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Are early stage investors biased against women?[☆]

Michael Ewens[a], Richard R. Townsend[b,*]

[a] California Institute of Technology, 1200 E California Blvd, MC 228-77, Pasadena, CA 91125
[b] University of California San Diego, Rady School of Management, 9500 Gilman Dr, La Jolla, CA 92093

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We study whether early stage investors have gender biases using a proprietary data set from AngelList that allows us to observe private interactions between investors and fundraising startups. We find that male investors express less interest in female entrepreneurs compared to observably similar male entrepreneurs. In contrast, female investors express more interest in female entrepreneurs. These findings do not appear to be driven by within-gender screening/monitoring advantages or gender differences in risk preferences. Moreover, the male-led startups that male investors express interest in do not outperform the female-led startups they express interest in—they underperform. Overall, the evidence is consistent with gender biases.

1. Introduction

It is well known that there is a significant gender gap in high-growth entrepreneurship. Recent studies of startup activity in the US find that only roughly 10%–15% of startups are founded by women (Gompers and Wang, 2017b).[1,2] The persistence of this gap over time runs counter to more general labor market trends (Goldin, 2006). Several potential explanations have been proposed, including gender differences in technical training or risk preferences.[3] However, many have also speculated that part of the gender gap may, in fact, be due to a lower propensity for investors to fund female entrepreneurs seeking capital (Coleman and Robb, 2009; 2016). This view largely stems from the fact that over 90% of venture capitalists (VCs) are men (Gompers and Wang, 2017b). For

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* Corresponding author.
E-mail address: rrtownsend@ucsd.edu (R.R. Townsend).

[1] Brush, C., Greene, P. G., Balachandra, L., Davis, A. E., 2014. Diana report: women entrepreneurs 2014–bridging the gender gap in venture capital. Arthur M. Blank Center for Entrepreneurship Babson College.

[2] Tracy, S. L., 2011. Accelerating job creation in America: the promise of high-impact companies. SBA Office of Advocacy, Washington.

[3] See Bertrand (2011) and Croson and Gneezy (2009) for surveys of empirical and experimental evidence of differences in risk attitudes by gender. For example, Bonin et al. (2007) find that risk preferences predict occupational sorting.

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example, a recent article in the New York Times states that "venture capitalists are, in a way, the gatekeepers to Silicon Valley, and if they are a group of white men … it is no wonder that most of the entrepreneurs fit the same mold."[4] According to this view, investors may be reluctant to fund female entrepreneurs due to unconscious or implicit bias. Alternatively, they may be overtly sexist, as highlighted by recent high-profile events in Silicon Valley.[5] However, despite popular perceptions, it remains entirely possible that, on average, investors are not actually biased against women. Most of the evidence to date has been indirect or anecdotal. In this paper, we directly examine whether female entrepreneurs are at a disadvantage in raising capital due to their gender and if so, why.

Examining these questions, even descriptively, has been difficult thus far for several reasons. First and foremost, standard data sources only provide information on startups that have successfully raised capital, as it is challenging to identify startups systematically in the prefinancing stage. From such data, it is evident that women are significantly underrepresented among *funded* entrepreneurs. However, this underrepresentation does not necessarily point toward differential treatment of women by investors. In particular, it may be that women are just as underrepresented, or even more underrepresented, in the pool of those seeking funding.

Using data on funded entrepreneurs, one could also examine whether funded female founders are more likely to have been funded by female investors. However, this would also not necessarily indicate that male investors are reluctant to fund women. It may be that male investors see fewer companies with female founders due to the nature of their networks but are no less likely to fund the female founders that they do see. In addition, investment is a two-sided decision; it must both be offered by an investor and accepted by an entrepreneur. Thus, even if female founders garnered equal interest from male investors, they may choose to accept funding from female investors due to their own preferences.

A second challenge is that female-led startups may differ from male-led startups in ways that make them less favorable investments on average. To the extent that such investment characteristics are unobservable in the data, but are observable to investors, it may appear that investors are reluctant to invest in women when in fact they are screening on nongender attributes.

To address these challenges, we use a proprietary data set obtained from AngelList, a popular online platform started in 2010 that connects investors with seed-stage startups. Companies create profiles on AngelList describing their businesses and founding teams. They can then start a fundraising campaign wherein they specify the amount of capital they are trying to raise along with other desired deal terms. Accredited investors—both angels and VCs—can register on the platform and subsequently connect with companies seeking funds. The site is widely used, even among high-quality startups. By 2013, over 60% of startups raising a seed round had an AngelList profile, and more than half of those startups attempted to raise capital through the site (Bernstein et al., 2017). Many well-known firms, such as Uber and Pinterest, have raised capital through AngelList.

There are several advantages of this setting for studying the impact of gender on entrepreneurial fundraising. First, we are not limited to studying startups that successfully raised capital. Instead, we observe a large set of startups that are trying to raise capital—some of which succeed and some of which fail. This allows us to examine more directly whether gender appears to be an important determinant of fundraising success. Second, because our data come directly from AngelList, we also observe other nonpublic investor actions. In particular, we see when an investor decides to "share" a startup profile with someone else or "request an introduction" to the founders. As noted earlier, investment is a two-sided decision, but we are able to study expressions of interest that only involve an action on the part of the investor. These actions also precede any personal interactions with founders that may differ across investors and thus complicate the analysis. Third, because of the nature of the platform, all investors have "access" to all deals in the sense that they can see the exact same information about the same set of companies and are free to take action on any company. Therefore, each investor's information and opportunity set is the same, at least with regard to the one-sided actions discussed above. Finally, we are also able to accurately observe the gender of both the founders and the investors, based on their names and profile pictures. This feature of the data means that we can benchmark the behavior of male investors to that of female investors for the same set of companies.

We find that female-led startups experience significantly more difficulty garnering interest and raising capital from male investors compared to observably similar male-led startups. In particular, women are less successful with male investors, even controlling for a battery of startup/founder characteristics that encompass much of the information that was available to investors online when making the decisions we are studying. The behavior of male investors is particularly consequential for startups since men constitute the bulk of early stage investors. Nonetheless, it is interesting to also examine the behavior of female investors for comparison. Interestingly, we find that the same female-led startups are actually more successful with female investors than the same observably similar male-led startups. We view the establishment of these facts as an important contribution. With existing data sets, it has not even been possible to examine the correlation between gender and investor interest. Had we found no evidence of differential treatment, there would be no need to investigate what drives it. In light of the fact that we do find evidence of differential treatment, we next explore potential explanations.

[4] See Miller, C., 2015. Female-run venture capital funds alter the status quo. New York Times.

[5] Several high-profile investors, including Justin Caldbeck (Binary Capital), Chris Sacca (Lowercase Capital), and Dave McClure (500 Startups), all recently resigned amidst allegations of sexual harassment by female entrepreneurs with whom they had business dealings. These cases, combined with similar allegations at Uber and other tech companies, have brought widespread attention to the treatment of women in Silicon Valley.

We partition potential explanations into two categories: explanations where investors have gender biases and explanations where they do not. Following Egan et al. (2018), we define gender biases to encompass both taste-based discrimination (Becker, 1957) as well as miscalibrated beliefs (Bordalo et al. (2016); Dobbie et al. (2017)). Taste-based discrimination would involve investors directly experiencing disutility from investing in entrepreneurs of the opposite gender (or, equivalently, utility from investing in entrepreneurs of the same gender). Miscalibrated beliefs would involve investors holding an incorrect stereotype of entrepreneurs of the opposite gender. It is possible that these biases co-exist. They may also be implicit in the sense that investors may not even be consciously aware of them (Bertrand et al., 2005).

In contrast to explanations involving gender biases, explanations involving no gender biases are ones in which differential treatment of female-led startups maximizes a purely financial objective function. This essentially amounts to statistical discrimination, broadly defined (Phelps (1972); Arrow (1973); Ewens et al. (2014)). Importantly, the fact that male and female investors respond to female founders in opposite ways is already suggestive of gender bias by at least one of these types of investors. For example, if all investors were unbiased and merely used founder gender as a proxy for startup quality (as in statistical discrimination), one would expect male and female investors to respond to female founders in the same way. Nonetheless, there remains potential explanations that do not involve gender bias.

First, it could be that investors have a screening and/or monitoring advantage with startups led by founders of the same gender as themselves. In other words, it may be more difficult for investors to assess the quality of a startup ex-ante or to add value to a startup ex-post when the startup is led by a founder of the opposite gender. Perhaps most obviously, that would be the case if female-led startups tend to operate in industries where male investors lack expertise, such as industries geared toward female customers. To explore this possibility, we repeat our analysis on various subsamples of "gender-neutral" startups—for example, startups that three independent evaluators categorized as equally likely to have been founded by a man or a woman when shown the nonfounder sections of their profiles. The results are similar in these subsamples, suggesting that female entrepreneurs do worse with male investors and better with female investors, even when there is nothing obviously female about their startup's business description.

We also find that male investors are less likely to share female-led startups, even when they are sharing with female investors. Similarly, female investors are more likely to share female-led startups, even when they are sharing with male investors. This result further suggests that the reason investors show more interest in startups with founders of the same gender as themselves is not simply because investors anticipate that they will work better with these founders. Were that the case, male investors would actually be more likely to share female-led startups with female investors (compared to observably similar male-led startups), and female investors would be less likely to share female-led startups with male investors (compared to observably similar male-led startups).

Another related possibility is that female-led startups may be less risky than male-led startups and female investors more risk averse (Croson and Gneezy, 2009). To investigate this, we examine the correlation between male and female investor interest among startups with founders who are all of one gender. Within the male-led-only (or female-led-only) sample, we find a strong positive correlation between female investor interest and male investor interest. Thus, male and female investors tend to agree with one another when comparing two observably similar founders who are both men or who are both women. However, male and female investors tend to disagree with one another when comparing two observably similar founders, one of whom is a man and one of whom is a woman. If our baseline results were driven by differences in risk, male and female investors would also disagree when comparing two founders of the same gender. In that case, the male-led startups that female investors were interested in would be the low-risk variety that male investors were not.

Having failed to find evidence in support of the most obvious nonbias explanations for our results, we investigate the possibility of bias more directly by examining long-run startup performance. If investors prefer founders of the same gender not due to bias, but for purely financial reasons, we would expect same-gender pairs to also outperform mixed-gender pairs. In contrast, if investors are biased, it is possible that same-gender pairs may underperform mixed-gender pairs. This test is along the lines of Fisman et al. (2017) who examine whether loan officers in India show a preference for within-caste lending due to financial or nonfinancial motives by comparing the ex-post loan performance of within-caste and across-caste loans. We find that, for a given male investor, the male-led startups that he pairs with underperform the female-led startups he pairs with in terms of the standard startup performance measures used in the literature—probability of success (i.e., exit via intital public offering (IPO)/acquisition), probability of failure (i.e., website no longer operational), and probability of raising a follow-on round from a venture capitalist. These results suggest that male investors are reluctant to reach out to startups led by female founders due to bias and therefore only do so for the most promising companies. We do not find a similar pattern for female investors.

We conclude by exploring whether the differential treatment of female-led startups that we have documented varies based on startup and investor characteristics. We find that the gap in male investor interest between female-led startups, and observably similar male-led startups, is even larger for startups that are affiliated with an incubator or have achieved some degree of "traction" in terms of users or sales. The reason for this is that incubator affiliation and startup traction help male-led startups in terms of garnering interest from male investors but help female-led startups significantly less. Such discounting of credentials for female-led startups potentially represents another form of bias. This behavior mirrors Bertrand and Mullainathan's (2004)) finding that employers are less responsive to resume quality for job applicants with

African American sounding names. Interestingly, there is no evidence of credential discounting by female investors. Separately, we also find that female-led startups are at less of a disadvantage with male investors when they seek low amounts of capital or operate in female-centric industries. This suggests that male investors may pigeonhole female entrepreneurs to some extent, believing them only able to succeed in relatively unambitious businesses or businesses oriented toward women. We again do not find a similar pattern among female investors. Finally, in terms of investor heterogeneity, we find that the gap between male and female investors in terms of interacting with female-led startups is smaller among more experienced investors.

Overall, our results are consistent with some form of bias among male investors. In general, we find weaker evidence of bias among female investors—for example, we do not find that female-female investor-founder pairs underperform female-male pairs—but it is possible that we simply lack power, as there are significantly fewer female investors in our sample. Therefore, we do not rule out the possibility that male and female investors are symmetrically biased in favor of their own gender. One could view symmetric biases as being reflective of "homophilistic" investor preferences (see, e.g., McPherson et al., 2001). Alternatively, female investor bias could arise as a response to male investor bias—in an attempt to offset it. In either case, given that the bulk of early stage investors are male, biases that lead investors to favor their own gender would be of greater concern for female-led startups than male-led startups. Thus, even with symmetric biases, one potential implication of our results is that more female investors may be necessary to support the entry of more female entrepreneurs.

2. Related literature

In a recent survey article on diversity among startup founders and venture capitalists, Gompers and Wang (2017b) show evidence that the entrepreneurship gender gap cannot be entirely explained by supply-side factors such as female education or work experience. They conclude that bias among investors remains a possible contributor to the gap, which should be further investigated: "a question arises about whether the lack of female [...] entrepreneurs is due to few venture capitalists who are female [...]. This seems like a critical question to address" (p. 40). As far as we are aware, this paper is the first to use large sample evidence to directly examine potential bias among early stage investors against female entrepreneurs.[6]

The literature thus far has focused largely on gender diversity in VC firms and its effects on firm performance. For example, Gompers and Wang (2017a) find that VCs with daughters are more likely to hire female partners in their firms. Using this as an instrument for VC firm gender diversity, they find that gender diversity leads to better fund-level performance, suggesting that diversity helps to prevent groupthink and inefficient decision making. Raina (2017) also finds that venture funds that hire women perform better. Our paper differs in that we focus on gender bias in investment decisions rather than hiring decisions.

Another set of related papers study gender differences in fundraising patterns on reward-based crowdfunding sites like Kickstarter (Marom et al., 2016; Lin and Pursiainen, 2018). However, crowdfunding sites are not an ideal laboratory for understanding gender bias among investors. First, the incentives of reward-based crowdfunders are very different from those of the equity investors we study. In exchange for small contributions, crowdfunders either receive a small token of appreciation (e.g., a keychain) or the product the entrepreneur is proposing to create. Therefore, reward-based crowdfunders can be viewed as more akin to donors or customers than they are to investors.[7] As a result, the research question these papers study is very different. For example, statistical discrimination is not even well defined in the context of donations or consumption, which are almost by definition driven by nonfinancial motives. In addition to having different incentives, the population of crowdfunders is also very different from the population of equity investors. Crowdfunders need not have high net worth, as the contributions they make are small. In terms of gender, they are almost 50% female. In contrast, we study the behavior of accredited equity investors, who have high net worth and are mostly men. The behavior of these investors is more plausibly related to the long-standing entrepreneurship gender gap, which predates the introduction of crowdfunding.

Finally, this paper is also related to Bernstein et al. (2017), which is the only other research we are aware of that uses proprietary data from AngelList.[8] They examine how the likelihood of an investor visiting a startup's profile is affected by the inclusion or omission of certain categories of information from an e-mail sent to investors highlighting the startup. The three categories of information they consider are the startup's founding team, its traction (i.e., performance metrics), and its existing investors. They find that that omitting information about

[6] A handful of papers in the management and strategy literature have examined this question using small sample evidence and different methodologies. For example, drawing upon regulatory focus theory, Kanze et al. (2017) analyze whether investors ask male and female founders different types of questions (promotion-focused versus prevention-focused) in a major business plan competition. However, it is not clear whether investors behave the same in public, when judging a business plan competition, as they do in private. Moreover, since judges do not invest in the competition winner, they have different incentives in this context. Finally, the entrepreneurs and investors selected to participate are unlikely to be representative of the average entrepreneur or investor. For example, organizers may make an effort to select more diverse participants. Brooks et al. (2014) conduct lab experiments where noninvestor participants rate startup pitches delivered by individuals of different genders and levels of attractiveness. However, participants in these experiments may not evaluate startups in the same way as professional investors or have similar incentives. In addition to having less expertise, experiment participants know that their decisions will not impact real people. They also know that they will not actually interact the people they rate highly. Thus, there is less scope for taste-based discrimination in such experiments.

[7] Crowdfunders may also partly be composed of an entrepreneur's friends and family.

[8] Other papers have used AngelList data. However, these papers scrape the data from the website. As a result, they cannot observe historical fundraising attempts and removed profiles. They also cannot observe the private signals of investor interest that we use, as these are not visible on the site.

the founding team has the largest negative impact on investor click-through rates from e-mails.[9] Given that investors on AngelList find it important to see information about the founding team, it is plausible that characteristics like founder gender may play an important role in their decision-making. In contrast to Bernstein et al. (2017), we use the full AngelList data set rather than focusing on the small set of companies featured in e-mails. We also study a broader set of investor actions that are more closely tied to investment rather than e-mail clicks.

3. The AngelList platform

Traditionally, seed-stage startup financing has largely been done through personal networks. Founders often seek capital from potential investors who they either know directly or indirectly through a mutual acquaintance. AngelList was founded in 2010 with the goal of making it easier for founders and investors to connect. Since launching, the platform has attracted much attention and grown rapidly in popularity, becoming an important part of the startup ecosystem. Bernstein et al. (2017) show that by 2013, some 60% of companies raising a seed round had an AngelList profile. More than half of these companies used the platform to raise capital.

The website allows founders to create startup profiles describing their idea, progress thus far, and personal/professional background. Founders can then start a fundraising campaign wherein they specify the amount of capital they are trying to raise along with other desired deal terms. Accredited investors—both angels and VCs—can register on the platform and subsequently connect with companies seeking funds. There are a variety of ways that an investor can interact with a startup. First, an investor can share a startup profile with someone else—either another AngelList user (through a private message) or someone off the platform (through an e-mail with an embedded link). Investors often share deals with others that they know may be interested. Second, an investor can request an "introduction" to a startup. If the request is accepted, the investor can communicate directly with the founders and view confidential documents such as pitch decks, financials, or in-depth business plans. Absent an introduction, communication is not possible nor is full data access. Importantly, introduction requests can only be made to startups with an active fundraising campaign. Thus, a request for an introduction can be viewed as a direct precursor to investment.

Finally, an investor can "fund" a startup. This last step happens offline, although founders can and do self-report consummated financing rounds in the funding section of their startup profile. They have an incentive to do so, as consummated financing rounds are a positive signal to potential future investors, as well as to potential employees, customers, and other stakeholders (Bernstein et al., 2017).

Aside from the cost of making an investment, investor actions on AngelList are both costless and private. For example, there is no limit on the number of introduction requests an investor can make, and no one on the platform other than the recipient can observe the request. In addition, all investors have access to all deals in the sense that they can see the exact same information about the same set of companies and are free to take action on any company.

In recent years, AngelList has also begun facilitating financings directly through the platform with equity crowdfunding syndicates. As of the time we obtained our data from AngelList, syndicates were still a fairly nascent addition to the site. Thus, we focus exclusively on the original "social network for startups" part of the platform as described above.

3.1. Offline networks

We argue that an advantage of the AngelList setting is that all investors have access to all deals in the sense that they can see the exact same information about the same set of companies and are free to take action on any company. However, investors may, in fact, continue to learn about startups raising capital on AngelList through their offline networks, and the offline networks of investors may tend to overlap more with those of founders of the same gender. This could, for example, lead female founders to garner less interest from male investors on AngelList than observably similar male founders, even if male investors on AngelList completely ignored gender. In particular, female-led startups may be less likely to be shared or funded by male investors on AngelList because the female founders of these startups lack existing offline relationships with the investors taking these actions.

Fortunately, however, we also observe requests for introductions. Offline relationship concerns are less likely to apply to requests for introductions, as it unlikely that investors request introductions to founders they are already connected to through their offline network. Indeed, if an investor on AngelList already knew a founder, requesting an introduction through the site would have no benefit in terms of opening up a line of communication. Doing so would also have no benefit in terms of signaling since introduction requests are private. Moreover, even for investors and founders who only shared a mutual acquaintance, it would seem more natural for the acquaintance to connect the two directly, rather than recommending the investor connect with the startup indirectly by requesting an introduction through AngelList. Thus, if anything, the existence of offline networks would bias us toward finding that investors are more likely to request introductions to founders of the opposite gender through AngelList because they are less likely to already be connected to such founders through their offline networks.

3.2. Outside information sources for investors

We also argue that an advantage of the AngelList setting is that we observe the same information that investors do prior to requesting an introduction. In particular, we are able to control for information from founders' AngelList profiles as well as their (often connected) LinkedIn

[9] Using survey evidence, Gompers et al. (2018) also find that VCs see the founding team as more important than business-related characteristics.

profiles. This helps to reduce concerns about investors directly screening on nongender characteristics that they observe but we do not. Nonetheless, it is true that investors may search for further information outside of AngelList and LinkedIn before requesting introductions, and female founders may tend to have more or less favorable outside information. However, it seems likely that a typical investor would first simply speak to a founder if they were interested, before doing deeper diligence. Indeed, the opportunity cost of investors' time is often high, and it is likely more efficient to ask for information directly rather than to search for it.

4. Data

In this section, we describe our key variables, data sources, and sample restrictions.

4.1. Investor interest

We measure investor interest in a startup using the three types of investor-startup interactions that are facilitated through AngelList, as described above. Specifically, we measure the number of investors who share, request an introduction, or invest in a startup. In most of our analysis, we focus on variation along the extensive margin, as most startups either receive no interest or interest from a single investor.

As mentioned before, we measure investor sharing and introduction requests from backend administrative data. The investment variable is self-reported by founders and therefore subject to greater measurement error, most likely in the form of underreporting. However, if anything, we think underreporting would push us toward not finding differential treatment of women in terms of investment, due to attenuation bias.[10]

In general, the fact that we can observe signals of investor interest at the individual level is advantageous. This means we can avoid issues one encounters in trying to determine the gender of investors such as venture capital firms, where multiple people are likely involved in an investment decision.

4.2. Long-run startup performance

We focus on three measures of long-run startup performance following a fundraising campaign. The first is an indicator equal to one if a startup has had a successful exit via IPO or acquisition according to VentureSource or Crunchbase. This is the standard measure of deal-level performance in the venture capital literature (e.g., Hochberg et al., 2007; Gompers et al., 2010; Ewens and Rhodes-Kropf, 2015; Nanda et al., 2018). The second measure of startup performance we use is an indicator equal to one if a startup has failed, based on whether its website is no longer active as of November 2016. We deem a website as inactive if it fails to load and/or if its domain is available for purchase. Given the recency of the AngelList platform, many of the startups that tried to raise capital on the site have neither failed nor had a successful exit yet. Therefore we also examine whether a startup has raised a follow-on round of venture capital investment as an interim measure of startup success.

4.3. Identifying gender

We identify the gender of founders and investors in our sample based on their name and profile picture. In particular, we run all first names through genderize.io, which gives the probability a first name corresponds to a woman based on a large sample.[11] For individuals with names that are at all ambiguous ($0 < Prob(Female) < 1$), we determine gender manually based on the user's profile picture. To do this, we use FigureEight, which is a service like Amazon Mechanical Turk with additional quality controls.[12] In particular, "test pictures" for which the correct answer has already been determined by us are randomly mixed in with pictures that have not been categorized. FigureEight contributors who fail too many test questions are excluded, and the work of less trusted contributors is double-checked by more trusted contributors.

While we observe gender at the founder level, the outcomes we examine are at the startup level. Therefore, it is necessary to assign a gender to a startup. Many of the startups in our sample have a single founder, in which case it is straightforward to categorize a startup as "female-led" or "male-led" based on the gender of that founder. Some of the startups in our sample have multiple founders. In these cases, we categorize startups based on the gender of the founder who is also listed as the CEO. As we will show, we find similar results whether or not we restrict attention to single-founder companies.

4.4. Nongender founder characteristics

A founder's AngelList profile can include a short bio with information on their education and past work experience. Founders often provide only sparse information about themselves on AngelList and instead use the option to link their AngelList profile to their LinkedIn profile. In addition, for some of the founders who do not link the two profiles, we are still able to find their LinkedIn profile manually by searching LinkedIn for their name along with the name of their AngelList startup. Overall, we are able to find a LinkedIn profile for 62% of our sample, although these profiles vary in terms of which categories of information are included.[13]

When educational information is included, we can observe the schools a founder attended, degrees obtained,

[10] There is no reason to think that underreporting would occur in a way that would bias our estimates toward finding discrimination. This would require female founders to be more reluctant to self-report having closed a round with a male investor as compared to a female investor. Moreover, our results for investment are qualitatively similar to our results for sharing and introduction requests, which further suggests that the investment results are not driven by selective reporting.

[11] http://genderize.io.

[12] FigureEight was previously called CrowdFlower.

[13] Public profiles were searched and evaluated manually by a research assistant.

and years of graduation. When we observe the year of college graduation, this provides a fairly accurate proxy for age (assuming individuals are 22 at graduation). We crudely categorize founders as having attended an “elite” school if they hold a degree from a top ten university according to the US News & World Report rankings. In terms of work experience, we can observe the number of jobs held, past job titles, and number of years in the workforce. We categorize individuals as previous founders if they held the title of founder at a different company prior to their AngelList fundraising campaign. Internet Appendix Table A1 provides a full listing of these background variables.

4.5. Startup characteristics

Startups on AngelList describe themselves in part through various categories of keyword “tags.” There are 1,805 distinct industry tags, and companies can use multiple tags in combination to describe themselves. We map these tag combinations into VentureSource industry categorizations using the subsample of AngelList startups that also appear in VentureSource. For startups in the overlapping sample, we already have both AngelList tags and VentureSource industries. For startups that are not in the overlapping sample (i.e., only in AngelList), we identify the nearest neighbors in the overlapping sample.[14] Based on these nearest neighbors we compute a probability distribution for each company over the seven major VentureSource industries. We then categorize a company according to its most probable VentureSource industry.[15]

Startups use 5841 distinct location tags. We geocode these using the Google Maps Application Programming Interface (API) and then categorize them according to the 19-region scheme used by the National Venture Capital Association (NVCA). The NVCA regions are coarse where there are few startups and more granular where there are many. For example, there is one region in the Southwest but four regions in California.

In a separate section of their profile, startups can also report any signs of progress, or traction, that they might already have. While most traction descriptions involve users or sales, they are not very uniform. These descriptions may refer to levels or growth rates, correspond to weekly, monthly, or yearly reporting periods, etc.[16] Due to the lack of uniformity in how traction is reported, it is difficult to quantify whether one startup has more traction than another. Instead, we simply create an indicator variable equal to one if a startup has reported any traction.

Finally, startups can also report affiliation with an incubator program as another signal of quality. We again capture this with an indicator variable equal to one if the startup is affiliated with an incubator program.

[14] Nearest neighbors are startups with the highest number of common AngelList tags.

[15] Our results are similar whether we control directly for the industry probabilities or assign according to the most probable.

[16] Examples of traction descriptions include “monthly active users,” “new users,” “beta customers,” “paying customers,” “annual revenue,” “sales pipeline,” “average revenue per user,” and “monthly recurring revenue.”

4.6. Final sample

The final sample of founders and startups satisfies several conditions that help to minimize measurement error and captures a representative set of startups seeking capital in our sample period. The sample begins with all first-time fundraising events for US startups founded between 2010 and November 2015. Next, we require that the startup has a founding team where we could confidently identify the gender of each founder. Any startup that raised venture capital before their AngelList fundraising campaign is excluded to ensure we study first-time financings. The startup’s fundraising campaign must also have a nonmissing value for capital sought and a nonmissing business description in their profile. Finally, we require that the startup maps to a VentureSource industry and NVCA region based on its tags. In the end, we have 17,780 startups in the sample.

5. Results

5.1. Summary statistics

We begin in Table 1 by examining the gender composition of entrepreneurs and investors on AngelList. Overall, 15.8% of founder CEOs who try to raise capital on AngelList are women (21% of all founders, including non-CEOs). By way of comparison, both Crunchbase and VentureSource, which cover funded startups, have a lower percentage of female founders. This suggests that women are more underrepresented among funded founders than they are among fundraising founders. However, women remain highly underrepresented among fundraising founders as well. It should be noted that many women may be discouraged from even trying to raise capital due to perceptions of gender bias among investors. This may account for some of the underrepresentation of women among those raising capital. In the next section, we directly examine whether the women who do try to raise capital have more difficulty garnering interest from investors, conditional on observables.

It is also interesting to examine the gender composition of investors across the three data sets. We find that some 8% of investors with some sharing, introduction, or investment activity on the AngelList platform are women. This number is lower than the female founder percentage on AngelList; however, it exceeds the female investor percentage in the alternative data sets.

Table 2 presents summary statistics separately for the male-led and female-led startups in our sample. Panel A shows startup characteristics, Panel B shows startup outcomes, and Panel C shows founder characteristics. The two groups are fairly similar along many dimensions. The main difference in startup characteristics is that male-led startups generally set higher fundraising targets ($690,000 versus $530,000) and are slightly more likely to have achieved some degree of traction (10% versus 9%). Approximately 11% of both male-led and female-led startups attended an incubator. In terms of outcomes, most startups that post a fundraising campaign appear to generate relatively low levels of interest from investors. Nonetheless, men are

Table 1
Gender distribution on AngelList, Crunchbase, and VentureSource.
This table reports the percentage of women in entrepreneurial firm founder positions or as investors in three databases. The AngelList sample includes the startups and investors active on the platform starting in late 2009. Startups are those that sought capital publicly on the website. Crunchbase is a Wiki-style website of startups, investors, and exits maintained since 2010. VentureSource is a database of venture capital financings and investors provided by VentureSource. Gender of both founders and investors was identified using the algorithm and manual assignment detailed in Section 4.3. Crunchbase numbers for founders are for firms founded between 2010 and the present and headquartered in the US. The VentureSource founder statistics are for firms founded between 2010–2015. The VentureSource investor statistics report the fraction of board members of firms financed between 2010–present that are women.

	AngelList	Crunchbase	VentureSource
% firms with female CEO/founders	15.8%	13%	11%
% firms with any female founder	20.9%	13.4%	17.3%
% female investors	8%	5%	6.5%

Table 2
Male-led versus female-led startups.
This table reports summary statistics for the set of firm and founder variables by whether the founder (founder-CEO if multiple founders) is male or female. Panel A show startup characteristics. Panel B shows startup outcomes. Panel C shows founder characteristics. Within Panel C, the first section reports the differences in observables for the full sample of founders, using AngelList data augmented with LinkedIn data where available. The second section uses only LinkedIn data for the subsample where it is available. Variables are as defined in Internet Appendix Table A1.

Panel A: Startup characteristics

	Male founder				Female founder			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
Team size (truncated at 4)	14,959	1.316	1.000	0.696	2821	1.230	1.000	0.583
Year fundraising start	14,959	2013.327	2013.000	1.376	2821	2013.490	2014.000	1.348
Solo founder	14,959	0.792	1.000	0.406	2821	0.837	1.000	0.369
Capital sought (millions)	14,959	0.685	0.400	0.811	2821	0.531	0.250	0.713
Attended incubator	14,959	0.110	0.000	0.313	2821	0.112	0.000	0.316
Has traction	14,959	0.104	0.000	0.305	2821	0.088	0.000	0.283

Panel B: Startup outcomes

	Male founder				Female founder			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
Shared	14,959	0.051	0.000	0.220	2821	0.030	0.000	0.170
Received introduction	14,959	0.192	0.000	0.394	2821	0.159	0.000	0.366
Funded	14,959	0.026	0.000	0.158	2821	0.014	0.000	0.117
Had IPO or acquisition	14,959	0.008	0.000	0.087	2821	0.006	0.000	0.077
Startup failed	14,959	0.462	0.000	0.499	2821	0.475	0.000	0.499
Raised VC	14,959	0.023	0.000	0.151	2821	0.017	0.000	0.128

Panel C: Founder characteristics

	Male founder				Female founder			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
LinkedIn & AngelList:								
Bach. degree	14,959	0.479	0.000	0.500	2821	0.494	0.000	0.500
MBA	14,959	0.082	0.000	0.275	2821	0.077	0.000	0.267
PhD/MD/JD	14,959	0.035	0.000	0.184	2821	0.033	0.000	0.178
Previous founder	14,959	0.181	0.000	0.385	2821	0.127	0.000	0.333
LinkedIn only:								
Number jobs on LinkedIn	8405	4.613	4.000	3.370	1396	4.630	4.000	3.360
Years experience pre-startup	7760	13.498	12.000	8.421	1278	12.862	11.000	8.273
Age	3,620	35.257	33.000	9.914	583	33.688	32.000	8.507

more successful than women in terms of generating interest. In particular, male-led companies are more likely to be shared (5% versus 3%), to receive an introduction request (19% versus 16%), or get funded (2.5% versus 1.5%). Male-led companies are slightly more likely to have had an IPO or acquisition (0.8% versus 0.6%) and are slightly less likely to have already failed (46% versus 48%). The average male founder in our sample is similar to the average female founder in terms of age (35.26 versus 33.69), years of work experience (13.5 versus 12.86), number of previous jobs held (4.61 versus 4.63), and number of co-founders (0.32 versus 0.23).

Table 3
Differences in female and male investors.
This table reports summary statistics for male and female investors for which we could find some biographical data on LinkedIn. All variables are as defined in Table 2 and Table A1. The variable "Previous founder" is defined only for individuals that have at least one listed position on their LinkedIn profile.

	Male investor				Female investors			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
Number jobs on LinkedIn	6017	8.41	7.00	6.19	517	8.81	8.00	7.41
Age	4532	40.38	39.00	9.42	396	38.89	37.00	10.12
Previous founder	6017	0.60	1.00	0.49	517	0.55	1.00	0.50
Bach. degree	5102	0.96	1.00	0.20	456	0.96	1.00	0.18
Masters	5102	0.21	0.00	0.41	456	0.25	0.00	0.43
MBA	5102	0.28	0.00	0.45	456	0.28	0.00	0.45
PhD/MD/JD	5102	0.09	0.00	0.29	456	0.09	0.00	0.29

The two groups also have similar levels of educational attainment and previous founder experience. In particular, male and female founders are similarly likely to hold a bachelor's degree (48% versus 49%), MBA degree (8% versus 8%), or other advanced degree (4% versus 3%). Likewise, they have similar previous founding experience (18% versus 13%). The education and founder experience variables are based on the information founders post on AngelList as well as LinkedIn. It is possible that actual educational attainment or founder experience in our sample is higher than reported if some founders choose to omit this information from the two online profiles. Nonetheless, we interpret these variables as reflecting the information that was available to investors at the time of the fundraising campaign. This is likely the information upon which investors decided to share or request an introduction to a company and thus is the appropriate information to control for in regressions where those are the outcome variables. In the process of actually funding a company, investors likely learn additional information from conversations with the founders. Thus, when fundraising success is our outcome variable, our ability to control for the information available to investors is more limited.

Table 3 compares the characteristics of male and female investors on AngelList who ever interacted with a fundraising startup (i.e., shared, requested an introduction, or funded) and who connected their LinkedIn profile with their AngelList profile. As with founders, we find that male and female investors are broadly similar in terms of age, experience, and education. Over half of investors of both genders have previous founding experience.

5.2. Baseline findings

We now explore in a regression framework whether the interest a startup receives from investors correlates with the gender of its founder. Specifically, we estimate equations of the form:

$$y_i = \alpha + \beta Female_i + \boldsymbol{\delta}' \mathbf{X_i} + \epsilon_i, \tag{1}$$

where i indexes startups, *Female* is an indicator variable equal to one if the startup has a female founder-CEO, and $\mathbf{X}$ represents a vector of startup-level and founder-level controls. The dependent variables we study are various measures of male investor interest and female investor interest. Specifically, these measures are indicator variables equal to one if startup i had a particular signal of interest from a male investor or a female investor, respectively.[17] We separate male and female investor interest in much of our analysis to allow for the possibility that male and female investors may differ in terms of their gender attitudes. Of course, because the bulk of investors are male, biases among this group would be particularly consequential. Because our outcomes are binary, Eq. (1) represents a linear probability model. However, all of our results remain similar under a probit or logit specification.

Observations in Eq. (1) are at the startup level. We could have alternatively estimated equations at the startup-investor pair level. In that case, the dependent variable would be an indicator for whether investor j signaled interest in startup i. We show in Internet Appendix Section A that doing the analysis at the startup-investor pair level adds no additional information since our key variable of interest, founder gender, only varies at the startup level and startups face the same set of investors. Specifically, the coefficient from a pairwise version of Eq. (1) is simply β divided by the number of investors who could have potentially expressed interest. Moreover, pairwise analysis also does not offer any advantage in terms of making it possible to include startup fixed effects or investor fixed effects in the regression. The inclusion of such fixed effects is either infeasible due to colinearity with the female founder indicator or else does not change the coefficient estimates. Intuitively, estimates of β in Eq. (1) cannot be biased by omitted investor characteristics since all startups raising capital at a given point in time face the same set of potential investors, regardless of founder gender.[18]

We begin by estimating Eq. (1) using investor sharing of a startup profile as a measure of interest. Because our

[17] All of our conclusions are robust to an alternative specification where the dependent variable is the number of signals of interest rather than an indicator equal to one if there is at least one signal of interest. See Internet Appendix Table A2.

[18] Similarly, pairwise analysis does not offer any advantage in terms of making it possible to include pairwise controls, such as the distance between a startup and an investor. One can control for this at the startup level using the average distance between a startup and all AngelList investors. Alternatively, one can control for geographic variation in investor interest due to distance and other factors by including startup location fixed-effects in Eq. (1).

Table 4
Sharing by male and female investors.
This table reports the linear probability model where the dependent variable is one if the startup raising capital on AngelList was shared by a male (columns 1–3) or female investor (columns 4–6) by the end of the sample (11/2015). A unit of observation is a US-based startup on the platform where we can identify the gender of all the founders and where the capital sought is at least $5000. All variables are as defined in Internet Appendix Table A1. "Round year FE" are fixed effects for the year the fundraising campaign opened. "Firm join year FE" are fixed effects for the year that the startup joined the AngelList platform. "Team size FE" are fixed effects for founding team size, which is truncated at five for teams larger than five. "Industry FE" are industry fixed effects (seven categories) defined in Section 4. "Location FE" are location fixed effects (19 categories) defined in Section 4. Robust standard errors are reported in parentheses. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	Startup was shared by a					
	Male investor			Female investor		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.019***	−0.011***	−0.013***	0.0069***	0.0081***	0.0078***
	(0.0033)	(0.0033)	(0.0033)	(0.0019)	(0.0020)	(0.0020)
Previous founder			0.034***			0.0027
			(0.0055)			(0.0019)
Bach. degree			0.015***			0.00091
			(0.0032)			(0.0011)
PhD/MD/JD			0.0015			0.0020
			(0.011)			(0.0043)
MBA			−0.011			−0.00021
			(0.0070)			(0.0025)
Elite school (any)			0.022***			0.0041
			(0.0078)			(0.0029)
Has traction			0.026***			0.0033
			(0.0070)			(0.0026)
Attended incubator			0.083***			0.011***
			(0.0080)			(0.0030)
Log capital sought		0.0072***	0.0056***		0.00079***	0.00056**
		(0.00083)	(0.00087)		(0.00023)	(0.00025)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.056	0.10	0.12	0.0071	0.015	0.018
Round year FE?	Y	Y	Y	Y	Y	Y
Firm join year FE?	Y	Y	Y	Y	Y	Y
Team size FE?	N	Y	Y	N	Y	Y
Industry FE?	N	Y	Y	N	Y	Y
Location FE?	N	Y	Y	N	Y	Y

sample consists only of startups that are raising capital, the sharing events that we observe likely represent communications among investors regarding the opportunity to invest. Despite the low cost of sharing on the platform, only 4.7% of startups in our sample were shared by an investor. This investor selectivity with sharing suggests that sharing may indeed be a good measure of interest. As discussed earlier, for companies with multiple founders, we consider the CEO to be focal. In other words, the female founder indicator and all other founder-level controls correspond to the CEO.

Results are shown in Table 4. Columns 1–3 examine sharing by male investors. In column 1, we include only minimal controls. Specifically, we include fixed effects for the year the startup joined AngelList and the year it posted its first fundraising campaign. These fixed effects account for the fact that older companies have had more time to generate interest among investors. We find that, on average, female-led companies are less likely to be shared by male investors, with differences significant at the 1% level. In terms of economic magnitudes, the coefficient suggests that female-led companies are approximately 2% less likely to be shared, which is large relative to a base sharing rate of 4.8%. In column 2, we control for the amount of capital sought as well as team size, industry, and location fixed effects. With the inclusion of these controls, the estimated coefficient on the female founder indicator declines somewhat but remains economically significant. Finally, the coefficient remains similar as we add additional controls for founder education and experience in column 3. The education and experience coefficient estimates have the expected signs. Startups founded by repeat founders, college graduates, or individuals who hold a degree from an elite university are more likely to be shared, as are startups with some demonstrated traction and startups that attended an incubator. Overall, the results suggest that female-led companies are less shared by male investors than observably similar male-led companies.

The behavior of male investors is particularly consequential for startups since men constitute the bulk of early stage investors. Nonetheless, it is interesting to also examine the behavior of female investors for comparison. Columns 4–6 of Table 4 repeat the analysis of columns 1–3 but examining sharing by female investors. Interestingly, we find that the sign of the estimated coefficient on the female founder indicator flips in this case. Thus, female-led companies are actually shared more by female investors than observably similar male-led companies. We will discuss the interpretation of these results in the sections that follow.

Table 5
Introduction requests by male and female investors.
This table reports the linear probability model where the dependent variable is one if the startup raising capital on AngelList received at least one introduction request from a male investor (columns 1–3) or female investor (columns 4–6) by the end of the sample period (11/2015). A unit of observation is a US-based startup on the platform where we can identify the gender of all the founders and where the capital sought is at least $5,000. Variables and FEs are as defined in Table A1 and Table 4. Robust standard errors are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Startup received introduction request from a					
	Male investor			Female investor		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.034***	−0.015**	−0.019***	0.013***	0.020***	0.018***
	(0.0070)	(0.0068)	(0.0066)	(0.0042)	(0.0042)	(0.0042)
Previous founder			0.037***			0.018***
			(0.0087)			(0.0050)
Bach. degree			0.042***			0.0091***
			(0.0058)			(0.0030)
PhD/MD/JD			−0.013			−0.0024
			(0.017)			(0.010)
MBA			−0.0032			−0.0065
			(0.011)			(0.0067)
Elite school (any)			0.055***			0.019**
			(0.012)			(0.0074)
Has traction			0.084***			0.019***
			(0.011)			(0.0065)
Attended incubator			0.19***			0.096***
			(0.011)			(0.0080)
Log capital sought		0.018***	0.012***		0.0059***	0.0045***
		(0.0017)	(0.0017)		(0.00078)	(0.00080)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.060	0.15	0.19	0.019	0.068	0.095
Round year FE?	Y	Y	Y	Y	Y	Y
Firm join year FE?	Y	Y	Y	Y	Y	Y
Team size FE?	N	Y	Y	N	Y	Y
Industry FE?	N	Y	Y	N	Y	Y
Location FE?	N	Y	Y	N	Y	Y

While the sharing behavior of investors is interesting, the way in which sharing relates to investment is somewhat unclear. To move one step closer to actual investment, we examine requests for introductions. As discussed earlier, such requests are a direct precursor to funding, as investors need to request an introduction to communicate with a startup's founder(s). Table 5 shows that we find qualitatively similar results for introduction requests as for sharing. In columns 1–3, we find that female-led companies are approximately 1.5%–3.5% less likely to receive a request for an introduction from a male investor, as compared to a baseline introduction rate of 18.7%. Again, startups led by repeat founders, college graduates, or individuals who hold a degree from an elite university are more likely to receive a request for an introduction, as are startups with some demonstrated traction and startups that attended from an incubator. In columns 4–6, we also again find that the sign on the female founder indicator flips when examining requests for introductions from female investors.

Finally, it is possible that early indications of interest segment along gender lines, but when it comes to actually raising capital, such segmentation disappears. Therefore, in Table 6 we examine actual fundraising outcomes. Again, the results are qualitatively similar to before. After controlling for observable firm, founder, and financing characteristics, female-led startups are significantly less likely than male-led startups to raise a round from a male investor. In terms of magnitudes, the estimated coefficients suggest a 0.8%–1.3% decline in fundraising success on a base fundraising success rate of 2.4%. We also again find that female founders are significantly more likely to raise a round from a female investor. Thus, the previous results do not appear to have been driven by the preliminary or lower stakes nature of investor sharing and introduction requests relative to actual investment.[19]

5.2.1. Robustness

As discussed earlier, when a startup has multiple founders, we consider the CEO to be focal. Internet Appendix Table A4 shows that our baseline results remain similar when the sample is restricted to only include startups with a solo founder, where the focal founder is unambiguous.

It is possible that our finding that female investors favor female-led startups is driven by investors associated with funds that have an explicit social mission to support female entrepreneurs. To investigate this, we manually

[19] As discussed earlier, financing rounds may be underreported on AngelList. To make sure that our results are not driven by selective underreporting, we construct an alternative investment outcome variable using three alternative data sources to find financing rounds that are not reported on AngelList (see table caption for details). Internet Appendix Table A3 repeats the analysis of Table 6 using this more comprehensive investment variable. The results remain similar.

Table 6
Funding by male and female investors.
This table reports the linear probability model where the dependent variable is one if the startup reported raising capital from a male (columns 1–3) or female (columns 4–6) investor on AngelList as of the end of the sample period (11/2015). A unit of observation is a US-based startup on the platform where we can identify the gender of all the founders and where the capital sought is at least $5000. Variables and FEs are as defined in Table A1 and Table 4. Robust standard errors are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Startup was funded by a					
	Male investor			Female investor		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.013***	−0.0083***	−0.0095***	0.0030*	0.0041**	0.0038**
	(0.0023)	(0.0023)	(0.0023)	(0.0017)	(0.0017)	(0.0018)
Previous founder			0.0078*			0.0036*
			(0.0040)			(0.0021)
Bach. degree			0.0055**			−0.00088
			(0.0025)			(0.0012)
PhD/MD/JD			−0.0040			−0.0029
			(0.0081)			(0.0035)
MBA			−0.0045			−0.00025
			(0.0053)			(0.0026)
Elite school (any)			0.0044			−0.00076
			(0.0057)			(0.0026)
Has traction			0.0053			−0.00057
			(0.0053)			(0.0025)
Attended incubator			0.060***			0.018***
			(0.0066)			(0.0035)
Log capital sought		0.0031***	0.0022***		0.00077**	0.00048
		(0.00061)	(0.00064)		(0.00035)	(0.00036)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.0095	0.034	0.050	0.0017	0.0090	0.015
Round year FE?	Y	Y	Y	Y	Y	Y
Firm join year FE?	Y	Y	Y	Y	Y	Y
Team size FE?	N	Y	Y	N	Y	Y
Industry FE?	N	Y	Y	N	Y	Y
Location FE?	N	Y	Y	N	Y	Y

compile a list of known female-focused angel and VC funds.[20] We find that only 2% of the female investors in our data are associated with such funds. Internet Appendix Table A5 shows that our baseline results remain similar when we exclude these investors. Of course, it is possible that female investors not associated with such funds still invest with social objectives in mind. We will further examine whether this appears to be the case in the analysis to come.

5.2.2. Do female investors offset male investors?

Given the results thus far, it is natural to ask whether female investors are able to fully offset the differential treatment of female-led startups by male investors such that, overall, female-led startups do as well with investors as male-led startups. Of course, even if female investors were able to fully offset male investors in the particular setting that we study here, that would not necessarily mean that they would be able to do so more generally. Indeed, as discussed earlier, women appear to be better represented on AngelList than they are among all traditional investors. Moreover, even if female investors were able to fully offset male investors in the current equilibrium, that remains an equilibrium in which women are highly underrepresented among founders. The current set of female investors may not have the resources to continue to offset male investors if there were an increase in female founders toward more representative numbers. In other words, our results would still imply that an increase in female investors would likely be necessary to support an increase in female founders. Nonetheless, in Table 7, we repeat our baseline analysis with the investor interest variables based on all investors rather than just male or female investors. Overall, female-led startups garner less interest from all investors than observably similar male-led startups, especially in terms of sharing and funding. However, the magnitudes are smaller than the baseline results for male investor interest. Thus, it appears that female investors are able to partially offset male investors but not fully.

5.3. Potential explanations with no gender biases

Thus far, we have found that female-led startups face significantly more difficulty garnering interest and raising capital from male investors compared to observably similar male-led startups. At the same time, these startups do better with female investors. We view the establishment

[20] These funds are: Valor Ventures, Golden Seeds, Pipeline Angels, Built By Girls Ventures, BELLE Capital USA, Female Founders Fund, The Womens' Venture Capital Fund, Forerunner Ventures, 500 Women, Angel Academe, Phenomenelle Angels Fund, Broadway Angels, Topstone Angels, Plum Alley, The Jump Fund, Astia, Scale, Cross Culture Ventures, Gotham Gal Ventures, True Wealth Ventures, Halogen Ventures, Sofia Fund, Female Funders, Women Angels, Women Founders Network, Women Launch, and Women Lead Inc.

Table 7
Pooled interest by male and female investors.
This table repeats the analysis of Tables 4–6, with outcomes corresponding to any investor. A unit of observation is a US-based startup on the platform where we can identify the gender of all the founders and where the capital sought is at least $5,000. Variables are as defined in Table A1. Variables and FEs are as defined in Table A1 and Table 4. Robust standard errors are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Shared by any investor		Intro. from any investor		Funded by any investor	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.012***	−0.0076**	−0.014**	−0.0044	−0.0086***	−0.0068***
	(0.0036)	(0.0035)	(0.0073)	(0.0069)	(0.0025)	(0.0026)
Previous founder		0.035***		0.039***		0.0083**
		(0.0056)		(0.0088)		(0.0041)
Bach. degree		0.014***		0.043***		0.0050**
		(0.0033)		(0.0059)		(0.0025)
PhD/MD/JD		0.0044		−0.0084		−0.0033
		(0.011)		(0.017)		(0.0083)
MBA		-0.0080		−0.00055		−0.0049
		(0.0072)		(0.012)		(0.0054)
Elite school (any)		0.025***		0.055***		0.0039
		(0.0080)		(0.012)		(0.0057)
Has traction		0.027***		0.082***		0.0074
		(0.0071)		(0.011)		(0.0054)
Attended incubator		0.087***		0.19***		0.062***
		(0.0081)		(0.011)		(0.0067)
Log capital sought		0.0058***		0.013***		0.0024***
		(0.00088)		(0.0018)		(0.00066)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.075	0.13	0.098	0.19	0.016	0.050
Round year FE?	Y	Y	Y	Y	Y	Y
Firm join year FE?	Y	Y	Y	Y	Y	Y
Team size FE?	N	Y	N	Y	N	Y
Industry FE?	N	Y	N	Y	N	Y
Location FE?	N	Y	N	Y	N	Y

of these facts as an important contribution. With existing data sets, it has not even been possible to examine the correlation between gender and investor interest. Had we found no evidence of differential treatment, there would be no need to investigate what drives it. In light of the fact that we do find evidence of differential treatment, we next explore potential explanations.

We partition potential explanations into two categories: explanations where investors have gender biases and explanations where they do not. Following Egan et al. (2018), we define gender biases to encompass both taste-based discrimination (Becker, 1957) as well as miscalibrated beliefs (Bordalo et al., 2016; Dobbie et al., 2017). Taste-based discrimination would involve investors deriving disutility from investing in entrepreneurs of the opposite gender. Miscalibrated beliefs would involve investors holding an incorrect stereotype of entrepreneurs of the opposite gender. It is possible that these biases co-exist. They may also be implicit in the sense that investors may not even be consciously aware of them (Bertrand et al., 2005). In contrast to explanations involving gender biases, explanations involving no gender biases are ones in which differential treatment of female-led startups maximizes a purely financial objective function. This essentially amounts to statistical discrimination, broadly defined (Phelps, 1972; Arrow, 1973).

Importantly, the fact that male and female investors respond to female founders in opposite ways is already suggestive of gender bias by at least one of these types of investors. For example, if all investors were unbiased and merely used founder gender as a proxy for startup quality (as in standard statistical discrimination), one would expect male and female investors to respond to female founders in the same way. However, from the results thus far, it is possible that only female investors are biased; male investors may be statistically discriminating against female-led startups, which are unobservably worse investments, while female investors favor female-led startups due to taste or miscalibrated beliefs. It is also possible that only male investors are biased; female investors may be statistically discriminating in favor of female-led startups, which are unobservably better investments, while male investors dislike female-led startups due to taste or miscalibrated beliefs.[21] Finally, it is also possible that male and female investors are symmetrically biased in favor of startups led by CEOs of the same gender as themselves. In that case, male and female investors may be biased for the same underlying reason, or female investor bias may arise as a response to male investor bias—in an attempt to offset it. Before exploring evidence of gender bias directly, we first explore potential explanations for the patterns we have documented thus far that do not involve gender bias.

[21] One plausible reason that female-led startups may be unobservably better investments than male-led startups is that there could be greater positive self-selection into entrepreneurship among women—due to perceived difficulties for them in that field.

5.3.1. Within-gender screening/monitoring advantages

One possibility is that it may be easier for investors to assess startups ex-ante, or to add value to them ex-post, when their founder is of the same gender. Even if our baseline results were driven by such within-gender screening/monitoring advantages, the findings would remain interesting, as they would still suggest that female investors are necessary to support female entrepreneurs. In that case, it would be because female investors are better suited to pick the best female-led startups to invest in or else are better suited to add value to female-led companies after making an investment.

If there are within-gender screening/monitoring advantages, investor-founder pairs of the same gender should outperform investor-founder pairs of different genders. In Section 5.4, we show evidence that this is not the case. Before getting to that analysis, we first explore the most obvious reasons there may be within-gender screening/monitoring advantages.

Industry differences

It is possible that female-led startups tend to operate in industries where female investors have expertise and male investors do not, such as industries geared toward primarily female customers. Although our baseline regressions include coarse industry fixed effects, we perform a variety of tests to explore this possibility further.

Recall that companies on AngelList describe their industry with a combination of multiple keyword tags. The tags are very granular as evidenced by the fact that there are 1,805 of them. In Panel A of Table 8, we remove startups from the sample that use any tag that is predominantly associated with one gender. We define a tag to be predominantly female if more than 32% of startups using that tag are female-led. Similarly, we define a tag to be predominantly male if less than 8% of startups using that tag are female-led.[22] The two cutoffs represent double and half the percentage of founders on AngelList that are female, respectively, as we are trying to identify tags where women are either over- or underrepresented. The idea behind this test is that, while male investors may have less insight into a female-led cosmetics company, or more insight into a male-led facial hair grooming company, they should have no differential insight into a male- or female-led biotech company. However, even in this restricted subsample of gender-neutral startups, we continue to find that male investors show less interest in female-led companies. We also continue to find that female investors show more interest in female-led companies. Internet Appendix Table A6 shows a second test along the same lines. In this case, we exclude all startups whose keyword tags map to consumer-related industries, as categorized by VentureSource.[23] This test attempts to remove startups from the sample that even have a potential gender component, regardless of whether they actually do. We again find very similar results in this restricted subsample.

In Panel B of Table 8, rather than trying to limit the sample to gender-neutral startups, we instead control directly for the way a company describes itself on AngelList by including a full set of industry tag combination fixed effects. This means that the estimation only uses variation in founder gender among companies that describe themselves in the same way. We again find similar results with these granular controls. In other words, even among companies that describe themselves in the same way on AngelList, male investors show less interest in female-led companies.

The above tag-based tests are still imperfect, as tags only represent part of the information available to investors. To address this concern, we have three independent evaluators from FigureEight manually categorize each startup based on the entire contents of its AngelList profile, excluding the founder section.[24] In particular, we ask each evaluator the following question:

> Based on the description of the company, would you guess that the founder of this company is: (1) highly likely to be female, (2) fairly likely to be female, (3) equally likely to be male or female, (4) fairly likely to be male, (5) highly likely to be male.

These evaluators' judgments are quite predictive of the true gender of the founder.[25]

We then use these data as conservatively as possible by limiting the sample to startups that all three evaluators unanimously categorized as "equally likely to be male or female." Only 24% of our original sample remains after this restriction. Nonetheless, as shown in Panel C of Table 8, we continue to find similar results in this subsample. Internet Appendix Table A7 shows that we also find similar results when, rather than requiring unanimity, we instead limit the sample to startups with a neutral mean response (i.e., a mean response strictly greater than two and strictly less than four). Together, the above evidence suggests that our baseline results are not driven by differences in industry focus that the controls used in our main specifications fail to capture.

[22] Examples of predominantly female tags include "bridal community," "mothers," "child care," and "lingerie." Examples of predominantly male tags include "cars," "console gaming," and "proximity services."

[23] The two groups are "consumer goods" and "consumer services."

[24] Specifically, we use FigureEight to obtain three "trusted judgements" from US-based contributors with the highest quality track record on similar "human intelligence tasks" (based on past experience and accuracy). Contributor quality is determined on a scale of one to three by FigureEight based on experience and accuracy. We only allowed the highest quality contributors to participate. To further ensure contributors were actually trying to answer the questions correctly, 20% of the questions any given respondent answered were test questions where the founder's gender was obvious (e.g., because it was explicitly identified in one of the nonfounder portions of the startup's AngelList profile). The judgments of those who failed more than 10% of these test questions were categorized as "untrusted judgments," as were judgments that were reached too quickly (<60 seconds). These untrusted judgments were excluded from the analysis.

[25] When we regress the true gender of a startup's founder on indicator variables corresponding to the first four responses to the question above, the probability that the founder is female increases monotonically with the evaluators' subjective assessment. At the extremes, startups labeled as highly likely to be female are five times more likely to actually have a female founder than startups that were labeled as highly likely to have a male founder. Probability differences from the omitted category ("highly likely male") are statistically significant at the 1% level in all cases.

Table 8
Robustness to detailed industry controls and gender-neutral subsamples.
This table repeats the estimation from Tables 4–6 for subsamples of entrepreneurial firms split by industry classification or alternative fixed effect specifications. Panel A presents the subset of firms excluding those with tags that are either predominantly used women or men. Here, predominantly female tags are tags where more than 32% (twice as large as population percentage) of firms with that tag are female-led. Predominantly male tags are tags where less than 8% (half as large as population percentage) of firms with that tag are female-led. Panel B presents the main specification where the industry fixed effects are replaced by industry tag combination fixed effects based on the combination of industry tags listed on a startup's AngelList profile. Startups can have more than one tag. Panel C includes only startups where there was consensus in an online survey showing the company's description that it was a gender-neutral firm (i.e., equally likely to have a male or female founder). All controls and fixed effects from Tables 4–6 are included in the regressions, except in Panel B, which replaces industry FE with tag combination FE. Robust standard errors are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Excluding startups with gender-dominant tags					
	Shared by		Intro. from		Funded by	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
Female	−0.0096** (0.0042)	0.0074*** (0.0025)	−0.023*** (0.0083)	0.016*** (0.0052)	−0.010*** (0.0028)	0.0046* (0.0024)
Observations	11,175	11,175	11,175	11,175	11,175	11,175
R^2	0.12	0.017	0.18	0.082	0.046	0.018
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y
	Panel B: Industry tag combination fixed effects					
	Shared by		Intro. from		Funded by	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
Female	−0.0121*** (0.00378)	0.00711*** (0.00197)	−0.0168** (0.00756)	0.0210*** (0.00472)	−0.0119*** (0.00284)	0.00408* (0.00212)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.243	0.170	0.261	0.224	0.205	0.137
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y
	Panel C: Manually categorized gender-neutral startups					
	Shared by		Intro. from		Funded by	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
Female	−0.018** (0.0073)	0.0060* (0.0033)	−0.032** (0.014)	0.021** (0.0096)	−0.013*** (0.0051)	0.0020 (0.0036)
Observations	4,330	4,330	4,330	4,330	4,330	4,330
R^2	0.085	0.023	0.20	0.095	0.062	0.020
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y

Differences in communication costs

There may also be within-gender monitoring advantages due to lower communications costs among those of the same gender. In this case, male investors would know that they are worse at adding value to female-led startups because they tend to work less well with female founders.

To explore this possibility, we examine how founder gender relates to cross-gender investor sharing. If male investors generally show less interest in female-led startups due to higher expected communication costs with those of the opposite gender, they should be more likely to share female-led startups with female investors compared to observably similar male-led startups. However, in the first column of Table 9, we find that male investors are still less likely to share female-led startups, even when they are sharing with female investors. Specifically, the outcome variable in this regression is an indicator equal to one if the startup was shared by a male investor with a female colleague. Female-led startups are less likely than observably similar male-led startups to have a male-to-female investor sharing event. Columns 3 and 4 also show that the same female-led startups are more likely than the same observably similar male-led startups to have a female-to-male investor sharing event. Thus, female investors continue to favor female-led startups, even when sharing those startups with male investors. Again, one would expect the opposite if our baseline results were driven by cross-gender communication costs. As we would expect, the results in column 2 show that male investors are also less likely to share a female-led startup with a male colleague. The results in column 3 show that female investors are also more likely to share a female-led startup with a female colleague.

Table 9
Investor sharing with opposite gender.
This table reports investor sharing regressions with an alternative measure of sharing. "Male-to-female" is an indicator variable equal to one if the startup was shared by a male investor with a female investor on the AngelList platform. "Male-to-male" is an indicator variable equal to one if the startup was shared by a male investor with a male investor on the AngelList platform. "Female-to-female" is an indicator variable equal to one if the startup was shared by a female investor with a female investor on the AngelList platform. "Female-to-male" is an indicator variable equal to one if the startup was shared by a female investor with a male investor on the AngelList platform. All fixed effects from Tables 4–6 are included in the regressions. Robust standard errors are reported in parentheses. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	Investor sharing			
	Male-to-		Female-to-	
	Female (1)	Male (2)	Female (3)	Male (4)
Female	−0.0069**	−0.0099***	0.0069***	0.0082***
	(0.0029)	(0.0031)	(0.0018)	(0.0019)
Previous founder	0.026***	0.030***	0.00087	0.0011
	(0.0048)	(0.0052)	(0.0015)	(0.0015)
Bach. degree	0.011***	0.013***	−0.000037	0.00034
	(0.0029)	(0.0031)	(0.00082)	(0.00082)
PhD/MD/JD	−0.0040	−0.00064	0.00074	−0.0012
	(0.0096)	(0.011)	(0.0033)	(0.0029)
MBA	−0.013**	−0.011*	0.0016	0.0012
	(0.0060)	(0.0067)	(0.0022)	(0.0021)
Elite school (any)	0.018***	0.022***	0.0022	0.0038
	(0.0069)	(0.0075)	(0.0023)	(0.0025)
Has traction	0.018***	0.023***	0.0016	0.0036*
	(0.0063)	(0.0067)	(0.0020)	(0.0021)
Attended incubator	0.070***	0.082***	0.0079***	0.0087***
	(0.0073)	(0.0078)	(0.0025)	(0.0025)
Log capital sought	0.0041***	0.0048***	0.00041**	0.00051**
	(0.00075)	(0.00081)	(0.00020)	(0.00022)
Observations	17,780	17,780	17,780	17,780
R^2	0.095	0.11	0.012	0.015
FEs?	Y	Y	Y	Y

5.3.2. Differences in payoff distributions

Another possibility is that investors are unbiased, but female-led startups better align with the risk preferences of female investors, while male-led startups better align with the risk-preferences of male investors (Croson and Gneezy, 2009). For example, female-led startups may offer relatively low expected payoffs but with relatively low variance as compared to male-led startups. In that case, if male investors are more risk tolerant than female investors, they may prefer to invest in male-led startups, while female investors prefer to invest in female-led startups.[26] Of course, since all of the companies in our sample are early stage, they are all quite risky in the sense that they are highly likely to fail without any capital recouped by investors. Moreover, the investors in our sample are all self-selected to be fairly wealthy and risk tolerant.

Nonetheless, to investigate whether gender differences in startup payoff distributions and investor risk preferences drive our results, we examine the correlation between male and female investor interest, holding founder gender fixed. First, we limit the sample to include only male-led startups. We rerun our baseline regressions within this male-led-only sample, replacing the female founder indicator with a female investor interest indicator corresponding to the outcome under study (i.e., an indicator equal to one if the male-led startup was shared by a female investor, received an introduction request from a female investor, or was funded by a female investor, respectively). If male and female investors target startups with different payoff distributions, then we should estimate a negative coefficient on the female investor interest indicator; among male-led startups, those that female investors are interested in should tend to be ones that male investors are not (e.g., the low mean, low variance type) and vice versa. However, as shown in the first three columns of Table 10, we instead find a strong positive coefficient on the female investor interest indicator, significant at the 1% level. This suggests that, holding founder gender fixed, the two groups of investors target startups with similar payoff distributions. We repeat the analysis in the last three columns of Table 10, here limiting the sample to include only female-led startups. The results are similar.

These estimates cannot be driven by male and female investors having opposing payoff distribution targets that are simply dominated by a separate shared objective to invest in "high-quality" startups. Startup quality is embedded in the payoff distribution. Loosely speaking, for an unbiased investor with purely financial motives, a high-quality startup is one with high expected payoffs and low variance. Put differently, an investor with purely financial

[26] If investors are unbiased, it cannot be that female-led startups offer the same expected payoffs with lower variance or higher expected payoffs with the same variance. If that were the case, male investors with solely financial (mean-variance optimizing) motives would prefer these startups as well.

Table 10
Relationship between male and female investor interest.
This table reports the linear probability estimates of male investor interest for startups by each founder gender. In columns 1–3, the sample is limited to male-led startups. In columns 4–6, the sample is limited to female-led startups. The variable of interest “Had female inv. interest” is equal to one if the startup received at least one share, introduction request, or investment round from a female investor, respectively. A unit of observation is a US-based startup on the platform where we can identify the gender of all the founders and where the capital sought is at least \$5,000. All fixed effects from Tables 4–6 are included in the regressions. Robust standard errors reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Male-led startups			Female-led startups		
	Male investors					
	Shared (1)	Introduced (2)	Funded (3)	Shared (4)	Introduced (5)	Funded (6)
Had female inv. interest	0.32***	0.47***	0.11***	0.17***	0.31***	0.065***
	(0.020)	(0.017)	(0.016)	(0.034)	(0.037)	(0.022)
Previous founder	0.030***	0.027***	0.0051	0.0094	0.037	0.0064
	(0.0058)	(0.0091)	(0.0044)	(0.012)	(0.023)	(0.0087)
Bach. degree	0.012***	0.037***	0.0048*	0.010*	0.042***	0.0027
	(0.0036)	(0.0063)	(0.0028)	(0.0054)	(0.013)	(0.0039)
PhD/MD/JD	0.0067	−0.0094	−0.0020	−0.026	−0.019	−0.018
	(0.012)	(0.018)	(0.0092)	(0.020)	(0.042)	(0.012)
MBA	−0.010	−0.0041	−0.0030	0.012	0.035	−0.0056
	(0.0073)	(0.012)	(0.0059)	(0.017)	(0.028)	(0.011)
Elite school (any)	0.018**	0.048***	−0.00040	0.016	0.038	0.022*
	(0.0084)	(0.013)	(0.0062)	(0.015)	(0.027)	(0.013)
Has traction	0.024***	0.088***	0.0062	−0.0019	0.0025	−0.016*
	(0.0075)	(0.011)	(0.0059)	(0.013)	(0.025)	(0.0088)
Attended incubator	0.058***	0.14***	0.057***	0.030**	0.18***	0.0082
	(0.0083)	(0.012)	(0.0073)	(0.015)	(0.027)	(0.011)
Log capital sought	0.0058***	0.0093***	0.0020***	−0.00096	0.017***	0.0015
	(0.00096)	(0.0019)	(0.00074)	(0.0015)	(0.0035)	(0.00096)
Observations	14,959	14,959	14,959	2821	2821	2821
R^2	0.20	0.23	0.069	0.15	0.25	0.051
FEs?	Y	Y	Y	Y	Y	Y

motives should only care about a company’s payoff distribution and should not have a separate, more heavily weighted investment criterion.

Overall, male and female investors tend to agree with one another when comparing observably similar founders of the same gender. However, male and female investors tend to disagree with one another when comparing observably similar founders different genders. This disparity implies that the latter disagreement does not concern risk, but rather is specifically about gender.

5.4. Startup performance

In this section, we investigate investor bias more directly by analyzing the long-run performance of startups that investors pair with. The tests in this section follow Fisman et al. (2017) who examine whether loan officers in India show a preference for within-caste lending due to bias by comparing the ex-post loan performance of within-caste and across-caste loans.

So far, we have shown that investors pair with founders of the same gender with greater probability. If this tendency arises, not due to bias, but for purely financial reasons, we would expect same-gender pairs to also outperform mixed-gender pairs. To demonstrate this, we use a simple conceptual framework illustrated in Fig. 1, Panel A. The figure shows hypothetical performance distributions for startups that an investor may be considering funding. Separate overlapping distributions are assumed for startups with founders of the same gender as the investor and founders of the opposite gender. The distributions shown are identical, except that the same-gender distribution is translated to the right of the opposite-gender distribution. Thus, the same-gender distribution first-order stochastically dominates the opposite-gender distribution, giving rise to the possibility of “statistical discrimination” against founders of the opposite gender. We assume the investor funds startups according to a simple cutoff rule, offering funding to all startups above a certain threshold. Since the investor is unbiased, he or she applies the same cutoff rule to all startups, regardless of founder gender. In this case, because the same-gender distribution first-order stochastically dominates the opposite-gender distribution, the investor will invest in founders of the same gender with greater probability. In addition, expected performance, conditional on funding, will be higher for same-gender investments.[27]

In contrast, if investors are biased, it is possible that same-gender pairs may underperform mixed-gender pairs. Recall that we define bias to encompass both taste-based discrimination as well as miscalibrated beliefs. Fig. 1, Panel B illustrates taste-based discrimination using the same framework. In the example shown, the performance

[27] For simplicity, the distributions in Fig. 1 are assumed to be translations of the same uniform distribution, but the discussion above generalizes to any two distributions, one of which first-order stochastically dominates the other.

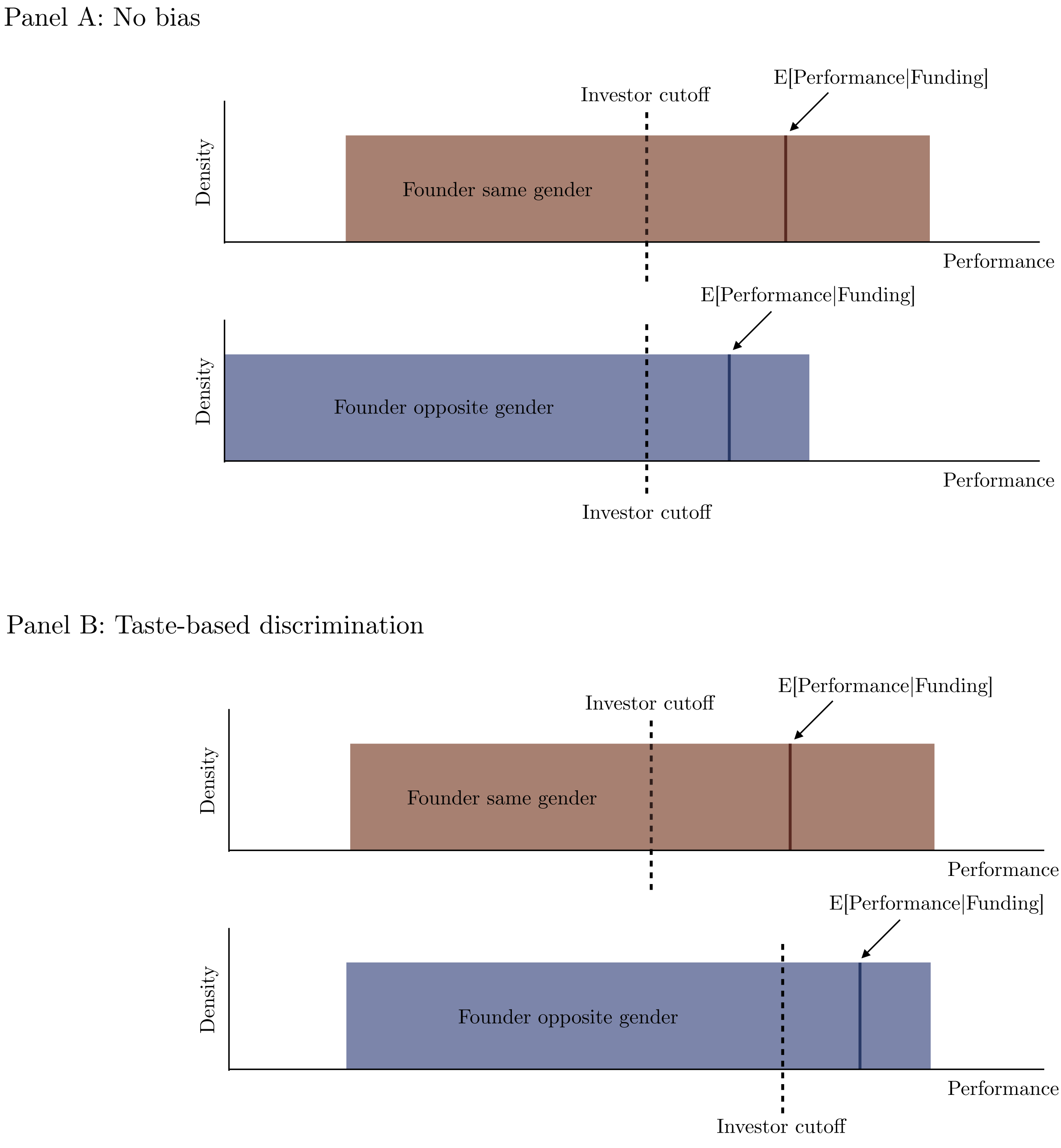

Fig. 1. Long-run startup performance. These figures present hypothetical startup performance distributions combined with investor decision rules under two assumptions. Panel A considers the situation where the investors have no bias, and startups founded by individuals of the opposite gender of the investor underperform their same-gender matches. Investors use the same performance cutoff rule (the vertical dashed line), and the solid vertical lines represent the expected performance conditional on the funding decision. Panel B considers the situation where investors exhibit taste-based discrimination and founders of both genders have the same performance distribution. The taste-based preference leads investors to have a higher cutoff rule (the vertical dashed line) for opposite-gender founders. This, in turn, leads to higher performance outcomes conditional on funding. Panel C presents the situation where investors have miscalibrated beliefs about founders of the opposite gender (see, e.g., Egan et al., 2018). The opposite-gender distribution is shifted to the right because of the miscalibration, which has the effect of increasing the expected performance conditional on funding.

distribution of same-gender and opposite-gender founders is now assumed to be the same. The investor continues to derive utility from startup performance but now also derives disutility from investing in startups led by founders of the opposite gender. As a result, the investor sets a higher cutoff for opposite-gender startups. In particular, the investor will set the cutoffs such that he or she is indifferent between same-gender startups at the "same-gender cutoff" and opposite-gender startups at the higher "opposite-gender cutoff." Thus, with taste-based

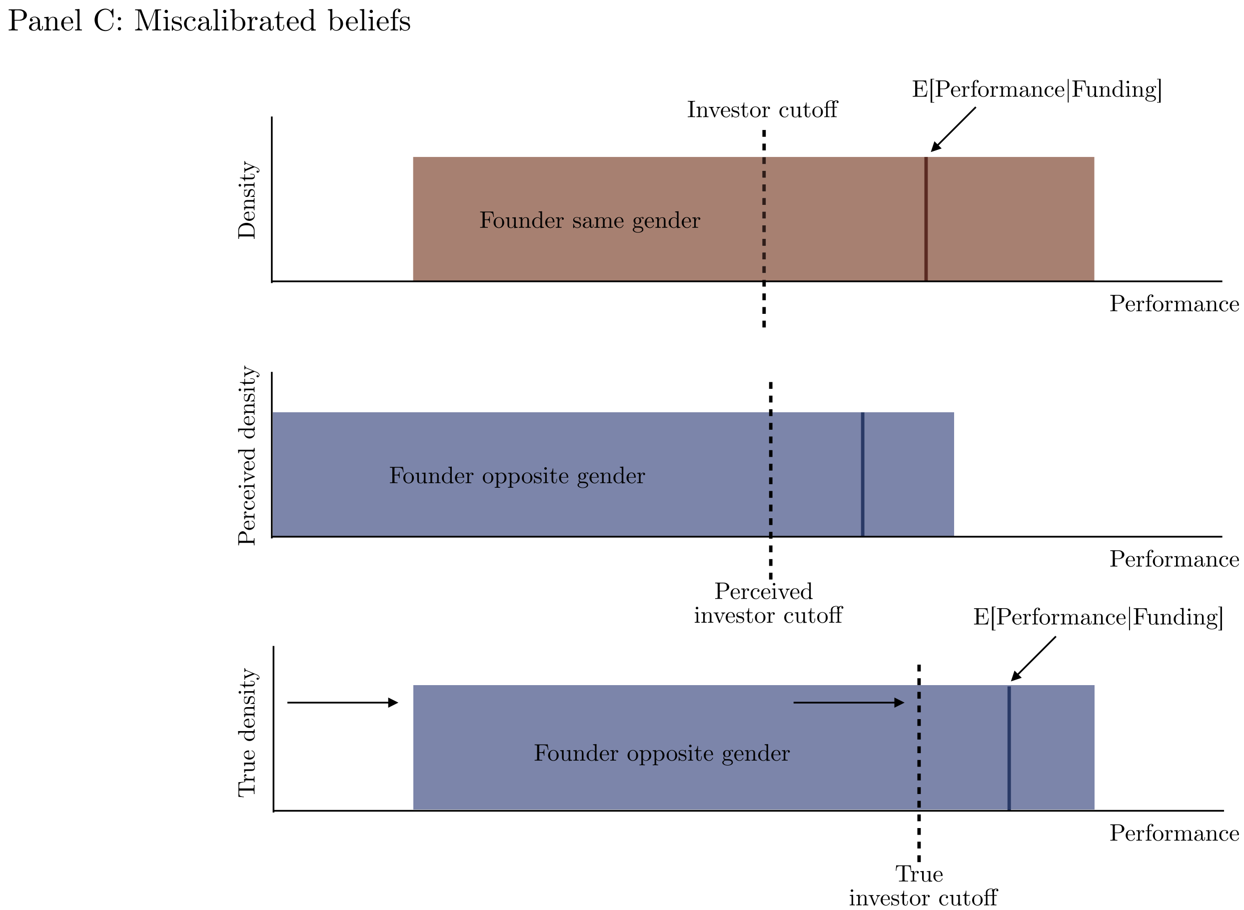

Fig. 1. Continued

discrimination, the investor will again fund founders of the same gender with greater probability. However, now, expected performance, conditional on funding, will be lower for same-gender investments.

Finally, Fig. 1, Panel C illustrates the case of miscalibrated beliefs. Miscalibrated beliefs imply a gap between the investor's perceived performance distribution for opposite-gender startups and the true performance distribution. In the example shown, the investor acts exactly like an investor with no bias according to the investor's perceived performance distribution. However, the investor acts exactly like a taste-based discriminator according to the true performance distribution. Thus, miscalibrated beliefs can also lead investors to fund founders of the same gender with greater probability while having lower (true) expected performance for those investments.

We have already shown that investors fund founders of the same gender with greater probability. Therefore, we next wish to examine whether their performance on these investments is higher or lower than on their investments in founders of the opposite gender. However, as discussed earlier, investment is a two-sided decision. Therefore, if one defines realized investor-founder pairs based on investment, it is unclear whether performance differences are driven by the way that investors select entrepreneurs or vice versa. To get around this issue, we define realized pairs based on investor introduction requests.

As discussed in Section 4.2, we measure startup performance in three ways. First, we examine whether a startup has exited via an IPO or acquisition, which is the standard measure of deal-level performance in the venture capital literature (e.g., Hochberg et al., 2007; Gompers et al., 2010; Ewens and Rhodes-Kropf, 2015; Nanda et al., 2018). Second, we examine whether a startup has failed, based on whether its website is no longer active. Finally, we also examine whether a startup has raised a follow-on round from a VC as an interim measure of startup success. Examining venture capital investment is also important in that it relates to potential concerns that investors may have regarding financing risk. For example, male investors may prefer male-led startups, not due to their own biases, but due to concerns that future venture capital investors may be biased, making it harder for female-led startups to raise subsequent financing rounds and ultimately succeed.

The results are shown in Table 11. Observations are now at the startup-investor pair level, and there is one observation for every realized pair. All regressions include year fixed effects based on the year a startup joined AngelList to address the concern that startups from different cohorts will have differential success/failure rates due to

Table 11
Long-run startup performance.
This table reports linear probability model estimates. A unit of observation is an investor-startup pair, where there is one observation for each pair where an investor requested an introduction to the startup. The variable “Founder same gender” is an indicator equal to one if the founder and investor are of the same gender. In Panel A, the sample is limited to pairs with male investors. In Panel B, the sample is limited to pairs with female investors. In columns (1) and (2) of each panel, the dependent variable is an indicator equal to one of the startup had a successful exit via IPO or acquisition. In columns (3) and (4), the dependent variable is an indicator equal to one if the startup's website is no longer operational. In columns (5) and (6), the dependent variable is an indicator equal to one if the startup raised a follow-on round from a VC. The even columns include investor fixed effects. All controls from Tables 4–6 are included in the regressions. Robust standard errors clustered at the investor level are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Male investors					
	IPO/Acq.		Startup failed		Raised VC	
	(1)	(2)	(3)	(4)	(5)	(6)
Founder same gender	−0.029***	−0.015*	0.063***	0.066***	−0.093***	−0.075***
	(0.0081)	(0.0090)	(0.012)	(0.015)	(0.012)	(0.015)
Observations	10,872	10,872	10,872	10,872	10,872	10,872
R^2	0.060	0.36	0.094	0.37	0.17	0.44
Controls?	Y	Y	Y	Y	Y	Y
Investor FE?	N	Y	N	Y	N	Y
Year FE ?	Y	Y	Y	Y	Y	Y
Industry FE ?	Y	Y	Y	Y	Y	Y
Location FE ?	Y	Y	Y	Y	Y	Y
Team size FE?	Y	Y	Y	Y	Y	Y
	Panel B: Female investors					
	IPO/Acq.		Startup failed		Raised VC	
Founder same gender	−0.0048	0.0050	−0.0036	−0.0096	0.044	0.053
	(0.024)	(0.044)	(0.046)	(0.062)	(0.043)	(0.055)
Observations	791	791	791	791	791	791
R^2	0.098	0.40	0.10	0.38	0.16	0.43
Controls?	Y	Y	Y	Y	Y	Y
Investor FE?	N	Y	N	Y	N	Y
Year FE ?	Y	Y	Y	Y	Y	Y
Industry FE ?	Y	Y	Y	Y	Y	Y
Location FE ?	Y	Y	Y	Y	Y	Y
Team size FE?	Y	Y	Y	Y	Y	Y

their age. The variable of interest, “Same gender,” is an indicator variable equal to one if the founder and investor are of the same gender. We include investor fixed effects in the even columns and therefore compare the performance of same-gender and cross-gender pairs involving the same investor.

In Panel A, the pairs are restricted to those with male investors. We estimate a significant negative coefficient on the same gender indicator in columns 1–2, meaning that the male-led startups that male investors connect with on AngelList are actually less likely to have a successful exit than the female-led startups that they connect with. We also estimate a significant positive coefficient in columns 3–4, meaning that the male-led startups that male investors connect with are more likely to fail than the female-led startups that they connect with. Finally, we estimate a significant negative coefficient in columns 5–6, meaning that the male-led startups that male investors connect with are also less likely to raise a follow-on round of venture capital than the female-led startups that they connect with. This result is inconsistent with a financing risk rationale for favoring male-led startups.

Panel B instead limits the sample to pairs involving female investors. We find that the female-led startups female investors connect with are statistically indistinguishable from the male-led startups they connect with in terms of probability of success, probability of failure, and probability of raising venture capital. Thus, there does not appear to be any evidence that female investors have a lower bar for female-led companies due to bias.

Overall, the fact that male-female pairs outperform male-male pairs would seem to suggest that male investors are reluctant to reach out to startups led by female founders due to bias and therefore only do so for the most promising companies. We do not find a similar pattern for female investors. However, it is possible that we lack power to detect such a pattern, as there are significantly fewer female investors. Thus, we cannot rule out the possibility that female investors are symmetrically biased in favor of their own gender.

If female investors were biased too, one could view symmetric biases as being reflective of homophilistic investor preferences (see, e.g., McPherson et al., 2001). Alternatively, female investor bias could arise as a response to male investor bias—in an attempt to offset it. In either case, given that the bulk of early stage investors are male, biases that lead investors to favor their own gender would be of greater concern for female-led startups than male-led startups. Thus, even with symmetric biases, one

Table 12
Startup heterogeneity: credential discounting.
This table reports linear probability model estimates, repeating the estimations found in Tables 4–6. Two new interaction variables are introduced. In Panel A, "Female X Incubator" is the interaction between the indicator for whether the startup attended an incubator and the female founder dummy variable. In Panel B, "Female X Traction" is the interaction of startup traction and the female founder dummy variable. All controls and fixed effects from Tables 4–6 are included in the regressions. Robust standard errors reported in parentheses. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	Panel A: Incubator affiliation					
	Male investors			Female investors		
	Shared (1)	Introduced (2)	Funded (3)	Shared (4)	Introduced (5)	Funded (6)
Female	−0.0080***	−0.025***	−0.0036*	0.0051***	0.019***	0.0050***
	(0.0029)	(0.0065)	(0.0020)	(0.0016)	(0.0038)	(0.0016)
Attended incubator	0.096***	0.20***	0.071***	0.0076***	0.10***	0.020***
	(0.0090)	(0.012)	(0.0075)	(0.0029)	(0.0087)	(0.0039)
Female X Incubator	−0.060***	0.0093	−0.060***	0.022*	−0.022	−0.012
	(0.018)	(0.028)	(0.013)	(0.012)	(0.022)	(0.0087)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.12	0.18	0.051	0.019	0.093	0.015
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y

	Panel B: Startup traction					
	Male investors			Female investors		
	Shared (1)	Introduced (2)	Funded (3)	Shared (4)	Introduced (5)	Funded (6)
Female	−0.0090***	−0.012*	−0.0061***	0.0066***	0.018***	0.0036**
	(0.0032)	(0.0068)	(0.0024)	(0.0019)	(0.0041)	(0.0017)
Has traction	0.038***	0.11***	0.014**	0.0023	0.026***	0.00026
	(0.0079)	(0.012)	(0.0059)	(0.0024)	(0.0070)	(0.0025)
Female X Traction	−0.042***	−0.083***	−0.032***	0.014	0.0047	0.0040
	(0.016)	(0.029)	(0.0093)	(0.011)	(0.020)	(0.0085)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.11	0.17	0.036	0.016	0.071	0.0090
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y

potential implication of our results is that more female investors may be necessary to support the entry of more female entrepreneurs.

5.5. Startup heterogeneity

In this section, we explore whether the differential treatment of female-led startups that we have documented varies based on startup characteristics.

5.5.1. Credential discounting

Another potential form of investor bias might be the discounting of credentials of female-led startups. Along these lines, Bertrand and Mullainathan (2004) find that employers are less responsive to resume quality for job applicants with African American sounding names. To investigate whether a similar pattern holds in our setting, we reestimate Eq. (1) now including a term representing the interaction between the *Female* founder indicator and variables representing startup credentials. The two startup credentials that we focus on are incubator affiliation and startup traction, as defined in Section 4.5. These credentials are among the most predictive of investor interest in our baseline results.

Table 12, Panel A examines incubator affiliation. Columns 1–3 define the investor interest variables based on male investors; columns 4–6 define these variables based on female investors. In columns 1–3, we estimate a positive coefficient on the uninteracted *Attended incubator* variable, meaning that incubator affiliation significantly increases male investor interest for male-led startups. However, in columns 1 and 3, we estimate a negative coefficient on the interaction term, *Female* × *Incubator*, meaning that incubator affiliation increases male investor interest significantly less for female-led startups than for male-led startups. This suggests that male investors discount incubator affiliation for female-led startups. We do not find evidence of similar discounting by female investors in columns 4–6. Panel B shows similar results for startup traction, suggesting that male investors also discount startup traction for female-led startups, while female investors do not. Overall, these findings are further suggestive of bias by male investors.

5.5.2. Pigeonholing

Yet another potential form of bias might be the pigeonholing of female founders into certain types of businesses. For example, investors may only be interested in female-led startups that are not too ambitious or operate

Table 13
Startup heterogeneity: pigeonholing.
This table reports linear probability model estimates, repeating the estimations found in Tables 4–6. Two new interaction variables are introduced. In Panel A, "Female X Capital (norm.)" is the interaction of the normalized capital sought by the startup and the female founder dummy variable. In Panel B, "Female X % female ind." is the interaction between the percent of female founders in the startup's industry tags and the female founder dummy variable. Specifically, for each industry tag used by fundraising startups on AngelList we compute the percent of the startups using that tag that are female-led. Then for a startup with one industry tag, we use this number to represent how female-centric its industry is. For a startup with multiple tags, we take the mean over all of its tags. All controls and fixed effects from Tables 4–6 are included in the regressions, except in Panel B where industry fixed effects are excluded. Robust standard errors reported in parentheses. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Panel A: Capital sought

	Male investors			Female investors		
	Shared (1)	Introduced (2)	Funded (3)	Shared (4)	Introduced (5)	Funded (6)
Female	−0.016***	−0.018***	−0.011***	0.0086***	0.019***	0.0047**
	(0.0036)	(0.0071)	(0.0026)	(0.0022)	(0.0046)	(0.0020)
Log capital sought (norm.)	0.011***	0.017***	0.0041***	0.00010	0.0061***	−0.00013
	(0.0014)	(0.0028)	(0.0011)	(0.00036)	(0.0012)	(0.00052)
Female X Log capital sought (norm.)	−0.016***	0.0055	−0.0054***	0.0039**	0.0021	0.0046***
	(0.0027)	(0.0054)	(0.0019)	(0.0016)	(0.0034)	(0.0017)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.12	0.19	0.050	0.019	0.095	0.015
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y

Panel B: Percent female industry

	Male investors			Female investors		
	Shared (1)	Introduced (2)	Funded (3)	Shared (4)	Introduced (5)	Funded (6)
Female	−0.031***	−0.043***	−0.016***	0.013***	0.020**	0.0069*
	(0.0067)	(0.014)	(0.0051)	(0.0042)	(0.0088)	(0.0039)
Percent female industry	−0.056**	−0.26***	−0.024	0.0013	−0.030	−0.0015
	(0.026)	(0.048)	(0.020)	(0.0058)	(0.024)	(0.0086)
Female X % female ind.	0.11***	0.20***	0.041*	−0.025*	0.0074	−0.013
	(0.033)	(0.066)	(0.025)	(0.015)	(0.038)	(0.016)
Observations	17,780	17,780	17,780	17,780	17,780	17,780
R^2	0.11	0.16	0.035	0.016	0.071	0.0091
Controls?	Y	Y	Y	Y	Y	Y
FEs?	Y	Y	Y	Y	Y	Y

in female-centric industries. Such pigeonholing may lead female founders to start stereotypically female businesses to avoid any disadvantages with investors relative to male founders starting similar businesses.

To investigate whether female founders are pigeonholed into less ambitious businesses, we re-estimate Eq. (1), now including a term representing the interaction between the *Female* founder indicator and the *Log capital sought* variable. If investors are only interested in female-led startups that are not too ambitious, we would expect this interaction to be negative. In other words, female-led startups should benefit less than male-led startups—and may even be hurt—by trying to raise a larger financing round. The results are shown in Table 13, Panel A. Columns 1–3 define the investor interest variables based on male investors; columns 4–6 define these variables based on female investors. To ease interpretation, we normalize the *Log Capital Sought* variable, subtracting its mean and dividing by its standard deviation. This means that the coefficient on the uninteracted *Female* indicator variable represents the effect of being female-led for a startup raising the average amount of capital. The coefficient on the uninteracted *Log capital sought* variable represents the effect of a one standard deviation increase in log capital sought for a male-led startup. The coefficient on the interaction term, *Female* $\times$ *Log capital sought,* represents the differential effect of such an increase for a female-led startup. In Columns 1 and 3 we estimate a negative coefficient on the interaction term. Moreover, the sum of the coefficients on *Log capital sought* and *Female* $\times$ *Log capital sought* is negative, suggesting that a one standard deviation increase in *Log capital sought* from its mean, increases male investor interest in male-led startups, and decreases male investor interest in female-led startups. These results are consistent with male investors pigeonholing female founders into less ambitious businesses. We do not find a similar pattern for female investor interest in columns 4–6. In fact, we estimate a positive coefficient on the interaction term in columns 4 and 6.

In Table 13, Panel B, we explore whether female founders are also pigeonholed into female-centric industries. To do so, we repeat the analysis of Panel A, replacing the *Log capital sought* variable with a variable representing how female-centric the startup's industry is, *Percent*

Table 14
Investor heterogeneity.
This table reports linear probability model estimates for the dependent variable that is equal to one if an investor ever signaled interest or provided funding to a female-founded startup. The unit of observation is an investor. “Male investor” is an indicator for investor gender, “Log(Experience)” is the the log of one plus the number of current and past portfolio companies reported on the investor’s AngelList profile page and “Silicon Valley” is an indicator for whether the investor in based in Silicon Valley. The variable “Elite school” is equal to one (zero otherwise) if the investor attended any elite school (as defined in Table A1), and “MBA” is equal to one (zero otherwise) if the investor has an MBA. “Investor Join Year FEs” are fixed effects for the year that the investor joined the AngelList platform. “Investor region FE” are fixed effects for the region (as defined in Table A1) where the investor is based. Robust standard errors clustered at the investor level are reported in parentheses. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	Interest in female-led startup				Interest in male-led startup			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male investor	−0.17***	−0.089***	−0.079***	−0.057**	0.12***	0.087***	0.073***	0.066***
	(0.021)	(0.018)	(0.027)	(0.026)	(0.017)	(0.013)	(0.019)	(0.017)
Log inv. experience	0.032***				0.039***			
	(0.012)				(0.0073)			
Male investor X Log inv. experience	0.049***				−0.029***			
	(0.013)				(0.0074)			
Silicon Valley		−0.042				0.13		
		(0.17)				(0.13)		
Male investor X Silicon Valley		0.0068				−0.032		
		(0.032)				(0.020)		
Elite school			-0.044				0.036	
			(0.045)				(0.028)	
Male investor X Elite school			0.093**				−0.049*	
			(0.047)				(0.029)	
MBA				−0.0067				0.022
				(0.047)				(0.030)
Male investor X MBA				0.027				−0.032
				(0.049)				(0.031)
Observations	13,318	13,318	5,558	5,558	13,318	13,318	5558	5558
R^2	0.091	0.057	0.053	0.051	0.022	0.018	0.016	0.015
Investor join year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Investor region FE	Y	Y	Y	Y	Y	Y	Y	Y

female industry.[28] We do not include industry fixed effects in Panel B, as they would absorb much of the variation in *Percent female industry*, making the results difficult to interpret. In columns 1–3, we estimate a positive coefficient on the interaction term, suggesting that female-led startups have less difficulty garnering interest from male investors when they operate in more female-centric industries. These results are consistent with male investors also pigeonholing female founders into female-centric industries. That same pattern is not found for female investor interest in columns 4–6.

In the extreme, pigeonholing of female founders could actually lead women starting stereotypically female businesses to have an easier time garnering investor interest than men starting such businesses. In Internet Appendix Table A8, we examine whether the direction of differential treatment reverses at the extremes. Specifically, we repeat the analysis of Table 13, replacing the continuous variables *Log capital sought* and *Percent female industry* with indicator variables *Low capital sought* and *High percent female industry*, equal to one when the underlying continuous variables are in the bottom or top quintile, respectively. The results in Panel A show that among startups with low fundraising targets, female-led startups are at less of a disadvantage with male investors. In the case of sharing, the sum of the coefficients on *Female* and *Female* × *Low capital sought* is actually positive, suggesting that the direction of differential treatment reverses. However, the sum is not statistically significant. In Panel B, the sum of the coefficients on *Female* and *Female* × *High percent female industry* remain negative or close to zero. Thus, among startups in very female-centric industries, female-led startups are at less of a disadvantage with male investors, but they still do not have an advantage.

5.6. Investor heterogeneity

Finally, in this section, we explore whether the differential treatment of female-led startups that we have documented varies based on investor characteristics. To do so, we change our unit of analysis from a startup to an investor, estimating equations of the form:

$$\begin{aligned} InterestedFemaleLed_i = \alpha + \gamma MaleInv_i + \lambda InvChar_i \\ + \beta MaleInv_i \times InvChar_i \\ + \boldsymbol{\delta}' \mathbf{X_i} + \epsilon_i, \end{aligned} \quad (2)$$

where i indexes investors; *InterestedFemaleLed* is an indicator variable equal to one if investor i shared, requested an introduction to, or funded a female-led startup; *MaleInv*is an indicator variable equal to one if investor i is male; and *InvChar* is some other characteristic of investor i. Given our findings thus far, we expect γ to be negative, as male

[28] Specifically, for each industry tag used by fundraising startups on AngelList we compute the percent of the startups using that tag that are female-led. Then for a startup with one industry tag, we use this number to represent how female-centric its industry is. For a startup with multiple tags, we take the mean over all of its tags.

investors are less likely than female investors to interact with female-led startups. The main coefficient of interest is that on the interaction term, β. If β is estimated to be positive, it would suggest that male and female investors with the characteristic being studied behave more similarly than those without that characteristic.

The results of estimating Eq. (2) are shown in Table 14. In column 1, the investor characteristic that we examine is investment experience. Specifically, we interact the male investor indicator with the log of one plus the number of current and past portfolio companies reported on the investor's AngelList profile page. We estimate a positive and statistically significant coefficient on the interaction term. This suggests that male and female investors with more experience behave more similarly to one another. In column 3, we also find that holding a degree from an elite university diminishes the gap between male and female investors in terms of interacting with female-led startups. In columns 2 and 4, we do not find any evidence that this gap is smaller among investors located in Silicon Valley or among investors who hold an MBA degree. In columns 5–8, we replace the dependent variable *InterestedFemaleLed* with *InterestedMaleLed*, an indicator variable equal to one if investor i shared, requested an introduction to, or funded a male-led startup. As we would expect, the signs flip in this case, but we continue to find that male and female investors with more experience behave more similarly as do male and female investors who graduated from an elite university. These results are suggestive that experience may decrease bias. Assuming that miscalibrated beliefs are more likely to change with experience than taste, this would mean that at least part of the bias we have documented comes from miscalibrated beliefs, while the other part may still come from taste. Of course, an important caveat is that the type of investor who accumulates a lot of experience may also be the type who was less biased all along. Therefore, these results, while suggestive, should be interpreted with some caution.

6. Conclusion

This paper examines whether early stage investors have gender biases that affect their investment decisions. To do so, we use a unique data set obtained from AngelList, which allows us to observe detailed investor-founder interactions for a large sample of fundraising startups, some of which succeed in raising capital and some of which fail. We find that female founders are significantly less successful garnering interest and raising capital from male investors compared to observably similar male founders. In contrast, the same female founders are actually more successful than male founders with female investors. The results do not appear to be driven by differences across founder gender in startup quality, industry focus, communication costs, or risk. Overall, our results are consistent with some form of bias among male investors. In general, we find weaker evidence of bias among female investors, but it is possible that we simply lack power, as there are significantly fewer female investors in our sample. Therefore, we do not rule out the possibility that male and female investors are symmetrically biased in favor of their own gender.

One could view symmetric biases as being reflective of homophilistic investor preferences (see, e.g., McPherson et al., 2001). Alternatively, female investor bias could arise as a response to male investor bias—in an attempt to offset it. In either case, given that the bulk of early stage investors are male, biases that lead investors to favor their own gender would be of greater concern for female-led startups than male-led startups. Thus, even with symmetric biases, one potential implication of our results is that more female investors may be necessary to support the entry of more female entrepreneurs. However, given that early stage investors are often drawn from the pool of former entrepreneurs (Gompers et al., 2005), which at this point is mostly male, the above conclusion gives rise to a "chicken and egg" problem. Thus, policies like the JOBS Act, which promote the democratization of capital by facilitating various forms of equity crowdfunding, may be key to changing the existing equilibrium.

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