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Working Paper 19-105



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Howell thanks the Kauffman Foundation and especially Sameeksha Desai for generous support. Nanda acknowledges support from the Division of Research and Faculty Development at Harvard Business School and Imperial College London, where he is a Visiting Professor for the academic years 2019-2021.

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Sabrina T. Howell & Ramana Nanda*

Abstract

We find that male participants in Harvard Business School's New Venture Competition who were randomly exposed to more VC investors on their panel were substantially more likely to start a VC-backed startup post-graduation, indicating that access to investors impacts fundraising independent of the quality of ideas. However, female participants experience no benefit from exposure to male or female VCs, which appears related to a reduced propensity to reach out to VCs to whom they were exposed. Our results therefore also demonstrate gender-based differences in the degree to which increased exposure to investors can address networking frictions in venture capital.

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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 study the role of networking frictions in VC-backed entrepreneurship. We define “networking frictions” as deviations from efficient capital allocation that occur when investors acquire information about investment opportunities through their personal networks, to the degree that networks deliver information in systematically imperfect ways.

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. Two examples from practitioners highlight the role of personal networks. Chris Sacca (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). The U.S. Chamber of Commerce advises firms seeking VC to “reach out to your network to secure an introduction. If that’s not an option, you can consider cold outreach but having a personal introduction is the best way to earn an investor’s trust quickly” (Johnson 2019).

VC investors may rely on personal networks because they face extreme information asymmetry with entrepreneurs (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 (Cohen, Frazzini & Malloy 2008). If access to networks is imperfectly correlated with the quality of ideas, reliance on networks for information could lead to inefficiencies in capital allocation.

Rigorously studying networking frictions is difficult. 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. Financing frictions are most readily observed via an intervention that alleviates them. For example, an exogenous cash influx can be used to assess whether a firm is financially constrained (Kaplan & Zingales 1997, Rauh 2006, Howell 2017). However, exogenously shifting access to networks is typically much harder. 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.² We examine whether random exposure to VC investors increases the likelihood of VC-backed entrepreneurship among participants after they graduate, and whether male and female founders benefit similarly.

Our interest in differential effects by gender stems from the striking gender gap in high-potential entrepreneurship, and more generally from 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 percent of VC-backed startup founders (Levine & Rubinstein 2017, Gompers & Wang 2017). Between 2008 and 2020, the share of annual U.S. VC capital raised by female founders ranged between 1.7 percent and 2.7 percent, with no upward trend.³ A growing literature, including Becker-Blease & Sohl (2007), Scott & Shu (2017), Gornall & Strebulaev (2018), and Ewens & Townsend (2019) has documented the gap in various ways, but has never directly addressed

¹The 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.

²Having 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.

³<https://pitchbook.com/news/articles/the-vc-female-founders-dashboard>

the potential role of networking frictions.⁴ As men comprise over 90 percent of VC investors (Gompers & Wang 2017), there is a possibility that gender-based homophily in networking could disproportionately impact women’s ability to access the personal networks that VCs rely on for deal flow (Gompers, Huang & Wang 2017).

The analysis in this paper focuses on the NVC’s first round, where each team is assigned to one of about 15 panels, each composed of about six judges. We exploit random variation in the number of VC judges across panels, which arises from how judges are allocated to panels. We find that random exposure to an additional VC increases the chances of post-VC entrepreneurship for male entrepreneurs by about 17 percent. VC judges rarely invest in the startups, and the effect persists when we control for instances when this happens. Instead, the effect occurs through indirect channels, offering compelling evidence for a financing friction stemming from VC reliance on their networks to screen potential investments.

Placebo effects support this conclusion. There is no effect of VC judges on non-VC backed entrepreneurship, and no effect on joining a VC-backed startup as an employee. Also, judges on the panel who are male, 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).

In contrast to the large effect of exposure to VCs on VC-backed entrepreneurship among male participants, this relationship is close to zero among women (see Figure 1). Why might exposure to VCs benefit men so much but not women? There are three possibilities, which are not mutually exclusive: (1) Additional exposure to VCs is not as valuable to women because they are less likely to seek VC financing; (2) Independent of their likelihood to seek

⁴Our paper offers three key distinct contributions relative to Ewens & Townsend (2019), who use data from AngelList to find evidence that angel investors prefer to invest in founders of their own gender. First, we focus on networking frictions rather than gendered preferences. Second, they study arms-length, digital interactions while our focus is on in-person interactions, which are known to be central to the early stage investment process and where gender may play a different role. Third, while they consider founders who are actively fundraising, our focus is on the pre-fundraising stage. Our ability to examine this stage of the venture is important because prior work suggests that the gender gap in high-growth entrepreneurship originates early in the startup lifecycle, at or near the moment of founding. Women comprise only 16 percent of the entrepreneurs seeking funding in Ewens & Townsend (2019)’s data, which is close to their overall share of VC-backed startup founders.

VC financing, women are not as proactive in networking with VC investors; (3) Women reach out to VCs after the NVC, but end up benefiting less from the referrals.

We cannot rule out channel (1), but it seems implausible that it fully explains our results, as the women in our data have a demonstrated interest in high-growth entrepreneurship and have identified a particular venture they wish to pursue. While women in our data raise VC on average at a lower rate than men (10 percent vs. 13 percent), the facts that many do become VC-backed entrepreneurs and random assignment of VCs to panels controls for any average differences across individuals together suggest that it is unlikely that all women exposed to additional VCs were uninterested in ultimately raising VC.

To further probe the channel, we conduct two exercises. First, a survey of NVC participants finds that men are nearly twice as likely as women to proactively reach out to VC investors after the NVC. Qualitative comments in the survey point to a possible explanation, 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, for example only reaching out to VCs when they are ready to fundraise. The phenomenon of women holding themselves to a higher standard has been identified in other settings (Chari & Goldsmith-Pinkham 2017, Kolev, Fuentes-Medel & Murray 2019).

The survey results reinforce an implication of our findings: that it is extremely difficult to network with VCs, even for HBS students. While men reported that the NVC was a rare opportunity for networking with VCs – and one that they exploited – women did not, instead voicing a desire for more feedback and interaction but uncertainty about whether it is appropriate to proactively reach out. This led men, on average, to benefit more from exposure to VCs than women.

Second, we show that male investors explain the strong effect of VCs on male VC-backed entrepreneurship. Exposure to female VC judges has no effect among male or female participants. Given that 90 percent of VC investors are male, this is consistent with gender-based homophily between entrepreneurs and VCs, together with homophily within

investor networks, disproportionately favoring 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, less observable discrimination may be at play and the lack of outreach by women could reflect expectations of bias or harassment. Together, our results offer the most support for channel (2) and are also suggestive of channel (3), but we cannot rule out a particular channel.

We believe our central contribution is to establish the existence of networking frictions in VC. If random exposure to VC investors can substantially increase the chance of VC-backed entrepreneurship for some entrepreneurs, then network-based access rather than only the quality of the idea must play a role in a startup’s ability to raise venture capital. In addition, we show that a structural intervention that creates opportunities for exposure to investors does not benefit all entrepreneurs equally and may not be sufficient to overcome the large barriers that women face in the networking process.

Our findings relate to prior research documenting the importance of networks in venture capital and how these can distort financing (e.g. Hochberg, Ljungqvist & Lu 2007). While this work has largely focused on syndication networks among VCs, our paper documents how these networks are a valuable potential source of deal flow for VCs, even when there is no explicit syndication between investors. Our findings also shed light on an important potential driver of the gender gap in entrepreneurship, even among highly ambitious, well-positioned female entrepreneurs. Of course, there are other drivers of the gender gap that our empirical strategy controls for but does not assess, such as different family obligations, industry interests, and risk preferences (Barber & Odean 2001, Niederle & Vesterlund 2007, Sapienza, Zingales & Maestripieri 2009, Bertrand et al. 2010, Bertrand 2013, Pew 2015, Bertrand, Kamenica & Pan 2015, Fang & Huang 2017, and Goldin et al. 2017). Our goal is not to address these potentially profound, population-wide explanations. Instead, we focus

on evaluating networking-related frictions to accessing VC among individuals demonstrating serious interest in high-growth entrepreneurship.

We offer evidence that networking affects capital allocation and that women benefit less from an intervention in which they were randomly exposed to VCs. From an economic perspective, these results suggest that systematic gender-related frictions lead high-quality entrepreneurs or ideas to go unfunded. They also have immediate implications for new venture competitions and accelerators, which often emphasize networking opportunities with investors, and which are now an important part of the entrepreneurial ecosystem (Howell 2020). Exposing entrepreneurs to networking opportunities and assuming that people will contact each other may not be enough. To facilitate the financing of the best – rather than just the best networked – ideas, programs might consider encouraging and formalizing networking opportunities or VC access to information about participating ventures.

2 Data

This section first describes the HBS NVC. We discuss 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 (Howell 2020).

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).⁵ 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.⁶ 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-related networking frictions 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

⁵We 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.

⁶The 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.

VC [...] Entrepreneurs from HBS have founded 13 unicorns — nearly double its closest competitor, Stanford.”⁷ 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 participants.⁸

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 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 we have a rich set of covariates about them 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.⁹ The participants are

⁷Examples 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>.)

⁸In 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>).

⁹The 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

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 D. Just over half of judges on a panel are VCs on average, though this can and does vary substantially due 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. We describe the most relevant variables in Table 1 and omit the remainder for parsimony.

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.

women (Bertrand et al. 2010).

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 sources of data on VC deals: 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 2 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.¹⁰ 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.

¹⁰See <https://indicators.kauffman.org/>.

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 more likely to participate in the labor force following graduation and more likely to start new ventures in industries that tend to receive VC. 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 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 2 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 D). 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.”

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. The large number of elite VCs who participate offer a rare opportunity for in-person interaction with such 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 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 pools of entrepreneurs who will be presenting their business plans and judges who are available have been established, an effort is made to assign entrepreneurs to panels with judges who claim 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.¹¹ 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 assigned to different classrooms, where

¹¹Consistent 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, startups in the IT/Software/Web category have on average 2.97 judges with related expertise, while non-IT startups have on average 2.25 judges with IT expertise on their panel, a difference that is 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.

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).¹²

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 D 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

¹²The 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.

panel. Finally, Appendix Table A.2 shows by sector that men are not more likely to have more VC judges in their own sector.

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 random assignment, 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, and judges know only their own score. 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. The upward slope is highly significant (confirmed in Appendix Table A.3 columns 1-2), indicating that score is a useful control for the latent quality of the venture.

Table 1 Panel D 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.

4 Results

This section first presents the main results, both visually and using regression models (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 3 Panel B shows the share of participants who subsequently become VC-backed entrepreneurs by gender and the panel’s number of VC judges. For 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 OLS 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 percent (column 3). This shows 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.

The second insight from Table 4 is 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 (columns 5-6). The third finding is that 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 (columns 2, 4, and 6).

It is useful to benchmark the 17 percent effect among men against other related findings regarding frictions in entrepreneurial finance. Bernstein et al. (2016) find that reducing travel time between a VC firm and its portfolio company by 126 minutes increases the portfolio company patent citations by 5.8-7.4 percent. Bernstein et al. (2017) find that revealing a small amount of information about a startup team to angel investors increases their probability that the investor demonstrates interest in the company by 13 percent. Ewens & Townsend (2019) show that female-led companies are 42 percent less likely to be

shared by male investors. Finally, González-Urbe (2020) shows that after startups join investors' portfolios, they increase information exchange with other members of the portfolio by 60 percent. In sum, our result joins others in documenting economically large frictions in early stage startup investing.

To probe these results further and to address other potential sources of unobserved heterogeneity, we move in Table 5 to estimating the impact of an additional VC on post-NVC VC-backed entrepreneurship for female relative to male participants. We use the following estimating equation:

$$VCEntrepreneur_i = \alpha_t + \mathbf{Female}_i \mathbf{Sector}_v' \mu + \beta_1 Female_i \#VCsPanel_j \quad (1) \\ + \beta_2 \#VCsPanel_j + \mathbf{X}'_{i,v} \delta + \mathbf{X}'_j \gamma + \varepsilon_{ijt}.$$

Here i denotes a participant, j a panel, and v a venture. The primary outcome of interest is an indicator for the participant becoming a VC-backed entrepreneur after HBS. The coefficient β_1 measures the differential impact of an additional VC for women relative to men. Note that since the variable $Female_i$ is an indicator, the coefficient β_2 measures the impact that an additional VC has on post-HBS VC-backed entrepreneurship among men.

In addition to individual-, venture-, and panel-level covariates ($\mathbf{X}'_{i,v} \delta$ and $\mathbf{X}'_j \gamma$), our regressions include female-by-sector fixed effects ($\mathbf{Female}_i \mathbf{Sector}_v' \mu$), which address 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 include fixed effects for the year of the NVC (α_t). In alternative specifications, we use female-by-year and panel fixed effects, the latter of which absorb the number of VCs.¹³ We cluster standard errors at the panel level, though the results are robust to clustering at the venture level. We also show the results are robust to venture-level analysis, comparing all-female, mixed, and all-male teams.

¹³There are six sectors: IT/Software/Web, Consumer Goods, Media/Education, Tough Tech (Tangible High-Tech), Financial/Real Estate, and Health.

This empirical strategy enables us to formally test the benefit of an additional VC for male relative to female participants. The first column of Table 5 Panel A 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 venture score, which is unobserved to participants and addresses concerns about unobserved quality of the pitches. Recall that the scores contain useful information, as Howell (2020) finds in a larger sample of competitions. On average scores are strongly correlated with VC-backed entrepreneurship (Appendix Table A.3 columns 1-2). In column (3) of Table 5 we add individual covariates such as college major and interest in entrepreneurship, which may be correlated with the decision to become an entrepreneur. The effects are quite stable across these specifications. In column (4) we further include panel fixed effects, which absorb the number of VCs on the panel, and find that the effect increases somewhat but continues 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.3 shows that women have slightly higher scores on average. One might be concerned that women’s ventures are “so good” that they do not need to network with NVC judges. 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 do not 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 does not affect our results. While the coefficient on judge investing is strongly positive, it does not attenuate the main finding. This suggests that the main effect is driven by referral networks among investors.

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 unspecialized (i.e. “generalist”) 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. We interact being female with the number of VCs of a particular stage. The coefficient for early stage VCs is 0.056, larger than our main estimate (column 3). The other two coefficients are insignificant, but the one for “Late” is .01 while the one for generalists is -.024, suggesting possible monotonicity in early stage deal making. The means for early, late, and generalist 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 who 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) and (2) consider the amount of VC financing within two years of the competition. In column (2), 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 (3) and (4) 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. The highly motivated, relatively well-networked students in our sample likely face fewer of these frictions than individuals 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 (4), 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. In column (5), we consider the number of judges in the participant’s sector and find a small and insignificant coefficient. In columns (6) and (7), we consider the number of entrepreneur and corporate executive judges, and find small, insignificant effects.

There may be concern 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. 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.

Last, 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 increases 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 for nascent male entrepreneurs than for 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. Note that while most VC judges are men, there is enough variation in female VC judges across panels to observe an effect if one exists. At the panel level, there are on average 0.5 female VC judges with a standard deviation of 0.67. Panels have between zero and three female VC judges. The results in columns 1 and 3 clearly indicate that our effect is driven by male VCs helping male participants, while female VCs have no effect on either male or female participants (columns 2, 5, and 6).

We confirm this result in the interaction model. Column (1) of Table 9 shows that the coefficient on male VCs is slightly larger 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. We expect this dynamic 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.

However, this pattern is not symmetric, as shown in Table 9 column (2). 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 hold 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 gender-based homophily in networking within the VC community. In other words, if referrals tend to be mediated by gender-based homophily, the fact that 90 percent of investors are men implies that referrals from male investors may on average lead to more meetings with investors. Consistent with this notion, Cullen & Perez-Truglia (2020) find evidence that male employees assigned to male managers were promoted faster in the following years than male employees assigned to female managers while female employees had the same career progression regardless of their managers' gender. 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 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 16.3-21.9 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 percent 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). Note that not only is the sample here very small, but in almost all cases the judge *did* respond, making it difficult to assess whether there was selection on quality in which participants reached out to VCs.

The survey results offer suggestive evidence that our main findings reflect women being less likely to initiate networking with VCs. This is corroborated by the responses to the final open-ended question in the survey about the importance or ease of networking at the NVC. The responses contrast strikingly across men and women. Men emphasized the importance of networking and how they used the NVC to gain access to VCs, while women did not. Among 57 responses, 63 percent of men wrote that networking was important at the NVC, or described reaching out to VCs after NVC. Only 12.5 percent of women did, and the difference between these means is significant at the .01 level.

The following responses underline these differences. Male respondents noted that:

“The NVC was hugely valuable in helping us generate awareness of our venture (we were on CNN!) and in attracting investors (we closed \$10.4M Series A with Sequoia, Marc Andreessen, and other great investors within weeks after the NVC event).”

“Networking with angel and early-stage startup investors can add tremendous value to startups at the NVC - not only does it provide access to potential early-stage capital but it also provides access to investors who can bring critical thinking with regards to business plan / viability.”

“A connection to a panel judge reached out to us. He was an angel investor.”

“Networking is the name of the game!”

“NVC was highly important to know and connect with investors in start-ups.”

In contrast, the following responses are representative of the reports from women:

“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.”

“I am not sure they had the background to understand our idea.”

“It would be really helpful for a new venture that is participating and pitching in the competition to have more exposure to investors at that stage in the business. Participation in NVC did not feel like a platform to fundraise for us.”

“I would have liked to receive some feedback as honestly participating in the contest felt like a waste of time. Thankfully, I keep doing the venture and despite the challenge it keeps going well.”

Together, our results are consistent with women holding themselves to a higher standard when deciding whether or not to reach out to VCs. 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.¹⁴

It is worth noting that our results could reflect excessive confidence among men. In this case, the fact that they are more aggressive in networking and this helps them to raise VC might not be socially optimal. Such a channel – along with the possibility that women reach out less because they hold themselves to a higher standard – only serves to reinforce the central point of this paper, which is that networking is critical to how VC is allocated, and appears to distort allocation away from the best ideas and towards the individuals who have the best access to networks. In turn, this has implications for the direction of innovation and the pace of economic growth.

¹⁴Also see Lerchenmueller et al. (2019). 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.

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 document the importance of one such friction: the fact that VCs rely on personal networks to source deal flow, which may lead them to systematically miss out on high quality ideas from less networked entrepreneurs. 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 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. Since our results are not due to these VCs directly investing in the startups on the panel, they imply indirect benefit through networks: in other words, among male participants of equivalent quality, those who were randomly given more access to VC investors were more likely to start VC-backed businesses after HBS. The magnitude of the effect is large, consistent with anecdotal evidence that potential entrepreneurs, even among highly networked HBS students, have trouble accessing the small number of VC investors.

Importantly, we also find that random exposure to additional VCs has 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. 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.

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. 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.

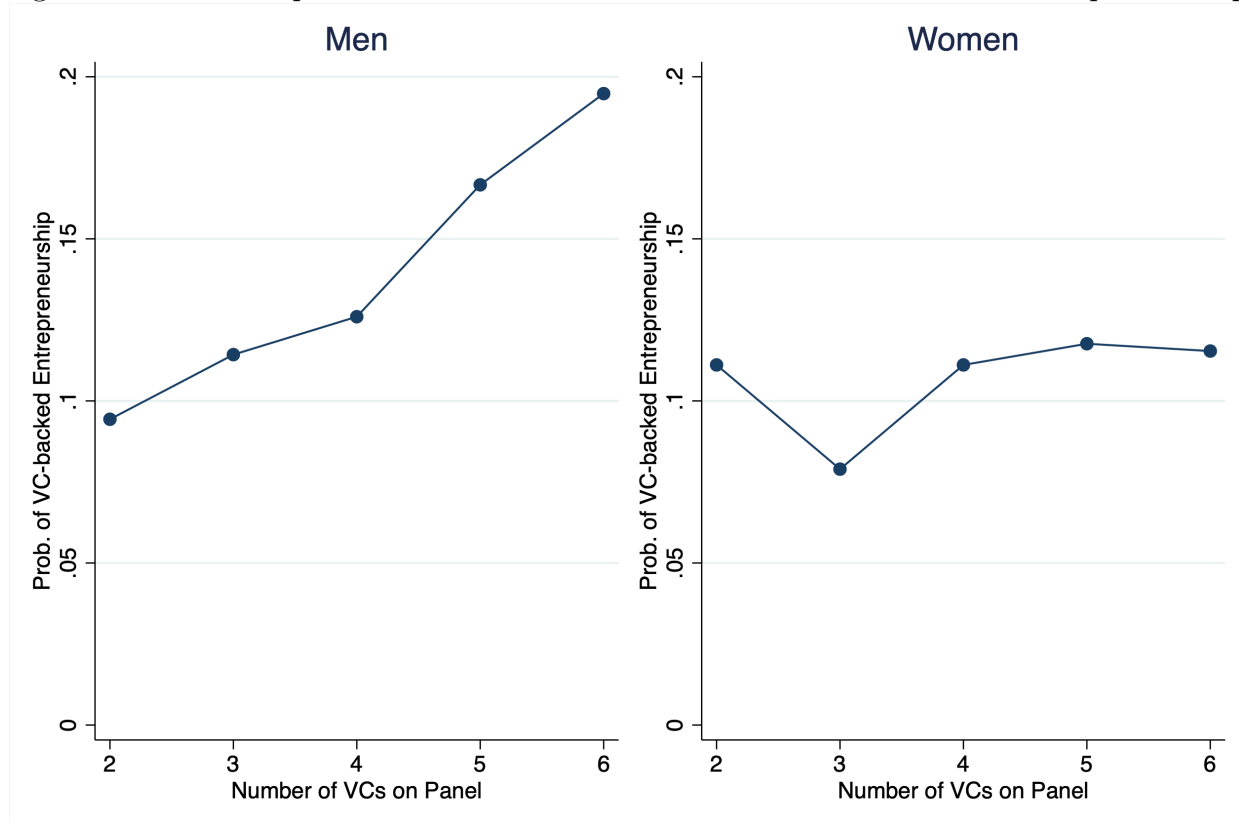
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Figure 1: Relationship between Number of VCs on Panel and VC-backed Entrepreneurship



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

<i>A. Count of individuals</i>				
	All	Female	Male	Fraction female
Number of individuals	964	307	657	0.32
<i>B. Team size (Means)</i>				
	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
<i>C. Professional background before HBS (Means)</i>				
	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

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.

D. 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 pctl (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: 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 to 2015. 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 3: Characteristics of NVC Judging Panels by Number of VC Judges on Panel

A. Number of judges and participants (Means)

	≤ 2 VCs	3-4 VCs	≥ 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

	≤ 2 VCs	3-4 VCs	≥ 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 ≤ 2 VCs, 81 panels with 3-4 VCs, and 37 panels with at least 5 VCs.

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** (0.013)	-0.033** (0.014)			
VCs on Panel	0.022** (0.011)	0.023** (0.011)			
Judge Invested	0.867*** (0.083)	0.791*** (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	VC-backed	Non-Investor	VC-backed Entrepreneurship			
	Entrep. (1)	Comp. Empl. (2)	Funding (3)	(4)	(5)	(6)	(7)
VCs on Panel x Female	-0.007 (0.016)	0.001 (0.022)	0.000 (0.008)				
VCs on Panel	-0.016 (0.011)	0.021 (0.013)	0.006 (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** (0.013)		0.028** (0.013)	-0.007 (0.016)		-0.008 (0.016)
Female VCs on Panel		-0.000 (0.020)	0.007 (0.020)		-0.036 (0.025)	-0.037 (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

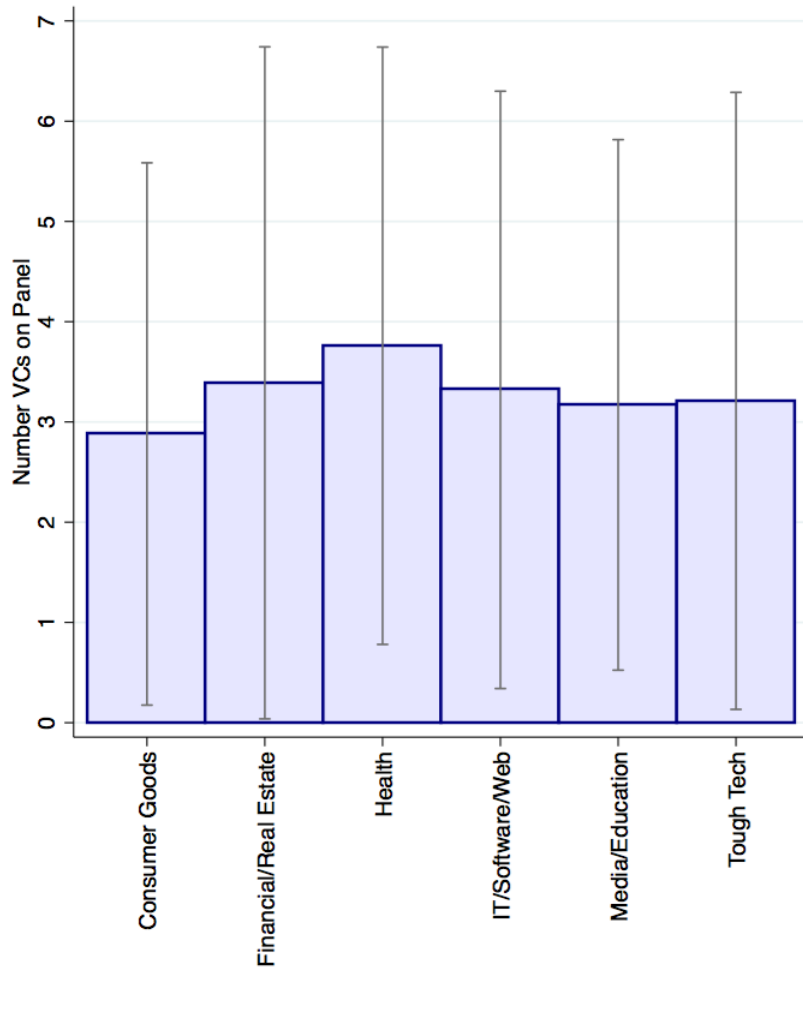
Sample:	All		Survey Respondents			Contacted Judge	
Dependent variable:	Responded to Survey		Contacted VC Judge		VC Judge Contacted Me	VC Judge Responded	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.019 (0.027)	-0.003 (0.027)	-0.177*** (0.063)	-0.163** (0.066)	-0.219*** (0.074)	-0.028 (0.058)	0.000 (0.162)
VCs on Panel		-0.004 (0.009)			-0.038 (0.027)		
VC-backed Entrep.		0.047 (0.040)			0.068 (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

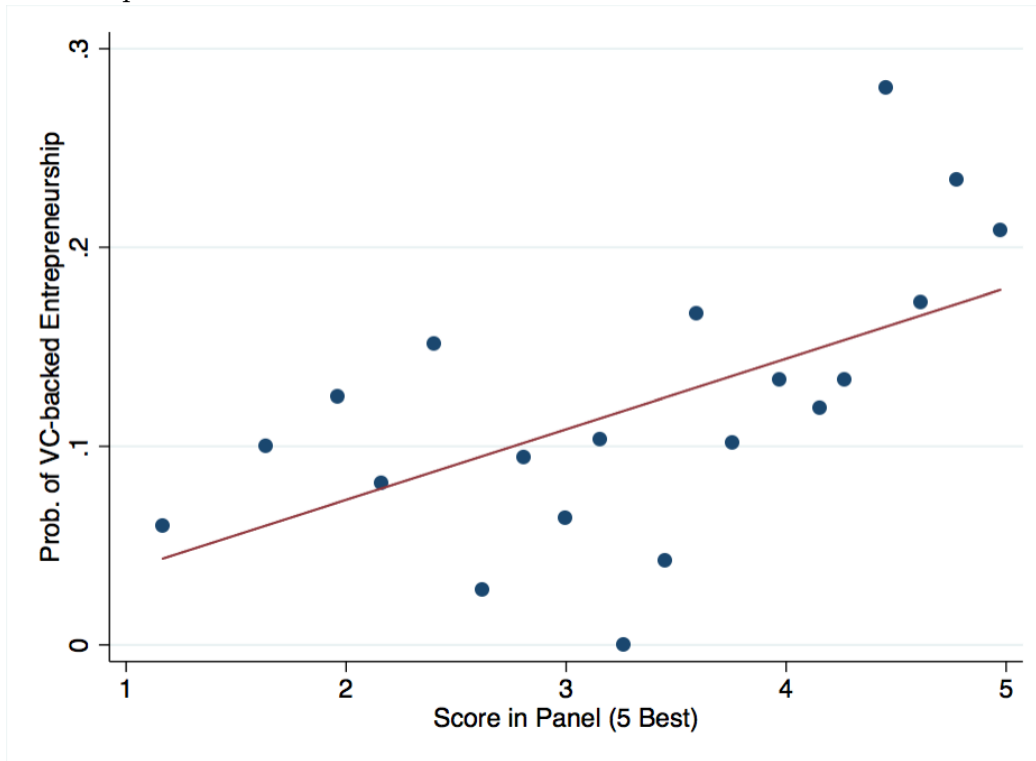
(for Online Publication)

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		Unique participants		
	All	VCs	All	Female	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?

VC Judge Sector	Venture Sector	Female participants		Male participants		Diff	P-value
		# female participants in sector	Mean # VC judges on panel this sector	# male participants in sector	Mean # VC judges on panel this sector		
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*** (0.011)	0.025** (0.012)		
Female		-0.029 (0.021)	0.118 (0.191)	0.208 (0.191)
VCs on Panel x Female			0.025 (0.052)	0.002 (0.049)
VCs on Panel			-0.009 (0.026)	0.004 (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:	<u>Amt VC Raised Within 2 Yrs</u>	<u>Acquired</u>	<u>>10 Employees</u>	
	<u>>90th Pctile</u>			
	(1)	(2)	(3)	(4)
VCs on Panel x Female	-23.184 (16.917)	-0.134 (0.089)	0.054 (0.037)	-0.011 (0.063)
VCs on Panel	10.118 (13.771)	0.006 (0.022)	-0.023 (0.026)	-0.031 (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 (0.008)	0.006 (0.010)	0.017 (0.013)	0.010 (0.009)	0.016 (0.010)	0.009 (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* (0.011)	0.016* (0.009)	0.010 (0.009)	0.012 (0.011)	0.003 (0.010)	0.017* (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** (0.014)	-0.033** (0.014)
VCs on Panel x Mixed Team	-0.028 (0.018)	
VCs on Panel	0.008 (0.007)	0.011 (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 (1)	After 2010 (2)	5 or Fewer (3)	5 or more (4)
VCs on Panel x Female	-0.027 (0.025)	-0.044** (0.018)	-0.029** (0.014)	-0.041** (0.020)
VCs on Panel	0.021 (0.015)	0.027* (0.015)	0.021* (0.011)	0.038*** (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.