Discoveries-through-Prose
Venturing through the Doors of Perception

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ABSTRACT

As anyone who has funded a startup knows from experience, a strong founding team is a prerequisite for new venture success. But are skilled founders essential because they make the business run well? Or are they needed because they impress potential investors, thus attracting more funding? To find an answer, one must distinguish the genuine skills and experience of the founding team—that is, *actual expertise*—from how the founding team presents itself, which we label *expertise signaling*. We analyze data on 4,190 new ventures drawn from CrunchBase and self-styled profiles that the founders of these companies posted on LinkedIn. Both in terms of liquidity events and amount of capital raised, we found, expertise signaling by startup founders played a significant role in company success. To be sure, when predicting a liquidity event, actual expertise was still the strongest predictor. But when it came to raising funds, we were surprised to discover that founders' expertise signaling was actually a more powerful predictor than their actual background and experience. Our findings have important practical implications and highlight the need for better theories of the role of the founding team in entrepreneurship and venture financing.

Keywords: venture financing; entrepreneurship; expertise signaling; human capital; founding teams

Picking the right people, conventional wisdom holds, is essential for business success. This belief may be most fervent in entrepreneurship, where “the founding team matters” is a well-established mantra. As legendary venture capitalist Arthur Rock put it, “Nearly every mistake I’ve made has been picking the wrong people, not the wrong idea.” On some level, this preoccupation with the founding team certainly makes sense. For one, having capable hands at the helm can help the venture execute on its goals (Beckman, Burton, & O’Reilly, 2007). A competent founding team can also help establish the new venture’s credibility, coaxing early-stage investors to take a chance with their money. And since raising capital is usually the single biggest challenge for early-stage companies, assembling a founding team capable of persuading funders to get on board is increasingly seen as indispensable. Yet recent headlines suggest investors’ obsessive, almost

exclusive focus on “investing in people”¹ can sometimes lead them astray and result in them making rather questionable bets.

What aspects of founders, specifically, tend to garner attention? Two aspects worth considering are founders’ self-presentation and their underlying skills. Although these two aspects are largely independent of each other, the latter may be more appealing – and readily observable – than the former. Consider the case of Theranos and its now-disgraced founder, Elizabeth Holmes. Holmes was a Stanford undergraduate when she developed an idea for an ostensibly revolutionary blood-testing technology requiring only tiny amounts of blood. Despite dropping out of college in 2003, Holmes was lionized as an entrepreneur, landed the covers of *Fortune* and *Forbes*, scored a profile in *The New Yorker*, and appeared often on TV, where she was frequently compared to Steve Jobs. Thanks in part to this coverage, she assembled over \$700 million in funding from investors, including famed venture capitalist Tim Draper and Oracle CEO Larry Ellison, and Theranos at one point was valued at \$10 billion. Yet the external perceptions of Holmes’s skills were largely untethered from fact; ultimately, the company’s technology failed to meet expectations and Theranos was driven out of business. This story mirrors that of real estate unicorn WeWork, whose founding team, comprising Adam Neumann and Miguel McKelvey, was initially able to raise billions of dollars by successfully making the case that their life experiences—growing up in a kibbutz in Israel and in a hippie commune in Oregon, respectively—made them uniquely suitable to lead the company, whose vision revolved around a communitarian ethos. By 2020, however, both founders had left the company after botching its IPO and essentially bringing it from a \$47 billion dollar valuation to near bankruptcy.² While these particular downfalls received substantial

¹ <https://medium.com/@divadsanders/venture-capitalists-can-see-incompetence-coming-from-a-mile-away-b09192d059a>

² <https://www.theguardian.com/business/2019/dec/20/why-wework-went-wrong>

exposure, similar collapses occur routinely with lower-profile startups once it becomes clear that the founders' promises diverge dramatically from what they are able to deliver.³

On the other end of the spectrum, however, investors routinely pass on capable founders whose self-presentation skills are less than earth-shattering. A textbook case is that of Zoom Communications, whose solo founder, Eric Yuan, had already established a substantial track record before becoming a founder. After joining the video conference startup WebEx in 1997—which was acquired by Cisco in 2007 for \$3.2 billion—Yuan was eventually promoted to vice president, leading a team of more than 800 engineers.⁴ When Yuan pitched the idea that lay the groundwork for Zoom to venture capitalists in 2012, however, they showed very little interest, largely because Yuan did not “look the part”—in other words, he did not fit the mold of a stereotypical young tech founder, despite his track record and extensive experience. As a result, Zoom had to raise funds from friends and family before being able to bring VCs on board. Eventually it would grow into a public company with a market capitalization of \$88 billion (as of May 2021).

These examples ultimately all point to the same dilemma: what is the role of self-presentation of the founding team in new venture success? And how is it weighed relative to founders' underlying skills and experience? Most of us are naturally inclined to attribute success to the human capital its members bring to the table, perhaps because we like to believe that the true engine of great companies is simply high-quality people. The reality, however, is that even an exceptionally qualified founding team is poised to fail if it cannot connect with investors and get

³ Some startups have arguably taken this dynamic to extremes, even committing fraud in the process. For instance, cryptocurrency project BHB advertised an outright fake founding team, having listed on its webpage as founders two university professors unaffiliated with the company, and was able to raise \$20 million before the scheme was discovered.

⁴ <https://www.cnbc.com/2007/03/16/cisco-to-pay-32-billion-for-webex.html>

them to open the taps. By contrast, founders who excel at self-presentation but are otherwise average might find themselves showered with investor cash, getting a better shot at success than their skills would predict. This raises a provocative question: *What if the founding team's ability to signal expertise to investors matters as much for success, if not more, than the actual expertise of the founding team—including its skills, experience, and background?*

Our Study

To explore this question, we set up a quantitative study of U.S. ventures founded between 2011 and 2017.⁵ We collected our data from Crunchbase, an online business information service focused on early-stage companies. The data included details such as USD amounts for each funding round with dates, as well as information on which companies were ultimately acquired or went public. To complement this information, we gathered data about the company founders in our Crunchbase sample from the online networking platform LinkedIn, focusing on the professional and educational history of founders. This process ultimately yielded a sample of 4,190 ventures, most of which hailed from California, New York, Illinois, Massachusetts, and Texas; the top three industries were Software, Internet Services, and Media and Entertainment. Please see the Appendix for further details about the data collection process.

Next, we looked at two different measures of firm success. The first was the occurrence of a liquidity event, or exit, which, for the purposes of this study, meant either that the venture was acquired or that it went public through an initial public offering (IPO). Of the 4,190 ventures we studied, all of which were private in August 2017, 183 were acquired and 7 went public between September 2017 and May 2020, for a grand total of 190 exits. The second success metric we examined was the dollar amount of funding each venture raised. We chose this variable to reflect

⁵ We operationally define new ventures as firms founded less than six years ago, following Stam, Arzlanian, & Elfring (2014). Because the main data collection took place in 2017, we decided to start our observation window in 2011.

the growing number of high-potential new ventures that now choose to stay private for extended periods of time—the so-called *unicorns*. Companies like Uber and Airbnb, for example, remained private long after achieving a \$1 billion market valuation. In cases like these, the absence of an exit within a specified time frame in no way means a lack of success. Bearing this trend in mind, we tracked the dollar amount of funding that investors supplied for each company between September 2017, when the LinkedIn data was collected, and May 2020, while also controlling for any prior funding the venture might have received.

At this point, we needed a way to assess the actual expertise of each company's founding team. Because entrepreneurship is known to require diverse skills, we structured our analysis around three different expertise types identified in the literature: *entrepreneurial*, *managerial* and *technical* (Boyatzis, 1982; Chandler & Jansen, 1992).⁶ To measure actual expertise in each of these areas, we used the Crunchbase and LinkedIn data to document the educational and work background of founding team members. We then created dummy variables to indicate when a founding team member: i) had prior founding experience (for *entrepreneurial expertise*); ii) had at any point worked in a managerial capacity in the past (for *managerial expertise*); and iii) held advanced technical degrees, defined here as a master's degree or a doctorate in a STEM subject (for *technical expertise*). For those ventures that had multiple founders, we coded each of these variables as the percentage of team members with that attribute or experience.

While the measurement of actual expertise was relatively straightforward, gauging expertise signaling required a more novel approach. Here, the availability of LinkedIn data was crucial, thanks to its Skills & Endorsements feature, which allows users to shape perceptions of their expertise in a way that is both easily observed and measurable at scale. LinkedIn users, in

⁶ Detailed definitions and a more extensive discussion of these expertise types are provided in the Appendix.

fact, are allowed to add up to 50 skills to their profiles as a way to showcase their abilities to other users. Crucially, the skills listed on a LinkedIn profile are hardly an accurate reflection of that person's level of expertise. There are few repercussions for insincerity, given that LinkedIn does not ask for verification that users actually possess the skills they list. Rather, these skills lists are a form of *impression management*, in that individuals list skills primarily to influence others' perceptions of them (Zott & Huy, 2007). As a result, individuals who value self-presentation should list more skills than those less inclined to curate how they come across to others. These characteristics all make LinkedIn skills a useful tool to separate expertise signaling from the underlying skills, experience, and qualifications of the founding team.⁷

To gather the skills data, we reviewed the LinkedIn pages of 8,243 founders, collecting a total of 80,348 skills with at least one endorsement,⁸ and to make them comparable to the types of actual expertise discussed above, we then manually classified them as entrepreneurial, managerial, or technical skills.⁹ For each venture, we then measured expertise signaling simply by summing up the number of skills of each type that were listed on the founder's profile. For ventures that had more than one founder, we took a simple average of skill counts across founding team members.¹⁰ This process thus yielded an entrepreneurial, a managerial, and a technical variable for both expertise signaling and actual expertise, for a total of six main variables.

What We Discovered

----- Figures 1 and 2 about here -----

⁷ Importantly, in choosing this measure we do not make the argument that investors actively look at founders' LinkedIn profiles upon making investment decisions (although some of them might). Rather, we assume that expertise signaling behavior on LinkedIn to be a good proxy for an individual's overall tendency to signal expertise, which we think is reasonable in light of how widespread LinkedIn usage is among professionals and of how prevalent networking activities on LinkedIn have become.

⁸ Only skills with at least one endorsement are publicly visible on LinkedIn profiles.

⁹ Some skills, such as languages, do not fit neatly into any of these categories and were coded as "Other".

¹⁰ Additional details about the coding process are reported in the Appendix.

Our empirical analyses yielded a number of surprising findings. For more detail about how they were conducted and for a comprehensive discussion of the other variables we included in our study, please see the Appendix. We began by carrying out a number of regression analyses. In line with our expectations, there was little correlation between expertise signaling and actual expertise. In other words, the founding teams that listed the most LinkedIn skills were generally not the most capable based on experience and qualifications (and vice versa). What really surprised us, however, was not only that expertise signaling appeared to matter a lot, but that it did so across the board. When we looked at whether startups were acquired or went public—one of our two measures of success—we found that expertise signaling wielded a sizeable influence, even though actual expertise narrowly carried the day (Figure 1). But when we looked at how much money new ventures were able to raise (Figure 2), the effect of expertise signaling *exceeded* that of actual expertise for both the entrepreneurial and the managerial component.¹¹ In other words, for founding teams, showing off appears to pay off *to a greater degree* than having the goods when it comes to raising capital, while longer-term outcomes such as acquisitions and IPOs are less sensitive to expertise signaling.

----- Figure 3 about here -----

Because these results were rather unexpected, we decided to run additional tests to assess the *relative*—rather than the *absolute*—importance of actual expertise and expertise signaling. More specifically, we carried out *dominance analyses* (Azen & Budescu, 2003) as a way to better gauge their respective power in predicting venture success. Relative to effect sizes in conventional regression approaches, dominance analysis is better suited to gauging the relative importance of

¹¹ Interestingly, the effect of actual entrepreneurial expertise was negative, which suggests that experienced founding teams may have trouble raising money.

predictor variables because it estimates the R^2 values of all possible combinations of predictors and then measures relative importance by means of pairwise comparisons of all predictors in the model as they relate to an outcome variable. One predictor is considered dominant over another if its predictive ability exceeds the other's predictive ability in all possible subset models. In so doing, dominance analysis produces a standardized dominance statistic for each predictor which can be used to assess relative importance. Accordingly, Figure 3 reports such standardized dominance statistics on the x-axis, so that the higher the standardized dominance statistics, the more relevant the component (i.e., actual expertise or expertise signaling) is as a predictor.¹² The results—depicted graphically in Figure 3—show that when it comes to being acquired or going public, actual technical expertise was the most important factor, which is not surprising given the high-tech nature of many startups. What *is* surprising, however, is that entrepreneurial and technical expertise signaling come a close second and third, trumping actual entrepreneurial and managerial expertise. And when it comes to explaining the amount of money raised, expertise signaling even makes a greater overall contribution (55.4 percent) than actual expertise (44.6 percent), in line with our earlier findings.

Why This Matters

So what does this all mean for how we think about venture success, and the role the founding team plays in it? To be sure, some of our findings fit neatly with existing research on entrepreneurship. For example, we have long known that success is overwhelmingly a function of capital availability for new ventures. This means that for founders, succeeding hinges to some degree on impressing venture capitalists and angel investors enough to convince them to invest. Actual expertise does appear to matter more when it comes to longer-term outcomes like

¹² Once again, for a detailed description of the procedure we followed, its rationale, and the full results, see the Appendix.

acquisitions and IPOs. This probably reflects the massive due diligence that these events require, which may temper the effect of expertise signaling in this case. At the same time, the amount of funding raised appears to be strongly influenced by expertise signaling (Martens, Jennings, & Jennings, 2007) – more so, in some cases, than by the founding team’s actual skills, experience, and background. Because early-stage financing is fraught with uncertainty, and because investors primarily rely on gut feeling in making funding decisions (Huang & Pearce, 2015), expertise signaling likely acts as a stand-in for measurable actual expertise. In this capacity, expertise signaling may end up playing a bigger role than investors themselves realize.

Along the same lines, it is certainly no surprise that “tooting one’s own horn” has a real-world impact; we know this to be true not only in the financing of new ventures (Brooks, Huang, Kearney, & Murray, 2014), but also in job interviews (Stevens & Kristof, 1995) and in the workplace more generally (Carlson, Carlson, & Ferguson, 2011). But our findings go beyond prior knowledge in two important ways. First, not only does signaling expertise matter—it matters about as much as the founding team’s actual background, if not more. Second, signaling matters irrespective of the actual qualifications of the founding team. In other words, average founding teams that are more adept at self-presentation may outcompete founding teams that, while otherwise excellent, do not command the spotlight. This is because venture financing is often a gut-driven game of belief (Huang, 2018), where success can materialize simply because of investor confidence, even when such confidence is misplaced. In some cases, investors may therefore end up placing their bets on founding teams that simply oversell their preparedness, while undervaluing others that may be competent, but less showy.

Our findings suggest several provocative conclusions. First, put bluntly: investors frequently say they look at the founding team first and foremost. And existing theory backs them

up: we know, for example, that human capital improves organizational effectiveness (Beckman et al., 2007). Early-stage investors therefore tend to view the background of the founding team as an especially strong marker of a venture's potential (Bernstein, Korteweg, & Laws, 2017). But when they look at the founding team, what do they really see? On this front, our findings suggest that the evaluation of new ventures is skewed by self-presentation, and especially when it comes to raising capital, how the founding team presents itself really carries the day –perhaps to an unintended degree. As a result, funding might flow to companies like Theranos, which raised over \$1 billion in its fifteen-year-run, rather than to companies like Zoom, which only raised \$146 million prior to going public. In turn, abundant funding might give showier entrepreneurs an unwarranted leg up, with detrimental effects on the ecosystem at large.

Second, hard skills, or actual technical abilities, remain highly valued and influential, more so in getting acquired and going public, but also in driving the amount of money raised (Aggarwal, Kryscynski, & Singh, 2015). This finding validates the beliefs of seasoned practitioners like famed venture capitalist Marc Andreessen, who said, “We would have a hard time funding a startup without a strong technical founder. I'd go so far as to say that it is irresponsible to start a technology company without a technical founder, for all but a very small number of non-technical entrepreneurs.” By the same token, a managerially prepared founding team is also predictive, albeit to a lesser degree, of both liquidity events and the amount of capital raised. This reinforces past findings that managerial expertise is valuable for business scaling and venture growth.

Finally, because startups are by no means the only setting in which the schism between actual expertise and expertise signaling may impact success, our findings are likely to have broad applicability. To the extent that organizations' ability to accumulate resources – whether in the form of capital, interorganizational ties, or intangible assets – is a function of the perceived quality

of its people, expertise signaling represents a viable path to resource acquisition. Our arguments thus potentially carry important implications for organizations of all stripes and sizes, from large industrial conglomerates to small nonprofits.

Putting These Results to Work

So, what are the practical implications of these findings for investors, whose choice to bet on a founding team and their idea may involve millions of dollars? While they themselves are likely aware of how subjective their choices often are, many would likely still welcome information to strengthen their decision-making. Given the daunting odds of success that characterize most private equity investments, a venture capitalist's job is often that of looking for diamonds in the rough, and the complexity of the task is such that investors must infer potential from subtle cues. Often, this leads investors to overweigh the role of founders while discounting their actual, measurable skills. "I don't back startups, I back founders," a partner at a prominent VC firm recently told us. "I do not pick just based on education or experience," the venture partner acknowledged, "since it can be a double-edged sword for two reasons: they can be too smart for their own good. And on the other side I want to see some edginess." In fact, in a recent startup he worked with, he said, "What convinced me to help them was that unmeasurable buzz," he said. "It can go very wrong. However, buzz is real."

Our results corroborate this argument: "buzz" very much matters, in that ventures whose founding teams were relatively more adept at expertise signaling appeared to receive more funding and achieve better outcomes, irrespective of actual expertise. And because securing abundant capital is often seen as one of the hallmarks of entrepreneurial success, making a positive impression on investors can often trigger a virtuous cycle, begetting more funding and sometimes even liquidity events. Yet, as the examples of WeWork and Theranos highlight, not all that glitters is gold, and at a minimum, our findings are suggestive of the fact that impression management can

have an insidious influence on investors' perceptions of entrepreneurs—something which investors taking the long view would be well advised to heed. Expertise signaling can be a plus when it serves to highlight the skills of founders, and by extension, the potential of the venture. All too often, however, the “buzz” of expertise signaling is little more than hot air—a shiny object with little correlation to actual value, and which should invite caution. After all, for any investor, there is nothing quite like seeing dollar signs in the billions—or hearing about a lost opportunity—to prompt reflection about whom they are opening the door for, and why.

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Figure 1. Effect sizes for logistic regression models with the occurrence of a liquidity event (acquisition/IPO) as a dependent variable (Model 5 in Table A2 of the Appendix).

Figure 2. Effect sizes for OLS regression models with the with logged dollar amount of funding raised as a dependent variable (Model 10 in Table A3, Appendix).

Figure 3. Standardized dominance statistics for the six components of actual expertise and expertise signaling for the two outcome variables of interest (Tables A4 and A5 of the Appendix).

APPENDIX

Data collection procedures and variable coding

We collected most of our data between August and September 2017 from CrunchBase, a large online repository of information about new ventures and investment histories, including USD amounts for each funding round with dates. We only included ventures that: a) were founded between 2011 and 2017;¹³ b) had their primary headquarters in the United States; c) were still private at the time of the primary data collection in the summer of 2017; and d) showed a complete funding history without any undisclosed USD amounts until 2017. These choices were driven by the desire to build on a high-quality domestic sample of ventures. To complement the CrunchBase data, we gathered data from the professional networking platform LinkedIn on all the founders of companies in our sample, with a focus on the founders' prior professional and educational history. Because constructing some of our variables required information about each venture's location, we also used the Google Maps API to track any venture for which no address or metropolitan area information was provided in either LinkedIn or CrunchBase. This process ultimately produced a final sample of 4,190 ventures.

Dependent variables. Entrepreneurial success is a multifaceted phenomenon, and as such, previous work has measured it in several different ways. To avoid capturing only a single facet of it, in this study we examine two distinct dependent variables. The first is the occurrence of a *liquidity event*, or exit—which, for the purposes of this study, means either that the venture was acquired or that it went public through an initial public offering (IPO). Of the 4,190 ventures in our data, which were all private in August 2017, 183 were acquired, and 7 went public between September 2017 and May 2020, for a grand total of 190 exits (approximately 4.5 percent of our

¹³ Here we operationally define new ventures as firms founded less than six years ago, following Stam, Arzlanian, & Elfring (2014). This fact, together with the fact that CrunchBase's coverage is known to be especially accurate for more recent ventures, made us decide to start our observation window in 2011.

sample). Our dependent variable is thus a dummy for whether the venture experienced a liquidity event, or exit, within our observation window, which—to avoid reverse causality concerns—runs between September 2017 and May 2020.

Our second dependent variable of interest is the *dollar amount of funding raised by the venture*. We chose this outcome variable primarily in recognition of the fact that an increasing number of high-potential new ventures are now choosing to stay private for extended periods of time—the so-called *unicorns*. Companies like Uber and Airbnb, for example, remained private long after achieving a \$1 billion dollar market valuation—a figure long considered a benchmark for unicorn status. Because of this, the lack of an exit within our observation window does not necessarily mean that a venture is unsuccessful, which points to the need for a separate dependent variable to account for this dynamic. To this end, we coded a variable for the dollar amount of funding received by the company from investors between September 2017 and May 2020 (while controlling for any prior funding the venture might have received).

Independent variables. Entrepreneurial success is known to require a diverse set of skills. Accordingly, we conceptualize founding team expertise around three distinct clusters (entrepreneurial, managerial, and technical), based on the definitions laid out by Boyatzis (1982) and expanded upon by Chandler and Jansen (1992). *Entrepreneurial expertise* refers to the ability to identify opportunities and bring them to fruition, which is an inherently creative endeavor. Idea generation and the development of innovation are driven by the exchange of knowledge, skills, and ideas, which are recombined to identify ideas for new products, services, markets, or business models. *Managerial expertise* comes into play when a business opportunity has been identified, and the strategic pursuit of it needs to be implemented. At that point, resources must be acquired and allocated, people hired and motivated, and marketing undertaken once the opportunity has

been developed. Thus, these skills refer to coordination and organizing, rather than creating. Finally, *technical expertise* pertains to the application of highly specialized knowledge (e.g., programming skills) that is largely acquired through education and experience.

To assess *actual expertise*, we leveraged CrunchBase and LinkedIn to code dummy variables for whether a founding team member: a) *had prior founding experience*, for entrepreneurial expertise; b) *had at any point worked in a managerial capacity in the past*, for managerial expertise; or c) *held advanced technical degrees*, defined here as a master's degree or a doctorate in a STEM subject, for technical expertise. Finally, we aggregated each of these variables at the venture level by dividing the number of founding team members with that attribute or experience by the size of the founding team. As detailed in the main body of the manuscript, to measure *expertise signaling* by founding team members we instead developed a novel measure based on LinkedIn's "Skills & Endorsements" (S&E henceforth). The data collection proceeded as follows: in the first step of the data collection process, we gathered the 80,348 skills with at least one endorsement from the LinkedIn pages of 8,243 founders. We then grouped them into the three expertise clusters. The assignment into clusters was carried out by the second author and by two research assistants working independently; all coders were provided with the definitions of entrepreneurial, managerial, and technical skills outlined above as a basis for classification. Fleiss's kappa was then used to assess inter-rater reliability, yielding a value of 0.87, which is over the threshold of 0.81 for almost perfect agreement, indicating reliable sorting into the three areas. Finally, the counts of skills in each cluster thus obtained were added to obtain aggregate scores at the founding team level, which we used in our models.¹⁴

¹⁴ Our results are robust to different aggregation approaches, including taking the mean of skill counts, rather than their sum. These results, which we have omitted for brevity, are available from the authors.

Control variables. To rule out potentially confounding factors, we also include a number of control variables in our regression models. First, because achieving a liquidity event is likely a function of the focal venture's stage in its lifecycle, we include a variable for *venture age (in months)*.¹⁵ We also control for the *percentage of women within the founding team* to account for well-established gender differences in the evaluation of entrepreneurial teams (Kanze, Conley, Huang, & Higgins, 2018), as well as for the *percentage of MBA holders within the founding team* because formal business training at the founding team level might positively correlate with new venture outcomes. Additional controls include the *size of the founding team*, as well as *the amount of funding received by the venture up to August 2017*, when the main data collection took place. To control for the founding team's *social capital* (Batjargal & Liu, 2004) we leveraged the professional and educational history of the founders, as reported on LinkedIn, to build a map of the relationships for all founders in our sample.¹⁶ Lastly, the venture's geographic location is likely to have an impact on funding raised and the likelihood of a liquidity event, as some ecosystems are likely to be more supportive of entrepreneurial endeavors than others or characterized by greater environmental munificence. Accordingly, we controlled for geography through dummy variables that capture the biggest entrepreneurial hubs on the West Coast, East Coast, the South, and the Mid-West.¹⁷

Results

Table A1 reports descriptive statistics for our dependent, independent, and control variables, as well as pairwise correlations. The correlation patterns in Table A1 indicate that

¹⁵ The results are robust to the inclusion of cohort (i.e., year of founding) fixed effects instead.

¹⁶ Further details on how this variable was constructed are available from the authors.

¹⁷ This is accomplished by including dummy variables for whether the venture is located in the Silicon Valley, elsewhere in California, the New York City metropolitan area, Massachusetts, Illinois, or Texas.

expertise signaling is largely decoupled from actual expertise. The relevant correlation coefficients across clusters in fact range from -0.11 to 0.067.

----- Insert Tables A1 and A2 about here -----

Table A2 reports the results for the logistic regression models we used to examine the effect of expertise signaling, as well as actual expertise, on the likelihood of achieving a liquidity event. To facilitate coefficient comparison and the evaluation of effect sizes, we standardized all non-dummy predictors across models. Additionally, we applied a Gram-Schmidt orthogonalization procedure to our main predictors (Golub & Van Loan, 1996)—i.e., the expertise signaling and actual expertise variables—to partial out the common variance between these variables and reduce the impact of multicollinearity. Model 1 includes just control variables; as predicted, the past amount of funding received by the venture (up to August 2017) is positively associated with the occurrence of a liquidity event ($\beta = 0.448$, $p < 0.001$). In particular, a one-standard-deviation increase in funding received by the venture up to August 2017 is associated with a 56.5 percent increase in the likelihood of being acquired or going public. Model 2 then adds the social capital variable, whose coefficient is also positive and significant ($\beta = 0.578$, $p < 0.01$), with a standard deviation increase being associated with a 78.2 percent increase in the odds of achieving an exit.

In Model 3, we add the three components of actual expertise. While all the coefficients are positive, only the managerial and technical components have a statistically significant effect ($\beta = 0.201$, $p < 0.01$; $\beta = 0.222$, $p < 0.01$), increasing the odds of a liquidity event by 22.2 and 24.8 percent, respectively, for a one standard deviation increase in the corresponding variable. Finally, Model 4 adds the expertise signaling variables and Model 5 is our full model. The latter model shows a positive and significant effect of entrepreneurial expertise signaling with a standard deviation increase in the variable producing a 19.8 increase in the likelihood of a liquidity event

($\beta=0.181$, $p<0.01$); conversely, the technical and managerial components of expertise signaling are insignificant. Additionally, all previously significant effects remain significant in the full model.

----- Insert Table A3 about here -----

In Table A3, we present the results of the OLS regression models we used to examine the effect of expertise signaling on the amount of capital raised by the venture. Here, the dependent variable in all models is the logged total dollar amount of funding received by the venture since September 2017. As previously, Model 6 includes only control variables: as expected, the amount of funding raised prior to September 2017 is highly predictive of subsequent funding raised thereafter ($\beta=1.466$, $p<0.001$). Model 7 adds the social capital variable, whose positive and significant coefficient indicates that a standard deviation increase in the social capital of the founding team is associated with a 31.8 percent increase in the dollar amount of funding received ($\beta=0.318$, $p<0.001$). Model 8 adds actual expertise, whose managerial and technical component shows a positive and significant association with the amount of capital raised, with an effect size suggestive of a 13.8 and 34.7 increase in the amount of capital raised for each standard deviation increase in the respective covariates ($\beta=0.138$, $p <0.1$; $\beta=0.347$, $p <0.001$). Surprisingly, however, the entrepreneurial component shows a *negative* and significant effect, with a standard deviation increase in the variable being associated with a 24.8 percent *decrease* in funding raised ($\beta=-0.248$, $p<0.001$).¹⁸ Finally, Model 9 adds the expertise signaling variables and Model 10 is the full model. Here, both the entrepreneurial and the technical components of expertise signaling show a positive

¹⁸ This could be a byproduct of censoring if it were the case that within the sample, very experienced entrepreneurs founded ventures whose degree of success made them exit prior to the summer of 2017. In a separate robustness check omitted for brevity and available from the authors, we run parametric event-history models with an accelerated-event time specification and find that our results continue to hold when the possibility of left- and right-censoring is accounted for.

association with the dependent variable, with a standard deviation increase in each resulting in an increase in the dollar amount raised by the venture of 29.5 and 33.2, respectively ($\beta = 0.295$, $p < 0.001$; $\beta = 0.332$, $p < 0.001$).

Dominance analysis

Based on the effect sizes presented in Tables A1 and A2, it would be reasonable to conclude that among our predictors of interest, actual technical expertise contributes the most to the odds of being acquired or going public, followed by actual managerial expertise and entrepreneurial expertise signaling. In a similar fashion, one might surmise that as far as raising capital is concerned, actual technical expertise and technical expertise signaling would explain the most variance among the founding team-level predictors considered here. A comparison of effect sizes, such as the one calculated above, can certainly be informative in assessing the relative contribution of each predictor to variations in the dependent variable. This is because a predictor with a large effect size will, in most circumstances, be associated with a more substantial change in the dependent variable than an alternative predictor with a small effect size, other things being equal. Since effect sizes are calculated by holding all other predictors constant at their sample means, however, the above is only true when the predictors are uncorrelated; otherwise, any change in predictor x would be associated with a change in predictor y , making effect sizes as calculated above not be especially meaningful.

An alternative approach to comparing predictors in regression without running into the above issue is *dominance analysis*, first introduced by Budescu (1993). The basic idea behind dominance analysis is that "one predictor is more important than another if it would be chosen over its competitor in all possible subset models where only one predictor of the pair is to be

entered" (Azen & Budescu, 2003: 134).¹⁹ To assess the relative predictive power of expertise signaling vis-à-vis the actual expertise of the founding team, therefore, we ran dominance analyses for our six main variables.

----- Insert Tables A4 and A5 here -----

Tables A4 and A5 report the general dominance statistics for the six predictors with the occurrence of a liquidity event (Table A4) and the amount of funding raised (Table A5) as dependent variables. For each independent variable, the statistic reported in the first column is the variable's weighted average marginal contribution to the pseudo- R^2 across all possible sub-models that include it, while the statistic reported in the second column is a standardized version, calculated so that the sum of statistics across predictors equals one.

Looking at Table A4, the ranking in the third column suggests that the most relevant predictors of the venture experiencing a liquidity event are: 1) actual technical expertise; 2) entrepreneurial expertise signaling; and 3) technical expertise signaling; a pattern which is not in line with our initial comparison of effect sizes. At the same time, actual technical expertise makes up 38.1 percent of the contribution to the fit statistics made by the six variables as a whole, versus 21.1 percent for entrepreneurial expertise signaling and 18.2 for technical expertise signaling. Taken together, the top three predictors thus account for approximately 77.4 percent of the fit statistics for the six variables combined. It is also worth noting that the three actual expertise variables have an overall contribution to the fit statistics of 60.2 percent, while the figure is 39.8 for expertise signaling. Similar patterns can be observed in Table A5: here, the variable with the

¹⁹ In this framework, importance is measured through the average contribution that a given predictor makes to improve the fit statistic for all possible sub-models to which it is added. In other words, for a given set of p predictors, dominance analysis compares the effect of each predictor in all the $2^{(p-2)}$ models that contain some subset of the other predictors.

largest contribution to the fit statistics is actual technical expertise (35.7 percent), with technical expertise signaling a close second (32.9 percent). Notably, however, when the amount of funding raised is the dependent variable, expertise signaling makes the largest contribution to the fit statistics (55.4 percent), relative to actual expertise (44.6 percent).

Further analyses

----- Insert Tables A6 and A7 here -----

In separate robustness checks whose results are reported in Tables A6 and A7 we look into whether: a) experienced investors are less sensitive to expertise signaling than relatively novice investors; and b) investors give more weight to expertise signaling in the first round of funding, when uncertainty is likely highest. For the former, for each venture we created a variable representing the *average experience of investors financing it*, which we coded as the mean number of funding rounds the investor participated in prior to financing the focal venture for the first time. We then split our sample into two subsamples at the median value of this variable, thus creating two equally large subsets of ventures financed by more (vs. less) experienced investors. We then reran the full models originally reported in Tables A2 (Model 5) and A3 (Model 10) on each of the two subsamples (Models 11 and 12 in Table A6). The results indicate that the effect of expertise signaling tends to be more pronounced among ventures financed by less experienced investors, at least for what pertains to funding raised.

For the possibility that expertise signaling could be weighed more heavily during the first round of funding, we opted to look at the amount of first-round funding received by the venture as a dependent variable, although to avoid reverse causality concerns we are only able to include ventures whose first round of funding took place after we collected the LinkedIn data (i.e., 2017 or later)—a total of 473 companies, after accounting for missing data—which limits the statistical power of our estimation. Given the small sample size, we decided to carry out dominance analyses,

which are arguably best suited to assessing the relative impact of expertise signaling vis-à-vis actual background and also less sensitive to changes in sample size and statistical power relative to regression analysis. The dominance analysis results in Table A7 can be directly compared to those in Table A5 and show that expertise signaling is weighed more heavily overall in the first round of funding, especially technical expertise signaling, which emerges as the number one predictor among those considered.

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Table A1. Pairwise correlations and descriptive statistics for all variables (before standardization and orthogonalization).

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Liquidity event (dummy)	0.046	0.21	0	1	1													
2 Funding raised (\$)	3.15E+06	2.91E+07	0	1.24E+09	0.06	1												
3 Venture age (in months)	57.042	13.014	24	80	-0.007	-0.012	1											
4 Founding team: percent women	0.181	0.332	0	1	-0.026	-0.026	0.012	1										
Founding team: percent MBA holders	0.066	9	0	1	-0.008	0	-0.004	-0.03	1									
6 Founding team: size	1.82	0.955	1	10	0.063	0.075	-0.031	-0.045	-0.006	1								
7 Past funding raised	3.11E+06	1.50E+07	0	4.45E+08	0.222	0.497	0.035	-0.038	-0.018	0.111	1							
Expertise signaling: entrepreneurial	2.149	1.953	0	21	0.062	0.033	0.039	-0.02	-0.015	0.523	0.079	1						
9 Expertise signaling: managerial	8.476	5.912	0	44	0.012	0.017	0.009	0.075	-0.011	0.581	0.024	0.353	1					
10 Expertise signaling: technical	5.43	6.041	0	44	0.063	0.079	-0.035	-0.137	0.004	0.582	0.099	0.1	-0.2	1				
11 Social capital	0.384	0.101	0	0.51	0.076	0.05	-0.014	0.012	0.02	0.294	0.082	0.167	0.136	0.232	1			
12 Actual expertise: entrepreneurial	0.318	0.411	0	1	0.031	-0.002	0.101	-0.073	0.004	-0.079	0.036	0.054	-0.061	-0.022	0.086	1		
13 Actual expertise: managerial	0.514	0.441	0	1	0.057	0.017	0.153	-0.048	0.005	-0.112	0.052	0.024	-0.05	-0.062	0.17	0.572	1	
14 Actual expertise: technical	0.341	0.423	0	1	0.1	0.068	0.113	-0.052	-0.001	-0.038	0.158	0.034	-0.11	0.067	0.201	0.196	0.32	1

Table A2: Logistic regression results with liquidity events (exits) as a dependent variable.

DV: liquidity event (acquisition or IPO)	Model 1	Model 2	Model 3	Model 4	Model 5
Venture age (in months)	-0.063 (0.072)	-0.071 (0.073)	-0.126+ (0.074)	-0.077 (0.074)	-0.140+ (0.075)
Founding team: percent women	-0.106 (0.083)	-0.121 (0.086)	-0.100 (0.086)	-0.106 (0.090)	-0.076 (0.089)
Founding team: percent MBA holders	-0.030 (0.080)	-0.038 (0.084)	-0.034 (0.082)	-0.035 (0.088)	-0.030 (0.086)
Founding team: size	-0.038 (0.091)	-0.060 (0.089)	-0.056 (0.094)	-0.062 (0.085)	-0.055 (0.089)
Past funding raised	0.448*** (0.086)	0.423*** (0.083)	0.391*** (0.080)	0.415*** (0.080)	0.379*** (0.077)
Founding team social capital		0.578** (0.182)	0.483** (0.179)	0.501** (0.180)	0.371* (0.172)
Actual expertise: entrepreneurial			0.095 (0.076)		0.106 (0.078)
Actual expertise: managerial			0.201** (0.073)		0.218** (0.076)
Actual expertise: technical			0.222** (0.072)		0.248*** (0.074)
Expertise signaling: entrepreneurial				0.152* (0.068)	0.181** (0.069)
Expertise signaling: managerial				-0.062 (0.073)	-0.057 (0.074)
Expertise signaling: technical				0.076 (0.073)	0.115 (0.072)
Ecosystem dummies	Yes	Yes	Yes	Yes	Yes
Constant	-3.233*** (0.145)	-3.265*** (0.155)	-3.297*** (0.156)	-3.261*** (0.154)	-3.293*** (0.155)
Observations	4,190	4,190	4,190	4,190	4,190
Pseudo-R2	0.0654	0.0808	0.0908	0.0848	0.0966
N	4190	4190	4190	4190	4190

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A3: OLS regression results with logged dollar amount of funding raised as a dependent variable.

DV: funding raised (\$, logged)	Model 6	Model 7	Model 8	Model 9	Model 10
Venture age (in months)	-0.333*** (0.075)	-0.331*** (0.075)	-0.345*** (0.074)	-0.331*** (0.074)	-0.353*** (0.073)
Founding team: percent women	-0.124* (0.060)	-0.127* (0.060)	-0.136* (0.059)	-0.086 (0.060)	-0.091 (0.060)
Founding team: percent MBA holders	-0.063 (0.059)	-0.068 (0.059)	-0.067 (0.059)	-0.061 (0.059)	-0.059 (0.059)
Founding team: size	0.153+ (0.081)	0.136+ (0.080)	0.138+ (0.080)	0.144+ (0.080)	0.147+ (0.080)
Past funding raised	1.466*** (0.347)	1.444*** (0.345)	1.401*** (0.338)	1.405*** (0.342)	1.354*** (0.334)
Founding team social capital		0.318*** (0.055)	0.271*** (0.054)	0.192*** (0.055)	0.127* (0.055)
Actual expertise: entrepreneurial			-0.248*** (0.063)		-0.227*** (0.063)
Actual expertise: managerial			0.138+ (0.070)		0.166* (0.071)
Actual expertise: technical			0.347*** (0.075)		0.378*** (0.075)
Expertise signaling: entrepreneurial				0.295*** (0.083)	0.311*** (0.083)
Expertise signaling: managerial				0.045 (0.074)	0.047 (0.074)
Expertise signaling: technical				0.332*** (0.090)	0.353*** (0.090)
Ecosystem dummies	Yes	Yes	Yes	Yes	Yes
Constant	1.435*** (0.119)	1.487*** (0.120)	1.477*** (0.119)	1.506*** (0.120)	1.498*** (0.119)
Observations	4,190	4,190	4,190	4,190	4,190
R-squared	0.107	0.111	0.119	0.118	0.128
N	4190	4190	4190	4190	4190

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A4. Dominance analysis: general dominance statistics for logistic regression with liquidity events as a dependent variable and expertise signaling and actual expertise as independent variables.

	Dominance statistic	Standardized dominance statistic	Ranking
Expertise signaling: entrepreneurial	0.0093	0.2106	2
Expertise signaling: managerial	0.0002	0.0053	6
Expertise signaling: technical	0.0080	0.1818	3
Actual expertise: entrepreneurial	0.0026	0.0581	5
Actual expertise: managerial	0.0072	0.1632	4
Actual expertise: technical	0.0169	0.3810	1

Table A5. Dominance analysis: general dominance statistics for OLS regression with logged dollar amount of funding raised as a dependent variable and expertise signaling and actual expertise as independent variables.

	Dominance statistic	Standardized dominance statistic	Ranking
Expertise signaling: entrepreneurial	0.0088	0.2227	3
Expertise signaling: managerial	0.0001	0.0022	6
Expertise signaling: technical	0.0130	0.3294	2
Actual expertise: entrepreneurial	0.0015	0.0388	5
Actual expertise: managerial	0.0020	0.0501	4
Actual expertise: technical	0.0141	0.3568	1

Table A6. Logit and OLS results with venture sample split by mean investor experience.

DV:	Exit		Funding raised	
Model:	Logit		OLS	
Investor experience:	Low	High	Low	High
VARIABLES	Model 11	Model 12	Model 13	Model 14
Venture age (in months)	-0.078 (0.095)	-0.242* (0.121)	-0.729*** (0.203)	-0.206*** (0.056)
Founding team: percent women	-0.122 (0.125)	0.016 (0.122)	-0.049 (0.196)	-0.078+ (0.043)
Founding team: percent MBA holders	-0.066 (0.121)	0.034 (0.122)	-0.061 (0.189)	-0.031 (0.045)
Founding team: size	-0.002 (0.096)	-0.080 (0.148)	0.330+ (0.194)	0.037 (0.065)
Past funding raised	0.335*** (0.078)	0.329** (0.109)	0.971* (0.440)	1.529*** (0.426)
Founding team social capital	0.279 (0.178)	0.381 (0.307)	0.274 (0.224)	0.061 (0.044)
Actual expertise: entrepreneurial	0.243* (0.101)	-0.042 (0.128)	-0.426* (0.191)	-0.149** (0.046)
Actual expertise: managerial	0.310** (0.110)	0.035 (0.113)	0.102 (0.201)	0.076 (0.051)
Actual expertise: technical	0.195* (0.098)	0.178 (0.119)	0.393* (0.189)	0.239*** (0.062)
Expertise signaling: entrepreneurial	0.067 (0.099)	0.117 (0.123)	0.247 (0.188)	0.061 (0.068)
Expertise signaling: managerial	-0.075 (0.096)	-0.124 (0.123)	-0.040 (0.183)	-0.005 (0.059)
Expertise signaling: technical	0.052 (0.089)	0.166 (0.120)	0.424* (0.191)	0.151* (0.075)
Ecosystem dummies	Yes	Yes	Yes	Yes
Constant	-2.720*** (0.213)	-3.753*** (0.237)	2.929*** (0.317)	0.891*** (0.119)
Observations	1,240	2,805	1,240	2,950
R-squared			0.070	0.179
Pseudo R-squared	0.0833	0.0732		

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A7. Dominance analysis: general dominance statistics for OLS regression with logged dollar amount of first-round funding raised as a dependent variable and expertise signaling and actual expertise as independent variables.

	Dominance statistic	Standardized dominance statistic	Ranking
Expertise signaling: entrepreneurial	0.0127	0.1003	4
Expertise signaling: managerial	0.0002	0.0016	6
Expertise signaling: technical	0.0594	0.4695	1
Actual expertise: entrepreneurial	0.0133	0.1054	3
Actual expertise: managerial	0.0020	0.0156	5
Actual expertise: technical	0.0389	0.3076	2

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