Networking Frictions in Venture Capital, and the Gender Gap in Entrepreneurship

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Abstract

Exploiting random variation in the number of venture capital (VC) investors assigned to judging panels at Harvard Business School's New Venture Competition (NVC), we find that exposure to VC judges substantially increases male participants' chances of founding a VC-backed startup after graduation but has no impact on VC-backed entrepreneurship among female participants. VC judges rarely invest in the startups, suggesting that men but not women benefit indirectly, through access to VC judges' networks. A survey suggests this is in part because men are twice as likely to proactively reach out to VC judges after the NVC. Our results highlight the salience of network-related information frictions in VC, which may cause good ideas that lack access to investors to go unfunded and may be an important contributor to the gender gap in high-growth entrepreneurship.

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1 Introduction

Venture capital (VC) is a crucial financing source for new ideas and technologies (Kaplan & Lerner 2010). Yet a relatively small number of VC firms and their investing partners account for a disproportionate share of the capital that VCs deploy (Lerner & Nanda 2020). Frictions in the process through which these gatekeepers learn about new ideas and select a subset for investment can therefore have consequential effects on the types of ideas that are commercialized in the economy.

In this paper, we examine a particular friction in VC-backed entrepreneurship: network-related access to VCs. It is widely known that face-to-face connections and trusted referrals are important, if not primary, deal sourcing methods for many top VC investors. Recent academic work highlights the importance of in-person interaction in startup investment decisions, including Huang et al. (2020) and Hu & Ma (2020) To provide an example from a practitioner, Chris Sacca, the Founding Partner of Lowercase Capital, noted that "We are no longer taking blind pitches. Instead, we are going to focus exclusively on deals that come to us through our trusted network of friends and colleagues whom we admire" (Baird 2017).

VC investors may rely on personal networks because they must overcome extreme information asymmetry between founders and VCs (e.g. Stuart & Sorenson 2005, Hochberg, Ljungqvist & Lu 2007, Kerr & Mandorff 2015). However, heavy reliance on trusted referrals may also privilege those whose networks give them better access to investors, independent of the quality of their ideas (Cohen, Frazzini & Malloy 2008).

Understanding networking frictions could shed light on the gender gap in high-potential entrepreneurship, and more generally on the lack of diversity among VC-backed entrepreneurs. While women's career trajectories differ from men's across a number of fields (Bertrand, Goldin & Katz 2010, Goldin, Kerr, Olivetti & Barth 2017), the gender gap is especially severe in high-growth entrepreneurship, with women composing only about 10% of VC-backed startup founders (Levine & Rubinstein 2017, Gompers & Wang 2017). A growing literature, including Becker-Blease & Sohl (2007), Scott & Shu (2017), Gornall & Strebulaev (2018), and Ewens & Townsend (2019) has documented the gap and aimed to characterize frictions that might lead to it. From an economic perspective, the gap is particularly worrying if it reflects systematic gender-related frictions causing high-quality entrepreneurs or ideas to go unfunded. For example, since over 90% of VC investors are men (Gompers & Wang 2017), gender-based homophily in networking could disproportionately impact women's ability to be part of, or to access to trusted networks that VCs rely on for deal flow.

Rigorously studying whether differential access to VC plays a role in who becomes an entrepreneur is challenging. Social networks are endogenous, making it hard to separate the role of networking frictions from unobserved variables, such as the quality of the idea or whether an entrepreneur's business model is a good fit with VC. We address this empirical challenge by employing exogenous variation in exposure to VC networks at Harvard Business School's (HBS) New Venture Competition (NVC).[1] Like most business plan competitions and accelerator programs, one of the main selling points of the NVC is the opportunity for face-to-face interaction with investors (Howell 2020).[2] Our goal is to examine whether random exposure to VC investors increases the likelihood of VC-backed entrepreneurship of participants after they graduate, and moreover, whether men and women founders benefit similarly.

In the first round of the NVC, each team is assigned to one of about 15 panels, each composed of about six judges. Our research design exploits random variation in the number of VC judges across panels, which arises from the way in which judges are allocated to panels in the NVC. Our core empirical specification estimates the differential effect of having an additional VC judge on the panel for a female participant's subsequent chances of VC-backed entrepreneurship relative to a male participant's chances of VC-backed entrepreneurship. Isolating the interaction between a participant's gender and exposure to a larger number of VCs on a panel enables us to distinguish effects stemming from random differences in exposure to

[1]The NVC is Harvard's flagship new venture competition and a key gateway to VC-backed entrepreneurship after HBS. Many successful founders, including those of 'unicorn' startups such as Rent the Runway and Oscar Health, have been participants in the NVC. Gompers & Wang (2017) note that among business schools, HBS accounts for the largest number of graduates that receive VC funding; the next-largest is Stanford GSB, which has half as many alumni who are VC-backed entrepreneurs. HBS therefore provides an important and interesting setting to study gender-related frictions in VC-backed entrepreneurship.

[2]Having delivered a pitch to the judges and answered their questions, the participants are in a position to reach out to judges after the competition, leveraging the connection to ultimately raise VC financing for their ventures. The competition does not, however, explicitly encourage such follow-up.

VCs from channels related to fixed differences between men and women in their demand for VC financing, or the degree to which businesses founded by women are a good fit with VC financing.

The impact of random exposure to VC investors is ambiguous: on the one hand, the NVC provides a professional forum for networking which may be more valuable for women entrepreneurs, as it may help surmount imbalances created by, for example, homophily. On the other hand, this type of structural intervention may not matter if random exposure to investors intensifies existing dynamics that disproportionately benefit male entrepreneurs. For example, male entrepreneurs may actually benefit more from exposure to VCs if follow-on referrals are driven by homophily within investor-networks.

We find that exposure to more VCs substantially benefits male participants, while this relationship is close to zero for women. Placebo tests show that the result is not present among participants starting ventures that do not rely on VC financing or participants joining VC-backed startups as employees. Also, judges on the panel in the same sector as the participant or with backgrounds besides VC, such as corporate executives, lawyers or academics, have no differential effect by gender on VC-backed entrepreneurship (nor do they have an independent effect).

Why might exposure to VCs benefit men so much but not women? We find that VC judges rarely invest in the startups, and the results we find continue to hold even when we control for instances when this happens. Our results therefore suggest that men benefit more from the referrals and access to investors made possible by the exposure to more VC judges. Further analysis suggests at least two ways in which this occurrs: first, a survey of NVC participants highlights that male participants are nearly twice as likely as women to proactively reach out to VC investors after the NVC. Second, our results are driven by male investors, suggesting that gender-based homophily between entrepreneurs and VCs, together with homophily within investor networks disproportionately favors outreach by male entrepreneurs.

We do not find obvious evidence of explicit bias among male VCs against female participants in our sample. In addition to VCs responding to outreach equally by participant gender, we show that the private scores of VC judges are in fact slightly lower for male-led ventures than for women-led ventures. However, it is important to emphasize that less observable discrimination may be at play and the lack of outreach by women could reflect expectations of bias or harassment.

Qualititative comments in the survey point to a possible explanation for women reaching out less, which may more broadly underlie networking frictions: women may be more cautious or hold themselves to a higher standard than men when "selling" their ventures. Since follow-up with judges at the NVC is not explicitly encouraged, women were more likely to have some reservation about leveraging the connection to discuss fundraising. This phenomenon has been identified in other settings. For example, Chari & Goldsmith-Pinkham (2017) find that gender differences in submission rates of papers to the National Bureau of Economic Research's elite Summer Institute conference can explain the substantial gender gap among accepted authors. As a second example, Kolev, Fuentes-Medel & Murray (2019) find that the reason women score lower in blinded grant application evaluations is because they tend to use more narrow words, despite having better scientific output conditional on funding.[3]

Our results indicate that exposure to more VCs can help reduce networking frictions, but the benefits of this intervention do not accrue to all entrepreneurs. The fact that women interested in high-growth entrepreneurship do not benefit as much from exposure to VCs as men may be important in understanding the gender gap in entrepreneurship given the size of the benefit we document among men. However, there are of course other drivers of the gender gap in entrepreneurship that our research does not address, and which are not mutually exclusive. For example, women may more often perceive family obligations to be incompatible with leading a high-growth startup. Women may also be more likely to found ventures in industries in which VCs tend not to invest. These and other explanations have been explored in a broader context in Bertrand et al. (2010), Bertrand (2013), Castillo et al. (2013), Pew (2013), Pew (2015), Bertrand, Kamenica & Pan (2015), Fang & Huang (2017), and Goldin et al. (2017). Women have also been shown to be more risk averse than men (e.g. Barber & Odean 2001, Niederle & Vesterlund 2007, Sapienza, Zingales & Maestripieri 2009). Our goal is not to address these potentially profound,

[3]Note that women are not universally less proactive in ways that are detrimental to their outcomes; Exley, Niederle & Vesterlund (2019) isolate the decision to negotiate in a laboratory experiment and find that while women tend to negotiate less, this is not suboptimal as negotiating more leads to losses.

population-wide explanations. Instead, we focus on evaluating a networking-related frictions to accessing venture capital among individuals demonstrating serious interest in high-growth entrepreneurship.

One advantage of this focus is that it has immediate implications for new venture competitions and accelerators, which often emphasize networking opportunities and access to investors, and are now an important part of the entrepreneurial ecosystem (Howell 2020). Our results suggest that there may be more than can be done to design networking between entrepreneurs and investors to facilitate the financing of the best (rather than just the best networked) ideas. In particular, our results point to benefits from encouraging and potentially formalizing networking opportunities between individuals, rather than assuming that people will contact each other independently.

2 Data

Before moving to the analysis, we describe the HBS NVC and the data from it that we employ in our analysis (Section 2.1). We discuss the HBS administrative and career history data in Sections 2.2 and 2.3. Section 2.4 explains the survey design.

2.1 HBS NVC data

The NVC is a startup "pitch" competition in which founders present their business ideas to expert judges. The NVC promotes itself as an opportunity for students to "put entrepreneurship principles into practice," to receive feedback on their ideas, and to get exposure to key stakeholders in the entrepreneurial ecosystem. There is also a cash prize for the ultimate winner and runners up in the competition. This type of business plan competition is now a standard component of many undergraduate and MBA programs, and is also a common stepping stone in an early stage startup's life, particularly for first-time founders and student entrepreneurs (?).

The NVC started in 1997 with a business track. It added a social enterprise track in 2001 and an alumni track in 2010. The core dataset for our analysis consists of comprehensive team and judging information for the business track between 2000 and

2015 (except for 2003, for which no data are available).[4] The competition has three rounds, but our analysis focuses on the first round, in which teams and judges are assigned to parallel sessions that run roughly simultaneously in separate rooms.[5] Judges formally score the pitches of participating ventures, and these scores determine which ventures proceed to the next round of judging. Each team's pitch and question period lasts only about 15 minutes, but there are opportunities for follow-up by a proactive student or judge. This follow-up could occur at the cocktail hour after the pitch sessions, or privately if the student or judge requests contact information directly or from HBS NVC administrators.

Several elements make the NVC's first round an attractive setting to explore the role of gender in early stage, high-growth entrepreneurship. First, participants not only demonstrate a revealed preference for joining the labor force (by virtue of attending business school), but also demonstrate an interest in pursuing high-growth entrepreneurial activity. Startups founded by HBS alumni have gone on to raise substantial amounts of venture capital. For example, one analysis of Pitchbook data found that "1,069 HBS MBAs have founded 961 companies that have raised $22.4 billion in VC [..] Entrepreneurs from HBS have founded 13 unicorns — nearly double its closest competitor, Stanford."[6] Among U.S. business schools that focus on entrepreneurship, HBS has among the largest student bodies and thus offers a substantial sample for study, even when the sample is restricted to NVC

[4]We do not consider participants in the social enterprise track for this analysis because of the potential mismatch between the goals and business models of such ventures and the objectives of for-profit venture capital investors. The alumni tracks are run by local alumni chapters, making the data inconsistent and hard to gather.

[5]The value of the cash prize and the number of runner up teams getting a prize has changed over time, but the structure of the judging – which forms the basis of our empirical strategy – has not changed during the period we study. Specifically, in 1997, the winning team at the business plan competition was awarded $10,000 and 3 runner-up teams were each awarded $5,000. In 2009, the winning team's award was changed to $25,000 and 2 runner teams shared $10,000 each. In 2013, the winning team received $50,000 and one runner up team was awarded $25,000. The cash prize for the winning team was raised to $75,000 in 2017, but this change was outside of our sample period. Also, the competition was re-branded from the HBS "Business Plan Competition" to the HBS "New Venture Competition" in 2013.

[6]Examples of these "unicorns" include health insurance company Oscar, fashion rental company Rent the Runway, and video game producer Zynga. (See https://www.businessbecause.com/news/mba-entrepreneurs/4183/harvard-startups-rake-in-venture-capital.)

participants.[7]

Second, as we elaborate below, our research design assesses how conditionally random variation in the number of VC judges across panels impacts VC-backed entrepreneurship after HBS. This enables us to overcome the challenge that exposure to VCs is typically non-random and unobserved, making it hard to effectively study networking frictions in VC-backed entrepreneurship. Beyond the research design, we observe individual and venture characteristics that, while not needed for identification, provide reassurance about the mechanism we document in our analysis. Of particular note is our access to the scores that judges assign to team. These data are private, so participants never observe their own or other teams' scores. Judges score independently and observe only their own scores, and never a venture's overall rank. The private scores enable us to control for a measure of venture quality when conducting our analysis.

To participate in the NVC, a founding team must have at least one member who is a current HBS MBA student. About 70 percent of participants are HBS students; other participants are mostly students elsewhere at Harvard, and a minority are students at other universities or recent graduates. We restrict our sample to the 964 unique participants who are HBS students at the time of the competition, because these are the students for which we have a rich set of covariates that are typically unobserved, as well as comprehensive outcome data post-graduation. As Table 1 Panel A shows, 32 percent of the participants are female, which is only slightly smaller than their share of the overall HBS population.[8] The participants are members of 647 teams, each of which has 2.5 members on average. Table 1 Panel B shows that average team sizes for female and male participants are quite similar. Across all years in our data, there are 573 unique judges, of which 243 are VCs. Some judges participate in multiple years. Each panel has on average six judges, as shown in Table 1 Panel E. Just over half of judges on a panel are VCs on average, though this can and does vary substantially due

[7] In 2017, U.S. News ranked HBS the third best MBA program for entrepreneurship, and it has more than double the annual enrollment of any other program in the top five (See https://www.usnews.com/best-graduate-schools/top-business-schools/entrepreneurship-rankings).

[8] The 36 percent of HBS graduates who are women is slightly less than the 43 percent in 2006 across all MBA programs, but higher than the 26 percent of Chicago Booth MBAs between 1990 and 2006 that were women (Bertrand et al. 2010).

to the way in which judges are assigned to panels.

2.2 HBS administrative data

Working with the staff at the HBS MBA program and alumni office, we were able to create an anonymized but individual level dataset that includes information on student backgrounds and interests while they were at HBS. Specifically, we matched each of the 964 students in our sample to administrative data from HBS on the candidate's gender, an indicator for being a U.S. citizen, and indicators for having an undergraduate degree in computer science, engineering, and economics, business or management. Additional controls include attending an undergraduate university that was in the Ivy League or was MIT, Stanford or Caltech, having founded or co-founded a company prior to HBS, having worked at a VC-backed startup prior to HBS and having worked at a VC firm prior to HBS. We also include indicators for the student having self-identified as having a personal or professional interest in entrepreneurship, or being involved in entrepreneurship or VC clubs at HBS.

As we explain below, our empirical design exploits random variation in the number of VCs across panels. Nevertheless, the rich set of individual characteristics are valuable as they help us further control for any differences in interests, skills and experience related to VC-backed entrepreneurship that may be correlated with the participant's gender, factors that are typically unobserved in most studies examining the gender gap in entrepreneurship. This allows us to verify the validity of our identification assumption, as our estimates remain quite stable with the inclusion of these additional covariates.

2.3 Career histories

We supplement the HBS administrative data with an anonymized but individual-level panel dataset of career histories for each NVC participant, based on collaboration with staff at the HBS alumni office. Our data include the names of the organizations at which they worked, their titles at each organization, and the years associated with each position. We use the titles to define whether an individual was a founder or co-founder of a business, and we determine if the startup received VC by looking for a match to the firm's name and location in two databases of VC portfolio companies: CB Insights and VentureXpert. By combining these pieces of information, we are able to create three sets of indicator variables: (1) VC-backed entrepreneurs, if they were a co-founder of a firm that matched to the database of companies with VC investment; (2) Non-VC backed entrepreneurs, if they were a co-founder of a firm that did not match to this database; and (3) Employed at VC-backed firm, if they were employed at but not a co-founder of a firm that did match to this database.

Table 3 shows entrepreneurship outcomes after HBS. As can be seen from these descriptive statistics, the probability that an NVC participant starts a VC-backed firm, at 12 percent, is large. In the overall U.S. population, about 0.3 percent of people start a new business in any given year.[9] And among all new U.S. firms, just 0.11 percent are VC-backed (Puri & Zarutskie 2012). Moreover, while there is a difference in the probability of male participants becoming VC-backed entrepreneurs relative to female participants in our data, it is small relative to the differences documented in the broader population of U.S. startups (e.g., Gompers & Wang 2017).

These differences between our sample and the broader population are to be expected. First, participants in the HBS NVC are much more likely to become VC-backed entrepreneurs than the population of potential entrepreneurs. Businesses founded by elite business school graduates are much more likely to be amenable to and attract VC financing than the average business started in the broader population. Second, relative to the average female entrepreneur, the sample of female participants at HBS in general, and those participating in the NVC in particular, appear to have several differentiating characteristics. They are much more likely to participate in the labor force following graduation, start new ventures in industries that tend to receive VC, and are likely less subject to the standard frictions facing typical entrepreneurs. Participation in the NVC reveals an interest in high-growth entrepreneurship, which places these women in a very selected category relative to the average woman or even the average female entrepreneur. These factors are likely to narrow the gap between the post-HBS VC-backed entrepreneurship rates across male and female participants relative to the broader population. Of course, they also

[9] See https://indicators.kauffman.org/.

mean that our results may be less externally valid. However, we believe that the elite and entrepreneurial nature of women in our sample should push against finding an effect of exposure to networking opportunities. That is, this group of women seems especially well positioned to network effectively with VCs.

Panel B of Table 3 shows that conditional on raising VC, the companies that women in our sample build are not lower quality than those that men build. Furthermore, NVC judges score women higher than men (Table 1 Panel E). This could reflect selection into the NVC; for example, it may be that because of additional challenges to high-growth entrepreneurship that women face, only extremely high-quality women select into the NVC. This is consistent with the above point, which is that selection into the NVC should favor individuals who proactively network.

2.4 Survey data

As part of an effort to help the administrators of the NVC consider ways to facilitate more interaction between participants and investors, we obtained access to survey data on the networking experiences of NVC participants. The survey asked all NVC participants who were HBS alumni four Yes/No questions:

1. "After the NVC did you reach out to any judges on your panel who were VC or angel investors?"
2. "If yes, did any respond?"
3. "After the NVC did any judges on your panel who were VC or angel investors reach out to you?"
4. "If yes, did you respond?"

The following open-ended question was also included: "Optional: Please let us know any thoughts you have about the importance and ease of networking with startup investors at the NVC."

As we outline below, we use the survey responses to provide suggestive evidence about the mechanism behind our results.

3 Research design

Our empirical strategy focuses on the first round of the NVC, where teams and judges are assigned to panels. NVC administrators invite individuals with a range of occupational backgrounds to judge, including investors, entrepreneurs, corporate executives, and lawyers working with startups. To facilitate allocating judges to panels, NVC administrators ask judges to fill out a self-assessment of their expertise across a number of industry sectors. This assessment is absolute rather than relative, so that a judge can claim to be an expert in more than one sector. A few days before the competition, once the pool of entrepreneurs who will actually be presenting their business plans as well as the list of judges who are available has been finalized, teams are grouped broadly along sector lines and there is some effort made to assign them to panels with judges who claimed to have expertise in their respective sectors. Administrators aim to have between five and seven judges per panel as they rightly anticipate some attrition of judges on the day of the competition. This size requirement means that some judges who are assigned to a panel may not have expertise in the sector comprising most of the ventures on the panel.[10] Importantly for our analysis, judge occupations are not used to allocate judges to panels and are not even explicitly recorded by administrators. The program design therefore yields variation in the number of VCs across panels.

For our identification strategy to be valid, it must be the case that the fluctuation in the number of VCs across panels is random. In other words, any matching on sector lines should not lead to systematic variation in the number of VCs across panels. Moreover, variation in the number of VCs across panels needs to be orthogonal to characteristics of ventures that may differ along gender lines. In this regard, our identification strategy maps closely to Lerner & Malmendier (2013), who rely on random variation in the prior entrepreneurial background of HBS students

[10] Consistent with a desire to match ventures to judges with related expertise, we observe that at the sector level, there is a correlation between company and judge expertise. For example, in the startups in the IT/Software/Web category have on average 2.97 judges with related expertise, while on average non-IT startups have 2.25 judges with IT expertise on their panel, a difference that is highly significant. Matching appears strongest in health care. The only sector without such a significant correlation is Media/Education, though as Appendix Table A.1 shows, this is a small sample with just 66 participants in this sector.

assigned to different classrooms, where assignment is determined by stratification on other observable characteristics, including education, ethnicity, gender, and country of origin. Both their setting and ours lack pure random assignment, but the key variable of interest is not used in the assignment rule. Moreover, since the NVC administrators have shared that their assignment is based only on sector expertise, which we can observe and explicitly control for, our identification is stronger than Lerner & Malmendier (2013) and is closer to conditional random assignment as described in Krueger (1999), Duflo et al. (2007), and Angrist & Pischke (2008).[11]

We next demonstrate the validity of our empirical design. One way in which matching along industry lines would lead to systematic variation in the number of VCs is if there were systematic differences in self-assessed sector expertise across occupations, which caused systematic differences in the number of VCs on panels by sector. Note that under conditional random assignment, controlling for gender by sector fixed effects obviates this concern (see Duflo et al. 2007). Below, we demonstrate that the results are robust to including these controls. However, to further confirm that this is not an issue, we show in Appendix Figure A.1 that the average number of VC judges on each panel is similar across venture sectors, and importantly there is wide variation in the number of VCs on the panel among participants in a given sector. Summary statistics about the sector composition of judges and participants are in Appendix Table A.1.

Having shown that there is no systematic variation in the number of VCs across panels by sector, we turn next to gender-specific statistics. Table 1 Panel E shows that there is no difference in the number of ventures per panel across male and female participants, nor is there systematic variation in the number of VCs or the number of sector experts that men and women are exposed to. We further show in Appendix Figure A.1 that sectors with relatively more male VC-backed entrepreneurs do not also have relatively more VCs on the panel. Finally, Appendix Table A.2 shows by sector that men are not more likely to have more VC judges in their own sector.

[11] The reason we do not assert that our identification is identical to these papers is because sectors varied slightly from year to year, so that sector fixed effects do not in all cases control explicitly for the specific expertise stated by the judge. For example, in some years but not others a "Defense/Security" category was included, but we have folded this into "Tough Tech." Our results are robust to restricting the sample to sectors that were consistent across years.

Together with the fact that the NVC administrators do not pay explicit attention to the occupation of judges, the results from these tests show that the program design yields random fluctuation in VCs across panels and is orthogonal to participant gender. This enables us to identify the effect of participant exposure to more relative to fewer VCs. It is important to note that our variation is not based on the gold standard of explicit gnment, as in for example Gornall & Strebulaev (2018). Instead, our variation stems from the NVC program design yielding random fluctuation in VCs across panels. As noted above, this is conceptually similar to, but somewhat stronger identification than Lerner & Malmendier (2013), who exploit the program design of HBS sections.

An important control variable that we observe is comprehensive judging data, including each judge's numeric score of the ventures on their panel. These scores are not observed by participants. Program administrators average them and then force-rank the ventures within a panel, which determines which ventures will proceed to the next round. Figure A.2 uses a binscatter to show that score is correlated with subsequent VC-backed entrepreneurship. The red line provides the linear fitted values, which is the same as the coefficient on a regression of the y-values on the x-values. This indicates that score is a useful control for the latent quality of the venture.

Table 1 Panel E shows that female participants' teams have an average score of 3.39, where one is the lowest possible score and five is the highest. Male participants' average is a bit lower, at 3.22 (statistically different at the .05 level). Female participants have a 21 percent chance of proceeding to the semifinals, compared to a 19 percent chance for male participants, though this difference is not statistically significant. Women also have a higher chance of ultimately winning the competition in the final round. Their chance of being a finalist or runner up is nine percent, compared to seven percent for men (though again the difference is not significant). We do not use semifinals or finals data because the number of participants is far fewer, there is only one panel in each of those rounds, and there is inadequate variation in the number of VC judges. Our vector of competition covariates consists of the venture score in the panel, an indicator for winning the round (semifinals participation), an indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the number of total judges on the panel.

Because we have (a) random variation in the number of VCs on a panel, (b) scores that are unknown to the participants, and (c) rich covariates on the individuals, we can estimate the differential benefit for a male entrepreneur of each extra VC investor on a panel. Specifically, we estimate variants of Equation 1, where t denotes the NVC year, i denotes the HBS student participant, v denotes the venture, and j denotes the competition-specific panel on which the participant pitched.

$$\begin{aligned} VCEntrepreneur_i = \alpha_t + \mathbf{Female_i Sector_v}'\mu + \beta_1 Female_i \# VCsPanel_j \\ + \beta_2 \# VCsPanel_j + \mathbf{X}_i'\delta + \mathbf{X}_j'\gamma + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

The outcome of interest is an indicator for the participant becoming a VC-backed entrepreneur after HBS. Our primary approach uses female-by-sector fixed effects, which addresses the potential concern that the baseline propensity for entrepreneurship may vary systematically by industry sector in a manner that might be systematically correlated with gender. We also show the results with female-by-year and panel fixed effects, the latter of which absorb the number of VCs.[12] The coefficient of interest is β_1 on the interaction between the participant being male and the number of VCs on the panel. We cluster standard errors at the panel level, and the results are also robust to clustering at the venture level.

4 Results

This section first presents the main results, both visually and from the regression model in Equation 1 (Section 4.1). Robustness tests are discussed in Section 4.2.

4.1 Main Results

Before showing regression evidence, we begin by presenting raw averages consistent with our main result. Table 2 Panel B shows the share of participants who subsequently become VC-backed entrepreneurs by gender and the panel's number of VC judges. For

[12] There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health.

women, the rate of VC-backed entrepreneurship exhibits no relationship to the number of VC judges. However, for men, there is a strong association. Men have a nine percent chance of becoming VC-backed entrepreneurs with two or fewer VCs on the panel, a 12 percent chance with three to four VCs, and an 18 percent chance with five or more VCs on the panel. This relationship is demonstrated graphically in Figure 1 using binscatters, in which each number of VCs on the panel is a bin. The dots indicate the average chance that an individual in the bin founds a VC-backed startup (that is, it is the mean of all observations in the bin). The left figure shows that venture backing is monotonically increasing in the number of VCs on the panel among men. In striking contrast, the right figure shows that there is a much weaker relationship for women, if any.

Table 4 shows the same result as the figure but in regression form and has three important insights. First, the results suggest an important potential networking friction in venture capital. When the sample is restricted to male entrepreneurs, we observe that random exposure to an additional VC on the NVC panel increases the chances of post-VC entrepreneurship for male entrepreneurs by about 17% (column 3). These findings point to the fact that access to investors appears to privilege those whose networks give them better access to investors, independent of the quality of their ideas. The relatively large magnitude of the effect among men is consistent with anecdotal accounts we have heard from HBS students that it is not trivial for them to get access to VCs' time. An analogy is to an academic who, even at a top department, may not easily be able to get her work in front of seniors in her field. It is very helpful to attend a conference with the seniors, where she will have specific topics to discuss and opportunities to make personal connections. Similarly, the pitch-specific, in-person discussion at the NVC appears to offer particularly valuable connections with VC investors. Second, however, the results point to the fact that while exposure to more VCs benefits men, this does not appear to be symmetric by gender. Women do not benefit from additional exposure to VCs the way that men do. Third, the inclusion of a large number of controls and fixed effects do not change the magnitude of the coefficients noticeably, reinforcing the premise of random variation in the VCs across panels.

To probe these results further and to address other potential sources of unobserved heterogeneity, we move in Table 5 to estimating the relative impact of an additional

VC on male participants' post-NVC entrepreneurship compared to female participants. This empirical strategy, also outlined in equation (1) above, has several benefits. First, it enables us to formally test for the difference in the benefit of an additional VC for men and women participants. Secondly and equally important, it allows us to control for more stringent set of fixed effects.

The first column of Table 5 includes only female-by-sector fixed effects as controls. The coefficient on the interaction indicates that an additional VC on a panel reduces the chances of women launching a VC-backed startup by 2.6 percentage points relative to men. Column (2) adds controls related to the competition, such as the ventures' score that was unobserved to participants but enables us to further address concerns about unobserved quality of the pitches. It is important to demonstrate that the scores contain useful information, as Howell (2020) finds in a larger sample of competitions. Indeed, on average scores are strongly correlated with VC-backed entrepreneurship, which is shown in Appendix Table A.3 columns (1) and (2). In column (3) of Table 5we add individual covariates such as major and interest that may be correlated with the decision to become an entrepreneur. As can be seen from the coefficients, both the main effect of an additional VC on the probability of VC-backed entrepreneurship after college and the relative effect of women compared to men is very stable. In column (4) we further include panel fixed effects, which absorb the number of VCs on the panel, and find that the results continue to be extremely robust.

Table 5 Panel B repeats these models but explores the possibility that there may be differential selection by gender into the NVC. While selection into the NVC does not impact the internal validity of the analysis, it does have a bearing on our ability to generalize the results. For example, Appendix Table A.3shows that women have slightly higher scores on average. One might be concerned that women's ventures are "so good" that they don't need NVC judges for networking help. We therefore restrict the sample to the participants who were between the 10th and the 90th percentile of the score distribution (recall that overall scores are unobserved to participants and judges). This forms a sample of relatively marginal candidates, whose outcomes might be more sensitive to networking opportunities. The coefficients in Panel B are extremely similar to the main effects in Panel A. These results are consistent with our proposed identification and demonstrate that especially high or low quality ventures are unlikely to explain the results.

We next examine which type of VC investor appears to drive the result. First, in Table 6 columns (1) and (2), we show that controlling for whether the judge himself invested in the venture explains our results. While the coefficient on judge investing is strongly positive, it does not attenuate the main finding. These results suggest that the overall effect is likely driven by referral networks among VCs.

Subsequent columns of Table 6 show that the results are largely driven by early-stage VCs. For this analysis, we manually researched whether the VCs' firms primarily do early, late, or not specialized investing. Where available, we relied on Crunchbase's categorization. Otherwise, we used Pitchbook deal types and firm websites. We were able to assign a stage to 126 unique VC firms. Of these, 40 are early specialists, typically focusing on Series A rounds (not the seed or angel deals that are more typically a startup's first outside financing). Of the remainder, 22 are late specialists, and 64 do not specialize. In Appendix Table A.4, we interact "Male" with the number of VCs of a particular stage. The coefficient on the interaction between "Male" and the number of early stage VCs is 0.055, larger than our main estimate (column 1). The other two coefficients are insignificant, but the one for "Late" is -.011 while the one for "Not Specialized" is .023, suggesting possible monotonicity in early stage deal making. The means for Early, Late, and Not Specialized are 0.48, 0.26, and 1.03, respectively. While our results are not driven by the VCs themselves investing in the very early stage participating ventures, it is not surprising that the VCs with the most relevant networks are those that specialize in early stage deals.

We explore whether the number of VCs on the panel leads to different startup outcomes by gender conditional on the startup receiving VC funding in Appendix Table A.4. A caveat to this analysis is that since we are conditioning on those who started VC-backed ventures, the sample is quite small. Columns (1)-(3) consider the amount of VC financing within two years of the competition. In column (3), we use an indicator for financing above the 90th percentile. The sign of the coefficient suggests that an additional VC increases the chances of very high funding for men relative to women but the small sample size means that the coefficient is imprecisely estimated. Columns (7)-(8) find no significant effects on real outcomes in the forms of acquisition or employment. These results, while imprecisely measured, suggest that the networking friction we observe acts on the extensive margin of becoming a VC-backed entrepreneur. Conditional on raising VC, women appear to have established the necessary networks to succeed.

In sum, the results indicate that exposure to VCs in particular is more useful to nascent male entrepreneurs than to their female counterparts. Beyond VC judges' expertise in evaluating startups, networking value is no doubt one reason why new venture competitions (including HBS) try to include as many of them in their judge pool as possible. We demonstrate that this networking value accrues disproportionately to male founders.

We believe that this finding can generalize to the broader population beyond HBS. We believe the highly motivated, relatively well-networked students in our sample likely face fewer of these frictions than those in the broader population. The fact that male participants benefit from random exposure to VCs suggests that networking frictions are likely to be important in other settings too. Moreover, the gender-based networking frictions we identify are likely present in high-growth entrepreneurship more generally. That said, the selected sample of HBS NVC participants is a potential limitation of our study.

4.2 Robustness Tests

Our first and most important robustness exercise consist of placebo tests, which offer compelling evidence that our effect is not spurious. In Table 7 columns (1)-(3), we examine alternative outcome variables: non-VC backed entrepreneurship, employment at a VC-backed company, and non-investor venture funding, defined as grants, incubators, accelerators, business plan competitions, and crowdfunding. In all three cases, there is no effect of the interaction between being female and the number of VCs on the panel.

In the remainder of the table, we ask whether other types of judges affect VC-backed entrepreneurship. All of the judges are highly successful individuals with some connection to entrepreneurship (e.g., lawyers for startups, executives running corporate venture programs), so it is possible that our effect reflects useful connections based on other characteristics that may be correlated with being a VC. In column (3), we interact female with the number of male judges on the panel in case gender homophily is the source of our effect. While the coefficient is negative, it is smaller and statistically insignificant. We consider the number of all judges that are not VCs in column (4), and more specifically the number of entrepreneurs and corporate executive judges in columns (5) and (6), respectively. In all cases, the coefficient is small, negative, and insignificant.

There may be concerns that the baseline propensity for entrepreneurship varies systematically over time, and this is somehow correlated with VC judges on the panels. In Appendix Table A.5, we replace the female-by-sector fixed effects from Table 5 with female-by-year fixed effects. The results are quite similar to the main effects, indicating that gender-specific time trends do not explain our findings. A related concern is that our main finding reflects some characteristic correlated with gender. In Appendix Table A.6 we interact $\#VCsPanel_j$ with a wide array of relevant previous job experiences: previous VC-backed entrepreneurship (column 1), previous non-VC-backed entrepreneurship (column 2), previous employment at a VC-backed company (column 3), previous employment at a VC firm (column 4), previous employment in management consulting (column 5), and previous employment in financial services (column 6). In no case do we observe an effect of the interaction between the job experience and the number of VCs on the panel. In Appendix Table A.7, we consider six additional binary participant characteristics: undergraduate degree from an Ivy+ college (column 1), HBS honors (column 2), computer science major (column 3), engineering major (column 4), econ/business major (column 5), and winning the NVC round (column 6). We again find no effects, with one exception. The interaction is significant for participants whose college major was economics/business. This major is uncorrelated with gender.

We also demonstrate that the results are robust to analysis at the venture level. In Appendix Table A.8 shows the effect of the number of VCs on the probability that a venture with female team members in the HBS NVC subsequently raises VC, relative to ventures with male team members. Analysis is at the venture level, using a categorical variable that takes one of three values for whether the team is: all female, mixed, or male. All male is omitted. In column (1), we consider all team types. The results indicate that the effect is clearly driven by all female and mixed teams, though the coefficient on mixed teams is insignificant. In column (2), we omit mixed teams and find a similar result. Note that as in the main model, fixed effects for team type by sector absorb the independent effect of team type.

In Appendix Table A.9 we split the sample by time period and number of ventures on the panel to test whether a part of our sample is responsible for the effect (though note we control for these factors in the main model). The results suggest a somewhat stronger effect in the later period, though the two coefficients are not significantly different. However, to the extent this difference may be substantive, it could indicate a higher value of networking resources in early stage entrepreneurship in more recent years, when the rise in entrepreneurial activity perhaps made it harder to screen ventures.

5 Potential Mechanisms

Our results provide robust evidence of networking frictions in venture capital. For male entrepreneurs, random exposure to additional VC investors on the NVC judging panels increased the likelihood of the participant engaging in VC-backed entrepreneurship after graduation. However, we don't find any such impact for women, implying that exposure to VCs is more useful to nascent male entrepreneurs than to their female counterparts.

While our data do not allow us to rule out specific channels that might be driving this differential impact on male and female participants, we provide two sets of analyses to examine some of the dynamics behind the pattern in greater detail.

5.1 Judge Gender

Our first analysis examines the degree to which judge gender plays a role in the results we see. Specifically, we separately examine the impact that male and female VC judges have on male and female participants. Table 8 repeats the models of Table 4 using the number of male or female VC judges on the panel. The results clearly indicate that our effect is driven by male VCs helping male participants (columns 1 and 3), while female VCs have no effect on either male or female participants (columns 2, 5, and 6). When both are considered together.

We confirm this result in the interaction model. Column (1) of Table 9 shows that the coefficient on male VCs on the panel is stronger than the equivalent model in Table 5 , suggesting that male participants benefit more from an additional male VC on the panel than the average VC judge. The negative and significant interaction on female participants and male VCs shows that an additional male VC has no measurable impact on female participants' VC backed entrepreneurship post HBS. This result is extremely consistent with gender-based homophily in networking. If male participants are more comfortable than female participants with reaching out and networking with male VCs, or if male VCs are more likely to make useful referrals to other investors in their network for male entrepreneurs, we would see such a pattern emerge.

Looking at column (2), however, shows that this pattern is not symmetric. While male participants do not benefit from an additional female investor on the panel as might be expected with gender-based homophily, neither do female participants. In fact, although this is not statistically significant, the point estimates suggest that male entrepreneurs still benefit more from an additional female VC investor on their panel more than female participants do. This "null result" for female participants, even when randomly exposed to female VCs, is surprising and suggests the presence of one or both of the following two elements. First, female participants may not proactively reach out and network as much as male participants, for example if they held themselves to a higher standard when choosing to reach out to VCs. If so, men may exploit networking opportunities much more than women. Second, the value of networking with a female VC may be diminished for both women and men if there is homophily in networking within the VC community. In other words, if referrals tend to be mediated by gender-based homophily, the fact that 90% of investors are males would imply that referrals from male investors may on average lead to more meetings with investors. While we are unable to directly verify the existence of the second channel, we can use survey evidence to examine the potential presence of the first channel.

5.2 Survey Results

The first step in examining the survey evidence is to test for response bias in the variables of interest. Table 10 columns 1 and 2 show that women were no more likely than men to respond to the survey. Further, there is no association between responsiveness and either the number of VCs on the panel or VC-backed entrepreneurship (column 2).

We then turn to analyzing the results within the sample of 172 respondents. Men were much more likely to report having reached out to a VC judge after the competition. Columns 3-5 show that women were 16-22 percentage points more likely to reach out. Among survey respondents, 26 percent reached out. Therefore, our preferred specification in column 5 implies that women were 84% less likely than men to reach out to VCs. However, men were not significantly more likely than women to report a VC judge reaching out to them after the competition (column 6). Conditional on reaching out to a judge, male and female participants report the judge responding in equal numbers (column 7). It is important to emphasize that the sample is very small, especially in column 7, so the results should be interpreted with caution.

Despite its limitations, the survey results offer suggestive evidence that our main findings reflect women being less likely to initiate networking with VCs. This is corroborated by some of the responses to an open-ended question in the survey about the importance or ease of networking at the NVC. For example, one woman wrote the following: "I think [networking at the NVC] would have been amazing. I didn't think it was appropriate at the time/or was perhaps a bit shy to reach out. In general, I think encouraging future entrepreneurs to be very comfortable scheduling meetings/coffees/chats with the community would be hugely beneficial.

6 Conclusion

This paper contributes to a small but growing literature looking more closely at frictions that might lead to systematic gaps in VC funding for new ventures, independent of the quality of ideas. We characterize one friction that might lead to the well-documented discrepancy between the rates at which men and women found VC-backed startups: barriers to networking between entrepreneurs and investors. There are of course many (not mutually exclusive) potential reasons why women might not receive VC in the same proportion as their share of the population. Our goal in this paper is not to investigate the relative importance of different drivers, but rather to study whether networking frictions could be a source of differential access that might play an important role in the variation we see in observed rates of VC finance. We expect that networking-related information frictions are likely to be particularly important in VC, given the large amount of asymmetric information and the high weight that VCs appear to place on face-to-face connections and trusted referrals as deal sourcing methods. This reliance on networks may privilege those who are more connected or those who are most comfortable forming connections with investors.

Exploiting random variation in the number of VCs across judging panels at the Harvard Business School New Venture Competition (HBS NVC), we find that additional VCs on a panel increase the likelihood of a male participant starting a VC-backed venture after graduation but have no meaningful impact among female participants. That is, women assigned to panels with many VCs benefit less from this 'lucky draw' than men who were assigned to these panels. Our survey evidence points to this difference being driven by the fact that women are less likely to proactively reach out to VCs after the NVC.

There are numerous reasons why women might be less likely to proactively network than men. Men and women may have different beliefs about appropriate networking norms. There may also be homophily in networking, where individuals might feel more comfortable networking with others of the same gender. Since most VCs are men, this would lead to lower rates of networking with VCs among women. Furthermore, women may not reach out if they anticipate discrimination or harassment on the part of investors. We cannot distinguish between these hypotheses. Nevertheless, the survey suggests that entrepreneurs rather than the VCs drive the networking discrepancy, consistent with evidence that women are less proactive or hold themselves to a higher standard than men.

More generally, since the individuals behind ideas are intricately tied to the ideas themselves at a venture's earliest stages, and the distribution of good ideas is not perfectly correlated to the distribution of good access to VC, our results suggest that promising ideas may go unfunded because of systematic variations in VC access rather than because of the inherent quality of the idea. This is likely to be particularly salient when such access is mediated by the extent to which entrepreneurs proactively reach out to, and network with investors. Our results suggest that future research studying which interventions most effectively reduce networking-related frictions will be extremely valuable.

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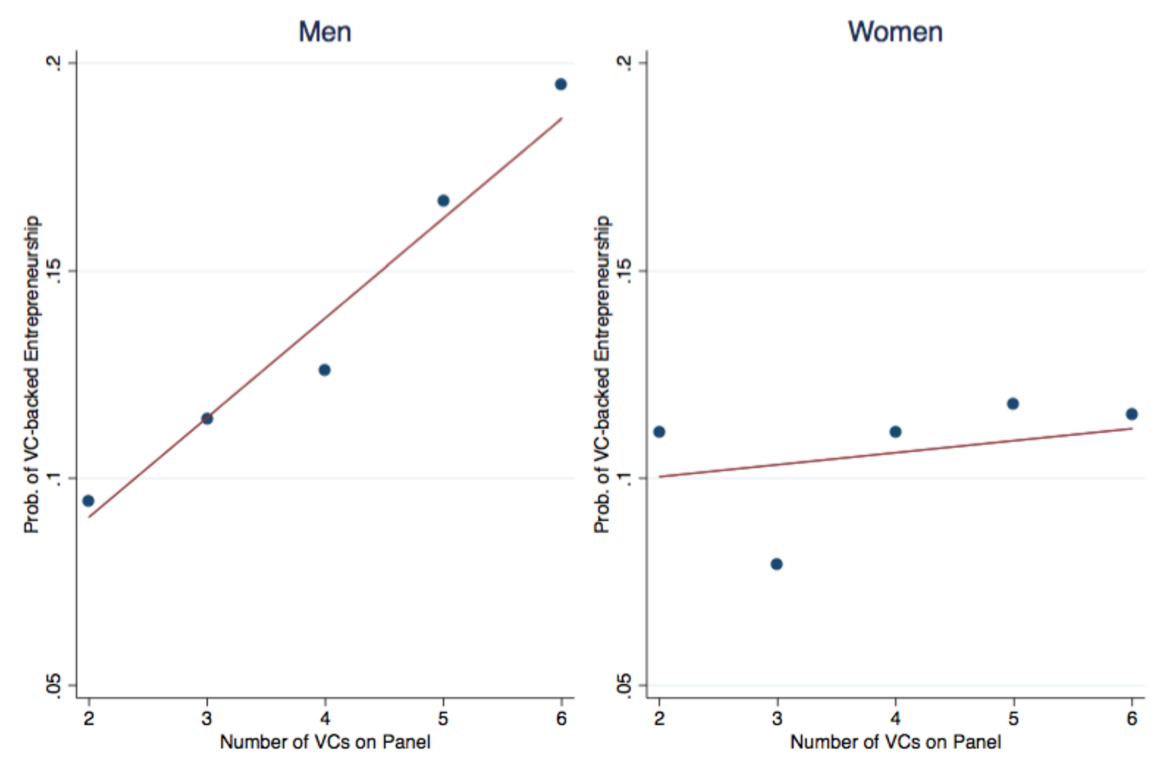
Figure 1: Relationship between Number of VCs on Panel and VC-backed Entrepreneurship



Note: These figures show binscatters of the relationship between the number of VCs on the judging panel for a participant, and the probability of VC-backed entrepreneurship for individuals on the venture's team. The left figure restricts the sample to men, and the right figure to women. 0-2 and 6-8 VCs are collapsed into a single category. Together, the figures include all 964 individuals in the HBS NVC.

Table 1: Characteristics of participants

A. Count of individuals

	All	Female	Male	Fraction female
Number of individuals	964	307	657	0.32

B. Team size (Means)

	All	Female	Male	P-value (male - female)
Mean team size including non-HBS participants	2.53	2.55	2.52	0.56
Mean team size, HBS participants only	1.79	1.83	1.77	0.24

C. Professional background before HBS (Means)

	All	Female	Male	P-value (male - female)
Entrepreneurship	0.26	0.23	0.27	0.17
VC-backed company employment	0.45	0.48	0.44	0.17
VC firm employment	0.04	0.04	0.04	0.85
Finance employment	0.27	0.32	0.25	0.01
Consulting employment	0.29	0.31	0.28	0.34

D. Stated relevant interests and activities at HBS (Means)

	All	Female	Male	P-value (male - female)
Interest in entrepreneurship	0.18	0.19	0.17	0.48
Interest in management	0.07	0.06	0.08	0.29
Interest in consulting	0.12	0.19	0.09	0.00
Interest in finance	0.28	0.24	0.29	0.08
HBS Entrepreneurship club member	0.08	0.08	0.08	0.91

Note: These panels contain statistics on the 964 HBS participants in the HBS NVC from 2000 to 2015. Team size is a venture-level variable, but is summarized at the individual level. Team size including non-HBS participants reflects additional individuals who are not included in estimation. Indicators for professional background (e.g. Finance employment) reflect whether the individual had any instance of that experience; participants may have had multiple jobs before HBS. P-value is two-tailed.

E. Panel composition and NVC outcomes (Means)

	All	Female	Male	P-value (male - female)
Total number of judges on panel	6.00	5.93	6.01	0.47
Number of VC judges on panel	3.29	3.21	3.33	0.28
Number of male VC judges on panel	2.78	2.71	2.81	0.32
Number of judges in own sector on panel	2.44	2.33	2.49	0.17
Match to judges in own sector on panel	0.80	0.84	0.79	0.09
Match to VC judges in own sector on panel	0.72	0.74	0.71	0.27
Number of entrepreneur judges on panel	0.85	0.87	0.84	0.61
Number of corporate executive judges on panel	0.97	0.93	0.99	0.32
Number of ventures on the panel	4.82	4.80	4.83	0.69
Score in panel (1 worst, 5 best)	3.27	3.39	3.22	0.01
Score in panel if 10-90th pctile (1 worst, 5 best)	3.30	3.37	3.27	0.11
First round winner	0.20	0.21	0.19	0.40
Finals winner or runner-up	0.07	0.09	0.07	0.25

Note: This panel contains statistics on the 964 HBS participants in the HBS NVC from 2000 to 2015. The unit of observation is the individual participant, but the first six variables are at the panel level (in the first round of the competition, which is the focus of our study, ventures pitch and are scored within panels). We observe a total of 180 panels across all years. As an example of interpretation, the first two rows indicate that female participants are assigned to panels that have on average 5.93 judges, of which 3.21 are venture capitalists (VCs). The last three variables are at the team (i.e. venture) level, though again the unit of observation is the individual. For example, female participants' teams average score is 3.39, and they have a 0.21 chance of winning the first round. P-value is two-tailed.

Table 2: Characteristics of NVC Judging Panels by Number of VC Judges on Panel

A. Number of judges and participants (Means)

	$\leq$2 VCs	3-4 VCs	$\geq$ 5 VCs
Number of judges on panel	5.8	5.9	6.5
Number of ventures in panel	3.6	3.6	3.6
Number of participants	5.2	5.4	5.5

B. Share of panel participants with post-HBS VC-backed entrepreneurship

	$\leq$2 VCs	3-4 VCs	$\geq$ 5 VCs
Share of males	0.09	0.12	0.18
Share of females	0.11	0.09	0.12

Note: This table reports descriptive statistics at the panel level, for the 180 judging panels in the HBS NVC from 2000 to 2015. We separately consider panels by the number of VCs. There are 62 panels with $\leq$ 2 VCs, 81 panels with 3-4 VCs, and 37 panels with at least 5 VCs.

Table 3: Participant Entrepreneurship Outcomes After HBS

A. Individual entrepreneurship-related outcomes (Means)

	All	Female	Male	P-value (male - female)
VC-backed entrepreneurship	0.12	0.10	0.13	0.36
Non-VC-backed entrepreneurship	0.20	0.17	0.21	0.23
VC-backed startup employment	0.48	0.52	0.46	0.07

B. Venture outcomes conditional on VC-backed entrepreneurship

	All		Female		Male		P-value (male - female)
	N	Mean	N	Mean	N	Mean	
Judge or judge's firm invested	114	0.02	32	0.00	82	0.02	0.38
Funding within 2 yrs of NVC (mill $)	73	45	21	37	52	48	0.84
>10 employees as of March, 2018	114	0.64	32	0.69	82	0.62	0.52
Venture acquired	114	0.22	32	0.16	82	0.24	0.31

Note: This table reports descriptive statistics on HBS participants in the HBS NVC from 2000 to2015. The number of observations is 964 (all participants) in Panel A. Panel B restricts the sample to the 114 ventures with VC funding founded by participants. Further, funding statistics are limited to the 73 ventures for which we have funding data. Note that indicators for professional outcomes (e.g. VC-backed startup employment) reflect whether the individual had any instance of the outcome; participants may have multiple jobs post-HBS. P-value is two-tailed.

Table 4: Effect of Number of VC Judges on VC-backed Entrepreneurship

Dependent variable: VC-backed Entrepreneurship After HBS

	Whole Sample		Men Only		Women Only	
	(1)	(2)	(3)	(4)	(5)	(6)
VCs on Panel	0.015*	0.012	0.022**	0.023**	-0.001	-0.013
	(0.008)	(0.009)	(0.010)	(0.011)	(0.012)	(0.013)
Year FE	No	Yes	No	Yes	No	Yes
Sector FE	No	Yes	No	Yes	No	Yes
Competition Controls	No	Yes	No	Yes	No	Yes
Person Controls	No	Yes	No	Yes	No	Yes
Observations	964	964	657	657	307	307
R^2	0.005	0.094	0.010	0.125	0.000	0.140
Outcome Mean	0.118	0.118	0.125	0.125	0.104	0.104

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that participants in the HBS NVC subsequently found VC-backed ventures. "VCs on Panel" is the continuous number of VC judges on the panel. See text for list of control variables. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 5: Effect of Number of VC Judges on VC-backed Entrepreneurship by Gender

Dependent variable: VC-backed Entrepreneurship After HBS

Panel A: Whole Sample

	(1)	(2)	(3)	(4)
VCs on Panel x Female	-0.026*	-0.029**	-0.032**	-0.045**
	(0.013)	(0.014)	(0.014)	(0.020)
VCs on Panel	0.021*	0.021*	0.023**	
	(0.011)	(0.011)	(0.011)	
Female x Sector FE	Yes	Yes	Yes	Yes
Competition Controls	No	Yes	Yes	Yes
Person Controls	No	No	Yes	Yes
Panel FE	No	No	No	Yes
Observations	964	964	964	964
R^2	0.062	0.081	0.101	0.255
Outcome Mean	0.118	0.118	0.118	0.118

Panel B: Participants in 10-90th Score Percentiles

	(1)	(2)	(3)	(4)
VCs on Panel x Female	-0.026*	-0.028*	-0.033**	-0.051***
	(0.014)	(0.015)	(0.014)	(0.018)
VCs on Panel	0.020	0.020	0.022*	
	(0.012)	(0.013)	(0.012)	
Female x Sector FE	Yes	Yes	Yes	Yes
Competition Controls	No	Yes	Yes	Yes
Person Controls	No	No	Yes	Yes
Panel FE	No	No	No	Yes
Observations	777	777	777	777
R^2	0.066	0.074	0.103	0.311
Outcome Mean	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that female participants in the HBS NVC subsequently found VC-backed ventures, relative to male participants. "VCs on Panel" is the continuous number of VC judges on the panel. "Female" is an indicator for the participant being female. In Panel B, the sample is restricted to participants in the 10-90th percentiles of score, which is the average of individual judge scores and is unobserved to both participants and judges. Female-by-sector fixed effects absorb the independent effect of female. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 6: Effect of Number of VC Judges on VC-backed Entrepreneurship by Gender and Judge Characteristics

Dependent variable: VC-backed Entrepreneurship After HBS

	(1)	(2)	(3)	(4)	(5)
VCs on Panel x Female	-0.027**	-0.033**			
	(0.013)	(0.014)			
VCs on Panel	0.022**	0.023**			
	(0.011)	(0.011)			
Judge Invested	0.867***	0.791***			
	(0.083)	(0.059)			
Early VCs on Panel x Female			-0.056*		
			(0.033)		
Early VCs on Panel			0.018		
			(0.022)		
Late VCs on Panel x Female				0.010	
				(0.042)	
Late VCs on Panel				-0.032	
				(0.025)	
Generalist VCs on Panel x Female					-0.024
					(0.022)
Generalist VCs on Panel					0.013
					(0.013)
Year FE	Yes	Yes	Yes	Yes	Yes
Female x Sector FE	Yes	Yes	Yes	Yes	Yes
Competition Controls	No	Yes	Yes	Yes	Yes
Person Controls	No	Yes	Yes	Yes	Yes
Observations	964	964	964	964	964
R^2	0.077	0.113	0.096	0.096	0.096
Outcome Mean	0.118	0.118	0.118	0.118	0.118

Note: Column 1 of this table shows the effect of the number of male and female VCs on the probability that a male participant in the HBS NVC subsequently founds a VC-backed venture, relative to female participants. Columns 1 controls for the judge investing in the venture (there are only 4 instances of this). Columns 2-5 assess whether the main effect differs by the stage of investing in which the VC specializes: early deals (Series A-B), late deals (subsequent series), or generalist (unspecialized in a particular stage). In each case we redefine the number of VCs on the panel to include only the number of VCs within a certain category of specialization. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 7: Placebo Tests

Dependent variable:	Non-VC-backed Entrep.	VC-backed Comp. Empl.	Non-Investor Funding	VC-backed Entrepreneurship			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VCs on Panel x Female	-0.007	0.001	0.000				
	(0.016)	(0.022)	(0.008)				
VCs on Panel	-0.016	0.021	0.006				
	(0.011)	(0.013)	(0.005)				
Male Judges on Panel x Female				-0.015			
				(0.014)			
Male Judges on Panel				-0.014			
				(0.015)			
Sector Judges on Panel x Female					-0.012		
					(0.013)		
Sector Judges on Panel					-0.002		
					(0.009)		
Entrep Judges on Panel x Female						0.013	
						(0.023)	
Entrep Judges on Panel						-0.021	
						(0.015)	
CorpExec Judges on Panel x Female							0.011
							(0.024)
CorpExec Judges on Panel							0.008
							(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female x Sector FE	Yes	Yes	Yes	Yes	No	Yes	Yes
Competition Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person Controls	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	964	964	964	964	964	964	964
R^2	0.061	0.138	0.106	0.079	0.086	0.098	0.098
Outcome Mean	0.195	0.482	0.033	0.118	0.118	0.118	0.118

Note: This table shows tests for whether VC judges interacted with participant gender predict outcomes besides VC-backed entrepreneurship, and whether non-VC judges interacted with gender predict VC-backed entrepreneurship. In all cases we include the independent effect of the number of judges (e.g. number of VCs on the panel or number of entrepreneur judges on the panel) but do not report it to keep the table parsimonious. Column 1 shows the effect of the number of VCs on the probability that the participant founds a firm that does not receive VC backing. Column 2 shows the effect on working as an employee at a company that is VC-backed. Column 3 considers early funding for the participant's startup from accelerators, grants, incubators, crowdfunding and competitions. Columns 4-7 repeat the main regression in Table 5 column 3, but use the number of judges in categories besides VC. Corp. Exec. is an abbreviation of Corporate Executive. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 8: Effect of Number of Male and Female VC Judges on VC-backed Entrepreneurship by Gender

Dependent variable: VC-backed Entrepreneurship After HBS

	Men Only			Women Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Male VCs on Panel	0.028**		0.028**	-0.007		-0.008
	(0.013)		(0.013)	(0.016)		(0.016)
Female VCs on Panel		-0.000	0.007		-0.036	-0.037
		(0.020)	(0.020)		(0.025)	(0.025)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Competition Controls	Yes	Yes	Yes	Yes	Yes	Yes
Person Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	657	657	657	307	307	307
R^2	0.126	0.116	0.126	0.137	0.141	0.142
Outcome Mean	0.125	0.125	0.125	0.125	0.125	0.125

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that female participants in the HBS NVC subsequently found VC-backed ventures, relative to male participants. "Male VCs on Panel" and "Female VCs on Panel" are the continuous number of male and female VC judges on the panel, respectively. "Female" is an indicator for the participant being female. Fixed effects for female by sector absorb the independent effect of female. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 9: Effect of Number of Male and Female VC Judges on VC-backed Entrepreneurship with Gender Interaction

Dependent variable: VC-backed Entrepreneurship After HBS				
	(1)	(2)	(3)	(4)
Male VCs on Panel x Female	-0.028*		-0.028*	-0.048**
	(0.016)		(0.016)	(0.023)
Male VCs on Panel	0.026**		0.027**	
	(0.012)		(0.012)	
Female VCs on Panel x Female		-0.046	-0.050	-0.035
		(0.035)	(0.034)	(0.051)
Female VCs on Panel		0.002	0.009	
		(0.020)	(0.020)	
Female x Sector FE	Yes	Yes	Yes	Yes
Competition Controls	Yes	Yes	Yes	Yes
Person Controls	Yes	Yes	Yes	Yes
Panel FE	No	No	No	Yes
Observations	964	964	964	964
R^2	0.102	0.096	0.104	0.255
Outcome Mean	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that female participants in the HBS NVC subsequently found VC-backed ventures, relative to male participants. "Male VCs on Panel" and "Female VCs on Panel" are the continuous number of male and female VC judges on the panel, respectively. "Female" is an indicator for the participant being female. Fixed effects for female by sector absorb the independent effect of female. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table 10: Survey Response Predictors and Analysis

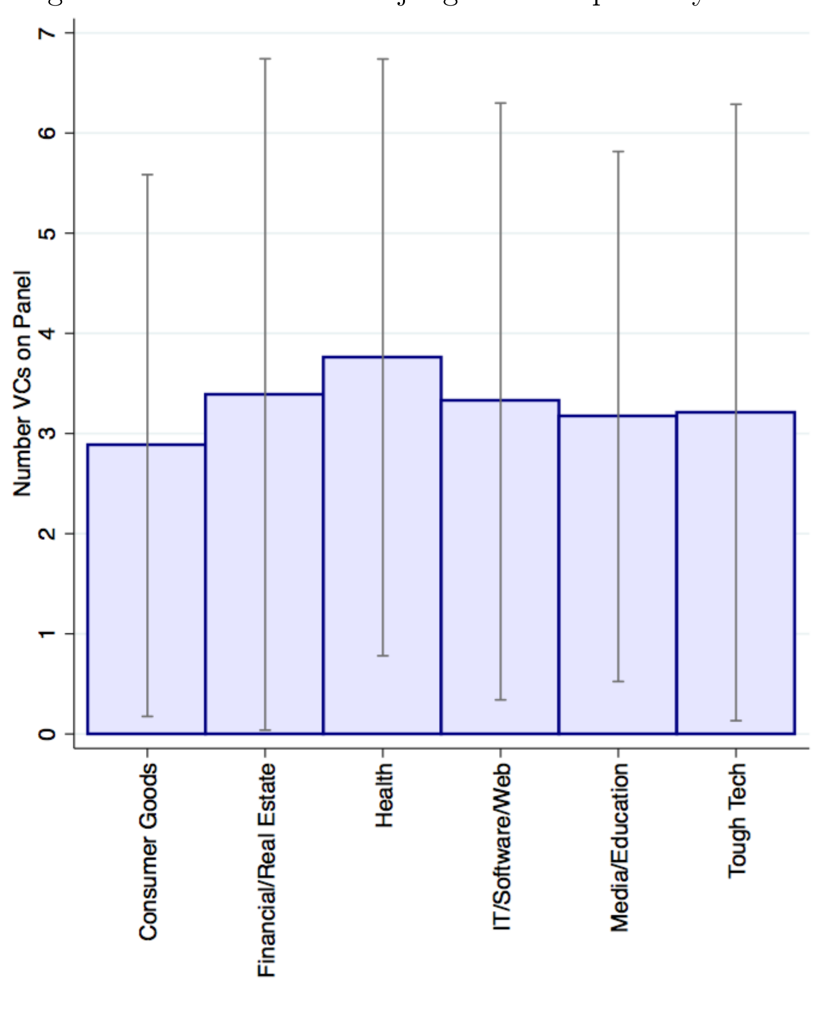
Sample:	All		Survey Respondents				Contacted Judge
Dependent variable:	Responded to Survey		Contacted VC Judge			VC Judge Contacted Me	VC Judge Responded
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.019	-0.003	-0.177***	-0.163**	-0.219***	-0.028	0.000
	(0.027)	(0.027)	(0.063)	(0.066)	(0.074)	(0.058)	(0.162)
VCs on Panel		-0.004			-0.038		
		(0.009)			(0.027)		
VC-backed Entrep.		0.047			0.068		
		(0.040)			(0.105)		
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes	No	No
Competition Controls	No	Yes	No	No	Yes	No	No
Person Controls	No	Yes	No	No	Yes	No	No
Observations	964	964	172	172	172	172	45
R^2	0.032	0.068	0.034	0.154	0.336	0.044	0.615
Outcome Mean	0.178	0.178	0.262	0.262	0.262	0.163	0.867

Note: This table shows results from the survey of NVC participants in our sample. Columns 1-2 of this table show predictors of responding to the survey (172/964 responded). Columns 3-5 examine whether reaching out to a judge varies by gender, conditional on responding. Column 6 examines whether judges are less likely to reach out to women. Column 7 examines whether, conditional on the participant reaching out to a VC judge, the judge is less likely to respond if the participant is female. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Appendix

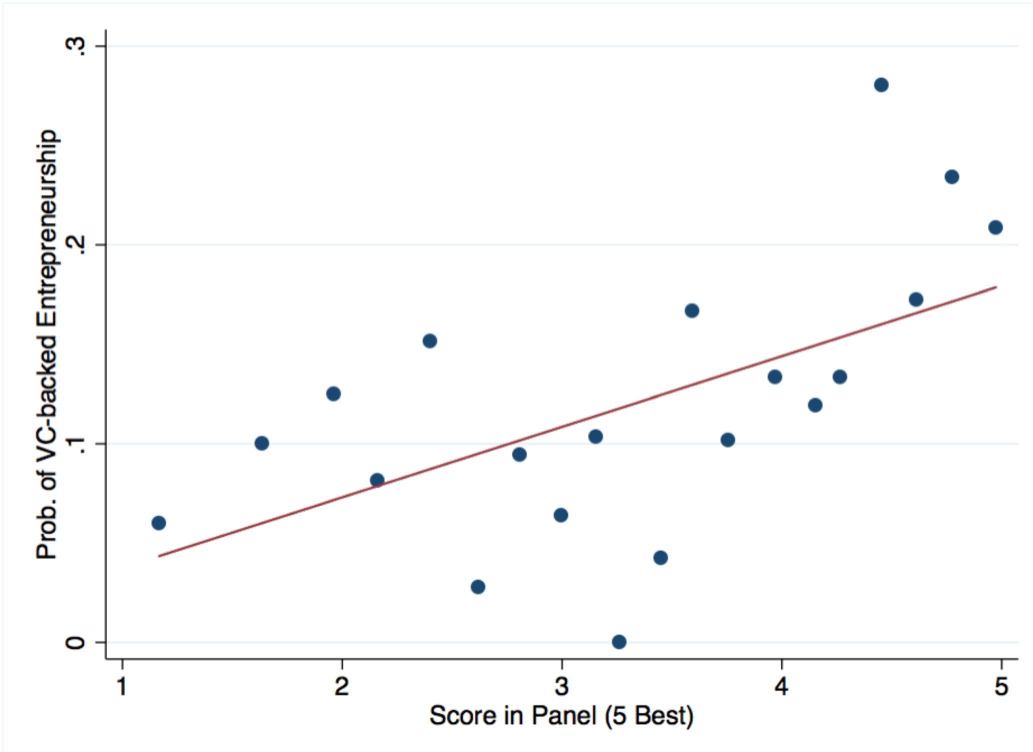
(for Online Publication)

Figure A.1: Number of VC judges on the panel by sector



Note: This figure shows that the average number of VCs on the panel is similar across sectors, with wide variation within each sector. The sector is defined at the participant (venture) level. For example, ventures in the IT sector face about 3.2 VC judges on average. We use the number of VCs rather than the fraction on the panel because that is what is used in our primary empirical analysis. Results are qualitatively the same using the fraction on the panel. The level of observation is the participant, and all 964 individuals in the HBS NVC are included. The number of participants in each sector is as follows: 187 in Consumer Goods, 33 in Financial/Real Estate, 100 in Health, 433 in IT/Software/Web, 66 in Media/Education, and 60 in Tough Tech.

Figure A.2: Relationship between Unobserved Venture Score in Panel and VC-backed Entrepreneurship



Note: This figure shows a binscatter of the relationship between the score that a venture receives, and probabilities of VC-backed entrepreneurship for individuals on the venture's team. The score is observed only by the competition organizers and the econometrician. Neither ventures nor judges observe overall venture scores (a judge observes only her individual score). All 964 individuals in the HBS NVC are included. A score of 5 is the best, and 1 is the worst.

Table A.1: Sector Composition

Sector	Judges: All	Judges: VCs	Unique participants: All	Unique participants: Female	Unique participants: Male
IT/Software/Web	0.39	0.42	0.45	0.45	0.52
Consumer Goods	0.17	0.17	0.19	0.28	0.18
Health	0.15	0.16	0.10	0.10	0.12
Media/Education	0.22	0.30	0.07	0.09	0.07
Tough Tech (Tangible High Tech)	0.19	0.25	0.06	0.05	0.08
Financial/Real Estate	0.31	0.32	0.03	0.02	0.04
Total	1,309	631	964	289	590

Note: This table shows the probability that judges and participants are in each of six sectors. Note that judges may be in more than one sector, while participants may not. 10 percent of participants are not assigned a sector. "Tough tech" refers to tangible High Tech sectors, such as energy, biotech, manufacturing, defense, and electronics.

Table A.2: Do males tend to face more VC judges in their own sector than females?

		Female participants		Male participants			
VC Judge Sector	Venture Sector	# female participants in sector	Mean # VC judges on panel this sector	# male participants in sector	Mean # VC judges on panel this sector	Diff	P-value
IT/Software/Web	IT/Software/Web	129	1.95	304	1.99	-.04	.80
Consumer Goods	Consumer Goods	82	.85	105	.76	.09	.45
Health	Health	30	2.47	70	2.29	.18	.56
Media/Education	Media/Education	26	1.04	40	1.35	-.31	.29
Tough Tech	Tough Tech	15	1.33	45	1.78	-.44	.26
Financial/Real Estate	Financial/Real Estate	7	1.71	26	1.38	.33	.45

Note: This table presents the difference in the means of the number of judges on panel in a certain sector conditional on the participant being in that sector, by gender of the participant. We first restrict the sample to consist only of ventures in a given sector, and then test whether males are more likely to have more VCs than females in their own sector. For example, in the first row, we restrict the sample to consist only of ventures in IT. We observe that women participants with an IT venture on average face 1.95 VC judges in IT. Male participants with an IT venture on average face 1.99 VC judges in IT. The difference is not significant. "Tough tech" refers to tangible High Tech sectors, such as energy, biotech, manufacturing, defense, and electronics.

Table A.3: Relationship between NVC Scores, Gender, and VC-backed Entrepreneurship

Dependent variable:	VC-backed Entrepreneurship		Score in Panel	
	(1)	(2)	(3)	(4)
Score in Panel	0.034***	0.025**		
	(0.011)	(0.012)		
Female		-0.029	0.118	0.208
		(0.021)	(0.191)	(0.191)
VCs on Panel x Female			0.025	0.002
			(0.052)	(0.049)
VCs on Panel			-0.009	0.004
			(0.026)	(0.026)
Year FE	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	Yes
Competition Controls	No	Yes	No	Yes
Person Controls	No	Yes	No	Yes
Observations	964	964	964	964
R^2	0.057	0.093	0.034	0.160
Outcome Mean	0.118	0.118	3.274	3.274

Note: This table shows the relationship between the venture's score, VC-backed entrepreneurship, and gender. "Score in Panel" is the average of individual judge scores on the panel, which varies from 1 to 5, with 5 being the best. "Female" is an indicator for the participant being female. "VCs on Panel" is the continuous number of VC judges on the panel. Columns 1-2 show the relationship between score and whether the participant team member subsequently founded a VC-backed startup. Columns 3-4 examine whether the relationship between participant gender and score differs depending on the number of VCs on the panel. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.4: Effect of VC Judges on Startup Outcomes Conditional on VC-backed Entrepreneurship

Dependent variable:	Amt VC Raised Within 2 Yrs		Acquired	>10 Employees
		>90th Pctile		
	(1)	(2)	(3)	(4)
VCs on Panel x Female	-23.184	-0.134	0.054	-0.011
	(16.917)	(0.089)	(0.037)	(0.063)
VCs on Panel	10.118	0.006	-0.023	-0.031
	(13.771)	(0.022)	(0.026)	(0.038)
Female x Year FE	Yes	Yes	Yes	Yes
Observations	73	73	114	114
R^2	0.235	0.305	0.395	0.246
Outcome Mean	44.563	0.110	0.026	0.076

Note: This table examines the effect of VC judges on the panel within the sample of 114 VC-backed startups founded by participants. There is funding amount data available for 73 of these startups. In column 1, the dependent variable is the amount of VC financing that the participant's startup raised within 2 years. In column 2, the dependent variable is an indicator for raising above the 90th percentile of funding, among the ventures included in the regression, within 2 years. In column 3, the dependent variable is an indicator for the startup being acquired. In column 4, the dependent variable is an indicator for the startup having at least 10 employees on LinkedIn. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.5: Effect of Number of VC Judges on VC-backed Entrepreneurship by Gender with Female-by-Year Fixed Effects

Dependent variable: VC-backed Entrepreneurship After HBS

Panel A: Whole Sample

	(1)	(2)	(3)	(4)
VCs on Panel x Female	-0.031*	-0.033**	-0.035**	-0.059**
	(0.016)	(0.016)	(0.016)	(0.023)
VCs on Panel	0.022*	0.021*	0.022**	
	(0.011)	(0.011)	(0.011)	
Female x Year FE	Yes	Yes	Yes	Yes
Competition Controls	No	Yes	Yes	Yes
Person Controls	No	No	Yes	Yes
Panel FE	No	No	No	Yes
Observations	964	964	964	964
R^2	0.058	0.078	0.098	0.260
Outcome Mean	0.118	0.118	0.118	0.118

Panel B: Participants in 10-90th Score Percentiles

	(1)	(2)	(3)	(4)
VCs on Panel x Female	-0.028*	-0.029*	-0.033**	-0.063***
	(0.016)	(0.017)	(0.016)	(0.021)
VCs on Panel	0.020	0.021	0.021*	
	(0.014)	(0.014)	(0.013)	
Female x Year FE	Yes	Yes	Yes	Yes
Competition Controls	No	Yes	Yes	Yes
Person Controls	No	No	Yes	Yes
Panel FE	No	No	No	Yes
Observations	777	777	777	777
R^2	0.062	0.071	0.099	0.314
Outcome Mean	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that female participants in the HBS NVC subsequently found VC-backed ventures, relative to male participants. "VCs on Panel" is the continuous number of VC judges on the panel. "Female" is an indicator for the participant being female. Female-by-sector (Panel A) or female-by-year (Panel B) fixed effects absorb the independent effect of female. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.6: Effect of VC Judges on VC-backed Entrepreneurship by Pre-HBS Professional Experience

Dependent variable: VC-backed Entrepreneurship After HBS

	(1)	(2)	(3)	(4)	(5)	(6)
VCs on Panel x Prev. VC-backed Entrep.	0.033					
	(0.041)					
VCs on Panel x Prev. Non-VC-backed Entrep.		0.027				
		(0.025)				
VCs on Panel x Prev. VC-backed Co. Emp.			-0.014			
			(0.014)			
VCs on Panel x Prev. VC Firm Emp.				0.051		
				(0.038)		
VCs on Panel x Prev. Consult Emp.					-0.015	
					(0.016)	
VCs on Panel x Prev. Finance Emp.						0.012
						(0.015)
VCs on Panel	0.010	0.006	0.017	0.010	0.016	0.009
	(0.008)	(0.010)	(0.013)	(0.009)	(0.010)	(0.010)
Year x Char FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	964	964	964	964	964	964
R^2	0.052	0.055	0.048	0.050	0.050	0.048
Outcome Mean	0.118	0.118	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that participants with a certain professional background in the HBS NVC subsequently found VC-backed ventures, relative to other participants. "VCs on Panel" is the continuous number of VC judges on the panel. "Char" denotes the particular professional background used in the column. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.7: Effect of VC Judges on VC-backed Entrepreneurship by Pre-HBS Education and NVC Win Status

Dependent variable: VC-backed Entrepreneurship After HBS

	(1)	(2)	(3)	(4)	(5)	(6)
VCs on Panel x Ivy+ BA	-0.023					
	(0.015)					
VCs on Panel x HBS Honors		-0.025				
		(0.024)				
VCs on Panel x Comp Sci Major			0.028			
			(0.026)			
VCs on Panel x Engineering Major				0.005		
				(0.018)		
VCs on Panel x Econ or Bus Major					0.034*	
					(0.019)	
VCs on Panel x Round Winner						-0.018
						(0.022)
VCs on Panel	0.020*	0.016*	0.010	0.012	0.003	0.017*
	(0.011)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)
Year x Char FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	964	964	964	964	964	964
R^2	0.052	0.050	0.049	0.050	0.054	0.066
Outcome Mean	0.118	0.118	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that participants with a certain education background or NVC win status in the HBS NVC subsequently found VC-backed ventures, relative to other participants. "VCs on Panel" is the continuous number of VC judges on the panel. "Char" denotes the particular participant characteristic used in the column. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.8: Effect at Venture Level

Dependent variable: VC-backing After HBS (Venture-Level)

	Full Sample	No Mixed Gender Teams
	(1)	(2)
VCs on Panel x Female Team	-0.029**	-0.033**
	(0.014)	(0.014)
VCs on Panel x Mixed Team	-0.028	
	(0.018)	
VCs on Panel	0.008	0.011
	(0.007)	(0.008)
Team Cat x Sector FE	Yes	Yes
Competition Controls	No	Yes
Observations	647	569
R^2	0.053	0.118
Outcome Mean	0.118	0.118

Note: This table shows the effect of the number of venture capitalists (VCs) on the probability that a venture with female team members in the HBS NVC subsequently raises VC, relative to ventures with male team members. Analysis is at the venture level, using a categorical variable that takes one of three values for whether the team is: all female, mixed, or male. All male is omitted. "VCs on Panel" is the continuous number of VC judges on the panel. Fixed effects for team type by sector absorb the independent effect of team type. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.

Table A.9: Sample Splits in Effect of VCs on VC-backed Entrepreneurship by Gender

Dependent variable: VC-backed Entrepreneurship After HBS

Sample:	Time period		Number ventures on panel	
	Before 2010	After 2010	5 or Fewer	5 or more
	(1)	(2)	(3)	(4)
VCs on Panel x Female	-0.027	-0.044**	-0.029**	-0.041**
	(0.025)	(0.018)	(0.014)	(0.020)
VCs on Panel	0.021	0.027*	0.021*	0.038***
	(0.015)	(0.015)	(0.011)	(0.014)
Year FE	Yes	Yes	Yes	Yes
Female x Sector FE	Yes	Yes	Yes	Yes
Competition Controls	Yes	Yes	Yes	Yes
Person Controls	Yes	Yes	Yes	Yes
Observations	549	415	890	657
R^2	0.105	0.155	0.112	0.114
Outcome Mean	0.118	0.118	0.118	0.118

Note: This table shows the effect of the number of VCs on the probability that a participant in the HBS NVC subsequently founds a VC-backed venture using alternative samples. Columns 1 and 2 split the sample roughly in half by year of the NVC. Columns 3 and 4 split the sample by the number of ventures in the panel. Five ventures are included in both groups because the majority (583) of observations have five ventures per panel. Person controls consist of these indicator variables: Interest in entrepreneurship, interest in finance, interest in management, entrepreneurship or VC clubs membership at HBS, previous VC-backed entrepreneurship experience, previous work for a VC-backed startup, previous work for a VC firm, previous non-VC backed entrepreneurship, honors at HBS, US citizen, computer science college major, engineering college major, economics/business/management college major, and college degree from an Ivy+ university. Competition controls consist of these variables: The venture score in the panel, indicator for winning the competition (overall or runner-up), the number of ventures on the panel, the number of male judges on the panel, and the total number of judges on the panel. There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health. Standard errors are clustered by panel. $*$, $**$, and $***$ denote significance at the 10 percent, 5 percent, and 1 percent levels.