Choosing Startup Investors: Does Gender Matter?[*]

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Abstract

We investigate the veracity of the frequent allegation that male founders marginalize female investors, often supported by female investors' anecdotal reports. Using a randomized field experiment framework, we examine the existence, intensity, and distribution of gender-based choices in startup culture. Leveraging the rapid increase in outbound origination, we perform a national field experiment involving 40,572 startups, sending unsolicited emails from fictitious male and female investors. Emails sent by male investors are substantially more likely to be read by startups than emails from female investors. Startups are also more likely to visit the male investor's website and subsequently attempt to make contact. This pattern is more pronounced with angel investors than with VC investors. Disclosing professional certifications increases a male investor's email's likelihood of being read but *reduces* the corresponding female investor's chances. A second experiment, involving a separate sample of 4,836 recently incorporated startups, reveals similar gender-based choices.

Keywords: entrepreneurial finance, startups, investor relations, non-labor discrimination, gender, credentials, investor matching

JEL Codes: G24; G32; M13; J16; L26

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1. Introduction

The shortage of female venture capitalists in the startup ecosystem is a significant issue to academics, policymakers, and business pundits (e.g., Gompers et al., 2021; Rocha and van Praag, 2020), mainly because venture capitalists are typically viewed as gatekeepers for financially constrained startups. A stream of the literature investigates how venture investors choose which startups to invest. Hu and Ma (2021) report that venture investors are more likely to invest in teams that show more warmth and passion in their pitch. Others explore whether investor preferences shape access to venture capital (e.g., Ewens and Townsend, 2020; Hebert, 2018; Zhang, 2020). For instance, Gornall and Strebulaev (2020) report that financiers do not seem to discriminate against female founders.

In contrast, management research documents that female entrepreneurs face more pressure to prevent losses than their male counterparts and that venture capitalists penalize women entrepreneurs more heavily for lack of 'industry fit' (Kanze et al., 2018; 2020). From this viewpoint, investor preferences for founders are likely to be a more crucial channel of discrimination in entrepreneurial finance than founder preferences for investors. If money is genderless, as many perceive, founders' preferences will have a limited impact on their willingness to work or interact with female investors.

However, this typical viewpoint seems at odds with venture capitalists' concerns about capital overhang in the entrepreneurial sector, with VCs competing intensely to garner promising startups (Aberman, 2019). The vast supply and abundant funding sources, coupled with the potential for a greater scarcity of talented human capital relative to physical capital (Murphy and Topel, 2016), put substantial bargaining power in founders' hands when selecting investors (Yuan, 2017). As Sørensen (2007) highlights, the startup-venture investing ecosystem is a two-sided matching process, with founders also selecting investors. A critical concern in this seemingly competitive selection process is that founder preferences could sway it for certain types of investors, potentially perpetuating the lack of diversity among investors in the entrepreneurial sector.

Do founders consider investor gender when evaluating funding sources? The popular press routinely portrays start-up firms with chauvinistic cultures, especially in major tech hubs (e.g., Chang, 2019). One common allegation is that women are sidelined from financing opportunities and discounted by male founders. Are these instances of perceived sexism and media accounts of startups exhibiting a strong "bro culture" merely isolated, sensationalized examples, or are they symptoms of a systemic pattern in tech startups? For the relatively new class of female investors in VC and angel finance, this is of particular interest and raises the question of whether they will struggle to find and seize investment opportunities.

It is, therefore, essential to examine the criteria that founders look at when selecting an investor. Howell and Nanda (2019) emphasize that gender-based differences in the startup-venture investor ecosystem depend on both founders and startups. With monetary financing being less heterogeneous than ideas, detecting discrimination against female investors is a crucial first step in mitigating their potential marginalization from the entrepreneurial sector. Therefore, we investigate the existence, prevalence, and intensity of gender-based preferences in startup culture across the US. More specifically, we question the extent to which founders or their startups use gender in choosing investors— is there a widespread preference for male investors?

We perform a large-scale, randomized field experiment (RFE) of tech startup firms throughout the United States, in which we contrive fictitious female and male investors. We assess startup firms' willingness to engage with either a fictitious female or male investor to evaluate whether these startups favor male investors. Trade press discussions about the rapid emergence of *"outbound origination"* via unsolicited or cold emails by angels and venture capitalists highlight the increasing importance of email communications (e.g., Brown, 2019; Hemmes, 2020; Rodriguez, 2019). Practitioners observe that cold emailing is a high-converting deal flow channel for investors in the startup ecosystem (Rodriguez, 2019). A wide range of venture capitalists incorporates outbound origination in their deal flow strategies. Leveraging this increasingly common deal flow practice, this RFE involves sending an unsolicited email to the email address that each startup provided to potential investors.

Our experiment focuses on two actions of the test subjects with differing costs and aggregate response rates. We compare the view rate, defined as the respondent's decision to *look*, or *not look*, at the email we send using the fictitious male versus a female investor. We also compare the visit rate, i.e., the respondent's willingness to *visit* the fictitious male vs. female investor's website.

This randomized field experiment allows us to answer three specific questions. First, do tech startups have a systemic preference for male investors? It would be surprising that they would, particularly for liquidity or cash-constrained startups. Nevertheless, numerous anecdotal accounts of sexism in the entrepreneurial sector hint at gender bias at work (e.g., Wiener, 2020). Our systematic, large-scale analysis allows us to detect any such preferences.[1]

Second, how prevalent are these gender-based preferences? Are they more pronounced in technology hubs such as Silicon Valley than in the rest of the country? Many anecdotal accounts of sexism in these hubs (e.g., elephantinthevalley.com) raise concerns about them amplifying gender biases. Due to the physical proximity of multiple technology firms, accelerated labor mobility through personal networks is an important characteristic of the technology hubs (Breschi and Lissoni, 2009; Kerr and Robert-Nicoud, 2020). The key role of personal networks in venture capital and startups (Howell and Nanda, 2019) potentially fosters gender-based corporate cultures arising from homophily or prejudice (Agarwal et al., 2016; Hyde, 2016)

Third, what is the intensity of gender-based preferences in tech startups? Preferences regarding certain types of investors could be because of perceived differences in qualifications across types, e.g., between male and female investors. To assess this potential channel, we compare startup gender-based preferences for angel investors versus venture capitalists and between investors with and without professional licenses.

In the randomized field experiments, we send identical unsolicited emails to a sample of recent startups in the Crunchbase database. The only difference is the sender name, randomly varying between (first) names associated with males and females. We use various names, including Jessica Davis, Michael Davis, Linda Miller, Bill Miller, and several others. Crucially, we verify that the (first) name of the sender is available for viewing in the mailbox's tab before the email recipient chooses whether to view the message's content. Our experiment focuses on two responses involving an active choice of the test subjects: opening an unsolicited email and visiting a potential investor's website. The recipient's decision to open the email is a relatively low-cost action, plausibly capturing implicit or unconscious gender preference. The choice to visit the investor's website comes at a higher

[1] All of emails were sent during the COVID-19 pandemic, which potentially limits the external validity of this study. Email communications are more viable during a period of lockdowns than in normal times. Thus, the simulated interaction could be perceived as more normal by founders in this experimental setting than one might think a priori.

commitment cost to the test subject and captures a more explicit or conscious version of gender-based selection

We compute how many unsolicited emails are delivered to the startups' email accounts, opened by the recipients, and followed by a visit to the respective investor's websites. Of the 40,572 emails delivered to startups' email accounts, they opened 31.12% or 12,625 of them. From these opened emails, 2,680 of the respondents (6.61% of delivered emails) visited the investor's website through the link provided in the email. These figures represent relatively higher response rates than email campaigns in other academic studies and marketing campaigns that employ unsolicited financial services contacts. These high response rates support the notion that technology startups are comfortable receiving unsolicited emails from angels and venture capitalists.

In analyzing the response differences to our fictitious male and female investors, we observe widespread evidence of startups exhibiting a substantial preference for male investors, relative to female investors in early-stage, outbound originations. Startups are 23% more likely to open an email from a fictitious male investor than an identical email from a fictitious female investor. Moreover, the more involved decision to visit the investor's website for additional information provides an even starker pattern of gender-based preferences. Startups are 27% more likely to visit a fictitious male investor's website than a fictitious female investor's.

Although male founders make up roughly 90% of the Crunchbase sample, a potential limitation of our RFE is that we do not know the exact identity of the individual controlling the email account each startup provides to potential investors. Since this distinction is relevant to our experiment's validity, we undertake three separate analyses to explore it. First, we evaluate the subset of startups that respond to the unsolicited email by directly contacting our fictitious investors. Second, we focus on the youngest firms in our sample, where a founder is likelier to control the email address supplied to potential investors. Third, we conduct a follow-up experiment, using a separate sample of 4,836 young firms in the Crunchbase dataset, where it is likely that a founder controls the email account.

Media accounts describing this gender-based preference as a "Bro Culture" suggest it is much more prevalent in Silicon Valley and other technology hubs than in secondary financing markets (e.g., Chang, 2019). Tech hubs attract considerable outside talent, creating potentially unique micro-environments that could amplify startup firms' gender-based preferences. To determine if these preferences are more pronounced in tech hubs, we separately analyze the field experiment results for startups located in states with high innovation levels, namely California, New York, and Texas. Startups in the three technology hubs are 21% more likely to view an unsolicited email sent by a male investor and 27% more likely to visit his website, all relative to a female investor. As these rates are almost identical to the respective rates observed for the full sample, the evidence is inconsistent with the hypothesis that technology startups in Silicon Valley have more pronounced gender-based preferences than their counterparts in the rest of the country. The large sample size and high open email rate in this experiment, give the hub tests sufficient power to detect reasonable differences in the technology hubs. In short, we find no amplification of gender preferences in the tech hubs, suggesting their gender bias provides a window into the prevalence of gender bias in technology startups across the country.

These documented preferences against female investors could arise from founders' perceptions about gender-based differences in investor qualifications or their assumptions about female occupations. Although still inequitable to female investors, these statistical discrimination channels provide an explanation that does not imply a distaste for female investors (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). We, therefore, design several experiments to explore potential channels of startup preferences against female investors.

First, we design a component of our field experiment to investigate whether the type of investor, angel investors versus venture capitalists (VC), influences founders' gender-based preferences. Prior literature emphasizes venture capitalists, serving as financial intermediaries, meet the criteria of certifying agents (Hsu, 2004). Consequently, we expect gender-based concerns about investor qualifications will be less pronounced for fictitious investors affiliated with VC than fictitious angel investors. Gender-based preferences should become weaker against female RFE investors associated with VC firms than against female RFE angel investors. Our analysis indicates that a male angel investor has 29% (49%) higher odds of having his email opened (his website visited) than a female angel investor. The corresponding rates are lower for investors affiliated with a VC firm, consistent with VC affiliations mitigating founders' perceptions about gender-based differences in investor qualifications. For example, a male investor experiences a 21% (19%) higher probability of having his email opened (his website visited) than a female VC-affiliated investor.

Another potential channel that we explore is homophily. One approach to exploring this concept centers on examining the subset of founders who actively reach out to our RFE investors via email. Although we did not design our research project to elicit email responses, a little over 1% of the email recipients contacted our fictitious investors. We analyze the correspondence rates conditional on (a) the gender of the RFE investor, and (b) the gender of the startup's email responder. We identify the gender of 451 email responders, typically founders or C-suite executives. We find that male RFE investors receive an elevated response rate from male startup executives.

In contrast, we observe a very minimal difference in female startup executives' response rates, inconsistent with the homophily channel driving our results. Still, the mechanism for our documented gender-based preferences of founders could arise from a general priority for investors similar to themselves and/or prejudice against female investors. Thus, both channels represent a form of gender-based discrimination.

Next, we develop another part of our field experiment to study whether professional certifications or accreditations help female investors overcome gender preferences in startup firms. Notably, startups receiving emails from female RFE investors may immediately assume that a secretary sent them (a form of statistical discrimination). To investigate this potential channel for founders' discrimination, we analyze the presence of professional certifications (such as a lawyer or medical doctor) associated with each investor. Consistent with professional certifications increasing credibility, a male investor with a professional certificate enjoys a slight (7.4%) increase in the likelihood that a startup reads his email relative to the same male investor without professional certification. However, for female investors, we find the exact opposite result. Instead of increasing the likelihood that a startup reads the email or visits the female investor's website, professional certificates *decrease* the probability that a startup reads the email by 28.2% (relative to the same female investor with no certification). While the absolute difference between males and females with professional certificates is interesting, these findings allow us to reject the secretary form of discrimination in our context.[2]

We record the number of emails rejected ("bounced") by each email campaign's cleaned email recipient list. In addition, we also count the number of email recipients who flag each RFE investor's emails as spam. We experience relatively low bounce and spam rates across our experimental email campaigns, making it unlikely that these rejected emails drive our empirical findings.

Decomposing the bounce/spam rates by sender names and comparing them for emails from male vs. female RFE investors reveal no discernible difference in these rates between the two groups. There also does not seem to be any plausible reason to expect that spam email senders are more or less likely to use male vs. female names. A careful search of the literature uncovers no empirical evidence to this effect, particularly in startup financing. The results reported by Gornall and Strebulaev (2020) are also inconsistent with the notion that spam filters of standard email programs and servers systematically screen out emails with female names. Another way to assess the field experiment's external validity is to compare it to observational data on realized financing deals. Prior research documents that male founders are undermatched with female investors and provides evidence against statistical discrimination (e.g., Ewens and Townsend, 2020).

One potential issue is external registration, which assures the researchers observed the experimental outcomes only after developing the hypotheses. Although we internally registered the study with our university's IRB, we did not declare the use of this public database (Crunchbase) with economics or psychology associations. A timeline showing the pre-experiment hypotheses' development is in Appendix 10A, which we can authenticate with time-stamped emails and documents.

We also undertook a follow-up experiment after circulating the first version of the paper, treating the circulation of the study as an external registration. Our main experiment used contact information from the 2019 snapshot of the Crunchbase dataset. Re-accessing the Crunchbase dataset in October

[2] If female and male investors enjoyed differential increases from professional credentials, then a potential concern would be that founders view female doctors as less wealthy than their male counterparts. However, we find those female investors with certification fare worse than female investors without certification, limiting concerns about gender-based wealth differences among lawyers and doctors.

2021, we identify firms incorporated in the last four years who were not present in the 2019 snapshot. This follow-up experiment uses a new naming pair (Connor/Claire Murphy), relies on 4,836 emails to young firms with verifiable email accounts, and receives a 39.6% open rate. This subsequent experiment finds 20% and 9% higher read and visit rates for the male investor than the female one. Focusing on the smallest firms (those with less than 10 employees), we find 22% and 17% higher open and visit rates for the male, relative to the female investor. Once again, we also receive a 20% higher email correspondence to Connor than to Claire. More importantly, 90% of the email correspondences are from a startup founder or a C-suite executive, suggesting that our analysis reflects the gender preferences of an important decision-maker in the firm.

This study makes contributions to several strands of the literature. First, the entrepreneurship literature shows the importance of connections, human capital, and networking in matching early-stage investors and startups (Hochberg et al., 2007; Bottazzi et al., 2008; Kerr et al., 2014). We contribute to this literature by showing that female investors are subject to uneven gender-based preferences in investment rounds across the country and through the startup's lifespan. Our evidence shows that much of this potential gender-based discrimination could remain undocumented, as it occurs in the matching process's pre-contracting phase. Our analysis uses two field experiments to assess startups' preferences in matching with male and female investors, finding widespread evidence of founders' gender-based preference against female investors.

Second, the intermediation literature documents that women are underrepresented in venture capital, financial analysis, and asset management (Gompers and Wang, 2017; Fang and Huang, 2017; Ellul et al., 2020). This paper contributes to the intermediation literature by showing that startups exhibit an overt preference for male intermediaries. Startups' preference for male investors is stronger when facing angel investors or investors with professional certifications. The credentials imparted by the intermediary firm (VC) could act to mitigate gender-based preferences. Combined with the evidence that professional credentials harm female investors but help male investors, the experiments provide evidence of both statistical and taste-based channels. Another salient difference between Angel investors and VCs is the nature of the relationship. With a VC, the founder works with a financial intermediary that may or may not replace the contact person working with the startup. In contrast, with an Angel investor, there is no intermediary. The founders are collaborating with this investor for the duration of their investment in the firm, again supporting a taste-based interpretation.

This study also builds on prior research using entrepreneurial and labor discrimination field experiments. Bernstein et al. (2017) show that investors look at the founder's background more than project projections in funding decisions. In a recent field experiment study, Bernstein et al. (2020) find that receiving funding from a leading VC draws prospective employees' attention, increasing their interest in working for the startup. Bertrand and Mullainathan (2004) find that different names on fictitious resumes receive different employers' responses. This literature generally focuses on how investor and firm preferences affect founders and labor market participants. We contribute to this literature by exploring how startups perceive investors differently based solely on their gender. In contrast to popular media accounts, we do not find that tech hubs amplify these gender preferences relative to the rest of the country. They are the canary in the coal mine rather than bias escalators.

2. Data and Sample

2.1 Crunchbase Data

Crunchbase is an online platform devoted to tech-related news. TechCrunch, the creator and former owner of Crunchbase, is an information platform for companies in the technology sector. Launched in 2007, Crunchbase gives subscribers insight into trends in technology and information of publicly listed and private companies.

The platform provides extensive coverage of startup financing activity. According to its website, Crunchbase collects data via four primary channels:

1. The Crunchbase community allows anyone to sign up and provide information on people and companies. Data is verified via social validation and moderator reviews.
2. An in-house team dedicated to collecting data and maintaining data integrity.
3. Machine learning algorithms used by Crunchbase.
4. The Venture Program, a collaboration with 3,000+ VCs worldwide, in which VCs provide timely updates on their portfolio firms in exchange for API access to Crunchbase data.

The major advantage of using Crunchbase's dataset is its widespread coverage. In early 2019 (when the data for the first experiment was downloaded), Crunchbase had information on 600,000+ companies with 200,000+ financing rounds involving 40,000+ investors. A recent paper concludes that Crunchbase is the leading data source in their coverage of the startup ecosystem, especially in the documentation of investment rounds (Raina, 2019).

An ever-present concern with crowd-sourced data, particularly voluntary disclosure, is potential self-selection bias: people are more inclined to share favorable data from their perspective. In this case, perhaps a serial founder is more likely to disclose past ventures if she reached an IPO or disclose an M&A price only when she is particularly pleased with the outcome. Crunchbase uses several tools to ease this concern, including data verification by the in-house Crunchbase team and the Venture Program.

Crunchbase is widely used by academics, practitioners, and the media alike. Recent citations include a case study taught in a reputable business school (Neumann, 2018), a working paper (Raina, 2019), and a series of media articles in respected publications, including *The New York Times* (Marikar, 2019), *The Washington Post* (Dewey, 2018), and *The Wall Street Journal* (O'Reilly, 2018). As the data is widely used and routinely validated, we feel confident using it in our analysis.

2.2 Crunchbase Samples

We start with the Crunchbase data obtained in 2019 and construct the primary dataset for the first experiment. The dataset contains firm-level observations, with all available information on each firm from Crunchbase, including company name, tech specification class (in which the firm self-identifies its area of operation), location of incorporation, the total amount of investment rounds, funders in each round, and (for VC funders) the name of VC partners connected to the firm. This firm-level dataset comprises the population of startups that we can potentially target in the field experiment. Our first selection criterion is that the startup is incorporated in the US; Crunchbase contains over 100,000 such firms. We then perform a more thorough cleaning of the firms in the dataset. First, we focus only on firms incorporated from 2006 to 2019. Second, we engage an email cleaning service that checks the validity of each company's email address in Crunchbase. This stringent process reduces the failure rate of email delivery in the field experiment. In the end, we are left with 40,572 observations for the first field experiment.

We supplement the first sample with a second, distinct experimental sample of young firms added to the Crunchbase database between early 2019 and late 2021. Specifically, we identify firms incorporated in the past 4 years that were not present in the early 2019 snapshot of the Crunchbase dataset (i.e., added after our first download in early 2019). The email addresses listed on Crunchbase for young, recently added firms are likely to correspond to a decision-maker in the startup. We undertake a similar data cleaning exercise as in the first sample, giving us a separate sample of 4,836 observations for the second field experiment. We also focus on new firms with 10 or fewer employees, comprising 2,963 of the observations in the second sample.

3. Randomized Field Experiment (RFE) Methodology

The objective of our field experiment is to document any differences in startups' response rates to an unsolicited pitch invitation from a fictitious male vs. female investor. We utilize the email campaign technology on WiX's platform to meet this goal. WiX is one of the leading web development websites, allowing users to build pages relatively easily. More importantly, for our purpose, WiX provides a premium-marketing-email campaign feature that enables subscribers to initiate (unsolicited) email campaigns, to track whether the targeted email recipients open the unsolicited email, and whether the recipients subsequently click on the link inside the email.

Before initiating the email campaigns, we pre-clean the list of US-based startup companies that make their email addresses available on Crunchbase. Pre-cleaning the email addresses reduces the number of bounces, allowing for more similar bucket sizes across different experimental treatments.[3] We use a third-party email verification service routinely used by marketing professionals called 'NeverBounce' to verify and validate email addresses.[4]

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[3] Bouncing occurs when an email address is invalid or no longer in use, refuses to accept emails from the sender or automatically sends the message to its spam folder. Avoiding a high bounce rate is one of the best practices included in Wix's guide in running successful email campaigns that comply with Wix's terms of use (https://support.wix.com/en/article/wix-email-marketing-best-practices).

[4] NeverBounce (https://neverbounce.com) is used by various companies, such as Uber, Dell and Yelp.

Using WiX's marketing campaign feature, we send one unsolicited email to each startup's verified email address, indicating that our fictitious sender is interested in investing in their business. We randomly divide our cleaned email sample into multiple groups of target recipients. We send an identical email to each group, but with differences across groups in the following dimensions: the sender's name, certification, and affiliation (VC/Angel network).

We choose commonly used names in the US that would form a clear impression regarding the gender of the sender in the recipient's mind. We choose 'Michael' and 'Jessica', with the same last name: Davis.[5] We further divide the email campaigns into senders with different certifications – the fictitious sender can have either: (1) no certificate, (2) a Certified Public Accountant (CPA), (3) an attorney at law accreditation, or (4) a medical doctor (MD).

We associate our fictitious senders with two different investor groups to control for potentially different response rates to direct and intermediary investors, a fictitious angel investor group, or a Venture Capital firm. Each investor group gets a private, live website URL. We preemptively prime these URLs using a search engine optimization procedure to ensure they are among the top hits when typing the related search terms on commonly used search engines.

Appendix A1 illustrates how each email label for various combinations of the experimental settings would appear in the email inbox of the startup. The email label saliently displays the sender's name, certificate (CPA/Atty/MD; if any), and affiliation (e.g., VC or Angel network) before the recipient opens the email and views its content. The email label provides sufficient and salient information to identify the gender of the sender, which forms a part of the information that the recipient can use to decide whether to open the email. The WiX system captures this action to monitor the performance of email campaigns.

Appendix A2 displays the specific email content of our campaigns, with the sender's name – and hence the sender's implied gender – displayed prominently at the top of the email. It illustrates this same email for different fictitious investors in our experiment; note that all emails contain identical

[5] Michael (100%) and Jessica (99%) have extremely high predictive values for being male and female, respectively, in the US (https://gender-api.com). Furthermore, these two names are the most popular names in the 1980's period (https://www.ssa.gov/oact/babynames/decades/names1980s.html). Davis was the 5th most common surname in that time period according to https://namecensus.com/most_common_surnames.htm.

text. The only differences across the 16 examples are the names of the sender, their professional credentials, and the firm's name. In the body of the message, we introduce our investor and express interest in their business. The text across all emails is the same, and we do not tailor our email to each firm.[6] A large part of our analysis centers on the open email rate. The text of the email is not particularly relevant as this part of the experiment is concluded by the time the recipient observes the text of the email.

Recipients who choose to open the email can click on the hyperlink at the bottom of the email, associated with the 'Check out our website' sentence or the arrow icon. The hyperlink will bring the email recipient to the fictitious investor's website. Each email contains a unique URL extension. The WiX system can identify repeated clicks by the same recipient (using the same unique URL extension) and record these repeated clicks as an individual click.

While WiX does not explain its proprietary tracking system employed to identify email openings, several mechanisms facilitate this technology. First, the most obvious mechanism is to track the hit on each unique URL extension. Second, each email contains images (as seen in the middle of Appendix A2) that are stored on WiX servers. When the email is opened, the recipient's email server sends a request to WiX servers to download these images, allowing WiX to identify which email is opened. Third, each email also contains a hidden image (typically 1x1 pixel) that requires almost no internet bandwidth. Opening the email would trigger a request for that hidden image to be downloaded, allowing the requester to be recorded. These image requests allow email campaign systems to track the IP address of the requesters, facilitating the matching between an email being opened and the website being visited. In particular, even if a recipient decides not to click on the link in the email and, instead, visits the website after searching for our fictitious firm online, WiX can still record the IP address for this unique visit. It also connects the IP address with the requesting images visible or

[6] Deception-based studies balance the benefit and cost of imposing greater costs on test subjects. Ideally, we would like to present the lowest cost options for test subjects in studies based on deception. As such, we are reluctant to customize the email to each firm, given our concern that it would impose a higher cost of building up their expectations about financing for start-up firms. Instead, we rely on WiX technology for tracking email reads and website visits to gauge founder-gender preferences.

hidden in each email.[7]

4. The Primary Field Experiment

We perform our primary field experiment in July 2020, sending the emails in the early morning hours in EDT time (corresponding to late evening hours in PDT time) to ensure that all recipients receive the email message outside normal working hours. We collect the results over the subsequent two weeks. The WiX email campaign technology provides a detailed report of the performance of each email campaign (e.g., all emails sent by Michael Davis, Atty, affiliated with our fictitious VC fund). Appendix A1 displays the number of emails under different scenarios and includes the *delivery rate* (i.e., how many emails are delivered to the inbox).

Our email marketing campaigns consistently receive at least 30% open rates, in line with what WiX views as a successful campaign (Figure 1). Moreover, our campaigns enjoy at least 5% visit rates, which is higher than WiX's corresponding average of 2%–5% across all email campaigns on the platform. Using private-client email lists, academic studies report open rates ranging from 9% to 20% (Balakrishnan and Parekh, 2014; Kumar and Salo, 2018; Sahni et al., 2018). The relative success of our fictitious email campaigners is particularly encouraging, given our prior that (unsolicited) funding offers enjoy a different dynamic from other types of unsolicited contacts, including funding requests. Our evidence provides some prima facie support for the emergence of "outbound" originations via unsolicited or cold emails by angels and venture capitalists (e.g., Brown, 2019; Hemmes, 2020), beyond anecdotal evidence from practitioners' report that cold emailing is one of the top-converting deal flow channels (Rodriguez, 2019).[8]

[7] In line with concerns of user's privacy, common email services such as Gmail, Outlook, and Apple Mail have begun taking steps to prevent email tracking. The default setting in Outlook does not download images to prevent unwanted tracking as well as unsolicited email campaigns (Banjac 2019; Arch 2019). However, the default settings for Gmail and Apple Mail still download images, despite these services allowing users to change this setting on their platforms. There is no reason to believe that the variations in the default settings or actual settings of email services impact the validity of the experiment as it does not seem likely that there is any differential rate in the automatic download of images between our fictitious male vs. female investors. It is important to note that our campaigns are relatively successful, with open and visit rates higher than the averages of typical campaigns hosted by WiX and other academic studies.

[8] One common question is whether founders will respond at all to unsolicited email correspondence. Some take the opposite perspective, predicting that founders will react to almost all unsolicited emails coming from a potential investor.

The investor websites also provide a contact form that interested startups can use to provide contact information and send messages to our fictitious investors. The startups can also directly reply to the unsolicited email message. On aggregate, our campaigns lead to hundreds of emails from startup companies—sharing information regarding their businesses and wanting to learn more about the fictitious investors—with some even trying to set up a meeting. A co-founder or C-suite executive sends around 83 percent of these messages. The correspondence rate of 1.12% to our outbound origination initiative is quite encouraging. Indeed, the correspondence rate is substantially higher at 2.90% among younger startups in our sample (i.e., those founded within the last three years). We discuss these correspondences further in Section 4.4.

We successfully delivered our random emails to a total of 40,572 email accounts in our first field experiment. We first perform a quick visual check of the geographical distribution of startups in our email sample versus the more general Crunchbase sample. The analysis is reported in Figure 2. The figure depicts the fractional representation of each state in our sample on the y-axis and its corresponding representation in the Crunchbase's sample on the x-axis. The observations generally line up on the 45-degree line, with some minimal oversampling in California (CA) and New York (NY). This pattern indicates that observations from specific geographical locations do not oversaturate our RFE sample.

4.1 Primary RFE Results

We start our primary RFE analysis by combining our email campaigns into two broad, mutually exclusive categories: those receiving emails from male RFE senders, and those receiving emails from

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Regardless of the view on the relative magnitude of the response rate, there is little reason to believe this would bias the gender differential result. Studies on investor responses in marketing and data analytics literature report lower email open rates than our study. Their figures are lower than the typical open rate of commercial email campaigns of around 24%, while ours are about twice as high. These benchmarks, highlighted in Appendix Table A9, indicate that our open email rate is relatively high. The high response rates in this study should alleviate concerns about email filter algorithms (Fuster et al., 2020) potentially lowering our response rates and simultaneously biasing our results. Consistent with the notion that opening an unsolicited email reflects the test subject's benefit and cost of the decision, we also find the response rates (opening emails or visiting websites) differ substantially among startups based on their year of incorporation. Panel A of Figure 1 demonstrates the open rate for the oldest firms in our sample (i.e., those incorporated in the first four years) is 28.9%, whereas, for those incorporated in the last four years, it is 38.5%. The difference in visit rates by the startup's age in Panel B is even more striking, with an over 200% increase from the oldest to the youngest firms.

female RFE senders.[9] Table 1 reports each group's average of the following observable characteristics in Crunchbase: the firm's incorporation year, the year that the firm last received funding, and the total funding amount received by the firm. Table 1 also reports the proportion of firms in each group with at least one female co-founder and the proportion of firms with ten or fewer employees. One noteworthy takeaway from Table 1 is that both groups have a large proportion (about 51%) of firms with ten or fewer employees. Sending an email to small startups increases the chance that the unsolicited message reaches a firm's founder or executive. Many of the target recipients likely have only a few employees or consist solely of co-founders. We generally observe similar average characteristics across the two groups, providing an initial validation of our randomized field experiment framework.

Our first analysis focuses on these two groups' differential open and visit rates: startups receiving emails originated from our female and male RFE investors, respectively. We report the results in Table 2. In aggregate, the recipient startups open 31.12 percent of unsolicited emails from our RFE investors. Slightly more than half of the startup firms receive an unsolicited email from female RFE investors, with 28 percent of those emails being opened. In comparison, emails originating from male RFE investors are opened by more than 34.38 percent of the randomly assigned recipients. In order to facilitate subsequent discussions, we calculate the excess probability ratio by dividing the response rate for male RFE investors by the corresponding rate for female RFE investors and subtracting one. A positive value would indicate an over-representation of responses to male RFE investors. In this particular comparison, the excess probability ratio of 0.23 (=34.38%/28.00% minus 1) corresponds to emails from male RFE investors being 23% more likely to be opened by the recipients than emails from female RFE investors.

A similar pattern of gender preferences emerges from examining the visit rate. Startups receiving unsolicited emails from female RFE investors visit the investors' websites at the rate of 5.84 percent.

[9] In our experiments, roughly 50% of the startups receive an email from a female investor, which is substantially higher than the fraction of female investors in the population. Each recipient, however, is unaware of the sampling rate. This sampling approach allows us to obtain robust and reliable estimates for each subgroup of male and female investors, which is the main objective of these experiments. However, if we wanted to use these numbers to describe the aggregate level of gender-preference in the start-up ecosystem, we would need to use population-weighted results.

In contrast, male RFE investors' websites are visited at the rate of 7.41 percent, about 27% higher. These differences are meaningful in terms of magnitude, and they are statistically significant using Pearson's X^2 test at conventional statistical levels.

In the randomized field experiment framework, univariate comparisons provide a sufficiently robust approach to analyzing gender-based preferences by startup firms. Nevertheless, we also perform a logit analysis for each univariate comparison to allow for conditional analysis and control for any potentially spurious correlation across the two samples (despite the absence of any discernible patterns in Table 1). One particular advantage of a logit analysis (relative to probit or linear probability models) is that the excess odds ratios, directly calculated from the logit parameter estimates for the male RFE investor variable, are comparable to the excess probability ratios we employ in the main univariate analysis.[10] We report the corresponding ratios for male investors from the logit analyses of the full RFE sample in Panel B of Table 2: 33% for open rate and 28% for visit rate. In these logit analyses, we cluster each state's errors, effectively treating the same state startups as correlated observations due to common regional economic conditions or labor markets. Despite this relatively restrictive assumption, we find that the gender-based preference for male investors in the pre-contracting (and indeed pre-contact) period is highly statistically significant.

4.2 Primary RFE Results, by Recipient's Locations

Anecdotal evidence has surfaced regarding the poor treatment of women in tech startups, particularly in Silicon Valley.[11] We are interested in answering whether these poor results are isolated events (e.g., only in tech clusters) or a result of a systemic treatment throughout the country. Therefore, the subsequent analysis focuses on the location of the email recipients to detect potential geographical clustering of gender-based preferences for male investors in technology startups.

[10] An alternative to providing excess probability ratios in the univariate analysis is to present excess odds ratios. These would be directly comparable to the logit-based odds ratios in multivariate analysis.

[11] A prominent example is the allegations against Uber's co-founder and former CEO. "Some female engineers have started to speak out on the issue, including a former Uber engineer who detailed a pattern of sexual harassment at the company, setting off internal investigations that spurred the resignation in June of Uber's chief executive, Travis Kalanick." (https://www.nytimes.com/2017/06/30/technology/women-entrepreneurs-speak-out-sexual-harassment.html)

The three states with the highest representations in both the Crunchbase dataset and our RFE sample, as depicted in Figure 2, are California, New York, and Texas. These coincide with three large hubs of tech startup activities, i.e., the San Francisco Bay area (Silicon Valley), New York City (Silicon Alley), and Austin, TX (Silicon Hills), respectively. Analyzing the response rates of startups located in these high-tech areas to our email campaigns helps examine whether the unsolicited, electronic funding offers in our RFE framework are out of place in these high-tech hubs.

One of the main rationales for urban agglomeration is the ease of face-to-face interactions among residents. A common concern in the entrepreneurial sector is the magnitude of information frictions between investors and startups (Howell, 2020), which are potentially lower in the tech hubs. Suppose face-to-face interactions are the dominant channel of startup funding allocations in tech hubs, to the extent that electronic interactions (and particularly unsolicited ones) are not a viable way to reach startups in these hubs. In that case, we should see lower response rates to our RFE experiment in such hubs.

Anecdotal accounts and the business press suggest that gender discrimination is much more pronounced in Silicon Valley and other tech hubs relative to the rest of the country. Pundits often emphasize that the micro-environments of these hubs, due to job-hopping and personal networks, encourage a frat-house-like culture (e.g., Chang, 2019). If tech hub firms have more pronounced gender preferences than other regions, we should see more pronounced gender response rate differences in these three states.

Table 3 repeats the RFE analysis in our first experiment sample, with the sole difference of dividing our sample by firms incorporated in these three states compared with those from the rest of the country. The pattern we observe in this subsample does not support the premise that the unsolicited, electronic-funding offers we employ are ineffective in high-tech hubs. Startups in these three states display slightly elevated response rates: an open rate of 32.76 percent (vs. 31.12 percent in the full sample and 29.57 percent in the rest of the states) and a visit rate of 7.14 percent (vs. 6.61 percent in the full sample and 6.10 percent in the rest of the states).

Our main interest is in the pattern of gender-based preferences in these states. We observe a quantitatively similar pattern of gender preference in these three states, with an excess male probability ratio of 0.21 (vs. 0.23) and 0.27 (vs. 0.27) for open and visit rates, respectively, relative to the full US sample. The logit analyses we report in Panel B also indicate minimal differences between the three states (in aggregate) and the remaining states, which are not statistically significant under formal statistical tests using the X^2 distribution.[12] Analyzing and comparing subsamples has less power than the main specification. Owing to the almost even split in the subsample sizes between Tech hub and non-Tech hub firms in our sample, this comparison is relatively powerful in detecting reasonable differences in gender preferences across two groups. Appendices A3 and A4 give baselines of the minimum detectable differences in founder preferences for male and female investors for and across various subsamples. In both tables, the diff-in-diff between high-tech hubs and non-high-tech hubs does not pass the threshold of minimum detectable differences at conventional significance levels (90% or 95%).

A potential confounding effect in this analysis is that startups operating in tech hubs may have less need to respond to cold emails from potential investors due to greater access to capital from reputable and nearby investors. We isolate two subsamples of startups in tech hubs to explore this possible confounding effect: young startups (incorporated from 2017 onwards) and small startups (with up to 10 employees). These subsamples represent startups that are likely starved for cash and, therefore, would be more eager to communicate with investors regardless of the initial mode of communication. We observe similar patterns in these subsamples. Young startups in tech hubs display an excess male probability ratio of 0.23 and 0.29 for open and visit rates. Similarly, small startups display an excess male probability ratio of 0.26 and 0.33 for open and visit rates.

These patterns indicate that the gender preference in startups is not concentrated in only these tech hubs or even the surrounding areas. The excess probability ratio for the open rate is slightly higher outside of the three states. In other words, gender-based preference in the startup sector is not occurring merely as isolated events in tech hubs; rather, it is systemic across the US.

[12] The high representations of startups in these locations allow us to examine each of these states separately. We, therefore, repeat this analysis for each state separately and report our results in Appendix A5. We observe gender-based preferences in each of the three states.

4.3 Validation Checks

Our results, so far, are derived from analyzing our full RFE sample. One potential concern regarding these analyses is that we do not know the actual identity or gender of the email recipients. To alleviate this concern, we perform two validation checks prior to proceeding with additional analyses.

First, we focus on startups with a small number of employees. In such startups, the unsolicited email from our RFE investors is likely to be received by one of the startup co-founders, who are likely to be male, since approximately 80 percent of startups have all-male co-founder teams. We repeat our main RFE analysis using this subsample of small startups (with ten or fewer employees) in the top portion of Panel A in Table 4. This subsample displays a quantitatively similar pattern of gender preference relative to the entire US sample, with an excess male probability ratio of 0.25 (vs. 0.23) and 0.29 (vs. 0.27) for open and visit rates, respectively. The ratios for startups with a larger or unknown number of employees in the bottom portion of Panel A in Table 4 are slightly lower (0.21 and 0.25). However, the logit analyses in Panel B indicate that these slight differences are not statistically significant.

Second, we classify startups in our sample as either young or old, depending on their vintage year. Firms in different stages of their life cycle will generally have varying needs for funding, which will affect their ability to exercise any taste-based preferences for investor gender. The young startups are more likely to have a decision-maker in the firm controlling the investor-relation email account available on Crunchbase. Moreover, there remains a possibility that older startups are at the stage that they are so established that the chances of them viewing an unsolicited funding email, let alone clicking on the link provided in the email, are too low, rendering these firms unsuitable for our experiments. We, therefore, repeat the RFE analysis separately for the subsample of young firms, defined as firms incorporated from 2017 onwards, and compare it to the subsample of older firms incorporated before 2017—see Table 5.[13]

[13] Another potential approach to investigating the gender of the recipient is to focus on the gender-composition of the founders in the startup. The analysis, presented in the appendix (see Appendix Table A6) indicates that gender bias against female investors is more pronounced in mixed-gender teams than all-male teams.

We observe a quantitatively similar pattern of gender-based preferences to the full sample. Not surprisingly, the open and visit rates are higher for young startups, reaching 38.25% (vs. 31.12% in the full sample, and 30.53% in the subsample of older firms) and 11.52% (vs. 6.61% in the full sample). These higher response rates indicate that younger firms are more open to unsolicited cold emails. Moreover, we continue to observe gender-based preference for male investors in this subsample of firms with potentially higher funding needs, with positive male excess probability ratios for open and visit rates of 0.26 and 0.33 at the top portion of Panel A in Table 5.

The differential response rates by startup age also highlight the recipients' costs in reading unsolicited emails and visiting the websites of our fictitious investors. Figure 1 displays the open and visit rates by the startup's incorporation year for our primary sample (the yearly averages and for male and female investors separately). The open rate ranges from less than 28% in the oldest firms to over 35% in the youngest firms. Unsurprisingly, the visit rate varies, depending on the startup's age, increasing from less than 3.5% in the oldest firms to over 12% in the youngest firms. The significant age-based slopes for these response rates indicate that both capture costly decisions, with the website visit reflecting the more costly action.

We use an alternative measure to capture each firm's marginal benefit in reading unsolicited emails and visiting the websites of our fictitious investors: the date of the last round of funding received by the firm. We then separate firms into two mutually exclusive categories: (1) those who received their last round of funding in 2017 onwards and (2) those receiving their last funding round in 2016 or earlier. We observe two related patterns. First, recently funded firms are more responsive to our RFE investors: almost 40% read rate and almost 10% visit rate for those firms, vs. approximately 30% and less than 6%, respectively, for firms receiving funding earlier. This indicates that firms facing more binding capital constraints are more likely to respond, consistent with the cost-benefit tradeoff associated with responding to unsolicited funding offers. Second, recently funded firms display less pronounced bias against our female RFE investors, particularly in terms of visit rate, which represents a more costly action for the email recipient. This indicates that the need for financing may reduce an inherently strong bias against female investors, potentially suppressing their underlying taste function. We report these results in Appendix Table A7.[14]

4.4 Statistical Discrimination?

The documented lower response rates to female RFE investors could arise from founders' perceptions of gender-based differences among (actual) investors. This perceived differential could form an entirely rational explanation for statistical discrimination against female investors (Phelps 1972; Arrow 1973; Aigner and Cain 1977). While statistical discrimination is still inequitable to individual investors (since the group's average characteristics may not translate to specific individuals in the group), we investigate three potential channels of statistical discrimination: fund affiliation, investor qualifications, and email legitimacy.

We explore the first two channels within the context of the randomized field experiment framework. First, our RFE framework includes a combination of fictitious investors affiliated with venture capital (VC) funds and fictitious investors who are acting as angel investors (affiliated with an angel investor network). The former would be perceived as professional investors or intermediaries who manage other investors' investments, whereas the latter would be perceived as direct investors. We exploit this differential, arguing that serving as a financial intermediary, even in a non-brand name VC, requires having other people trust you with their money. Becoming an angel investor simply requires that you have money and does not provide the same level of certification as a VC.[15] Second, our RFE framework also includes a combination of some fictitious investors endowed with professional qualifications (and indicate them in the unsolicited email campaign) and the remaining investors who indicate no professional certification in their email campaign. As both fund affiliation (VC) and professional certification are earned externally, these costly signals should work to attenuate

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[14] We can also compare the results across technology sectors. In Appendix A8, we compare the results in sectors with high and low female representations. The founder-gender preference arises in the sectors with both high and low female representations. However, the effect is more pronounced in low female participation sectors, using both email open and website visit rates.

[15] If our investors had pretended to be affiliated with a very well-known VC firm, it is highly plausible that we would have observed much higher response rates for both male and female investors. Drawing on our results on the effects of various types of certification, it seems plausible that gender-based differences in response rates would be even more pronounced for a name-brand VC.

the perceived differences between our male and female RFE investors (Deming et al., 2016). As such, we expect that the startup firms' gender-based preference for male investors would be weaker for investors endowed with VC affiliations or professional qualifications.

Table 6 reports the results from our RFE analysis after separating the sample based on the fictitious investor's VC affiliation. We differentiate between VC-affiliated and Angel investors using the firm's name, which is observable in the name line to the reader (see Appendix A2). The text of the email is identical for both groups. The top portion of Panel A in Table 6 reports angel (i.e., non-VC) investors, whereas the bottom portion reports VC-affiliated investors. As predicted, we observe a stronger pattern of gender-based preference when startups receive emails from angel investors, with an excess male probability ratio of 0.29 (vs. 0.23 in the full sample, and 0.21 for VC-affiliated investors) and 0.49 (vs. 0.27 in the full sample, and 0.19 in the VC sample) for open and visit rates, respectively. This elevated gender-based preference against female angel investors is verified in the formal statistical tests reported in Panel B of Table 6.

These results are consistent with VC affiliation reducing gender-based preferences faced by female investors. However, they may also be consistent with a "female secretary" hypothesis, in which an email from a female individual working for a VC fund is assumed to be sent by a female secretary who may be a conduit of a male individual who is assumed to be the material decision-maker, and, therefore, receive a similar treatment to an email from a male individual working for a VC fund. We devised our next test to provide some additional evidence with regard to this secretary hypothesis. Nevertheless, it is important to note that gender-based preference persists even for the VC investor sample.

Table 7 reports the results from our RFE analysis after separating the sample based on whether the RFE investor discloses having a professional qualification: a Certified Public Accountant (CPA), an attorney at law (Atty), or a medical doctor (MD). Panel A reports the results for the RFE investors who include their qualifications on the email (both in the "From:" field and the body of the email). To focus on the qualification effect in this analysis, we eliminate one source of variation from our analysis, i.e., the investor's name. We include only email campaigns using two names: Michael and Jessica Davis.

We observe a stronger pattern of gender-based preference in the sample of investors with a professional qualification, with an excess male probability ratio of 0.45 (vs. 0.23 in the full sample) and 0.62 (vs. 0.27) for open and visit rates, respectively. This pattern stands in stark contrast relative to the bottom portion of Panel A, which reports the results for the same RFE investors who do not carry any professional qualifications. Indeed, for this pair of names, the preference against female investors is observed only in the subsample with professional qualifications. These patterns indicate that gender preference is exacerbated—rather than mitigated or eliminated—against women with professional certifications across the US. In other words, female investors experience a *negative* return on this type of credentials. Appendices A3 and A4 demonstrate that the gender-credential effect is at least 5x the respective minimal detectable effect at conventional significance levels.

The negative return to credentials for females may be particularly relevant for female individuals associated with VC funds. An email from a female individual who works for a VC fund *and* has a professional certification (CPA/Atty/MD) is less likely to be assumed as coming from a female secretary. It may receive worse treatment than a similar email from an otherwise identical female individual working for a VC fund that does not have (or disclose) a professional certification and, therefore, could be assumed to be a secretary and a potential conduit for a male decision-maker. In contrast, the credential hypothesis predicts that the presence of professional certification, particularly in the VC setting, would mitigate any gender-based preference from startups. We repeat the analysis in Table 7 in the sample of investors affiliated with VC funds to examine these competing hypotheses.

The results reported in Table 8 indicate that the return to professional certifications continues to be harmful to female investors affiliated with VC funds. A female VC-affiliated RFE investor is about 20 to 35 percent less likely to receive a response from startups if she has a professional certification than if she does not have or disclose one. Appendices A3 and A4 show the certificate carrying results for the VC investor sample are above the minimum detectable open rates, at 95% significance level for open rates in Appendix A3 and at 90% significance level for visit rates in Appendix A4, while the no certificate results are indistinguishable from zero in both Appendices.

In summary, while the entity-based credentialing channel (i.e., the VC fund affiliation) positively reduces gender-based preferences, the individual-based credentialing channel (i.e., a professional certification) does not substitute or complement the entity-based mechanism. Instead, the individual credential seems to hurt female individuals in the entrepreneurial sector.

None of these tests provides evidence consistent with the statistical discrimination channel. Instead, this series of tests provides evidence against statistical discrimination in aggregate. Statistical discrimination arguments range from the idea that founders use gender to proxy for some deficient, unobservable attributes to the notion that startups view credentials as providing less information for women due to signal error or bias (Bertrand and Mullainathan 2004). The latter group of statistical discrimination models predicts lower, positive returns to professional qualifications for women relative to men. Yet, this paper documents strong, *negative* returns to professional certifications for women, even in the presence of another type of credential.

4.5 Direct Correspondence

Although our tests were not designed to generate email correspondence, several startups did reach out to our fictitious investors. In our first experiment's last set of analyses, we analyze the direct correspondence initiated by the startups receiving unsolicited emails from our RFE investors. In particular, we examine the correspondence rate, i.e., the rates at which email recipients respond to the unsolicited email contact by directly contacting our fictitious RFE investors, based on the gender of the RFE investors. This analysis allows us to perform an additional validity check of our RFE framework and explore homophily as a potential channel.

One potential concern with our framework is that we cannot identify the actual recipient of the emails sent by our RFE investors, i.e., the exact identity of the individual controlling the email account that each startup provides to potential investors. While we find evidence of gender-based preferences in the sample of startups in which the email recipient is more likely to be one of the founders, i.e., startups with fewer than ten employees (which is the smallest firm category in Crunchbase) as well as the youngest startups in the sample (e.g., firms founded within the last three years), our analyses, so far, do not provide any direct evidence regarding the actual recipient. Examining direct contacts allows us to explicitly observe the gender of each respondent, as well as their position in the startup, e.g., founders or C-suite executives.

In aggregate, our RFE campaigns lead to hundreds of emails from startup companies – sharing information regarding their businesses, expressing genuine interest in our investors, and many trying to set up a meeting to learn more about the fictitious investors. The basic summary of these direct correspondences is provided in Table 9. Of the 552 email messages received by our investors, 458 (around 83 percent) are sent from material decision-makers in the firm (founders or C-suite executives). This corresponds to about a 1.12% response rate, which is not trivial since our outbound origination initiative is quite rudimentary by design: we completely automated the email campaigns, devoid of any identifiable or personalized information regarding the recipient's business; while our investor websites are almost barren, vacant from any valuable information on the investor's portfolio firms, past investments, etc. Nevertheless, a careful read of the vast majority of emails received by these investors conveys a high level of interest from startup founders and executives, many of whom are anxious to make our investors' acquaintance and send their pitch decks. The response rate is substantially higher for young startups. In the sample of startups established in 2017 or after, we observe a response rate of 2.90%, consistent with these young startups needing more funding.

We next calculate the corresponding response rates conditional on the gender of the RFE investor. After searching for the email responders on Google and LinkedIn to identify their gender, we can ascertain the gender of 451 email responders (out of 458), of which 395 are male recipients and 56 are female. Table 9 reports the results of the gender-based analysis, indicating that the response rate is elevated for male RFE investors, particularly from male founders/C-suite executives. In contrast, we observe a very minimal difference in the response rates of female founders/C-suite executives, inconsistent with the homophily channel driving our results. We observe similar patterns among young startups (startups established in 2017 or after); their correspondence rate with male RFE investors is 3.12 percent, whereas their correspondence rate with otherwise identical female RFE investors is 2.69 percent, more than 15% lower than that of male investors.

5. The Follow-up Experiment

Our primary experiment uses the contact information from the 2019 snapshot of the Crunchbase dataset. We conduct a follow-up experiment focusing on recent startups appearing in the 2021 snapshot of the Crunchbase dataset. This second experiment offers several advantages. First, young firms that are recently added to Crunchbase are likely to be resource-deprived, which suggests a greater need for external financing. Second and relatedly, these new startups are apt to assign the investor relation email account (recorded on Crunchbase) to an important decision-maker in each firm. Third, this follow-up experiment offers a new naming pair in a different time period to validate the primary experiment.

Accessing the Crunchbase dataset in October 2021, we identify firms incorporated in the last four years—but who were not present in the 2019 snapshot. These 4,836 young, newly added startups on Crunchbase comprise the subjects for our second experiment. We sent an unsolicited email to each of these firms in November 2021. We observe a higher open rate by these new firms than the corresponding rate in the first experiment (36.9% versus 31.1%), consistent with the notion that these young firms provide a good laboratory for our analysis. Panel A of Table 10 reports the results, revealing that over 40% of the emails from the male investor are opened, relative to only 33.6% for the female investor. We calculate the excess probability ratio of 0.20 (=40.15%/33.60% minus 1), which corresponds to emails from the male RFE investor being 20% more likely to be opened by the recipients than emails from his female counterpart. We find a similar pattern in the visit rate, although the magnitude is lower. Startups receiving an unsolicited email from Claire Murphy visit her website 7.82 percent of the time. In contrast, 8.56 percent of the recipients visited Connor's website, about 9% higher than Claire's.

In Panel B, we explore the 2,963 startups in the new experiment with 10 or fewer employees. The open rate among these young, small firms is 44.26% for the male investor, which falls to 36.33% for the female investor. This corresponds to startups having a 22% higher likelihood of opening Connor's email than Claire's. Young, small startups are also 17% more likely to visit the website of the male investor relative to the female investors. Power calculations in Appendices A3 and A4 show that this second sample has limited power in detecting gender-based response differences relative to the primary sample; significant differences are detected for open rates (A3) but not for visit rates (A4).

Table 10, Panel C combines the observations from both experiments for all firms incorporated from 2017 onwards. This gives us an aggregate sample of 7,908 observations of young startups. Young startups are 22% more likely to view an unsolicited email sent by a male investor and 20% more likely to visit his website than his otherwise identical female counterpart. Adding the second experiment increases the power of the tests substantially for detecting differences among young firms (Appendices A3 and A4). Similar to the analysis in Panel B of Table 5, we also conduct a multivariate analysis, including location and year-fixed effects. In untabulated results, we observe a 34% higher open rate and a 19% higher visit rate for male investors than female investors in the multivariate analysis.

6. Conclusion

Do founder preferences for investors pose a significant barrier to female participation in entrepreneurial finance? The traditional view is that while investors discriminate against female founders, it is unlikely that founders would be biased against female investors when raising capital for their startups. Yet, female investors report that they feel ignored and snubbed from investment opportunities in tech startup firms. A prominent incident occurred in the nationally broadcast television series 'Shark Tank' in which founders pitch their ideas to a panel of investors, including Laurie Greiner. In one episode of the show (S6.11), she called out a male founder, saying: "Why are you ignoring me? … I feel like you don't respect me as a female sitting here. I sense some chauvinism here…" This perspective suggests that female investors in VC and angel finance face a substantial hurdle to finding investment opportunities if the "boys club" known in the investor world also exists on the founder side.

We undertake a large-scale, randomized field experiment focusing on founders' gender-based preferences in funding sources. We send emails to more than 40,000 startup companies, displaying an interest in their business, focusing on whether the founder/startup opens the email or visits the investor's website. We randomly sort the sender's identity, delivering identical unsolicited emails from either fictitious male or female individuals, either working in a VC or as an angel investor, and either holding or not holding different professional qualifications.

We use several approaches to ensure and evaluate our experimental approach's validity for this research question. We first seek to legitimize our investors before sending out the emails by building unique websites and promoting them using search engine optimizations. The resulting response rates from startups in our experiments are 300% to 400% higher than those in studies in the VC space that focus on investor responses. Presumably, the cost of opening an email is similar for investors and founders, which suggests that this is an especially relevant approach for evaluating founder preferences. Our aggregate response rates differ substantially among young and old startups, by investor credentials, and among firms that appear capital constrained. Taken together, our results indicate that founders/startups took these unsolicited emails seriously, with substantial variations based on a startup's financing needs and the relative attractiveness of the investor to the startup.

The analysis provides compelling evidence that technology startups prefer male investors across the US. Startups are substantially more likely to read unsolicited emails, visit their websites, or subsequently reach out to fictitious male investors relative to female investors. Technology startups are 27% less likely to pursue deals from fictitious female investors than male investors in these early-stage contacts about funding opportunities. While popular press accounts suggest gender bias in startup culture is especially problematic in Silicon Valley, this seems to be merely a function of the sheer volume of startups in the region. We find California (including Silicon Valley) to be on the lower end of the startup gender preference spectrum. Gender preferences by startups in other technology hubs also do not seem to be amplified relative to other locations across the United States.

Gender preferences displayed by startups could be because of founders' concerns about female investor professionalism. Differentiating between angel and venture capital investors, we find that the preference for male investors is more pronounced for angel investors. This preference is consistent with VC affiliation reducing founders' concerns regarding female investor professionalism. Nevertheless, we observe that the preference for male investors remains even for VC-affiliated investors, indicating that the inherent preference against female investors is not eliminated by professional affiliation.

Another related channel for these gender-based preferences is that startup founders who receive emails from a female individual may assume they are from a secretary (which is also a form of discrimination). The final portion of the RFE centers on professional credentials. Unsurprisingly, professional certifications, such as an attorney, are associated with more interest from startups for male investors. Perhaps the most striking finding of the analysis is that the exact opposite holds for female investors. Startups are substantially less interested in funding from female investors with professional certifications than women without such certifications. These results provide evidence against the premise that the patterns we observed arise merely from founder assumptions about the occupation roles of males and females.

Taken as a whole, our evidence implies that female financiers face substantial impediments and are often overlooked by male founders in early-stage contacts. This barrier impedes the crucial role that female financiers could play in the startup ecosystem. In particular, Philippon and Reshef (2012) document that corporate finance activities associated with the valuation of new firms relating to new technology or business models have fueled the growth of the financial sector as a high-skill, high-wage industry. While female participation in financial intermediaries has not always been appreciated by investors (Niessen-Ruenzi and Ruenzi, 2019), higher involvement of women in startup financing (particularly in the context of VC) is often championed as a solution to the lower startup capital that female founders receive relative to their male counterparts (Greenberg and Mollick, 2017; Ewens and Townsend, 2020; Kanze et al., 2020). Our large-scale, experimental evidence of founders' gender-based preference in selecting potential investors implies that these calls for more female intermediaries are only a partial solution in addressing the systematic patterns of "bro culture" in technology startups across the US.

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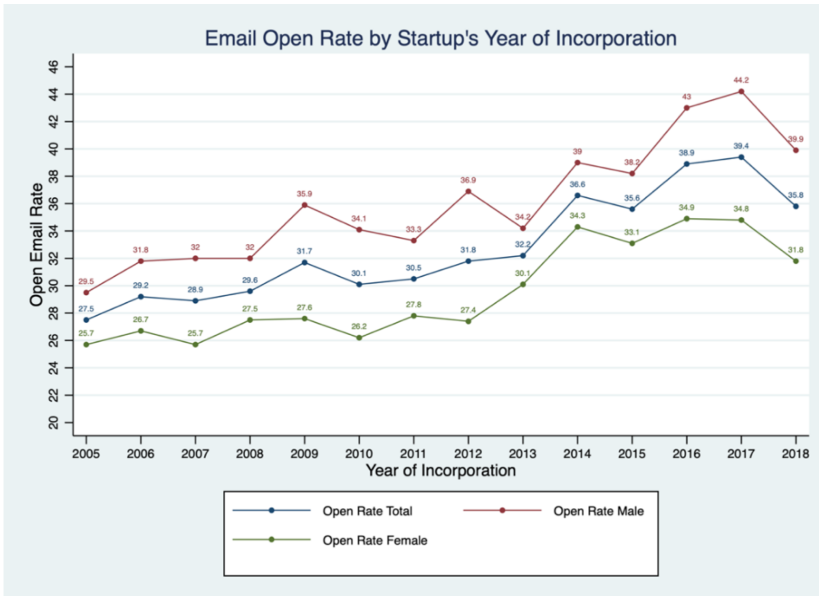
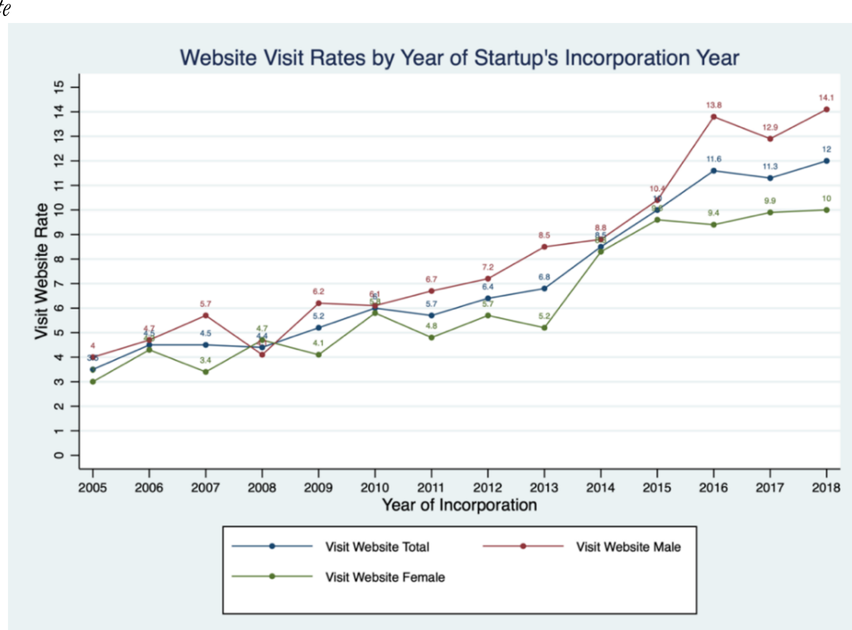
Figure 1: Startup Response Rates, by Year of Incorporation

Panel A depicts the average rate of email opening by the startup's year of incorporation. Panel B depicts the average rate of website visits by the startup's year of incorporation.

Panel A: Open Rate



Panel B: Visit Rate



<u>Figure 2: US State Representation in RFE and Full Sample</u>

This scatterplot depicts the representation ratio of each state and Washington DC in the Crunchbase database, against the sample included in our RFE experiment, together with a 45-degree line.

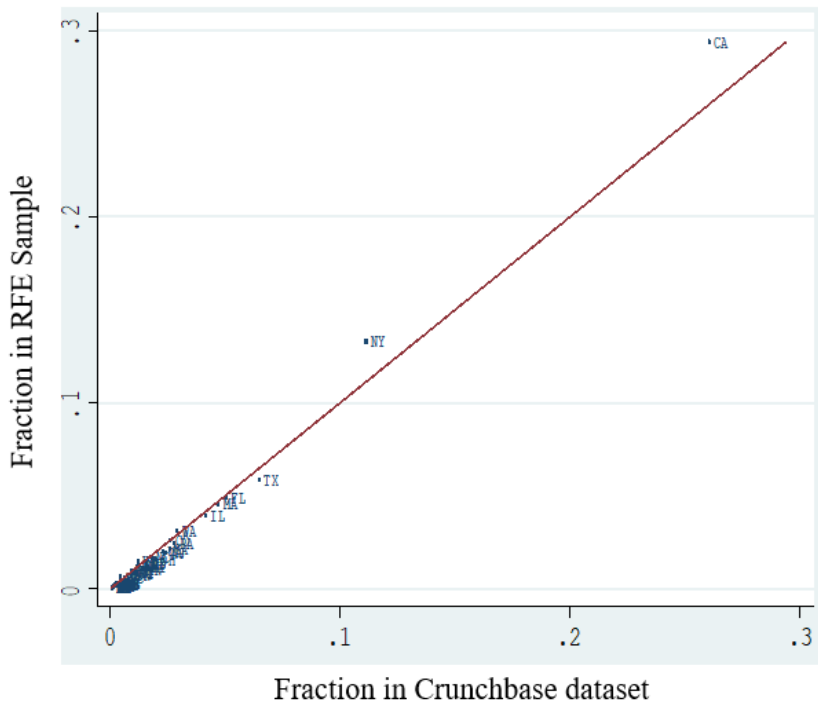


Table 1: Summary Statistics

The following table provides the summary statistics for our primary experiment. This table reports the summary characteristics of firms in our primary RFE sample, segregated by whether they receive an unsolicited email from our male or female RFE investors. We report the total number of observations for each group (at the top) and the number of observations with valid data for each characteristic next to the average value of that characteristic. We also report the difference in means, along with the corresponding t-stat.

	Male RFE Investors (N = 19,830)		Female RFE Investors (N = 20,742)		Diff
	#Obs	Mean	#Obs	Mean	(t-stat)
Firm Incorporation Year	15,706	2012	16,266	2012	0.002
					(0.052)
Last Funding Year	6,809	2016	6,902	2016	-0.006
					(-0.131)
Total Funding Received	5,020	$9.9 Mill	5,109	$9.3 Mill	$0.59 Mill
					(0.723)
All Male Co-Founders?	8,346	0.80	8,503	0.79	0.008
					(1.330)
Ten or Fewer Employees?	16,823	0.51	17,495	0.51	0.000
					(0.159)

Table 2: Primary RFE Sample

This table reports the full sample of observations in the primary RFE analysis. Panel A reports the number of entrepreneurs who receive an email from the RFE investors of each gender and the number of those who open the email and visit the corresponding website of each investor, respectively. The percentage of email recipients who opened the email and visited the website is reported in parentheses under each corresponding number. We calculate the Male-to-Female probability ratio of each set of corresponding percentages and subtract 1 from the ratio. A positive value can be interpreted as an over-representation of responses to male RFE investors. We report the Pearson's X^2 test result at the bottom of Panel A. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients, relative to female RFE senders'. These excess odds ratios are estimated using logit regression models with various indicator variables. The main indicator variable is that the RFE Sender is Male. The parameter estimates for other indicators variables are suppressed to conserve space; they include: whether the RFE sender is affiliated with a venture capital (VC) firm, RFE sender's certificate (one for each certificate type as well as no certificate), firm's state location fixed effects (one for each state and Washington DC), firm's employee size fixed effects (one for each size category on Crunchbase: 1-10 employees, 11-50, 51-100, 101-250, 251-500, 501-1,000, 1,001-5,000, 5,001-10,000, more than 10,000, and unknown), and firm's incorporation year fixed effects (one for each vintage year). The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: RFE Observations

	Full Sample (N=40,572)			
	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female-1)	All Obs.
Received Email	19,830	20,742		40,572
Opens Email	6,817	5,808		12,625
(% of Receiving Email)	(34.38%)	(28.00%)	0.23	(31.12 %)
Visits Website	1,469	1,211		2,680
(% of Receiving Email)	(7.41%)	(5.84%)	0.27	(6.61%)

Pearson's X^2 test [1] = 101.873 (0.000)

Panel B: Logit Analysis

	(1) Opens Email	(2) Visits Website
RFE Sender is Male	0.33***	0.28***
	(15.03)	(6.94)
RFE VC indicator	✓	✓
RFE certificate FE	✓	✓
Firm location state FE	✓	✓
Firm employee size FE	✓	✓
Firm incorporation year FE	✓	✓
Observations	40,572	40,563
Pseudo R^2	0.0268	0.0341

Table 3: Primary RFE Results – Recipients in Different Locations

This table reports the primary RFE results after separating the sample of recipients based on their location: US states with major Tech Hubs (California, New York, and Texas), and the remaining US states. Panel A reports the number of entrepreneurs in each group of states who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each group of states, relative to female RFE senders'. We control for other indicators variables similar to Table 2, except for the firm's state location fixed effects. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. We also report the formal statistical test result comparing the parameter estimates for "RFE Sender is Male" across the two groups of Tech Hubs vs. Not Tech Hubs. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Tech Hubs vs. Non-Tech Hubs

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Tech Hubs (CA/NY/TX) Combined (N=19,671)				
Received Email	9,607	10,064		19,671
Opens Email	3,460	2,984		6,444
(% of Receiving Email)	(36.02%)	(29.65%)	0.21	(32.76%)
Visits Website	770	634		1,404
(% of Receiving Email)	(8.01%)	(6.30%)	0.27	(7.14%)

Pearson's X^2 test [1] = 46.713 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Non-Hubs (Rest of States) Combined (N= 20,901)				
Received Email	10,223	10,678		20,901
Opens Email	3,357	2,824		6,181
(% of Receiving Email)	(32.84%)	(26.45%)	0.24	(29.57%)
Visits Website	699	577		1,276
(% of Receiving Email)	(6.84%)	(5.40%)	0.27	(6.10%)

Pearson's X^2 test [1] = 55.783 (0.000)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	0.32***	0.35***	0.27***	0.29***
	(8.09)	(10.52)	(4.58)	(4.75)
RFE VC indicator	✓	✓	✓	✓
RFE certificate FE	✓	✓	✓	✓
Firm location state FE	×	×	×	×
Firm employee size FE	✓	✓	✓	✓
Firm incorporation year FE	✓	✓	✓	✓
Observations	19,671	20,901	19,634	20,842
Pseudo R^2	0.0239	0.0263	0.0284	0.0350
χ^2 Test: (RFE Sender is Male) is equal across subsample	0.371		0.045	
Subsample:	Tech Hubs	Non-Hubs	Tech Hubs	Non-Hubs

Table 4: Primary RFE Results – Recipients in Large and Small Startups

This table reports the primary RFE results after separating the sample of recipients based on their firm size: Firms with up to 10 employees compared to firms that have a larger, or unknown number of employees. Panel A reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each group of firm size, relative to female RFE senders'. We control for other indicator variables similar to Table 2, except for firm employee size fixed effects. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. We also report the formal statistical test result comparing the parameter estimates for "RFE Sender is Male" across the two groups number of employed personnel. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Small vs. Large Startups

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Up to 10 Employees (N=17,557)			
Received Email	8,614	8,943		17,557
Opens Email	2,944	2,445		5,389
(% of Receiving Email)	(34.18%)	(27.34%)	0.25	(30.69%)
Visits Website	728	585		1,313
(% of Receiving Email)	(8.45%)	(6.54%)	0.29	(7.48%)

Pearson's X^2test [1] = 51.575 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	More than 10 Employees or Unknown (N= 23,015)			
Received Email	11,216	11,799		23,015
Opens Email	3,873	3,363		7,236
(% of Receiving Email)	(34.53%)	(28.50%)	0.21	(31.44%)
Visits Website	741	626		1,367
(% of Receiving Email)	(6.61%)	(5.31%)	0.25	(5.94%)

Pearson's X^2test [1] = 50.851 (0.000)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	0.37***	0.31***	0.32***	0.24***
	(8.53)	(12.76)	(6.39)	(4.45)
RFE VC indicator	✓	✓	✓	✓
RFE certificate FE	✓	✓	✓	✓
Firm location state FE	✓	✓	✓	✓
Firm employee size FE	×	×	×	×
Firm incorporation year FE	✓	✓	✓	✓
Observations	17,557	23,015	17,423	22,961
Pseudo R^2	0.0288	0.0259	0.0406	0.0272
χ^2 Test: (RFE Sender is Male) is equal across subsample	0.969		1.021	
Subsample:	Up to 10 Employees	More than 10 Employees	Up to 10 Employees	More than 10 Employees

Table 5: Primary RFE Results – Recipients in Young and Old Startups

This table reports the RFE results after dividing our primary sample of email recipients based on their firm's vintage year: Firms incorporated in 2017 onwards compared to firms that were incorporated prior to 2017 (or if the incorporation data is not available in Crunchbase). Panel A reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each fund type, relative to female RFE senders'. We control for other indicator variables similar to Table 2, except for the firm's fund type indicator. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. We also report the formal statistical test result comparing the parameter estimates for "RFE Sender is Male" across the two groups firm's age. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Young Startups vs. Old Startups

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Firm Incorporated on 2017 onwards (N= 3,072)				
Received Email	1,508	1,564		3,072
Opens Email	645	530		1,175
(% of Receiving Email)	(42.77%)	(33.89%)	0.26	(38.25%)
Visits Website	199	155		354
(% of Receiving Email)	(13.20%)	(9.91%)	0.33	(11.52%)

Pearson's X^2 test [1] = 11.812 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Firm Incorporated prior to 2017 (N= 37,500)				
Received Email	18,322	19,178		37,500
Opens Email	6,172	5,278		11,450
(% of Receiving Email)	(33.69%)	(27.52%)	0.22	(30.53%)
Visits Website	645	530		1,175
(% of Receiving Email)	(3.52%)	(2.76%)	0.27	(3.13%)

Pearson's X^2 test [1] = 89.825 (0.000)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	0.47***	0.31***	0.40***	0.27***
	(7.02)	(13.50)	(3.52)	(7.23)
RFE VC indicator	✓	✓	✓	✓
RFE certificate FE	✓	✓	✓	✓
Firm location state FE	✓	✓	✓	✓
Firm employee size FE	✓	✓	✓	✓
Firm incorporation year FE	×	×	×	×
Observations	3,063	28,900	2,977	28,781
Pseudo R^2	0.0354	0.0173	0.0212	0.0129
χ^2 Test: (RFE Sender is Male) is equal across subsample	4.402**		1.151	
Subsample:	2017 Onwards	Prior to 2017	2017 Onwards	Prior to 2017

Table 6: Primary RFE Results – Different Fund Types

This table reports the RFE results after dividing the primary RFE sample based on the email sender's affiliation: Emails sent from an angel or a Venture Capital Firm. Panel A reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each group of firm's incorporation year, relative to female RFE senders'. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. We also report the formal statistical test result comparing the parameter estimates for "RFE Sender is Male" across the two groups fund type. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Angel Investor vs. VC Fund

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
		Angel Investor (N= 11,935)		
Received Email	5,522	6,413		11,935
Opens Email	2,099	1,895		3,994
(% of Receiving Email)	(38.01%)	(29.55%)	0.29	(33.46%)
Visits Website	442	344		786
(% of Receiving Email)	(8.00%)	(5.36%)	0.49	(6.59%)

Pearson's X^2 test [1] = 52.706 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
		VC Fund (N= 28,637)		
Received Email	14,308	14,329		28,637
Opens Email	4,718	3,913		8,631
(% of Receiving Email)	(32.97%)	(27.31%)	0.21	(30.14%)
Visits Website	1,027	867		1,894
(% of Receiving Email)	(7.18%)	(6.05%)	0.19	(6.61%)

Pearson's X^2 test [1] = 58.817 (0.000)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	0.43***	0.31***	0.52***	0.20***
	(9.89)	(14.96)	(5.80)	(4.31)
RFE VC indicator	×	×	×	×
RFE certificate FE	✓	✓	✓	✓
Firm location state FE	✓	✓	✓	✓
Firm employee size FE	✓	✓	✓	✓
Firm incorporation year FE	✓	✓	✓	✓
Observations	11,934	28,637	11,793	28,530
Pseudo R^2	0.0282	0.0320	0.0378	0.0380
χ^2 Test: (RFE Sender is Male) is equal across subsample	6.494**		7.582***	
Subsample:	Angel	VC	Angel	VC

Table 7: Primary RFE Results – Professional Certifications

This table reports the RFE results after dividing the primary RFE sample based on the email sender's professional certifications: those toting a CPA/MD/Atty certificate, compared to those without certificate. Panel A reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each group of investor type, relative to female RFE senders'. We control for other indicators variables similar to Table 2, except for RFE certificate FE. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Certificate Carrying vs. Non-Certificate Carrying Investors

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Investor Carrying a Certificate (N= 18,482)			
Received Email	8,882	9,600		18,482
Opens Email	3,389	2,532		5,921
(% of Receiving Email)	(38.16%)	(26.38%)	0.45	(32.04%)
Visits Website	645	430		1,075
(% of Receiving Email)	(7.26%)	(4.48%)	0.62	(5.82%)

Pearson's X^2test [1] = 155.159 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Investor Not Carrying a Certificate (N= 6,283)			
Received Email	3,064	3,219		6,283
Opens Email	1,088	1,182		2,270
(% of Receiving Email)	(35.51%)	(36.72%)	-0.03	(36.13%)
Visits Website	223	242		465
(% of Receiving Email)	(7.28%)	(7.52%)	-0.03	(7.40%)

Pearson's X^2test [1] = 0.467 (0.494)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	-0.05	0.73***	-0.02	0.69***
	(-1.16)	(15.09)	(-0.23)	(8.83)
RFE VC indicator	✓	✓	✓	✓
RFE certificate FE	×	×	×	×
Firm location state FE	✓	✓	✓	✓
Firm employee size FE	✓	✓	✓	✓
Firm incorporation year FE	✓	✓	✓	✓
Observations	6,261	18,482	6,107	18,457
Pseudo R^2	0.0245	0.0270	0.0536	0.0363
χ^2 Test: (RFE Sender is Male) is equal across subsample	79.74***		35.52***	
Subsample:	No Certificate	Holding a Certificate	No Certificate	Holding a Certificate

Table 8: Primary RFE Results – Professional Certifications within VC Fund

This table reports the RFE results after dividing the primary RFE sample of senders *within* our VC subsample based on their professional certification: Those toting a CPA/MD/Atty certificate, compared to those without but bearing the same name. Panel A reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. Panel B reports the excess odds ratio of male RFE senders' email being opened and their websites being visited by the email recipients in each group of investor type, relative to female RFE senders'. We control for other indicators variables similar to Table 2, except for RFE certificate FE. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. We also report the formal statistical test result comparing the parameter estimates for "RFE Sender is Male" across the investor credential groups within the VC fund. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: VC Investors Carrying Certificate vs. VC Investors Not Carrying Certificate

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	VC Investor Carrying a Certificate (N= 9,655)			
Received Email	4,858	4,797		9,655
Opens Email	1,810	1,282		3,092
(% of Receiving Email)	(37.26%)	(26.73%)	0.39	(32.02%)
Visits Website	303	214		517
(% of Receiving Email)	(6.24%)	(4.46%)	0.40	(5.35%)

Pearson's X^2 test [1] = 63.469 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	VC Investor Not Carrying a Certificate (N= 3,175)			
Received Email	1,566	1,609		3,175
Opens Email	568	537		1,105
(% of Receiving Email)	(36.27%)	(33.37%)	0.09	(34.80%)
Visits Website	123	114		237
(% of Receiving Email)	(7.85%)	(7.09%)	0.11	(7.46%)

Pearson's X^2 test [1] = 1.448 (0.228)

Panel B: Logit Analysis

	(1)	(2)	(3)	(4)
	Opens Email		Visits Website	
RFE Sender is Male	0.15**	0.64***	0.15	0.42***
	(1.96)	(11.94)	(1.37)	(5.41)
RFE VC indicator	×	×	×	×
RFE certificate FE	×	×	×	×
Firm location state FE	✓	✓	✓	✓
Firm employee size FE	✓	✓	✓	✓
Firm incorporation year FE	✓	✓	✓	✓
Observations	3,158	9,655	2,954	9,479
Pseudo R^2	0.0326	0.0283	0.0842	0.0419
χ^2 Test: (RFE Sender is Male) is equal across subsample	20.61***		3.464*	
Subsample:	No Certificate	Holding a Certificate	No Certificate	Holding a Certificate

Table 9: Primary RFE Results – Correspondence Ratio Test

This table reports the summary of direct correspondences addressed to our investors in our primary RFE analysis. Of the 552 email messages received by our investors, 458 are sent by a startup's material decision-maker (i.e., a founder, a C-Suite executive, or those carrying similar titles, e.g., 'President', 'Managing Director'). Of these 458 emails, we are able to identify the gender of 451 individual senders using LinkedIn and Google searches. The table is structured similarly to Panel A of Table 2 to facilitate direct comparisons. We first divide the recipients' direct contacts based on the gender of the RFE investors. When available, we then divide the contacts based on the gender of the startups' executives (i.e., the senders). We calculate the (Male/Female) probability ratio of each set of corresponding percentages and subtract 1 so that a positive value can be interpreted as an over-representation of responses to male RFE investors. We also report the Pearson's X^2 test results.

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)
Delivered Emails	19,830	20,742	
Contact from Founder/C-Suite	236	222	
(% of Delivered Emails)	(1.19%)	(1.07%)	11.20%
Pearson's X^2test [1] = 1.304 (0.253)			
Contact from Male Founder/C-Suite	204	191	
(% of Delivered Emails)	(1.03%)	(0.92%)	11.72%
Pearson's X^2test [1] = 1.224 (0.268)			
Contact from Female Founder/C-Suite	27	29	
(% of Delivered Emails)	(0.14%)	(0.14%)	-2.61%
Pearson's X^2test [1] = 0.009 (0.921)			

Table 10: Secondary RFE Results – A Follow-up Experiment

This table reports the RFE results from an additional experiment in November 2021. In this experiment, we identify young firms that are newly added to the Crunchbase dataset post our initial data downloading for the primary RFE analysis. Panel A reports the RFE results for the new sample. Panel B reports the corresponding results for the subsample of startups with 10 or fewer employees in the new sample. Panel C combines the initial and new samples, but include only firms incorporated from 2017 onwards. Each panel reports the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action, after subtracting 1 from the ratio. A positive value can be interpreted as an over-representation of responses to male RFE investors. We report the Pearson's X^2 test for each panel. The t-stats reported in parentheses are calculated using standard errors adjusted using state-level clustering. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Follow-Up RFE Analysis

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Firm Incorporated on 2017 onwards (N= 4,836)			
Received Email	2,431	2,405		4,836
Opens Email	976	808		1,784
(% of Receiving Email)	(40.15%)	(33.60%)	0.20	(36.89%)
Visits Website	208	188		396
(% of Receiving Email)	(8.56%)	(7.82%)	0.09	(8.19%)

Pearson's X^2test [1] = 100.421 (0.000)

Panel B: Follow-Up RFE Analysis- Startups with 10 or Fewer Employees

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Firm Incorporated on 2017 onwards (N= 2,963)			
Received Email	1,471	1,492		2,963
Opens Email	651	542		1,193
(% of Receiving Email)	(44.26%)	(36.33%)	0.22	(40.26%)
Visits Website	154	134		288
(% of Receiving Email)	(10.47%)	(8.98%)	0.17	(9.72%)

Pearson's X^2test [1] = 70.449 (0.000)

Panel C: Combine Experiment Samples – Incorporated on 2017 Onwards

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
	Firm Incorporated on 2017 onwards (N= 7,908)			
Received Email	3,939	3,969		7,908
Opens Email	1,621	1,338		2,959
(% of Receiving Email)	(41.15%)	(33.71%)	0.22	(37.42%)
Visits Website	407	343		750
(% of Receiving Email)	(10.33%)	(8.64%)	0.20	(9.48%)

Pearson's X^2test [1] = 176.862 (0.000)

Appendix

Table A1: Email View by Recipients

This table demonstrates the name and subject line of the emails of the 16 main variations in the experiment as shown in the recipient's email inbox. Each recipient receives only one of these variations. We demonstrate how they appear in email programs that display the information horizontally. We use alternative fictitious names of the VC (Faber Grove) and Angel group (Orange Mountain) for illustrative purposes in this panel rather than redacting their names. WiX's technology allows us to know whether the recipient viewed the email. We also note that the recipient can see, before considering the body of the email, the investment firm, and the sender's name (e.g., Michael Davis). We randomly chose 2,500 emails from the cleaned Crunchbase database for each group. Across the 16 groups, 2.5% of the emails were never delivered because the email server indicated they were invalid or no longer in use. Among the email recipients of these 16 groups, automated or manual spam filters flagged 1.99% of our emails. WIX suspended one email campaign midway (Orange Mountain Angel Group, Michael Davis, MD), likely because it had five consecutive bounces. We debated whether to complete that run later to maintain bucket sizes or to accept the smaller bucket size and maintain email campaign date-timing.

Email Labels as Viewed by Recipients		**# Emails Attempted**	**# Emails Sent**	**# Emails Received**	**Receiving Rate**
Name Field:	**Subject Field:**				
Faber Grove VC	Michael Davis	2,500	2,454	2,419	98.57%
Orange Mountain Angel Group	Michael Davis	2,500	2,252	2,026	89.96%
Faber Grove VC	Michael Davis, JD	2,500	2,460	2,432	98.86%
Orange Mountain Angel Group	Michael Davis, JD	2,500	2,417	2,352	97.31%
Faber Grove VC	Michael Davis, MD	2,500	2,433	2,379	97.78%
Orange Mountain Angel Group	Michael Davis, MD	1,350	1,319	1,288	97.65%
Faber Grove VC	Michael Davis, CPA	2,500	2,450	2,421	98.82%
Orange Mountain Angel Group	Michael Davis, CPA	2,500	2,454	2,423	98.74%
Faber Grove VC	Jessica Davis	2,500	2461	2,436	98.98%
Orange Mountain Angel Group	Jessica Davis	2,500	2459	2,426	98.66%
Faber Grove VC	Jessica Davis, JD	2,500	2472	2,451	99.15%
Orange Mountain Angel Group	Jessica Davis, JD	2,500	2477	2,459	99.27%
Faber Grove VC	Jessica Davis, MD	2,500	2445	2,416	98.81%
Orange Mountain Angel Group	Jessica Davis, MD	2,500	2446	2,410	98.53%
Faber Grove VC	Jessica Davis, CPA	2,500	2461	2,439	99.11%
Orange Mountain Angel Group	Jessica Davis, CPA	2,500	2418	2,349	97.15%

Table A2: Email Campaign Example

This figure illustrates the emails sent as part of the RFE. It provides 8 illustrative examples of identical emails except for the sender's name (and professional certification, if applicable). The 'Check out our website' sentence and arrow icon adjacent to are links to the investor's company website, and by clicking on either one, the recipient will open the main page of the website. This action is recorded by WiX and will count as a unique click. Clicking more than once, or independently entering the website again from the same IP number will *not* count as additional clicks.

Jessica Davis

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Faber Grove Team

Check out our website

Jessica Davis

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Orange Mountain Team

Check out our website

Jessica Davis, JD

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Faber Grove Team

Check out our website

Jessica Davis, JD

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Orange Mountain Team

Check out our website

Michael Davis

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Faber Grove Team

Check out our website

Michael Davis

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Orange Mountain Team

Check out our website

Michael Davis, JD

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Faber Grove Team

Check out our website

Michael Davis, JD

Our team identified your startup as an interesting investment opportunity, and we would like to invite you to set up a meeting with us at one of our offices or online. We are looking to extend our portfolio companies and will be taking in pitches on a rolling basis. Please feel free to read about our firm, and contact us either via email or through the 'Contact us' option on the website.

Orange Mountain Team

Check out our website

Note: We use alternative fictitious names of the VC/Angel group for illustrative purposes rather than redacting the names in this panel.

Table A3: Power Calculations Open Email

This table reports the minimum detectable effects within or across subsamples in the analysis for an experiment with two possible outcomes {open email, not open email}. The effects are calculated with Type 1 Error set to be 5% and Type 2 Error set to be either 5% (95% power) or 10% (90% power).

Panel A: Open Email Rate

This panel provides minimum detectable effects within each subsample. We report the minimum detectable effect calculated at different power levels, assuming unconditional opening email rates of 30%. These minimum detectable effects are calculated using the Stata function "**power twoproportions**", with the **bold** font indicating a detected effect larger than the corresponding minimum detectable effects.

	Associated Table in Manuscript	Sample Size	Minimum Detectable Effect 90% power	Minimum Detectable Effect 95% power	Detected Effect
Primary Sample	2	40,572	1.49%	1.65%	**6.38%**
Tech Hub	3	19,671	2.14%	2.38%	**6.37%**
Non-Tech Hub	3	20,901	2.07%	2.31%	**6.39%**
Small	4	17,557	2.27%	2.52%	**6.84%**
Large	4	23,015	1.98%	2.20%	**6.03%**
Young	5	3,072	5.49%	6.11%	**8.88%**
Old	5	37,500	1.55%	1.72%	**6.17%**
Angel	6	11,935	2.75%	3.07%	**8.46%**
VC	6	28,637	1.77%	1.97%	**5.66%**
Certificate Carrying	7	18,482	2.21%	2.46%	**11.78%**
No Certificate	7	6,283	3.81%	4.25%	-1.21%
VC Certificated	8	9,655	3.07%	3.41%	**10.53%**
VC No Certificate	8	3,175	5.39%	6.01%	2.90%
Secondary Sample	10	4,836	4.35%	4.85%	**6.55%**
Small Startups	10	2,963	5.59%	6.23%	**7.93%**
All Young Firms	10	7,908	3.39%	3.78%	**7.44%**

Panel B: Diff-in-Diff Open Email Rates

This panel reports the minimum detectable differences in response rate differentials to two different treatments (male vs. female sender) between two subsamples (e.g., between tech hub and non-tech hub on the first row).

Difference - in - Difference	Associated Table in Manuscript	Total Sample Size	Minimum Detectable Diff-in-Diff 90% Power	Minimum Detectable Diff-in-Diff 95% Power	Detected Diff-in-Diff
Tech - Non-Tech Hub	3	40,572	0.73%	0.81%	-0.02%
Small - Large	4	40,572	0.73%	0.82%	0.81%
Young - Old	5	40,572	1.42%	1.58%	**2.71%**
Angel - VC	6	40,752	0.80%	0.89%	**2.80%**
Certificate - No Certificate	7	24,765	1.08%	1.21%	**12.99%**
Cert VC - No Cert VC	8	12,830	1.53%	1.73%	**7.63%**

Table A4: Power Calculations Visit Website

This table reports the minimum detectable effects within or across subsamples in the analysis for an experiment with two possible outcomes {visit website, not visit website}. The effects are calculated with Type 1 Error set to be 5% and Type 2 Error set to be either 5% (95% power) or 10% (90% power).

Panel A: Visit Website Rate

This panel provides minimum detectable effects within each subsample. We report the minimum detectable effect calculated at different power levels, assuming unconditional website visit rates of 6%. These minimum detectable effects are calculated using Stata function "**power twoproportions**", with the **bold** font indicating a detected effect larger than the corresponding minimum detectable effects.

	Associated Table in Manuscript	Sample Size	Minimum Detectable Effect: 90% Power	Minimum Detectable Effect: 95% Power	Detected Effect
Primary Sample	2	40,572	0.79%	0.88%	**1.57%**
Tech Hub	3	19,671	1.15%	1.28%	**1.71%**
Non-Tech Hub	3	20,901	1.11%	1.24%	**1.44%**
Small	4	17,557	1.22%	1.36%	**1.91%**
Large	4	23,015	1.06%	1.18%	**1.30%**
Young	5	3,072	3.09%	3.47%	3.29%
Old	5	37,500	0.82%	0.91%	0.76%
Angel	6	11,935	1.49%	1.66%	**2.64%**
VC	6	28,637	0.94%	1.05%	**1.13%**
Certificate Carrying	7	18,482	1.18%	1.32%	**2.78%**
No Certificate	7	6,283	2.09%	2.35%	-0.24%
VC Certificated	8	9,655	1.66%	1.86%	1.78%
VC No Certificate	8	3,175	3.03%	3.41%	0.76%
Secondary Sample	10	4,836	2.41%	2.70%	0.74%
Small Startups	10	2,963	3.15%	3.54%	1.49%
All Young Firms	10	7,908	1.85%	2.07%	1.69%

Panel B: Diff-in-Diff Visit Website Rate

This panel reports the minimum detectable differences between tech hub and non-tech hub. We use a baseline difference of 1% for visit website to compute minimal detectable effects.

Difference - in - Difference	Associated Table in Manuscript	Total Sample Size	Minimum Detectable Diff-in-Diff: 90% Power	Minimum Detectable Diff-in-Diff: 95% Power	Detected Diff-in-Diff
Tech - Non-Tech Hub	3	40,752	0.35%	0.39%	0.27%
Small - Large	4	40,752	0.35%	0.39%	**0.61%**
Young - Old	5	40,752	0.72%	0.80%	**2.53%**
Angel - VC	6	40,752	0.39%	0.43%	**1.51%**
Certificate - No Certificate	7	24,765	0.52%	0.59%	**3.02%**
Cert VC - No Cert VC	8	12,830	0.76%	0.87%	**1.02%**

Table A5: RFE Results – Recipients in Tech Hubs Separately

This table reports the RFE results after separating the sample of recipients based on their location, limiting our results to California, New York, and Texas. The structure is identical to that in Table 2 to facilitate direct comparisons. We divide the emails and recipients' subsequent actions based on the gender of the RFE investors. We report the number of entrepreneurs who received the email from investors of each gender and the number and percentage of those who opened the email and visited the corresponding website of each investor, respectively. We calculate the (Male/Female) probability ratio of each set of corresponding percentages and subtract 1 so that a positive value can be interpreted as an over-representation of responses to male RFE investors. We also report the Pearson's X^2 test result.

California (N=11,854)				
Received Email	5,758	6,096		11,854
Opens Email	2,127	1,821		3,948
(% of Receiving Email)	(36.94%)	(29.87%)	0.24	(33.31%)
Visits Website	461	384		845
(% of Receiving Email)	(8.01%)	(6.30%)	0.27	(7.13%)

Pearson's X^2test [1] = 33.489 (0.000)

New York (N=5,411)				
Received Email	2,681	2,730		5,411
Opens Email	967	851		1,818
(% of Receiving Email)	(36.07%)	(31.17%)	0.16	(33.60%)
Visits Website	220	193		413
(% of Receiving Email)	(8.21%)	(7.07%)	0.16	(7.63%)

Pearson's X^2test [1] = 7.226 (0.000)

Texas (N=2,406)				
Received Email	1,168	1,238		2,406
Opens Email	366	312		678
(% of Receiving Email)	(31.34%)	(25.20%)	0.23	(28.18%)
Visits Website	89	57		146
(% of Receiving Email)	(7.62%)	(4.60%)	0.65	(6.07%)

Pearson's X^2test [1] = 9.877 (0.000)

Table A6: RFE Results – Recipients in Startups with Different Co-Founder Compositions

This table reports the RFE results after separating the sample of recipients based on the gender composition of the startup's co-founders. The first two panels report the RFE results for the sample with information regarding the gender composition of the startup's co-founders: startups with all-male co-founder teams in the first panel, and startups with at least one female co-founder in the second panel. The last panel reports the remaining startups with unverifiable information regarding the co-founder teams. The structure of each panel is identical to that in Table 2 to facilitate direct comparisons. We divide the emails and recipients' subsequent actions based on the gender of the RFE investors. We report the number of entrepreneurs who received the email from investors of each gender and the number and percentage of those who opened the email and visited the corresponding website of each investor, respectively. We calculate the (Male/Female) probability ratio of each set of corresponding percentages and subtract 1 so that a positive value can be interpreted as an over-representation of responses to male RFE investors. We also report the Pearson's X^2 test result.

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
All Male Co-Founder Team (N=13,465)				
Received Email	6,701	6,764		13,465
Opens Email	2,682	2,243		4,925
(% of Receiving Email)	(40.02%)	(33.16%)	0.21	(36.58%)
Visits Website	612	483		1,095
(% of Receiving Email)	(9.13%)	(7.14%)	0.28	(8.13%)

Pearson's X^2 test [1] = 32.909 (0.000)

At Least One Female Co-Founder in Team (N=3,521)				
Received Email	1,709	1,812		3,521
Opens Email	618	566		1,184
(% of Receiving Email)	(36.16%)	(31.24%)	0.16	(33.63%)
Visits Website	141	120		261
(% of Receiving Email)	(8.25%)	(6.62%)	0.25	(7.41%)

Pearson's X^2 test [1] = 5.191 (0.074)

Gender Composition in Team is Unverifiable (N=23,723)				
Received Email	11,484	12,239		23,723
Opens Email	3,517	2,999		6,516
(% of Receiving Email)	(30.63%)	(24.50%)	0.25	(27.47%)
Visits Website	716	608		1,324
(% of Receiving Email)	(6.23%)	(4.97%)	0.26	(5.58%)

Pearson's X^2 test [1] = 63.361 (0.000)

Table A7: RFE Results – Recipient's Last Funding Year

This table reports the RFE results after separating the sample of recipients based on the year of their last funding round. In this analysis, we combine the sample from both experiments. Firms whose last funding round is recent, i.e., from 2017 onwards, are included in Panel A, whereas firms whose last funding round is less recent, i.e., 2016 or before, are included in Panel B. We drop all observations for which the information regarding the last funding round is missing on Crunchbase. We report the number of recipients in each group of firms who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female probability ratio of each set of corresponding percentages of entrepreneurs taking each action after subtracting 1 from the ratio. A positive value can be interpreted as an over-representation of responses to male RFE investors. We also report the Pearson's X^2 test results. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Last Funding Round 2017 Onwards

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Last Funding Round 2017 Onwards (N= 13,152)				
Received Email	6,539	6,613		13,152
Opens Email	2,760	2,390		5,150
(% of Receiving Email)	(42.21%)	(36.14%)	0.16	(39.16%)
Visits Website	682	593		1,275
(% of Receiving Email)	(10.43%)	(8.97%)	0.17	(9.69%)

Pearson's X^2test [1] = 296.223 (0.000)

Panel B: Last Funding Round up to 2016

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Last Funding Round up to 2016 (N= 6,695)				
Received Email	3,303	3,392		6,695
Opens Email	1,041	896		1,937
(% of Receiving Email)	(31.52%)	(26.42%)	0.19	(28.93%)
Visits Website	219	163		382
(% of Receiving Email)	(6.63%)	(4.81%)	0.38	(5.71%)

Pearson's X^2test [1] = 79.950 (0.000)

Table A8: RFE Results – Recipients Operate in Industry with High or Low Female Participations

This table reports the RFE results after separating the sample of recipients based on their respected industry sector: Firms that operate in industry sectors with above-average female investor participation rates and those with below-average rates. We report the number of entrepreneurs in each group who opened the email from male vs. female RFE investors and the number of those who visited the corresponding website of each investor, respectively. We report the Male-to-Female Probability ratio of each set of corresponding percentages of entrepreneurs taking each action after subtracting 1 from the ratio. A positive value can be interpreted as an over-representation of responses to male RFE investors. We also report the Pearson's X^2 test results. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: High Female Participation vs. Low Female Participation

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
High Female Participation (N= 23,104)				
Received Email	11,279	11,825		23,104
Opens Email	4,027	3,515		7,542
(% of Receiving Email)	35.70%	29.73%	0.20	32.64%
Visits Website	875	732		1,607
(% of Receiving Email)	7.76%	6.19%	0.25	6.96%

Pearson's X^2test [1] = 375.434 (0.000)

	Male RFE Investor	Female RFE Investor	Excess Probability Ratio (Male/Female - 1)	All Obs.
Low Female Participation (N= 17,468)				
Received Email	8,551	8,917		17,468
Opens Email	2,790	2,293		5,083
(% of Receiving Email)	32.63%	25.71%	0.27	29.10%
Visits Website	594	479		1,073
(% of Receiving Email)	6.95%	5.37%	0.29	6.14%

Pearson's X^2test [1] = 263.975 (0.000)

<u>Table A9: Benchmark Response Rates</u>

This table summarizes various correspondence studies in venture capital, academic studies in marketing, and commercial email campaigns by financial intermediaries. We report open email rates (in Column 2) and website visit rates (in Column 3) from four academic studies and three different websites analyzing commercial email campaigns. We report the averages for all commercial campaigns and for campaigns by financial service providers from each website. Column 4 reports the advantage of our open email rate in the primary experiment (31.1%) to each corresponding benchmark.

	Open Email Rate	Visit Website Rate	Our Primary Experiment Open Rate Advantage
Academic Studies			
Zhang et al., 2017 (solicited emails)	23.7%	NA	31.2%
Sahni et al., 2018 (unsolicited large scale)	9.9%	NA	214.1%
Kumar and Salo, 2018 (multi-country)	20%	3.3%	55.5%
Zhang, 2020 (venture capital study)	12%	1.7%	159.2%
Commercial Email Campaign Averages			
Mailchimp: Aggregate Average	21.3%	2.6%	46.0%
MailChimp: Business Finance	21.6%	2.7%	44.0%
Campaign Monitor: Aggregate Average	21.5%	2.3%	44.7%
Campaign Monitor: Financial Services	27.1%	2.4%	14.8%
Smart Insights: Aggregate Average	25.4%	1.2%	22.9%
Smart Insights: Financial Service Firms	24.9%	3.2%	24.9%
Our Open/Visit Rates (Incorporation Years)			
Primary Experiment (2005 – 2019)	31.1%	6.6%	
Secondary Experiment (2017 – 2021)	36.9%	8.2%	
Young Startups (2017 – 2021)	37.4%	9.5%	

Note 1: We started the project with uncertainty about the open and visit rates because of the relative scarcity of human capital to physical capital. Due to the intense competition by venture capital firms for promising startups (Abermand, 2019), our prior is that founders are less likely to respond to unsolicited contacts than financial intermediaries. We compare the response rates of recent papers that explore the other side of this founder-investor matching exercise using field experiments (Gornall and Strebulaev, 2020; Zhang, 2020). Zhang (2020) reports investors have an open rate of 12%, a visit rate of 1.7%, and an email reply rate of 1.5%. Their results also suggest concerns about email program algorithms (Fuster et al., 2020) potentially lowering our response rates and biasing our results are unwarranted.

<u>Note 2: Websites for Commercial Averages include</u> https://mailchimp.com/resources/email-marketing-benchmarks/; https://www.campaignmonitor.com/resources/guides/email-marketing-benchmarks/; https://www.smartinsights.com/email-marketing/email-communications-strategy/statistics-sources-for-email-marketing/

Appendix A10: Hypothesis Development Timeline

This chart provides a timeline of the hypothesis development. We started the project using observational data, leading to the full development of the hypotheses in May 2020. The experiment was conducted in July 2020. The follow-up experiment was conducted in November 2021.