moreover, increasing the frequency of entrepreneurial meetings from $r_1 = 0.45$ to $r_1 = 0.55$ now generates additional gains, achieving a long-term successful share of 6.3%, which is a 17% gain relative to the baseline. Thus, there is a complementarity between the two policy parameters r_1 and r_2 : increasing the frequency of meeting entrepreneurs generates larger gains when these meetings feature a higher share of successful entrepreneurs.

One way to assess the magnitude of these effects is to benchmark them to the first best share of successful entrepreneurship, which is 7.5%. Thus, there are $7.5 - 5.4 = 2.1\%$ of individuals who would implement a successful business idea if they received informative feedbacks. In the presence of bias correction ($r_2 = 1$), short-run peer effects would eliminate 22% and long-run peer effects would eliminate 31% of this gap. In the presence of both bias correction and increasing the share of entrepreneurs ($r_2 = 1,\ r_1 = .55$) long-run peer effects would eliminate 40% of the gap. Further increasing r_1 (not shown in the table) would take the economy very close to the first-best.

A second way to benchmark these effects is to assume that the rate of successful entrepreneurship is proportional to the long-term rate of economic growth. Then the counterfactuals we evaluate have the potential to increase the rate of economic growth by $9 - 17\%$.

These gains appear large compared to the relatively small cost, at least in the business school context, of the interventions we evaluate. Simple changes in the environment that enable students to meet more successful entrepreneurs have the potential to meaningfully improve entrepreneurship.

6 Conclusion

Our study of peer effects in entrepreneurship has shown that unsuccessful entrepreneur peers decrease successful entrepreneurship, while successful entrepreneur peers increase successful and decrease unsuccessful entrepreneurship. These results are inconsistent with knowledge- or morale-based mechanisms, but are consistent with peer effects based on screening business ideas. The screening peer effect highlights an important friction in the allocation of talent to entrepreneurship: incomplete information about the potential of a business idea. It also suggests a natural solution: exposure to peers with entrepreneurial experience who screen out bad ideas and screen in good ideas. Our counterfactual policy analysis demonstrates that this approach can yield significant positive effects, but only when the pool of entrepreneurial peers is of high quality. Policies that foster this condition amplify long-term effects by improving the group of entrepreneurs responsible for screening future business ideas.

We established our results in the context of LBS, but the facts that (i) these results are consistent with a model, (ii) that model can explain the seemingly contrasting patterns of prior work, suggest that our results may apply more broadly. The source of peer effects we emphasize is that potential entrepreneurs are uncertain about the quality of their business idea. Since LBS MBA students are presumably quite knowledgeable about business, we expect that in many other contexts potential entrepreneurs are equally if not more uncertain, and would benefit at least as much from screening by successful entrepreneurs. We therefore believe that our results support policies that increase interactions with such entrepreneurs more broadly. Moving beyond entrepreneurship, academics appears to be another context in which screening by experienced and successful researchers can create large value for PhD students.

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Appendix for Online Publication

A Empirics: additional details and results

Appendix A.1 describes the process used by LBS to create stream, study group and seat assignment. Appendix A.2 provides additional empirical results.

A.1 Stream, study group and seat assignment process

The stream, study group, and seat assignment process for the LBS MBA program is a quasi-random procedure with three distinct stages. First, incoming cohort t with N_t students is divided into S_t streams. Second, each stream is subdivided into G_{ts} distinctive groups; n_{tsg} is the number of students in cohort t, stream s, and study group g. Third, students are assigned to seat numbers within their stream s given their group g allocation.

Both streams and study groups must satisfy specific requirements set by the program office to ensure several characteristics are stratified evenly across all cohort divisions. This is achieved by approaching both the stream allocation and, once the streams are created, the study group allocation as a binary programming problem. In solving this problem, a computer searches the solution space to find an allocation that satisfies all constraints.

Consider the stream assignment first. There are four kinds of constraints:

1. Single assignment: all students are assigned only once.

2. Stream size: the number of students in each stream are equal to the sizes set by the program office (e.g. if $N_t = 401$ and $S = 5$, then $n_{ts} = 80$ for $s \in \{1, 2, 3, 4\}$ and $n_{ts} = 81$ for $s = 5$).

3. Range constraints for continuous characteristics: the average value of characteristic c is within $\bar{c}_t \pm b_c$, where $\bar{c}_t$ is the cohort-level average and b_c is the deviation permitted by the program office.

4. Integer constraints for discrete characteristics: the number of students with characteristic d is either equal to $\bar{d}_t$ (if possible) or within $\bar{d}_t \pm 1$ where $\bar{d}_t$ is the total number of students

with that characteristic divided by the number of streams in cohort t.

Continuous characteristics c balanced using stream/group averages are age, GMAT score (total), and years of work experience. Discrete characteristics d balanced using integer constraints are prior industry, previous firm, geographic region, primary nationality, male/female, and native English speaker. The algorithm handles missing data in the continuous characteristics (discrete characteristics are never missing) by computing the averages for students without missing data and balancing those with missing data on the non-missing characteristics. The study group assignment is structured in the same way, however the range constraints for continuous variables are wider and the integer constraints reflect the composition of each respective stream.

Seating charts are created using the stream and group assignments according to another, separate algorithm. That procedure takes the list of students in a stream and scrambles the order up to $5,000$ times. For each iteration it computes the number of clashes, which are when two students who would be seated next to each other have the same gender, nationality, or study group.[40] The algorithm also uses a weighting scheme whereby a gender-clash carries a weight of 1, nationality 2, and study group 3. If the weighted sum of clashes is zero the process stops, but if not then it continues. The allocation with the lowest number of clashes after $5,000$ draws is ultimately retained and implemented.

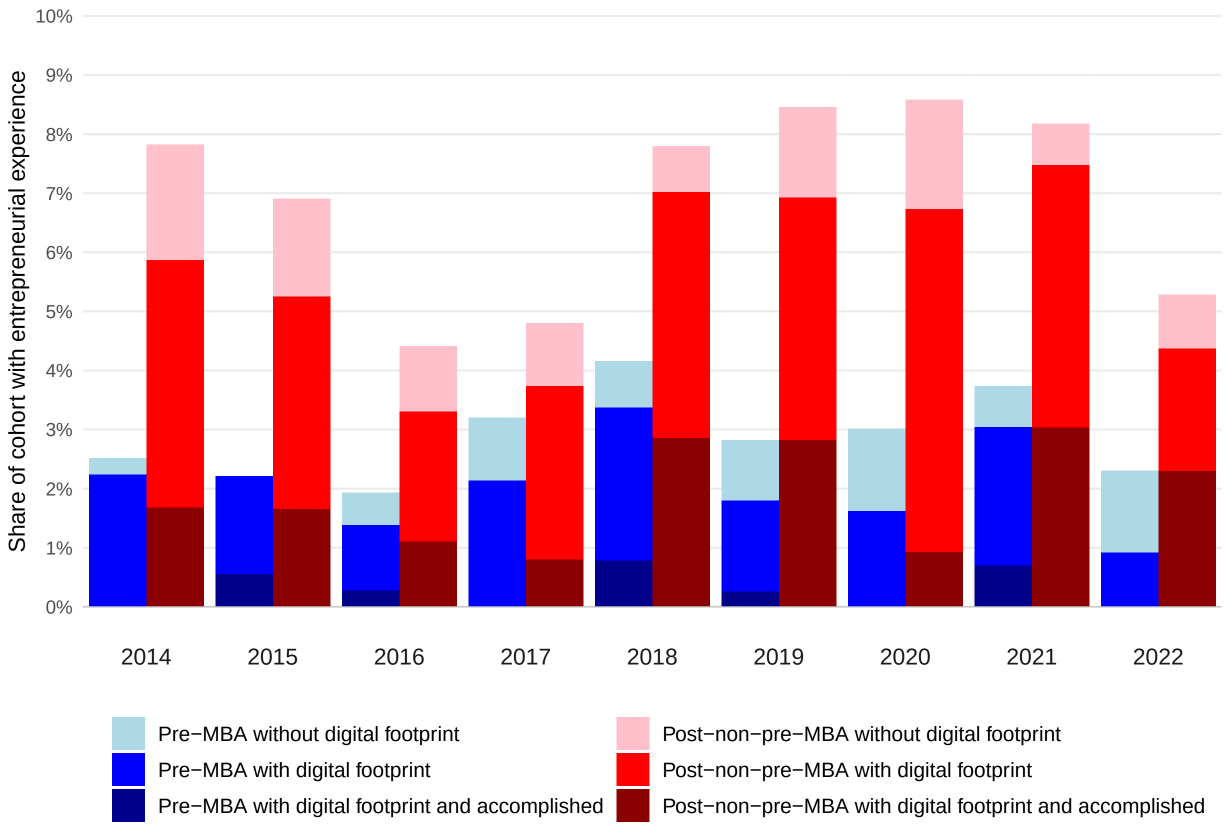
Entrepreneurship is not a stratification criteria at any stage of the process. This means stream and study group stratification does not mechanically ensure pre-MBA entrepreneurs are evenly distributed across cohort subsets, nor does it affect their seating assignments.

We have access to the full algorithm used to create assignments, including all the original code files. This allows us to create counterfactual allocations of the stream, study group, and seating assignments by replicating each process exactly as implemented.

[40] Seating adjacency refers to two students seated next to each other in the same row and extends across aisles.

A.2 Additional empirical results

Figure A1: Share of cohorts with pre-MBA and post-non-pre-MBA entrepreneurial experience



A.2.1 Balance regressions

Table A1: Balance regression coefficients with clustered standard errors

Spec	DepV	All pre-MBA entrepreneurs		Without footprint		With footprint		Footprint, not accomplished		Footprint, accomplished	
OLS	Age	-0.335	(0.362)	0.468	(0.532)	-0.732	(0.479)	-0.374	(0.500)	-3.291	(0.875)***
	Male	-0.344	(0.193)*	-0.452	(0.378)	-0.277	(0.217)	-0.329	(0.232)	0.247	(0.716)
	Engl	0.244	(0.241)	0.708	(0.294)**	-0.001	(0.214)	0.073	(0.242)	-0.589	(0.714)
	Asia	-0.167	(0.157)	-0.290	(0.323)	-0.098	(0.231)	-0.119	(0.264)	0.107	(0.963)
	Euro	0.091	(0.176)	0.605	(0.296)*	-0.175	(0.262)	-0.170	(0.281)	-0.143	(0.805)
	NoAm	0.104	(0.166)	0.054	(0.313)	0.126	(0.192)	0.185	(0.223)	-0.398	(0.536)
	Exp	-0.874	(0.343)**	-0.518	(0.545)	-1.026	(0.524)*	-1.066	(0.533)*	-0.297	(1.369)
	Cons	0.105	(0.304)	-0.296	(0.737)	0.306	(0.318)	0.313	(0.320)	0.132	(0.695)
	Fin	-0.099	(0.269)	-0.475	(0.468)	0.096	(0.327)	0.353	(0.364)	-1.986	(1.184)
	GMAT	0.276	(0.468)	0.919	(0.818)	-0.061	(0.467)	-0.244	(0.524)	1.418	(1.610)
IV	Age	-0.362	(0.376)	0.427	(0.591)	-0.758	(0.483)	-0.412	(0.510)	-3.183	(1.059)**
	Male	-0.200	(0.236)	-0.316	(0.422)	-0.134	(0.252)	-0.203	(0.263)	0.474	(0.998)
	Engl	0.265	(0.252)	0.499	(0.406)	0.137	(0.223)	0.202	(0.263)	-0.442	(0.772)
	Asia	0.002	(0.187)	-0.083	(0.373)	0.046	(0.259)	0.004	(0.276)	0.361	(1.055)
	Euro	0.049	(0.182)	0.605	(0.315)*	-0.239	(0.259)	-0.255	(0.273)	-0.005	(0.820)
	NoAm	0.059	(0.187)	-0.053	(0.334)	0.115	(0.201)	0.207	(0.236)	-0.663	(0.544)
	Exp	-0.721	(0.367)*	-0.342	(0.585)	-0.894	(0.509)	-0.990	(0.517)*	0.270	(1.351)
	Cons	0.005	(0.314)	-0.459	(0.710)	0.244	(0.318)	0.241	(0.327)	0.166	(0.659)
	Fin	-0.227	(0.270)	-0.492	(0.489)	-0.084	(0.371)	0.149	(0.396)	-1.904	(1.249)
	GMAT	0.319	(0.448)	1.102	(0.780)	-0.094	(0.482)	-0.266	(0.532)	1.320	(1.612)

Notes: Observations from core sample. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. 'Spec' is the specification, where OLS refers to equation (3) and IV to (4). 'DepV' is the dependent variable of the balance regression, and the entries are abbreviations of the characteristics listed in Table 3 (same order, excluding other nationalities and other industries). *p<0.1; **p<0.05; ***p<0.01.

Table A2: Balance regression coefficients with random inference standard errors

Spec	DepV	All pre-MBA entrepreneurs		Without footprint		With footprint		Footprint, not accomplished		Footprint, accomplished	
OLS	Age	-0.335	(0.441)	0.468	(0.838)	-0.732	(0.486)	-0.374	(0.528)	-3.291	(1.307)**
	Male	-0.344	(0.200)	-0.452	(0.414)	-0.277	(0.225)	-0.329	(0.238)	0.247	(0.609)
	Engl	0.244	(0.205)	0.708	(0.422)	-0.001	(0.225)	0.073	(0.245)	-0.589	(0.585)
	Asia	-0.167	(0.197)	-0.290	(0.323)	-0.098	(0.207)	-0.119	(0.244)	0.107	(0.625)
	Euro	0.091	(0.177)	0.605	(0.322)*	-0.175	(0.200)	-0.170	(0.221)	-0.143	(0.471)
	NoAm	0.104	(0.164)	0.054	(0.320)	0.126	(0.179)	0.185	(0.202)	-0.398	(0.526)
	Exp	-0.874	(0.390)*	-0.518	(0.712)	-1.026	(0.460)*	-1.066	(0.479)**	-0.297	(1.223)
	Cons	0.105	(0.266)	-0.296	(0.503)	0.306	(0.288)	0.313	(0.327)	0.132	(0.717)
	Fin	-0.099	(0.262)	-0.475	(0.469)	0.096	(0.315)	0.353	(0.328)	-1.986	(0.760)**
	GMAT	0.276	(0.450)	0.919	(0.872)	-0.061	(0.486)	-0.244	(0.517)	1.418	(1.323)
IV	Age	-0.362	(0.474)	0.427	(0.898)	-0.758	(0.524)	-0.412	(0.567)	-3.183	(1.390)**
	Male	-0.200	(0.223)	-0.316	(0.445)	-0.134	(0.245)	-0.203	(0.252)	0.474	(0.661)
	Engl	0.265	(0.221)	0.499	(0.457)	0.137	(0.249)	0.202	(0.271)	-0.442	(0.624)
	Asia	0.002	(0.205)	-0.083	(0.354)	0.046	(0.223)	0.004	(0.264)	0.361	(0.652)
	Euro	0.049	(0.192)	0.605	(0.345)*	-0.239	(0.217)	-0.255	(0.240)	-0.005	(0.509)
	NoAm	0.059	(0.175)	-0.053	(0.343)	0.115	(0.191)	0.207	(0.216)	-0.663	(0.569)
	Exp	-0.721	(0.418)*	-0.342	(0.771)	-0.894	(0.497)*	-0.990	(0.514)*	0.270	(1.315)
	Cons	0.005	(0.287)	-0.459	(0.537)	0.244	(0.309)	0.241	(0.348)	0.166	(0.769)
	Fin	-0.227	(0.283)	-0.492	(0.505)	-0.084	(0.345)	0.149	(0.367)	-1.904	(0.818)**
	GMAT	0.319	(0.484)	1.102	(0.932)	-0.094	(0.523)	-0.266	(0.555)	1.320	(1.392)

Notes: Observations from core sample. Standard errors are generated using the random inference technique recommended by Borusyak and Hull (2023). 'Spec' is the specification, where OLS refers to equation (3) and IV to (4). 'DepV' is the dependent variable of the balance regression, and the entries are abbreviations of the characteristics listed in Table 3 (same order, excluding other nationalities and other industries). *p<0.1; **p<0.05; ***p<0.01.

A.2.2 Placebo regressions

Table A3: Placebo post-MBA employment

	Entrepreneurship	Consulting	Finance	Tech
Panel A	(1)	(2)	(3)	(4)
All entrepreneurs	-0.085	0.148	-0.234	-0.186
(with or w/o footprint)	(0.227)	(0.424)	(0.413)	(0.339)
Panel B	(5)	(6)	(7)	(8)
Without footprint	-1.085^{**}	0.586	-0.662	0.051
	(0.457)	(0.500)	(0.501)	(0.357)
With footprint	0.427^{**}	-0.077	-0.014	-0.307
	(0.195)	(0.503)	(0.475)	(0.598)
Cohort fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. Entrepreneurship refers to post-MBA with footprint within one year of graduation. Consulting, finance, and tech are the three largest categories created by the LBS career office. *p<0.1; **p<0.05; ***p<0.01.

Table A4: Placebo club event registrations (count)

	Entrepreneurship	Consulting	Finance	Social
Panel A: count	(1)	(2)	(3)	(4)
Without footprint	-11.397^{*}	0.476	3.307	17.511
	(6.762)	(2.652)	(9.584)	(12.626)
With footprint	10.051^{**}	0.588	-5.090	0.291
	(3.986)	(3.570)	(4.017)	(8.695)
Panel B: share	(5)	(6)	(7)	(8)
Without footprint	-0.254^{**}	-0.066	-0.120	0.167
	(0.106)	(0.054)	(0.177)	(0.169)
With footprint	0.119^{**}	-0.005	-0.113	-0.078
	(0.058)	(0.059)	(0.083)	(0.121)
Cohorts fixed effect	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. Social refers to events organized by all clubs categorised as ‘social’. *p<0.1; **p<0.05; ***p<0.01.

Table A5: Placebo elective course enrolments (count)

	Entrepreneur	Strategy	Finance	Accounting
Panel A	(1)	(2)	(3)	(4)
All entrepreneurs	0.171	0.364	2.288	0.174
(with or w/o footprint)	(1.211)	(1.141)	(1.567)	(1.023)
Panel B	(5)	(6)	(7)	(8)
Without footprint	-3.617^{***}	1.902	-0.511	1.282
	(1.386)	(2.044)	(1.873)	(1.621)
With footprint	2.113^{**}	-0.424	3.723^{**}	-0.394
	(1.065)	(1.225)	(1.782)	(1.316)
Cohort fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425

Notes: All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native English speaker. Strategy refers to electives run by the Strategy & Entrepreneurship department that are not categorised as entrepreneur. *p<0.1; **p<0.05; ***p<0.01.

A.2.3 Different measures of successful entrepreneurship

Table A6: Accomplished peer effects on post-MBA entrepreneurship

	Post-MBA entrepreneur				
	All	Without footprint	With footprint	Footprint, not accomplished	Footprint, accomplished
	(1)	(2)	(3)	(4)	(5)
Without footprint	-0.908^{**}	0.137	-1.045^{**}	-0.660^{**}	-0.385
	(0.403)	(0.191)	(0.447)	(0.321)	(0.239)
With footprint,	0.038	-0.272^{***}	0.310	0.234	0.076
not accomplished	(0.203)	(0.091)	(0.213)	(0.216)	(0.196)
With footprint,	2.039^{***}	0.465	1.573^{**}	0.884	0.690
accomplished	(0.658)	(0.365)	(0.617)	(0.590)	(0.502)
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Post-MBA entrepreneurs	245	45	200	132	68
Observations	3,425	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

A.2.4 Interaction

Table A7: Post-MBA entrepreneurship using interaction between without and with footprint

	Post-MBA entrepreneur				
	All	Without footprint	With footprint	Footprint, not accomplished	Footprint accomplished
	(1)	(2)	(3)	(4)	(5)
Without footprint	-1.011^{***}	0.122	-1.134^{***}	-0.715^{**}	-0.418^{*}
	(0.366)	(0.179)	(0.402)	(0.290)	(0.237)
With footprint	0.125	-0.185^{*}	0.310	0.212	0.099
	(0.228)	(0.101)	(0.207)	(0.205)	(0.193)
Without × With	−31.343	5.896	−37.240	−26.307	−10.933
	(27.197)	(11.004)	(24.752)	(16.852)	(18.421)
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Post-MBA entrepreneurs	245	45	200	132	68
Observations	3,425	3,425	3,425	3,425	3,425

Notes: All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

A.2.5 Gender heterogeneity

Table A8: Post-MBA entrepreneurship using gender-peer effect interactions

	Post-MBA entrepreneur (1)	Without footprint (2)	With footprint (3)
Male (indicator)	-0.006	-0.002	-0.004
	(0.020)	(0.007)	(0.018)
Without footprint × Male	-1.014^{*}	0.168	-1.183^{*}
	(0.523)	(0.234)	(0.615)
Without footprint × (1-Male)	-0.896	0.016	-0.912^{*}
	(0.591)	(0.174)	(0.539)
With footprint × Male	0.512	-0.118	0.630^{*}
	(0.356)	(0.127)	(0.337)
With footprint × (1-Male)	-0.242	-0.345^{**}	0.103
	(0.588)	(0.151)	(0.542)
Cohort fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Without equal (p-value)	0.875	0.511	0.725
With equal (p-value)	0.373	0.316	0.501
Observations	3,425	3,425	3,425

Notes: All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

Table A9: Post-MBA entrepreneurship using same-gender peer effects

	Post-MBA entrepreneur	Without footprint	With footprint
Panel A: core (3,425 obs.)	(1)	(2)	(3)
Without footprint & same gender	-0.867^{***}	-0.004	-0.863^{***}
	(0.238)	(0.125)	(0.244)
Without footprint & different gender	0.013	0.149	-0.136
	(0.360)	(0.166)	(0.328)
With footprint & same gender	0.155	-0.106	0.261^{*}
	(0.164)	(0.079)	(0.151)
With footprint & different gender	0.154	-0.068	0.221
	(0.203)	(0.081)	(0.192)
Without equal (*p*-value)	0.054	0.461	0.062
With equal (*p*-value)	0.997	0.779	0.884
Panel B: male (2,190 obs.)	(4)	(5)	(6)
Without footprint & same gender	-1.006^{**}	-0.002	-1.004^{**}
	(0.451)	(0.221)	(0.427)
Without footprint & different gender	0.065	0.192	-0.127
	(0.515)	(0.273)	(0.411)
With footprint & same gender	0.149	-0.122	0.271
	(0.317)	(0.124)	(0.288)
With footprint & different gender	0.331	0.005	0.326
	(0.295)	(0.138)	(0.239)
Without equal (*p*-value)	0.203	0.641	0.157
With equal (*p*-value)	0.698	0.576	0.887
Panel C: female (1,235 obs.)	(7)	(8)	(9)
Without footprint & same gender	-0.649^{**}	0.005	-0.654^{***}
	(0.282)	(0.138)	(0.234)
Without footprint & different gender	-0.172	0.035	-0.208
	(0.590)	(0.189)	(0.585)
With footprint & same gender	0.146	-0.089	0.235
	(0.343)	(0.093)	(0.318)
With footprint & different gender	-0.306	-0.247^{*}	-0.059
	(0.430)	(0.130)	(0.401)
Without equal (*p*-value)	0.511	0.904	0.526
With equal (*p*-value)	0.261	0.315	0.455
Cohort fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

A.2.6 Further localization in peer effects: study groups and seating charts

Table A10: Study group peer effects

	Post-MBA entrepreneur	Without footprint	With footprint	Course enrollments	Club registrations
Panel A	(1)	(2)	(3)	(4)	(5)
All entrepreneurs	−0.048	−0.026	−0.023	−0.002	0.772
(with or w/o footprint)	(0.056)	(0.018)	(0.050)	(0.201)	(0.763)
Panel B	(6)	(7)	(8)	(9)	(10)
Without footprint	−0.055	-0.060^{***}	0.005	−0.229	0.541
	(0.099)	(0.013)	(0.098)	(0.371)	(1.514)
With footprint	−0.045	−0.012	−0.033	0.086	0.861
	(0.066)	(0.024)	(0.056)	(0.229)	(0.855)
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,425	3,425	3,425	3,425	3,425

Notes: Observations from core sample. All regressions estimated using re-centered IV. Standard errors clustered at the study group level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. *p<0.1; **p<0.05; ***p<0.01.

Table A11: Seating chart peer effects

	Post-MBA entrepreneur (1)	Without footprint (2)	With footprint (3)	Course enrollments (4)	Club registrations (5)
Without footprint,	-0.799^{***}	-0.068	-0.731^{***}	-1.180	-2.805
inside circle	(0.225)	(0.083)	(0.196)	(0.741)	(3.904)
Without footprint,	-0.795^{*}	0.219	-1.014^{**}	-1.356	-14.862^{*}
outside circle	(0.409)	(0.199)	(0.438)	(1.460)	(7.702)
With footprint,	0.193	-0.022	0.215	0.722	3.514^{*}
inside circle	(0.165)	(0.057)	(0.138)	(0.603)	(1.982)
With footprint,	-0.149	-0.106	-0.042	2.149^{**}	7.851^{**}
outside circle	(0.242)	(0.104)	(0.206)	(0.976)	(3.874)
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Without equal (p-value)	0.994	0.176	0.534	0.902	0.031
With equal (p-value)	0.358	0.554	0.394	0.255	0.223
Observations	2,294	2,294	2,294	2,294	2,294

Notes: Observations from the 2016-2021 cohort subset of the core sample. All regressions estimated using re-centered IV. Standard errors clustered at the stream level using the Imbens and Kolesár (2016) variance estimator. Controls included are indicators for aspiring entrepreneur, male, and native english speaker. Circle refers to local neighbourhood populated by students within a fixed distance (i.e. radii) of a student's seat, which was set at the 25th percentile of the seat-distance distribution. *p<0.1; **p<0.05; ***p<0.01.

B Theory

In Appendix B1, we write a formal model of peer effects that allows for individual investment in human and social entrepreneurial capital. We state and prove Proposition 1, which implies Predication A of Section 2 and Prediction B of Section 4.3. In Appendix B2, we derive the equations (1) and (2) described in Section 2.1.

B.1 A model of peer effects

We present a generalization of the model in Section 2 in which the return to a successful project is given by $H(e, f)$, instead of a constant $H = 1$, where $e \in \mathbb{R}^+$ is the student's investment in entrepreneurial knowledge, $f \in \mathbb{R}^+$ is the peer level of entrepreneurial knowledge, and $H(\cdot, \cdot)$ is increasing in each argument and concave in e. Investment e involves a private cost $C(e)$, which is an increasing and convex function. We make the technical assumptions that $C'(0) < H'(0, 0)$. We maintain the assumption that a high quality business idea, if implemented, succeeds with probability one, and a low quality idea always fails and that the return of a failed idea is 0.

Let ρ be the prior belief of a student that her project is of high quality. If the student becomes an entrepreneur, she will invest $e^*(\rho, f)$ so that:

$$\underbrace{\rho \times \frac{\partial H(e^*(\rho, f), f)}{\partial e}}_{\text{Expected MR}} = \underbrace{\frac{\partial C(e^*(\rho, f))}{\partial e}}_{\text{MC}},$$

and becomes an entrepreneur if, and only if,

$$R < \underbrace{\rho \times H(e^*(\rho, f), f) - C(e^*(\rho, f))}_{\text{Value of entrepreneurship}} := R^*(\rho, e^*(\rho, f), f)$$

Prior to the realization of R, the likelihood that the student becomes an entrepreneur is $\Gamma(R^*(\rho, e^*(\rho, f), f))$, where Γ is the CDF of outside options. We allow for student's investment and peer's knowledge to be either complement or substitute. Formally, e and f are complement if the cross partial derivative of U is positive and, otherwise, are substitute. We obtain the following result:

Proposition 1. The probability that a student implements her idea and becomes an entrepreneur is increasing in ρ and f. The student's investment in entrepreneurial knowledge: a) increases with ρ, b) increases with f if e and f are complement, c) decreases with f if e and f are substitute.

Proof of Proposition 1. Fix the optimal investment $e^*(\rho, f)$ and take $\rho' > \rho$. Then, for the same investment, the value of entrepreneurship is higher under ρ' than under ρ such that

$$R^*(\rho', e^*(\rho, f), f) > R^*(\rho, e^*(\rho, f), f).$$

Hence, at the optimal level of investment under ρ', it must hold that:

$$R^*(\rho', e^*(\rho', f), f) > R^*(\rho', e^*(\rho, f), f) > R^*(\rho, e^*(\rho, f), f).$$

Hence, the likelihood of becoming an entrepreneur increases in ρ. The same argument can be used to show that the the likelihood of becoming an entrepreneur increases in f.

We now turn to investment. Note that an increase in ρ increases expected marginal returns, such that concavity of H with respect to e and convexity of C implies that investment must increase. If e and f are complement, then an increase in f increases expected marginal returns to private investment, and so private investment increases; if they are substitute, then an increase in f decreases expected marginal returns and so private investment decreases. This concludes the proof of Proposition 1.

The implication of the three peer effects, summarised by Prediction A and Prediction B in Section 2 are a direct consequence of Proposition 1.

B.2 Derivation of Equations (1) and (2) of Section 2.1

We specialise the above settings as follows. First, we abstract away from individual's investment in human and social capital, i.e. $H(e, 0) = H$ for all e and, without loss, we normalise $H = 1$. Second, we denote the prior belief of an individual with an idea of quality X by ρ_X and we assume that $\rho_h \geq \rho_l$; this captures the case where individuals start with the same prior but obtain private informative signals, perhaps due to individual information acquisition. Third, we assume that each student spends an amount of time $\hat{p}$ to interact with each individual in his or her stream and this effort is allocated equally across all the stream peers. The peer effect, regardless of the specific channel, occurs only when two individuals meet and this happens with probability $p = \hat{p}/(n-1)$; hence, on average, there are $\hat{p}$ meetings.

Knowledge peer effect. We assume that each meeting with a successful entrepreneur increases the probability of becoming entrepreneur by $\delta > 0$, whereas meeting an unsuccessful entrepreneur increases by $0 < \omega \leq \delta$. The probability that student i becomes a successful entrepreneur is: n entrepreneur and has a high quality idea $Y_{i,h}$ is:

$$\Pr{}_i(\text{successful entrepreneur}) = q\Gamma(\rho_h) + q\delta \sum_{k=0}^{N_S} k \binom{N_S}{k} p^k (1-p)^{N_S - k} + q\omega \sum_{k=0}^{n_U} k \binom{N_U}{k} p^k (1-p)^{N_U - k}$$

where N_X is the number of i's peers of type $X = S, U$. Developing the binomial sum, using $p = \hat{p}/(n-1)$ and that $gamma_X = N_X/(n-1)$, the above expression becomes:

$$\Pr{}_i(\text{successful entrepreneur}) = q\Gamma(\rho_h) + q\delta\hat{p}\overline{\gamma}_{-i,S} + q\omega\hat{p}\overline{\gamma}_{-i,U}$$

Denoting by $c_{i,h} = q\Gamma(\rho_h)$, $\beta_{i,h;S} = q\delta\hat{p}$, and $\beta_{i,h;U} = q\omega\hat{p}$, this is equivalent to equation (1).

Similar calculations implies that the probability that i becomes an unsuccessful entrepreneur is

$$\Pr{}_i(\text{unsuccessful entrepreneur}) = (1-q)\Gamma(\rho_l) + (1-q)\delta\hat{p}\overline{\gamma}_{-i,S} + (1-q)\omega\hat{p}\overline{\gamma}_{-i,U},$$

and denoting by $c_{i,l} = (1-q)\Gamma(\rho_l)$, $\beta_{i,l;S} = (1-q)\delta\hat{p}$, and $\beta_{i,l;U} = (1-q)\omega\hat{p}$, this is equivalent to equation (2).

Morale peer effect. Each meeting with a successful peer boosts morale, thereby increasing the likelihood of becoming entrepreneur by δ, whereas a meeting with an unsuccessful entrepreneur lowers morale and so decreases the probability of becoming entrepreneur by $\omega > 0$. These effects do not depend on the underlying quality of the idea. Hence,

$$\begin{aligned}\Pr{}_i(\text{successful entrepreneur}) &= q\Gamma(\rho_h) + q\delta\hat{p}\overline{\gamma}_{-i,S} - q\gamma\hat{p}\overline{\gamma}_{-i,U},\\ \Pr{}_i(\text{unsuccessful entrepreneur}) &= (1-q)\Gamma(\rho_l) + (1-q)\delta\hat{p}\overline{\gamma}_{-i,S} - (1-q)\omega\hat{p}\overline{\gamma}_{-i,U}.\end{aligned}$$

Denoting by $c_{i,h} = q\Gamma(\rho_h)$, $c_{i,l} = (1-q)\Gamma(\rho_l)$, $\beta_{i,h;S} = q\delta\hat{p}$, $\beta_{i,h;U} = q\omega\hat{p}$, $\beta_{i,l;S} = (1-q)\delta\hat{p}$, and $\beta_{i,l;U} = (1-q)\omega\hat{p}$, we obtain equations (1) and (2)

Screening peer effect. Let $\rho_X(x_h, x_l)$ be the belief of student i with an idea of quality X who receives x_h positive message, x_l negative message. Note that $\rho_X(0,0) = \rho_X$ is the prior of students with an idea of quality X. We assume that $p = \hat{p}/(n-1)$ is small and derive the first order approximation of $\Pr{}_i$(successful entrepreneur) and and $\Pr{}_i$(unsuccessful entrepreneur).

Consider an individual with a good idea. Note that when p is small any term which is p^2 or higher will have second order effects. Hence, we have three events that matter. One event is when the student receives one good signal and no other feedback. This happens with probability pN_S, in which case the student becomes an entrepreneur with probability $\Gamma(\rho_h(1,0))$. The second event is when the student receives no signal at all, which happens with probability $(1-p)^{N_S+N_U}$, which is approximately $1-(\gamma_S+\gamma_U)p$; in this even the student becomes entrepreneur with probability $\Gamma(\rho_h(0,0))$. Finally there are events in which the student receives no good signal and receives $x_l \geq 1$ bad signals. Because the student has a high quality idea bad signals must come from bad peers, and among all of those events the only event which is first order is when $x_l = 1$. Therefore, all of these events are approximated by probability pN_U. When this event occurs the student becomes an entrepreneur with probability $\Gamma(\rho_h(0,1))$. By setting $p = \hat{p}/(n-1)$, we have that

$$\Pr{}_i(\text{successful entrepreneur}) \approx q\Gamma(\rho_h(0,0)) + q\hat{p}[\Gamma(\rho_h(1,0)) - \Gamma(\rho_h(0,0))]\gamma_S + q\hat{p}[\Gamma(\rho_h(0,1)) - \Gamma(\rho_h(0,0))]\gamma_U.$$

Denoting by $c_{i,h} = q\Gamma(\rho_h(0,0))$ and

$$\begin{aligned}\beta_{i,h;S} &= q\hat{p}[\Gamma(\rho_h(1,0)) - \Gamma(\rho_h(0,0))]\\ \beta_{i,h;U} &= q\hat{p}[\Gamma(\rho_h(0,1)) - \Gamma(\rho_h(0,0))],\end{aligned}$$

we obtain equation (1). In a similar fashion, observe that

$$\Pr{}_i(\text{unsuccessful entrepreneur}) \approx (1-q)\Gamma(\rho_l(0,0)) + (1-q)\hat{p}[\Gamma(\rho_l(0,1)) - \Gamma(\rho_l(0,0))](\gamma_S + \gamma_U),$$

and denoting by $c_{i,l} = (1-q)\Gamma(\rho_h(0,0))$ and

$$\beta_{i,l;S} = \beta_{i,l;U} = (1-q)(1-q)\Gamma(\rho_l(0,0)) + (1-q)\hat{p}[\Gamma(\rho_l(0,1)) - \Gamma(\rho_l(0,0))]$$

we obtain equation (2).

C Structural Model and Estimation

In Appendix C1, we derive the probabilities of becoming an entrepreneur without the first order approximation. In Appendix C2, we provide technical details for our GMM estimation of the deep parameters.

C.1 Model

We derive the probability of an individual becomes a successful entrepreneur and the probability of an individual becomes an unsuccessful entrepreneur, dispensing the first order approximation (based on the assumption $\hat{p}/(n-1)$ is small.)

Given peer composition (γ_S, γ_U) the fraction of individuals who becomes successful and unsuccessful entrepreneurs are, respectively,

$$\begin{aligned}
\hat{n}_S &= q\Gamma(\rho_h(0,0)) + \\
&+ q\left(1-\left(1-\gamma_S\frac{\hat{p}}{k}\right)^k\right)[\Gamma(\rho_h(1,0)) - q\Gamma(\rho_h(0,0))] \\
&- \left(\left(1-\gamma_S\frac{\hat{p}}{k}\right)^k - \left(1-(\gamma_S+\gamma_U)\frac{\hat{p}}{k}\right)^k\right)\Gamma(\rho_h(0,0)) \qquad \text{(A1)} \\
\hat{n}_U &= (1-q)\left(1-(\gamma_S+\gamma_U)\frac{\hat{p}}{k}\right)^k\Gamma(\rho_l(0,0)). \qquad \text{(A2)}
\end{aligned}$$

If we make the assumption that $\hat{p}/k$ is small and that $r_1 = r_2 = 1$, then the first order approximation of equations (A1) and (A2) become equations (7) and (8).

C.2 Estimation

We use GMM to estimate a set of seven deep parameters:

$$\mathcal{P} = \{q, \hat{p}, \Gamma(\rho(0,0|H)), \Gamma(\rho(0,0|L)), \Gamma(\rho(1,0|H)), r_1, r_2\}.$$

We consider seven moments. The first three moments correspond to equations (9)–(11), which are the regression coefficients measuring the effect of entrepreneurial peers in the data. The next two moments, corresponding to equations (12)–(13), are the shares of successful and unsuccessful post-MBA entrepreneurs in streams with no pre-MBA entrepreneurs. The last two moments correspond to equations (14)–(15), which are the shares of successful and unsuccessful pre-MBA entrepreneurs in each stream.

There are four implementation details worth noting. First, because our empirical design is an IV, the regression coefficient moments we use are orthogonal to their respective instruments. Second, to estimate these regression coefficients with GMM while accounting for control variables, we residualize both outcome and treatment variables. This involves regressing these variables on the cohort fixed effects and controls and extracting the residuals for use in the GMM. Thirdly, the variables used to compute the third moment (coefficient of successful-pre on unsuccessful-post) are residualized again using IV regressions where the only dependent variable is observed share of pre-MBA unsuccessful instrumented by the re-centred share of pre-MBA unsuccessful. Fourth, estimation is constrained such that $\hat{p} \in [1, 100]$ and all other parameters are between zero and one.

Stated formally, the moment conditions are:

$$\mathbb{E}\left[(Y_{i,h} - q\hat{p}(\Gamma(\rho_h(1,0)) - \Gamma(\rho_h(0,0)))\bar{X}_{-i,S} + q\hat{p}\Gamma(\rho_h(0,0))\bar{X}_{-i,U})Z_{i,h}\right] = 0 \tag{A3}$$

$$\mathbb{E}\left[(Y_{i,h} - q\hat{p}(\Gamma(\rho_h(1,0)) - \Gamma(\rho_h(0,0)))\bar{X}_{-i,S} + q\hat{p}\Gamma(\rho_h(0,0))\bar{X}_{-i,U})Z_{i,l}\right] = 0 \tag{A4}$$

$$\mathbb{E}\left[(\widetilde{Y}_{i,l} + (1-q)\hat{p}\Gamma(\rho_l(0,0))\widetilde{X}_{-i,S})\widetilde{Z}_{i,h}\right] = 0 \tag{A5}$$

$$\mathbb{E}\left[S_{i,j_0} - qM_{i,j_0}\Gamma(\rho_h(0,0))\right] = 0 \tag{A6}$$

$$\mathbb{E}\left[U_{i,j_0} - (1-q)M_{i,j_0}\Gamma(\rho_l(0,0))\right] = 0 \tag{A7}$$

$$\mathbb{E}\left[H_{i,j} - r_1 r_2 q\Gamma(\rho_h(0,0))\right] = 0 \tag{A8}$$

$$\mathbb{E}\left[L_{i,j} - r_1(q\Gamma(\rho_h(0,0))(1-r_2) + (1-q)\Gamma(\rho_l(0,0))\right] = 0 \tag{A9}$$

where Y, X, Z are residualised individual-level outcome, treatment, and instrumental variables (respectively) and overset-tildes indicate further residualisation; S_{i,j_0} (U_{i,j_0}) is the number of post-MBA successful (unsuccessful) entrepreneur for individual i in stream j_0 without any pre-MBA entrepreneurs; M_{i,j_0} is the number of non-pre-MBA entrepreneur for individual i in stream j_0 without any pre-MBA entrepreneurs; $H_{i,j}$ ($L_{i,j}$) is the share of pre-MBA successful (unsuccessful) entrepreneurs for individual in stream j. Note also that the plus-signs in the first three moments ensure all parameters are positive.

In addition to estimating the GMM on the core sample, we compute standard errors and 95% confidence intervals using 500 bootstrapped simulations. For each iteration y we draw 48 streams with replacement and combine those students into a dataset on which residualizations are performed. These variables are then used to estimate $\hat{\mathcal{P}}_y$ without imposing parameter bounds. The standard errors and confidence intervals are constructed using the columns of the resulting $\hat{\boldsymbol{\mathcal{P}}}_{500\times 5}$ matrix of parameter estimates.