ASYMMETRIC GENDER HOMOPHILY IN THE STARTUP LABOR MARKET

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ABSTRACT

Homophily, or the tendency for individuals to be attracted to those who resemble them, is significantly influential in the formation of startup founding and top management teams. But its role in subsequent stages of startup growth remains largely unclear. We consider the impact of homophily on matching of early workers to startups. We propose that, in the case of underrepresented minority groups, the tendency toward homophily plays an important role in this matching process, albeit in an asymmetric way. In particular, homophily exerts a stronger influence on the supply than the demand side: job candidates are more inclined to favor startups with demographically similar founders than startup founders are inclined to favor demographically similar job-seekers. Focusing on an important group of historically disadvantaged workers – women – we examine these arguments using unique data on the online recruiting of high-tech startups concentrated in the Silicon Valley. We find evidence suggesting that female candidates' propensity to apply to a job at a given startup increases with the proportion of female founders. However, startups with a higher proportion of female founders are not more likely than other startups to favor female candidates in personnel selection.

Homophily, or the tendency of individuals to associate with similar others (Lazarsfeld & Merton, 1954; McPherson, Smith-Lovin, & Cook, 2001), is a potent and pervasive force in today's organizations (e.g., Ibarra, 1991; Kleinbaum, Stuart, & Tushman, 2013; Greenberg & Mollick, 2017). The role of homophily along various demographic dimensions is particularly well established with respect to the demography of new ventures. For example, ample

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research has provided systematic evidence that social proximity plays a critical role in influencing the composition of startup founding and top management teams (e.g., Beckman & Burton, 2008; Ruef, Aldrich, & Carter, 2003). However, we know little about how, if at all, homophily also influences the subsequent stages of startup growth: namely the recruitment and hiring of early employees. Yet understanding *who* new ventures hire, as they grow and mature, is especially important because growing startups are a key engine of sustainable job creation and employment (Haltiwanger, Hyatt, McEntarfer, & Sousa, 2012; Kane, 2010; Santarelli & Vivarelli, 2002; Stangler & Litan, 2010). Hence, in this study, we examine how startups fill the positions they create, and to what extent homophily – known to be influential in the formation of early top teams – persists in affecting the matching of workers to firms in later stages of startup development.

In examining the influence of homophily on matching worker to new ventures, both sides of the market need to be considered. Indeed, an employer–employee match is determined both by workers' selection of firms (i.e., supply side), and firms' selection of workers (i.e., demand side) (e.g., Fernandez & Friedrich, 2011; Fernandez & Sosa, 2005). Studies of homophily, however, have generally focused on documenting the prevalence of relationships among similar actors relative to other possible relationships, and thus are generally silent about whether the general tendency toward homophily is equally influential on both sides of the relationship (e.g., Bengtsson & Hsu, 2015; Hegde & Tumlinson, 2014). But in the context of startup labor markets, starkly different objectives and challenges can drive the relationship choices of founders and job-seekers. Hence, the motivation to seek or accept relationships with demographically similar others need not be equally strong on each side of the market. A fuller understanding of homophily and its influence on new-venture demography therefore requires considering the motivation of actors on each side of the market and their attempts to seek relationships with demographically similar others.

In this study, we therefore consider the influence of demographic homophily on the supply side and the demand side of the startup labor market. We propose that, in the case of underrepresented minority groups, homophily between founders and job-seekers will be much more likely to influence job-seekers' choices of startups than startups' choices of job candidates. From the perspective of job-seekers, founders' profiles are among the few cues to judge the viability of a startup (Burton, Sørensen, & Beckman, 2002; Hallen, 2008; Hsu, 2007). Thus, we expect job-seekers' assessments of a startup as a potential employer to be partly based on the profile of a startup's founders. Further, minority job candidates use cues related to a firm's demographic composition to make assessments as to whether workers like themselves can successfully fit in and be successful at a firm (Paddison, 1990; Rynes, Bertz & Gehal, 1991). The motivation to find a well-matched employer will therefore incline these job candidates to favor firms with demographically similar founders during their job search. But similarity-based attraction will not be equally influential on the demand-side for at least two reasons. First, when hiring for positions outside the top management team, the benefits of social similarity to the founders will be muted given that (1) these workers will work less directly with the founders; and (2) the firm can put in place more formalized management procedures, which reduce the need to manage based on trust induced by similarity (e.g., Baron, Hannan, & Burton, 1999). These more formalized procedures can also mitigate the influence of in-group bias in the recruitment process, making it less likely that firms will penalize dissimilar workers (Baron, Hannan, Hsu, & Kocak, 2007). Further, minority founders may want to avoid favoring demographically similar workers for important positions to avoid reinforcing the association of the startup with their particular minority group, given possible negative bias against minorities by key stakeholders (Fairlie, 1999; Hout & Rosen, 1999; Keister & Moller, 2000; Kim, Aldrich, & Keister, 2006; Younkin & Kuppuswamy, 2019). These arguments thus suggest that, from the point of view of minority founders, there are fewer advantages and some potential disadvantages to favoring demographically similar workers.

Examining these claims empirically presents a formidable challenge to researchers because it requires identifying job-seekers' application choices separately from startups' recruitment choices. In most cases, however, researchers have observed only realized matches between job-seekers and startups (e.g., Dahl & Klepper, 2015; Roach & Sauermann, 2015), which limits the potential of prior studies to elucidate minorities' job search choices in a startup context, or startups' screening choices. Given that young organizations are generally less likely to keep systematic HR records, comparable, large-scale data on startups' recruiting are rarely available. Here, we take advantage of a unique online recruiting setting which provides information on job applications submitted to a sample of high-growth startups and the companies' subsequent candidate screening choices. In this context, it is possible to examine factors that influence job-seekers' application choices, as well as startups' recruitment choices.

THEORY

Research in entrepreneurship and sociology has long emphasized the key role of startups in creating new jobs (e.g., Blanchflower, 2000; Haltiwanger et al., 2012). Given these presumed benefits of new, fledgling ventures, scholars have devoted significant attention to the antecedents of entrepreneurship, and multiple studies have identified initiatives that can facilitate the act of launching a new firm more effectively in regions, states, or nations (e.g., Armanios, Eesley, Li, & Eisenhardt, 2017; Conti, Kacperczyk, & Valentini, 2018; Lanahan & Feldman, 2015). The preponderance of research has focused on startups' role in job creation, but there currently is much less understanding of how these jobs are filled, as startups grow and mature.

In particular, researchers have rarely examined the demographic distribution of workers across startup jobs and little is known about processes that govern hiring of minorities into startups. Although some studies have examined the demographic and professional backgrounds of startups' workforces, this research has been limited in its focus to founding and top management teams (Baron &

Hannan, 2002; Beckman & Burton, 2008; Burton & Beckman, 2007; Phillips, 2005; Ruef et al., 2003). For example, some scholars have found that co-founding teams are characterized by strong homophily because founders choose their partners from among their friends, relatives, co-workers, and members of a pre-existing network, generating high degrees of social and functional similarity within founding teams (Ruef et al., 2003). Other studies have argued that founders perpetuate initial startup homophily because they imprint their vision on key organizational choices within the new venture (Baron, Hannan, & Burton, 2001, 1999; Baron & Hannan, 2002; Boeker, 1989; Stinchcombe, 1965), including decisions regarding the selection of executives (Beckman & Burton, 2008). Importantly, given that racial minorities and women tend to be underrepresented among founders, these studies imply that tendency toward homophily will inevitably perpetuate the underrepresentation of minorities among top management teams in startups (Blanchflower, Levine, & Zimmerman, 2003; Fairlie & Robb, 2007; Thébaud, 2010; Tinkler, Whittington, Ku, & Davies, 2015; Younkin & Kuppuswamy, 2018).

Given that most scholarly attention has been focused on the demography of top teams, in what follows below, we shift the attention to early employees and examine the mechanisms that govern their recruitment into startup jobs. Because recruitment into any firm is jointly determined by employers' demand-side screening of job candidates and candidates' supply-side choices of employers, we consider both sides of the hiring interface to theorize about the role of demographic similarity on each side of the market.

Candidate Job Search Strategies

We begin by considering job candidates' search choices, shown to be a critical determinant of individuals' placement into firms (e.g., Barbulescu & Bidwell, 2013; Heckman, 1998; Lundberg & Startz, 2007; Pager & Pedulla, 2015). In evaluating startup jobs, a key question for a job candidate is how to assess a prospective employer when faced with limited evidence. In a startup context, job-seekers are likely to rely on founders' profiles as cues to evaluate the prospective employer. Because startups lack the standard benchmarks – such as a performance record or an established reputation – founders' profiles play a crucial role in influencing the assessments by key audiences, including investors or prospective partners (Burton et al., 2002; Hallen, 2008; Hsu, 2007). Job-seekers are equally likely to rely on such cues, given that data on founders are accessible and easy to evaluate. For example, startups frequently profile their founders, and open-access startup databases (e.g., Crunchbase) include information on the founders in the first few lines of the company profile.

To the extent that founders' profiles influence the selection of target employers, minorities will disproportionally target startups with minority founders. Job candidates are more likely to be attracted to startups with demographically similar founders because social proximity breeds attraction, trust, ease of communication, and perceived belonging (Festinger, 1954; Lazarsfeld & Merton, 1954; Tajfel & Turner, 1986). Although such attraction may be experienced by all minority job-seekers, minorities who are generally underrepresented in entrepreneurship will be particularly concerned with their fit within the new startup. For these groups, their underrepresentation will motivate them to seek evidence that a firm they target one where they are likely to fit in, belong, or succeed (Paddison, 1990). Because the presence of similar minorities among a firm's leaders is a positive signal of such a high-quality match (Rynes et al., 1991), jobs-seekers will be attracted to job opportunities at startups with minority founders. Hence, we expect that, when assessing their prospects at a firm, historically disadvantaged individuals will favor jobs in startups with demographically similar founders.

H1. When considering jobs at startups, minorities' attraction to a given startup will increase with the proportion of demographically similar founders present in the founding team.

Startup Screening of Job Candidates

In contrast, there is a strong rationale to expect that the influence of homophily will be relatively less profound on the demand side of the market. Prior studies have established that homophily might be pervasive among founding-team members (Ruef et al., 2003) or within a startup top management team (Beckman & Burton, 2008), but whether similar tendencies persist beyond top management remains an open question. Indeed, as a startup grows and matures, the benefits of hiring similar workers – which include greater trust, or ease of communication (Festinger, 1954; Lazarsfeld & Merton, 1954; Tajfel & Turner, 1986) – are likely to decline because each subsequent hire is less likely to interact with the founder or the founding team directly. Further, the processes that govern interaction and communication will become more formalized (e.g., Baron et al., 1999), dampening both the motivation and the opportunity to engage in similarity-based recruitment. When relationships become more formalized, as is the case when formal rules, such as HR policies, are put in place within startups, the value of similarity-based recruitment generally declines (e.g., Puranam & Vanneste, 2009) because relying on trust to govern relationships is less necessary. Relatedly, more formalized structures, including HR practices, will limit the scope for founders to be swayed by an in-group bias toward candidates belonging to their own demographic group (Baron et al., 2007). Together, these arguments suggest that the motivation and opportunities to engage in similarity-based recruitment, which tends to pervade early stages of founding, will weaken – as startups grow and mature. Indeed, the organizational psychology literature finds that, in more traditional recruitment contexts, demographic matches between candidates and hiring agents are not consistently associated with more positive hiring evaluations (see Huffcutt, 2011 for a review).

In addition, minority founders may be reluctant to favor candidates with whom they share demographic background, given the presumptive discounting their group identity may carry, especially in the context of entrepreneurship (Fairlie, 1999; Hout & Rosen, 2000; Keister & Moller, 2000; Kim et al., 2006). Indeed, ample research has found that historically disadvantaged minorities, including women and non-Whites, face systematic bias and negative stereotypes in the context of entrepreneurship (e.g., Thébaud, 2015; Younkin & Kuppuswamy, 2019). Such biases against minorities may incline founders against favoring minority candidates, at least when hiring for "core" scientific-technical positions (Baron et al., 1999). These technical positions are precisely the ones likely to be scrutinized by investors and other stakeholders, given that high-growth, high-tech startups often receive external funding and thus are subject to greater scrutiny (e.g., Hellmann & Puri, 2002). To the extent that potential or actual investors may hold systematic bias against minorities, minority founders may be motivated to forgo favoring minority candidates and, instead, make hiring choices that conform to the industry norm and thus appease external stakeholders. Taken together, these arguments suggest that demographic homophily will be significantly weaker on the demand-side of the recruitment process.

H2. Demographic similarity between founders and job candidates is less likely to influence founders' choices of job candidates than job candidates' choices of startup employers.

METHODS

To examine these arguments, we focus on gender similarity and its influence on job application and recruitment patterns across high-growth startups concentrated in the San Francisco/Silicon Valley area. Our data are sourced from an online job applicant tracking system that allows firms to create job postings, disseminate them online, and subsequently capture and track job applications. The job postings include information about the firm and the position, but not about salary. When candidates apply, they upload their resume which is parsed and stored in a database. The Candidates also fills out a short job application. Importantly for the purpose of this study, the job application form includes optional demographic questions (i.e., gender and ethnicity). We examined these firms' recruiting for software engineer/developer positions on the system from the period of March 2008 to March 2012. Our dataset includes anonymized, parsed resumes (except for first names) and job applications received during this period. It also includes screening outcomes (e.g., selection for interviews) associated with each application.

This setting provides a number of important advantages. First, job application information allows us to assess job candidates' attraction to startups, separately from startups' selection of job candidates. Indeed, extant studies of startups' workforce composition are based on matched employee–employer datasets (e.g., Coad, Daunfeldt, Johansson, & Wennberg, 2014; Dahl & Klepper, 2015), and thus provide limited insight into the demand and supply-side processes that produce such matches. Further, the online recruitment context is particularly appropriate for our study, as the broad dissemination of job listings and the open recruitment process lessens the potential effects of homophily induced by differences in relationship opportunities across groups (e.g., Fernandez & Su, 2004; Greenberg & Mollick, 2017; Kerka, 2001). Also, most startups in the sample are high-growth and a majority had already achieved key milestones, such as securing venture capital financing. Although this limits our ability to generalize beyond high-growth ventures, these kinds of startups are responsible for a significant portion of new-job creation (e.g., Stangler, 2010). In elucidating how startups fill jobs, it is particularly instructive to focus on those new firms that are responsible for a large share of the jobs created and workers hired. Finally, our study focuses on software engineering positions. Because concerns about minority underrepresentation are especially acute in these core technical positions (e.g., Baron et al., 2007), understanding factors that influence the placement of minorities in such jobs is particularly valuable.

Sample Construction and Characteristics

The dataset includes information on 104,273 applications to 1,986 software engineer/developer job postings at 529 firms. Based on a number of exclusion criteria, we reduced our sample to 82,981 applications to 823 software engineer/developer job postings at 228 companies.[1] We further set aside 7,844 internal applications because internal applicants are unlikely to be at risk of applying to other firms and 8,994 candidates applying from sources other than the internet (who are also not at risk of applying to other job postings on the online platform). Note, however, that we find the same results in our analyses of the demand-side (i.e., no evidence of a *Female Similarity* effect) if we retain internals and candidates who apply via other sources (available upon request). The resulting sample includes 66,143 applications to 777 job postings at 220 firms, of these firms 166 were younger than five years at the time they started recruiting on the platform.

Consistent with past research (e.g., Sauermann, 2018), we focused on these younger firms as our "startup" sample and retained the sample of older firms to test the evolution of founder effects as startups age (see Table 4). The startup sample includes 57,260 applications to 588 job postings. We further excluded a number of cases due to missing data, which resulted in an analysis sample of 39,704 applications to 547 job postings at 164 firms. Given potential concerns about the selection of cases with non-missing data, we replicated our subsequent results both on the full startup dataset without controls, as well as controlling for all variables in Table 1, except those variables related to the candidate's education (which had the most missing cases): excluding these education controls allows us to retain 82.8% of cases. These additional analyses (available upon request) provide substantively similar results to those reported below (in Table 2).

[1]We excluded 849 job postings for which no candidate was interviewed as these postings were censored by the design of the study and 70 job postings for which there was only one application: 23 of these single-person job postings had an internal candidate, indicating that these were internal promotions and that the remaining cases were targeted recruitments. We also excluded 119 job postings for positions outside the United States, 10 headhunter firms, and 42 firms for which we could not identify founders.

Table 1. Descriptive Statistics for Control Variables.

Firm/Founder Characteristics (*N* = 164)	**Mean (s.d.)**
VC financing	0.54
N employees/100	0.32 (0.30)
Press mentions/100	0.22 (0.71)
Tech sector (other omitted category):	
• online content	0.27
• non-content-related software development	0.30
• online business services	0.23
Team non-White ethnicity share (Asian/Indian/Hispanic)	(0.06/0.05/0.04)
Team ethnic diversity (HHF)	0.89 (0.21)
Years founder experience/10	1.45 (0.67)
Founder Top 10 education	0.52
Founder Top 500 experience	0.35
Founder no prior founding experience	0.43
N founders	2.10 (0.91)
N founders with engineering background	1.33 (1.00)
N founders with managerial background	1.63 (0.92)
N founders with sales background	0.41 (0.65)
N founders with operations background	0.43 (0.70)
N founders with finance background	0.74 (0.80)
Job Characteristics (*N* = 547)	
Firm age	2.62 (1.43)
Days job open/100	3.84 (2.91)
Applications per job/100	1.25 (3.75)
Engineer job	0.68
Quality assurance job	0.12
Year job created	2010.4 (0.97)
Job level:	
• Interns	0.07
• Jr-level	0.04
• Mid-level	0.65
• Sr-level	0.24
Job location:	
• San Francisco	0.41
• Silicon Valley	0.35
• Other US locations	0.24
Candidate Characteristics (*N* = 39,704)	
Candidate ethnicity (Asian/Indian/Hispanic/Other)	(0.27/0.38/0.02/0.05)
Candidate years of education	17.29 (1.27)
Candidate Top 10 education	0.04
Candidate years of work experience	5.20 (5.63)
Candidate years of management experience	1.10 (2.41)
Candidate years of engineering experience	3.37 (4.48)
Candidate Top 500 experience	0.14
Candidate sales background	0.03
Candidate operations background	0.04

***Table 1.** (Continued)*

Candidate finance background	0.25
Referral	0.40
Miles home – job/100	10.62 (16.26)
Day of application	862.71 (345.12)
Functional homophily	0.21
School status homophily (Top 10 × Top 10)	0.01
Professional background homophily (Top 500 × Top 500)	0.06

Application Risk Set

In our supply-side analyses, we follow the case-cohort method to model the probability of application from among a set of possible alternative applications (e.g., Bengtsson & Hsu, 2015; Hedge & Tumlinson, 2014). We refer to these possible alternative applications as the "application risk set." Our main specification considers as the application risk set all other job listings open at the time of application in the same location as the focal job application. Timing is an important criterion, given that job search is usually delimited within a specified period of time (e.g., Kuhn & Mansour, 2014). Thus, we identify other jobs open at the time of the focal application. Similarly, because geographic location is a central criterion in job search (Fernandez & Su, 2004), we identify job postings in the same location as the focal job.[2] The following example illustrates our approach: for an application to a job in San Francisco on 01/03/2010, we include in the risk set all other jobs posted on the platform in San Francisco on 01/03/2010. Under this specification, each realized application to a job is matched, on average, with 93.26 at-risk jobs yielding a dataset of 3,702,626 observations.

For robustness, we considered two additional specifications of the application risk set. First, we impose an additional criterion, considering only job postings at startups in the same technology sector as the factual application, given that the choice of sector is an important and somewhat persistent feature of an individual's career (Wu & Dokko, 2007). For example, an application to a startup engaged in developing online content (e.g., games) in San Francisco on 01/03/2010 will have in its risk set jobs open at *other online content startups* in San Francisco on 01/03/2010. Considering this alternative risk set, each realized application is matched with an average of 25.67 possible other jobs yielding a dataset of 1,019,347

[2]Note that the jobs in our dataset are concentrated in the San Francisco Bay Area: 41% of jobs are in San Francisco and 35% in Silicon Valley. The remainder of jobs is located in other US locations. For the purpose of constructing the risk sets, we matched jobs that were collocated in San Francisco, Silicon Valley, or in one of eight other US regions. However, to alleviate concerns about our results being sensitive to the definition of the other location dummies, we replicate our results focusing only on jobs in the San Francisco Bay Area (i.e., San Francisco or Silicon Valley) and obtain similar results (available upon request).

observations. As a third risk set specification, we add the condition that jobs in the risk set must be of the same hierarchical level (intern, junior, mid-level, senior), given that job-seekers tend to apply to jobs of matching level (e.g., Bidwell, 2011). Under this scenario, an application to a junior position at a startup engaged in developing online content in San Francisco on 01/03/2010 will be matched with *other junior-level jobs* at online content startups open in San Francisco on 01/03/2010. Using this final specification of the risk set, each realized application to a job is matched with an average of 9.38 at-risk jobs yielding a dataset of 372,518 observations. As reported in Table 2 and Fig. 1 overleaf, regardless of whether a more or less restrictive risk set is used, our results continue to persist, reinforcing our confidence that the baseline specification we used is robust.

Dependent Variables

Application. In our supply-side analyses, we measured the probability that a candidate applied to a job posting relative to a risk set of alternative job postings. Accordingly, the dependent variable is coded "1" for a realized application to a job posting, and "0" for other job postings in the risk set.

Interview. With respect to firms' selection of job candidates, we focused on the interview stage and coded this outcome as "1" if, conditional on applying, a candidate received an interview, and "0" otherwise. Because we lack information that was incorporated in subsequent screening steps (e.g., details of candidates' performance on interviews), predicting subsequent screening outcomes on the basis of resume information alone poses a greater risk of omitted variable bias (Fernandez & Weinberg, 1997). Further, any disparities at the initial screening stage will likely influence the final hiring outcomes in the same direction (e.g., Ewens, Tomlin, & Wang, 2014).

Explanatory Variable: Founder-Candidate Gender Similarity

We identified founders' gender based on profiles available on websites or social media. Consistent with prior studies (e.g., Ruef et al., 2003), we measured female representation in the founding team as the proportion of female founders (mean = 5.8% female founders). Using the alternative measure of "at least one" female, 9.2% of firms in the sample had at least one female founder. This rate of female founder representation is within the range of typical venture-backed firms (i.e., estimates of the prevalence of female-led firms among venture-backed startups suggest that fewer than 10% of such firms are led by women, Greene et al., 2001).

For job candidates, we relied on candidates' self-reported gender in most cases and gender-coded first names for cases where self-reported gender was missing.[3]

[3]79.5% of job candidates reported gender. For the remaining candidates, we used the IBM InfoSphere Global Name Management Tool to code gender based on first names (Maguire, 2012). We assigned gender when a name had more than 85% probability of corresponding to that gender (Pool, Stoffman, & Yonker, 2015).

Table 2. Linear Probability Models of the Probability of Application.

	(1)	(2)	(3)	(4)	(5)	(6)
Female similarity	0.0024***	0.0083***	0.0328***	0.0028***	0.0084***	0.0262***
	(0.0005)	(0.0014)	(0.0046)	(0.0004)	(0.0014)	(0.0044)
Female candidate	−0.0002**	−0.0007**	−0.0021***			
	(0.0001)	(0.0003)	(0.0008)			
Proportion female founders	0.0031***	−0.0039***	0.0033	0.0034***	0.0037***	0.0201***
	(0.0002)	(0.0008)	(0.0024)	(0.0002)	(0.0007)	(0.0024)
Hispanic similarity	0.0061**	0.0105**	0.0189	0.0050**	0.0116**	0.0299**
	(0.0029)	(0.0050)	(0.0138)	(0.0025)	(0.0051)	(0.0152)
Indian similarity	0.0052***	0.0098***	0.0191***	0.0053***	0.0116***	0.0226***
	(0.0012)	(0.0028)	(0.0061)	(0.0012)	(0.0029)	(0.0070)
Asian similarity	−0.0024***	−0.0027	−0.0138**	−0.0027***	−0.0043*	−0.0202***
	(0.0008)	(0.0021)	(0.0058)	(0.0008)	(0.0022)	(0.0068)
Functional similarity	0.0013***	0.0020***	0.0034***	0.0014***	0.0028***	0.0039***
	(0.0001)	(0.0004)	(0.0010)	(0.0001)	(0.0005)	(0.0012)
Educational status similarity	−0.0008**	−0.0018	0.0051	−0.0008**	−0.0054***	−0.0129***
	(0.0004)	(0.0011)	(0.0043)	(0.0004)	(0.0013)	(0.0049)
Professional status similarity	0.0028***	0.0073***	0.0113***	0.0025***	0.0063***	0.0087***
	(0.0003)	(0.0010)	(0.0024)	(0.0003)	(0.0010)	(0.0025)
Number of founders	0.0005***	−0.0010**	−0.0152***	0.0013***	−0.0004	−0.0119***
	(0.0001)	(0.0004)	(0.0009)	(0.0001)	(0.0004)	(0.0010)
N founders with engineering background	0.0003***	−0.0004	0.0108***	0.0009***	0.0031***	0.0177***
	(0.0001)	(0.0003)	(0.0007)	(0.0001)	(0.0003)	(0.0007)
N founders with manager background	0.0009***	0.0018***	0.0023**	−0.0001	−0.0034***	−0.0128***
	(0.0001)	(0.0004)	(0.0010)	(0.0001)	(0.0004)	(0.0010)
N founders with sales background	−0.0027***	−0.0083***	−0.0110***	−0.0029***	−0.0075***	−0.0109***
	(0.0001)	(0.0003)	(0.0007)	(0.0001)	(0.0003)	(0.0007)
N founders with ops background	−0.0006***	−0.0016***	0.0028***	−0.0002**	0.0021***	0.0096***
	(0.0001)	(0.0003)	(0.0008)	(0.0001)	(0.0003)	(0.0008)

Table 2. (*Continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
N founders with finance background	−0.0008***	0.0039***	0.0142***	−0.0012***	0.0024***	0.0137***
	(0.0001)	(0.0003)	(0.0008)	(0.0001)	(0.0004)	(0.0009)
Proportion Indian founders	0.0235***	0.0561***	0.1034***	0.0231***	0.0522***	0.0955***
	(0.0005)	(0.0016)	(0.0034)	(0.0005)	(0.0017)	(0.0036)
Proportion Asian founders	−0.0125***	−0.0096***	−0.0420***	−0.0129***	−0.0075***	−0.0776***
	(0.0006)	(0.0017)	(0.0041)	(0.0006)	(0.0018)	(0.0046)
Proportion Hispanic founders	−0.0042***	0.0066***	0.0225***	−0.0016***	0.0062***	0.0209***
	(0.0004)	(0.0010)	(0.0027)	(0.0004)	(0.0010)	(0.0027)
Team diversity (HHF)	−0.0098***	0.0005	0.0044	−0.0113***	−0.0006	−0.0100***
	(0.0003)	(0.0012)	(0.0030)	(0.0003)	(0.0013)	(0.0031)
Founder Top 10 education	−0.0076***	−0.0094***	−0.0318***	−0.0075***	−0.0088***	−0.0371***
	(0.0001)	(0.0004)	(0.0011)	(0.0001)	(0.0004)	(0.0011)
Founder Top 500 experience	−0.0066***	−0.0187***	−0.0205***	−0.0075***	−0.0187***	−0.0245***
	(0.0001)	(0.0004)	(0.0010)	(0.0001)	(0.0004)	(0.0011)
No prior founding experience	0.0004***	0.0010***	−0.0029***	0.0001	−0.0021***	−0.0127***
	(0.0001)	(0.0002)	(0.0006)	(0.0001)	(0.0003)	(0.0006)
Mean years of founder experience/10	−0.0010***	−0.0043***	−0.0119***	0.0001	−0.0044***	−0.0124***
	(0.0001)	(0.0004)	(0.0007)	(0.0001)	(0.0004)	(0.0008)
VC financing	0.0036***	0.0079***	0.0125***	0.0033***	0.0033***	0.0063***
	(0.0001)	(0.0005)	(0.0011)	(0.0001)	(0.0005)	(0.0011)
N employees/100	−0.0044***	−0.0072***	−0.0182***	−0.0024***	0.0035***	−0.0002
	(0.0002)	(0.0007)	(0.0015)	(0.0002)	(0.0007)	(0.0016)
Firm age	−0.0012***	−0.0050***	−0.0095***	−0.0013***	−0.0052***	−0.0103***
	(0.0000)	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0002)
Firm press mentions/100	0.0044***	−0.0018***	−0.0078***	0.0044***	−0.0014***	−0.0064***
	(0.0002)	(0.0003)	(0.0007)	(0.0002)	(0.0003)	(0.0008)
Applications per job/100	0.0117***	0.0384***	0.0857***	0.0114***	0.0366***	0.0853***
	(0.0001)	(0.0002)	(0.0006)	(0.0001)	(0.0002)	(0.0006)

Days job open/100	0.0016***	0.0038***	0.0077***	0.0012***	0.0035***	0.0062***
	(0.0000)	(0.0002)	(0.0004)	(0.0000)	(0.0002)	(0.0004)
Engineer job	−0.0008***	−0.0030***	0.0014	−0.0007***	−0.0032***	−0.0017*
	(0.0001)	(0.0004)	(0.0010)	(0.0001)	(0.0004)	(0.0010)
Quality assurance job	0.0001	0.0039***	0.0054***	0.0006**	0.0068***	0.0167***
	(0.0003)	(0.0009)	(0.0019)	(0.0002)	(0.0009)	(0.0020)
Year job created	0.0056***	0.0154***	0.0361***	0.0086***	0.0276***	0.0653***
	(0.0002)	(0.0005)	(0.0012)	(0.0001)	(0.0005)	(0.0012)
Candidate home–job distance/100	−0.0000***	−0.0001***	−0.0001***	−0.0000***	0.0000	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Region, level, tech sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
Candidate controls	Yes	Yes	Yes	–	–	–
Candidate-fixed effects	No	No	No	Yes	Yes	Yes
Constant	−11.24***	−30.83***	−72.14***	−17.32***	−55.44***	−130.82***
	(0.37)	(0.97)	(2.34)	(0.26)	(1.03)	(2.47)
Risk set criteria	Time, location	Time, location, sector	Time, location, sector, level	Time, location	Time, location, sector	Time, location, sector, level
Degrees of freedom	62	62	62	45	45	45
Observations	3,702,626	1,019,347	372,518	3,702,626	1,019,347	372,518

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

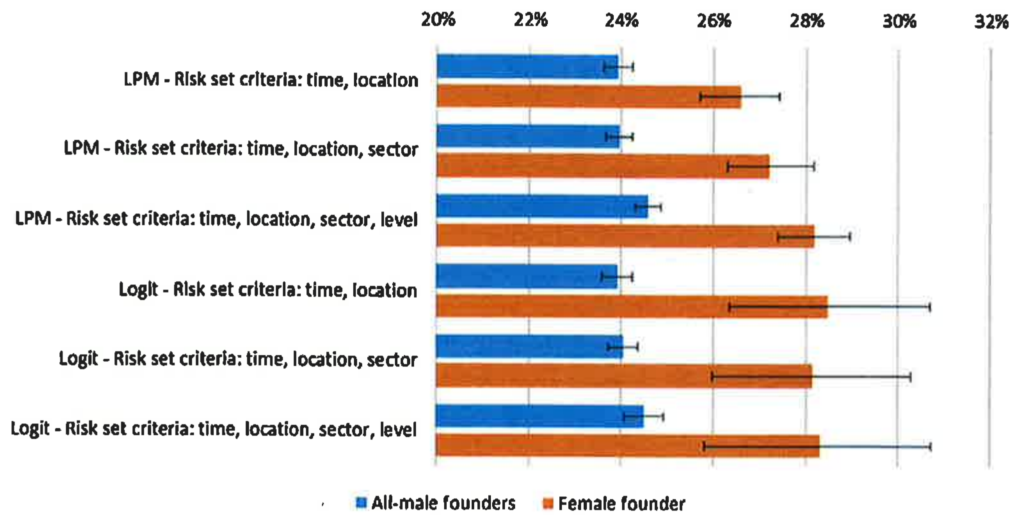

Fig. 1. Expected Female Share of the Applicant Pool.

Of the 39,704 applications, 24.3% were female. The corresponding share of females among San Francisco Bay Area software engineers (based on the US Census) is 19.9%, indicating that our sample is within the range of what would typically be observed in this setting. We constructed a *Female Similarity* measure, computing the product of the female proportion on the founding team and the female candidate dummy.

Explanatory Variables: Controls

Our models account for heterogeneity at three different levels: the firm/founder, the job, and the applicant. Below, we describe the key covariates we included in our models. Table 1 reports summary statistics for these controls.

Firm Characteristics. We controlled for firm size (number of employees) and whether the firm had received venture financing by the time we observed their recruiting. Given that some technologies may be more attractive to prospective workers than others, we coded indicator variables corresponding to the startup's technology sector (based on Venture Expert Industry Categories).

Founder Characteristics. We controlled for the size and ethnic composition of founding teams as well as a measure of founding team ethnic diversity (Herfindahl–Hirshman index). We also controlled for founding team members' professional backgrounds, including years of experience and the status of their educational backgrounds (Top 10 universities based *US News and World Report*) and professional backgrounds (*Fortune 500* technology companies). We account for functional backgrounds present in the founding team (Beckman & Burton, 2008) as well as prior founding experience among founders (Hsu, 2007). With these extensive measures of human capital and experience, we mitigate the concern that founder-candidate matching along demographic similarity is confounded with similarity in human capital or skills.

Job Characteristics. We controlled for the age of the firm at the time each job posting was created. We also accounted for the total number of applications received during the observation period. It is important to note that the jobs we considered generated a sufficient number of applications to lead to a competitive recruitment process (mean applications/job = 124.5). Thus, despite the fact that startups in our sample are, on average, quite young (mean age = 2.6 years old), the job listings they posted generated sufficient interest. Note that we winsorized the applications/job variable at the 10% level to reduce its skew (although alternative specifications of this variable, such as a log specification, yield substantively similar results). We also measured the number of days the job was open. Further, we included dummy variables to account for other job-level heterogeneity, distinguishing between "software developer" and "software engineer" jobs, and jobs in software quality assurance. Finally, to account for spatial heterogeneity, our models include job-location dummies. Jobs were distributed by location as follows (percentage of jobs): San Francisco (41), Silicon Valley (35), and other US locations (24).[4]

Candidate Characteristics. We control for candidate characteristics that might be correlated with gender and associated with the probability of job application. These include candidates' ethnicity as well as a battery of controls for human capital (e.g., academic credentials, years and type of professional experience).[5] We also control for application date (Fernandez & Weinberg, 1997) and the distance in air-miles between the candidate's home and the job location (Zenou, 2002). In our demand-side analyses, we controlled for whether the candidate applied via a network referral (e.g., Fernandez & Sosa, 2005; Petersen, Saporta, & Seidel, 2000). Because we lacked information on whether the candidate had received referrals to other jobs in the risk set, we were unable to control for referrals in our supply-side analyses.

Founder–Candidate Ethnic Similarity. In our models, we account for ethnic similarity between founders and job candidates. Similar to gender, we constructed our ethnic similarity measures as the product of the candidate's ethnicity dummy and the proportion of founders of that ethnicity in the founding team: labeled *Hispanic similarity*, *Indian similarity*, and *Asian similarity*. Note that because of the small number of non-Asian minority founders and candidates, we were unable to conduct a reliable test of our argument about ethnic minorities.

[4]Other US locations included (percentage of jobs): Southern California (7), Northeast (7), Pacific Northwest (2), Southwest (3), Mid-Atlantic (3), Midwest (<1), and South (<1).

[5]With respect to the candidates' ethnicities, 76% reported ethnicity on their application. For the remaining candidates, we used first names to infer ethnic background. Following other studies (Pool et al., 2015), we relied on a well-established algorithm, the Lydia name-ethnicity classifier, developed by Ambekar, Ward, Mohammed, Male, and Skiena (2009) and based on data extracted from Wikipedia. We classify an applicant as belonging to a given group, if the predicted probability assigned by the algorithm is above 85%. We inspected the data to confirm that the algorithm performs well.

However, our results with respect to ethnic similarity are in line with our main gender results (see Footnote 6).

Founder–Candidate Functional Background and Status Similarity. Given that similarity with respect to functional background may affect the likelihood of an employment match (e.g., Beckman & Burton, 2008), we calculated a functional similarity variable equal to "1" if the candidate shares a functional background with at least one member of the founding team, and "0" otherwise. Further, given that similarity with respect to status of educational and professional backgrounds may also affect the matching process (Rivera, 2012), we constructed a measure equal to "1" if both the candidate and a founder have a Top 10 educational background, and "0" otherwise, and another measure equal to "1" if both the candidate and a founder have worked at a Fortune 500 technology company, and "0" otherwise.

Empirical Strategy

We implement a two-step empirical strategy. First, we assess supply-side factors by examining the application process and modeling the probability of applying to a particular job. Second, we assess demand-side factors by examining the screening process and modeling the probability of an interview conditional on an application. In order to facilitate the interpretation of our main variables of interest, we implement linear probability models (Mood, 2010). For robustness, we estimated logit models which yield substantively similar results (available upon request). We also estimated candidate-fixed effect models in our supply and demand-side analyses to account for unobserved differences across job candidates. In all our models, we cluster standard errors by candidate to account for potential autocorrelation (models clustering standard errors by candidate and firm which yield similar results, available upon request).

RESULTS

Job Search Results

We begin by assessing H1 descriptively by comparing the composition of the applicant pool at ventures with no female founders to ventures with at least one female founder. Startups with a female founder have applicant pools with 31% of women, whereas startups with all-male founders receive only 24% of their applications from women (LR chi2 = 32.3, $p < 0.01$). These descriptive results provide initial evidence that female candidates target startups with female founders.

[6]Without considering the application risk sets, we find that the proportion of Hispanic founders is a marginally significant predictor of Hispanic candidates accounting for all other observables ($p < 0.1$). Considering the risk sets as in Table 2, the *Hispanic Similarity* coefficients positive, significant, and comparable in magnitude to the *Female Similarity* coefficients in all cases expect in the specification reported column 3 where *Hispanic Similarity* is positive but not statistically significant. With respect to the demand-side, we find no association between *Hispanic Similarity* and the probability of interviews. These additional results are available from the authors upon request.

We next assess the influence of founder profiles more formally, by examining these descriptive patterns in a regression framework. As previously discussed, this analysis considers three different risk sets to specify possible job postings that a candidate could consider in their job search. Table 2 reports a series of linear probability models of the probability of application. These models control for all firm, job, and candidate characteristics reported in Table 1. Models (1) to (3) correspond to each of the three different risk set specifications considered. As can be seen, regardless of the criteria considered to specify the risk set, the *Female Similarity* coefficient is positive and statistically significant, suggesting that the propensity of a female job candidate to seek startup employment increases with the proportion of female founders (H1).

To assess the substantive significance of these effects, we computed the expected gender composition of the applicant pool as a function of the gender of the founders using both LPM and logit specifications. For each model specification, we generated a thousand simulated expected values of the probability of application in each of the following four cases: males to all-male founder firms, males to firms with female founders, females to all-male founder firms, and females to firms with female founders (using the Clarify package in Stata, Tomz, Jason, & King, 2003). We then multiplied the expected probabilities of application by the number of possible applications in each of the four cases to yield the expected number of realized applications. Finally, we used these expected realized applications to calculate the expected gender composition of the applicant pool at all-male founder firms and firms with female founders.

Fig. 1 shows the results indicating that, across model specifications, the expected female share of applicants at startups with female founders is between 3 and 4% higher than at a firm with all-male founders. As a comparison, Holzer and Neumark (2000) studied the impact of affirmative action recruiting policies on the demographic composition of applicant pools using a survey of employers in large US cities and found that the impact of such policies was an increase of 3–4% points in the prevalence of certain minority groups in the applicant pool. In their case, the baseline representation of the groups studied in the applicant pool was on the order of 10%, implying that the policies considered increase the relative representation of minority groups in the applicant pool by 30–40%. In our case, the baseline representation of females in the applicant pool is 24%, implying that 3 to 4% more females represent an increase in relative representation in the applicant pool of 13–17%. So, compared to a set of policies explicitly designed to increase the share of minorities in the applicant pool, the effect of having a female founder is certainly smaller as we would expect, but of a similar order of magnitude. We consider the magnitude of these effects to be of substantive significance, especially considering that here we are studying recruiting for high-skilled positions where the supply of qualified applicants may be more constraint and therefore less sensitive to signals sent during recruitment.

Although these results include a rich set of controls for other characteristics of the candidate, job, and firm, we next address the potential remaining unmeasured candidate heterogeneity by re-estimating these baseline analyses with candidate-fixed effects. Table 2, columns 4–6 show the results using each of three risk set specifications. As can be seen, the positive and significant coefficients on the similarity variables suggest that – even when accounting for heterogeneity between candidates – female job candidates are still more likely to apply to a startup with a higher proportion of female founders. This is the case regardless of the particular risk set considered.

Robustness Checks and Alternative Explanations

We performed a number of robustness checks and investigated several alternative explanations related to these supply-side results.

Differential Networks. An alternative explanation for our findings on the supply-side might be that minorities seek employment at startups with minority founders because shared social networks with these founders generate opportunities to apply. In particular, employees can systematically sort into organizations based on referrals they obtain, and such referrals are often transmitted via homophilous social networks (Rubineau & Fernandez, 2013). In the context of startup recruiting, these processes may be particularly likely because networks are central to entrepreneurs' ability to gather the resources on which scaling a new venture critically depends (Stuart & Sorenson, 2007). Thus, founders might rely on their networks to "spread the word" about their startups and find talented candidates.

To alleviate this possibility, we examine whether the homophily effects are amplified among candidates who reach the firm via a network referral. Although information on whether a candidate applied via a network referral is available in our data, referrals cannot be observed for nonrealized applications in the risk set (i.e., applications to job postings that a candidate did not to pursue). Thus, we could not include referrals as a control in the preceding analysis. Nevertheless, it is possible to examine whether the presence of referrals strengthens the association between the gender composition of the founding team and the gender composition of applicants. To the extent that an uneven distribution of referrals by gender contributes to the founder effects, there should be a closer demographic match between founders and candidates among referrals.

Table 3 presents a number of linear probability models of the probability that a candidate is female as a function of the proportion of female founders and controls. We start by replicating our main analyses of the association between the presence of female founders and the probability of female candidates considering this specification. The results in model 1 show that, consistent with our main findings, the proportion of female founders is predictive of the proportion of females in the applicant pool. The coefficient on the "proportion of female founders" variable indicated that going from a team without female founders to an all-female founding team is associated with 8.9% points higher representation of females in the applicant pool. This further validates our main findings, showing that they are not an artifact of the approach taken to model the incidence of applications (i.e., criteria considered to specify the risk sets). In column 2, we add the interaction between "proportion of female founders" and referrals in predicting the application by female candidates. The insignificant coefficient on

Table 3. Linear Probability Models of the Probability of Female Candidates.

	(1)	(2)
Proportion female founders	0.089***	0.083**
	(0.025)	(0.035)
Referral	−0.013**	−0.013**
	(0.006)	(0.006)
Proportion female founders × Referral		0.011
		(0.044)
Number of founders	−0.006	−0.006
	(0.006)	(0.006)
N founders with engineering background	−0.013**	−0.013**
	(0.006)	(0.006)
N founders with manager background	0.011	0.010
	(0.008)	(0.008)
N founders with sales background	0.014*	0.014*
	(0.007)	(0.007)
N founders with ops background	−0.007	−0.007
	(0.005)	(0.005)
N founders with finance background	0.016***	0.016***
	(0.005)	(0.005)
Proportion Indian founders	−0.026	−0.026
	(0.020)	(0.020)
Proportion Asian founders	−0.087***	−0.087***
	(0.029)	(0.029)
Proportion Hispanic founders	−0.016	−0.016
	(0.043)	(0.043)
Team diversity (HHF)	−0.048**	−0.048**
	(0.019)	(0.019)
Founder Top 10 education	−0.006	−0.006
	(0.008)	(0.008)
Founder Top 500 experience	0.012*	0.012*
	(0.007)	(0.007)
No prior founding experience	0.000	0.000
	(0.005)	(0.005)
Mean years of founder experience/10	−0.002	−0.002
	(0.007)	(0.007)
VC financing	−0.010	−0.010
	(0.009)	(0.009)
N employees/100	−0.008	−0.008
	(0.011)	(0.011)
Firm age	0.016***	0.016***
	(0.003)	(0.003)
Firm press mentions/100	−0.005	−0.005
	(0.003)	(0.003)
Applications per job/100	0.000	0.000
	(0.000)	(0.000)
Days job open/100	−0.005**	−0.005**
	(0.002)	(0.002)
Engineer job	−0.020**	−0.020**
	(0.008)	(0.008)

Table 3. *(Continued)*

	(1)	(2)
Quality assurance job	0.207***	0.207***
	(0.011)	(0.011)
Year job created	−0.021***	−0.021***
	(0.006)	(0.006)
Candidate home–job distance/100	−0.002***	−0.002***
	(0.000)	(0.000)
Indian candidate	0.092***	0.092***
	(0.010)	(0.010)
Asian candidate	0.102***	0.102***
	(0.009)	(0.009)
Hispanic candidate	−0.043***	−0.043***
	(0.014)	(0.014)
Other ethnicity candidate	0.046***	0.046***
	(0.015)	(0.015)
Candidate years of education	0.015***	0.015***
	(0.002)	(0.002)
Candidate Top 10 education	−0.011	−0.011
	(0.014)	(0.014)
Candidate years of experience	0.000	0.000
	(0.002)	(0.002)
Candidate years of management experience	−0.015***	−0.015***
	(0.002)	(0.002)
Candidate years of experience^2	−0.000	−0.000
	(0.000)	(0.000)
Candidate years of management experience^2	0.000***	0.000***
	(0.000)	(0.000)
Candidate years of engineering experience	−0.003	−0.003
	(0.002)	(0.002)
Candidate years of engineering experience^2	−0.000	−0.000
	(0.000)	(0.000)
Candidate Top 500 experience	0.002	0.002
	(0.011)	(0.011)
Candidate sales background	0.028	0.028
	(0.020)	(0.020)
Candidate operations background	−0.008	−0.008
	(0.015)	(0.015)
Candidate finance background	0.020**	0.020**
	(0.008)	(0.008)
Day of application	0.003***	0.003***
	(0.001)	(0.001)
Region, level, tech sector dummies	Yes	Yes
Constant	41.993***	41.921***
	(12.130)	(12.131)
Degrees of freedom	57	58
Observations	39,704	39,704

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the interaction term suggests that the effect of female founders among referral candidates is as strong as among nonreferral candidates, suggesting that the influence of female founders is unlikely to operate via a referral mechanism.

Decay of Founder Effects with Firm Age. As new ventures mature, we expect alternative performance metrics by which to evaluate a startup to become available to job candidates, thus undermining the signaling role of the founders' profiles (Hallen, 2008). Over time, founders might also be replaced by professional managers, and thus the tendencies we document here should be weaker or even no longer present. Thus, we expect founders' profiles to exert weaker influence on job candidates' application choices, as firms mature and age. To examine this claim, we take advantage of information on applications to firms that no longer are startups (i.e., firms older than five years), as founder-similarity effects should be much weaker among these older firms than among startups. In Table 4, we report a number of LPM models of the probability of application across a broader sample, including firms which were over five years old. We use these models to test the interaction between *Female Similarity* and the *Startup* (less than five years old) dummy. Starting with the first risk set specification in column 1, the results show a strongly positive *Female Similarity* and *Startup* interaction, consistent with these arguments. Columns 2 and 3 show analogous

Table 4. Linear Probability Models of the Probability of Application – Including Older Firms.

	(1)	(2)	(3)
Startup firm	0.003***	0.008***	0.008***
	(0.000)	(0.001)	(0.002)
Female candidate	0.003***	0.006***	0.018***
	(0.000)	(0.001)	(0.003)
Proportion female founders	0.009***	0.032***	0.052***
	(0.001)	(0.004)	(0.007)
Female similarity	−0.002*	−0.020***	−0.049***
	(0.001)	(0.006)	(0.011)
Female candidate × Startup	−0.003***	−0.008***	−0.023***
	(0.000)	(0.001)	(0.003)
Proportion female founders × Startup	−0.009***	−0.034***	−0.046***
	(0.001)	(0.004)	(0.007)
Female similarity × Startup	0.006***	0.029***	0.086***
	(0.001)	(0.006)	(0.012)
Location, level, tech sector dummies	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Risk set criteria	Time, location	Time, location, sector	Time, location, sector, level
Constant	−10.726***	−30.344***	−71.738***
	(0.328)	(0.912)	(2.153)
Degrees of freedom	66	66	66
Observations	4,312,119	1,185,759	445,178

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

models but with alternative risk set specifications. As can be seen, these models yield similar results. Overall, these estimates suggest that the mechanisms we hypothesized are most likely to pertain to startups – young and small organizations – in which founder demographics exert influence in attracting early hires.

Coarsened Exact Matching. In order to test for robustness to alternative specifications of the control variables, we conducted a coarsened exact matching procedure (Iacus, King, & Porro, 2012), where we matched firms with female founders to all male-founded firms. Specifically, we matched on covariates which are unbalanced between these two groups of firms. Female-founded firms are, on average, less likely to have Indian founders and they exhibit lower ethnic diversity among founding-team members (HHF index). Female-founded firms also tend to have founders that are less experienced, they tend to be younger firms, and they tend to receive fewer press mentions. Our findings further suggest that these firms are also different with respect to their spatial distribution and technology sector, relative to firms with all-male founders. We thus matched on these characteristics and then estimated models of the probability of application as a function of founder–candidate *Female Similarity* on the matched dataset (N = 158,144). Table 5 shows the results. As can be seen, using either the LPM or logit specification, the *Female Similarity* coefficient remains positive (in fact, larger in magnitude than in the unmatched dataset) and statistically significant. This result further strengthens our confidence that our findings are not sensitive to the specification of the control variables considered in our main analysis.

Employer Screening Results

We next turn to the screening of candidates by startups. Our core argument is that, although females may target startups with female founders, it is less likely that female founders will favor females in screening (H2). We begin to examine this claim by assessing whether startups with higher representation of female

Table 5. Coarsened Exact Matching – Models of the Probability of Application on Matched Dataset.

	(1) LPM	(2) Logit
Female similarity	0.012***	1.511***
	(0.002)	(0.365)
Female candidate	−0.001	−0.247
	(0.001)	(0.159)
Proportion female founders	0.009***	1.787***
	(0.001)	(0.177)
Constant	0.003***	−5.726***
	(0.000)	(0.072)
Degrees of freedom	3	3
Observations	158,144	158,144

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

founders are more likely to favor female candidates in screening than equivalent startups with lower representation of female founders. Table 6 shows the results of a number of linear probability models of the probability of interview aimed at assessing this claim. In column 1, we assess this relationship in the full sample of 39,704 applications, controlling for all candidate, job, and firm characteristics reported in Table 1. As can be seen, female candidates are significantly less likely to be invited to an interview. However, *Female Similarity* is not a significant predictor of interviews. This implies that, while females are less likely to be interviewed overall, the extent of their disadvantage is not dependent on the presence of females in the founding team.

An important concern with this result is that – although we control for many characteristics of job candidates – there could still remain unmeasured candidate characteristics that differ between firms, and are associated with the presence of female founders. For example, firms with female founders may attract comparatively lower-quality female candidates. This would be the case if it takes a higher level of confidence for a female to apply to a startup with an all-male team, and these confident female job candidates are also better quality candidates in ways that are unmeasured in the data. In order to address such concerns, in column 2, we estimate our results adding candidate-fixed effects. Unmeasured differences in the candidate pool across different types of firms are accounted for in these analyses. It is important to note that this analysis can only be estimated for candidates who applied to more than one job and are interviewed for at least one job, thus providing within-applicant variation in the dependent variable. This reduces our sample size from 39,704 applications to 2,563 applications from 621 individual re-applicants (i.e., applicants who applied more than once). Modeling the probability of interview on this subsample, the results in column 2 show that, even when accounting for between-candidate heterogeneity, there is no statistically reliable effect of *Female Similarity* on the probability of interview. In order to examine this result further, in columns 3 and 4, we split the sample of re-applicants into male re-applicants (column 3) and female re-applicants (column 4). In either model, the proportion of female founders is not a statistically significant predictor of interviews, suggesting that the gender composition of the founding team does not affect the probability of interview for candidates of either gender. In sum, our demand-side analyses indicate that females are less likely to be interviewed, but their disadvantage is not a function of the gender composition of the founding team. This is the case even "within" a given female applicant.

Thus, the combination of our supply- and demand-side findings provides support for H2. As we showed previously, higher representation of female founders is associated with a higher propensity of female job candidates favoring a given startup in their job search. The resulting representation of female candidates is 3–4% points at startups with female founders. However, on the demand-side, our null (and directionally negative) effect of *Female Similarity* on the probability of interviews suggests a relatively weaker influence of demographic similarity on the demand-side. Based on these different analyses, we thus

Table 6. Linear Probability Models of the Probability of Interviews.

	(1)	(2)	(3)	(4)
Female candidate	−0.008***			
	(0.002)			
Proportion female founders	−0.008	0.072	0.055	0.008
	(0.019)	(0.093)	(0.096)	(0.212)
Female similarity	−0.026	−0.279		
	(0.030)	(0.198)		
Number of founders	0.012***	0.048	0.059	0.017
	(0.004)	(0.031)	(0.036)	(0.060)
N founders with engineering background	0.025***	0.106***	0.118***	−0.008
	(0.004)	(0.026)	(0.029)	(0.054)
N founders with manager background	−0.030***	−0.079**	−0.110***	0.112
	(0.006)	(0.032)	(0.034)	(0.081)
N founders with sales background	−0.007	−0.013	−0.046	0.157*
	(0.005)	(0.032)	(0.034)	(0.083)
N founders with ops background	−0.011***	−0.032	−0.048**	0.014
	(0.003)	(0.021)	(0.023)	(0.054)
N founders with finance background	0.007*	−0.014	0.016	−0.157***
	(0.004)	(0.024)	(0.026)	(0.054)
Proportion Indian founders	−0.003	−0.168**	−0.173**	−0.153
	(0.011)	(0.075)	(0.086)	(0.151)
Proportion Asian founders	−0.064***	−0.370***	−0.456***	0.158
	(0.019)	(0.119)	(0.135)	(0.306)
Proportion Hispanic founders	−0.041	−0.212	−0.211	Not est.
	(0.031)	(0.232)	(0.256)	
Team diversity (HHF)	−0.008	−0.107	−0.158*	0.197
	(0.011)	(0.078)	(0.092)	(0.180)
Founder Top 10 education	0.015***	0.030	0.040	0.068
	(0.006)	(0.040)	(0.044)	(0.090)
Founder Top 500 experience	−0.020***	−0.049	−0.049	−0.092
	(0.004)	(0.032)	(0.036)	(0.068)
No prior founding experience	0.005	0.010	0.003	0.057
	(0.003)	(0.022)	(0.026)	(0.050)
Mean years of founder experience/10	−0.007	−0.002	0.005	−0.092
	(0.005)	(0.033)	(0.039)	(0.067)
VC financing	−0.008	−0.006	−0.026	0.070
	(0.006)	(0.036)	(0.039)	(0.094)
N employees/100	0.037***	0.090*	0.094*	0.217*
	(0.008)	(0.048)	(0.052)	(0.115)
Firm age	−0.004**	−0.001	0.001	−0.015
	(0.002)	(0.013)	(0.014)	(0.030)
Firm press mentions/100	−0.011***	−0.055***	−0.059***	−0.002
	(0.002)	(0.014)	(0.016)	(0.035)
Applications per job/100	−0.000	−0.004***	−0.003**	−0.004
	(0.000)	(0.001)	(0.002)	(0.004)
Days job open/100	0.000	0.005	−0.001	0.016
	(0.001)	(0.009)	(0.010)	(0.018)
Engineer job	−0.030***	−0.084**	−0.092**	0.044
	(0.005)	(0.038)	(0.041)	(0.105)
Quality assurance job	−0.012***	0.056	0.003	0.158**
	(0.004)	(0.048)	(0.059)	(0.076)

Table 6. *(Continued)*

	(1)	(2)	(3)	(4)
Year job created	0.016***	0.074***	0.063*	0.086
	(0.003)	(0.027)	(0.033)	(0.060)
Candidate home–job distance/100	−0.000***	−0.003**	−0.003*	−0.004
	(0.000)	(0.002)	(0.002)	(0.005)
Referral	−0.000	0.112***	0.117***	0.124**
	(0.002)	(0.026)	(0.030)	(0.055)
Indian candidate	−0.034***			
	(0.003)			
Asian candidate	−0.030***			
	(0.003)			
Hispanic candidate	−0.022***			
	(0.008)			
Other ethnicity candidate	−0.029***			
	(0.005)			
Candidate years of education	−0.003***			
	(0.001)			
Candidate Top 10 education	0.060***			
	(0.008)			
Candidate years of experience	0.001			
	(0.001)			
Candidate years of management experience	−0.002**			
	(0.001)			
Candidate years of experience^2	−0.000**			
	(0.000)			
Candidate years of management experience^2	0.000			
	(0.000)			
Candidate years of engineering experience	0.004***			
	(0.001)			
Candidate years of engineering experience^2	−0.000***			
	(0.000)			
Candidate Top 500 experience	0.024***			
	(0.004)			
Candidate sales background	−0.009			
	(0.006)			
Candidate operations background	−0.006			
	(0.005)			
Candidate finance background	−0.005**			
	(0.002)			
Day of application	−0.001**	−0.012	−0.011	−0.034*
	(0.000)	(0.008)	(0.008)	(0.019)
Region, level, tech sector dummies	Yes	Yes	Yes	Yes
Constant	−32.64***	−147.82***	−125.78*	−172.50
	(6.72)	(54.69)	(65.82)	(120.39)
Degrees of freedom	59	41	40	36
Observations	39,704	2,563	2,062	501

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

conclude that homophily exerts a less significant influence on founders than on job candidates (H2).

DISCUSSION

Whereas the creation of jobs by startups has been a subject of a long inquiry (e.g., Blanchflower, 2000; Haltiwanger et al., 2012), how these positions are filled is not been well understood. In this study, we shed light on one aspect of this question, by focusing on the influence of homophily on the hiring of minority job candidates into startups. To the extent that entrepreneurship scholars have paid attention to a demographic composition of startup workers, the prevailing accounts have largely been limited in their analyses to founding and top management teams. For example, multiple studies have found a significant tendency toward homogeneity among startup founders and executives (e.g., Beckman & Burton, 2008; Ruef et al., 2003).

In this study, we shift the attention from founding teams to early hires and theorize about the processes responsible for recruitment of minority workers at startups. Because researchers have long recognized that hiring is a two-sided process, whereby the key outcomes are determined not only by firm screening but also by the supply-side job search strategies (e.g., Pager & Pedulla, 2015), we propose that a joint consideration of both the supply and demand sides of the hiring interface is necessary also in the startup context. In particular, we posit that minorities (i.e., women) are disproportionately attracted to startups with demographically similar founders (i.e., other women), whereas startups with minority founders (i.e., women) are unlikely to disproportionately favor minorities (i.e., women) in screening. We exploit a unique empirical setting that allows us to assess the choices of both candidates and startups at the hiring interface and provide evidence consistent with this argument.

Our study makes several contributions. First, whereas scholars have increasingly highlighted the importance of supply-side job search strategies in contributing to workplace segregation by gender and race (e.g., Barbulescu & Bidwell, 2013; Fernandez & Friedrich, 2011; Pager & Pedulla, 2015), these processes have not been theorized in the context of startups. Perhaps because of data limitations, research to date has made only limited progress in illuminating a set of predictors which could explain why individuals seek employment in a new venture and which ventures they target (Dahl & Klepper, 2015; Roach & Sauermann, 2015). Similarly, whereas the screening processes in established firms have been well documented (e.g., Fernandez & Sosa, 2005), relatively less is known about such processes in young and small ventures, even though early employees play a critical role in the growth and success of nascent firms. We contribute to this growing line of inquiry by shedding light on how supply- and demand-side factors jointly operate to perpetuate the demographic segregation of startup workforces.

Second, our study contributes to an emerging literature on job search strategies, especially in the context of minority underrepresentation in the labor market. Scholars have debated the nature of search in response to the widespread discrimination (Heckman, 1998), especially in conditions where employer behavior is difficult to predict *ex-ante* (e.g., Pager & Pedulla, 2015). We contribute to this debate by theorizing the nature of job search in the context of startups: here, we find evidence that founders' profiles incline minorities to tailor their job search, and that these job-seekers tend to target startups based on the resemblance to the founder. Whereas our findings shed light on search processes in the startup context, they also highlight conditions under which job search strategies might be ineffective. Some scholars have suggested that targeted search might reduce the prevalence of discrimination (e.g., Heckman, 1998; Lundberg & Startz, 2007), while others have questioned the effectiveness of such strategies based on the difficulties in accurately identifying the desirable employers (Goldsmith, Sedo, Darity, & Hamilton, 2004; Pager & Pedulla, 2015). Our study contributes to this latter line of work by further highlighting the conditions under which targeted search might not be effective in the sense of leading minority candidates toward firms who might be more likely to hire them.

Our findings are consistent with the notion that job candidates and founders have different information and different incentives when evaluating each other in the startup labor market. Importantly, these differences account for the differential propensity toward homophily on each side of the market. However, future research may further disentangle when and why asymmetry in homophily tends to arise and persist. It might, for example, be that the asymmetry we document here is contingent upon the scarcity of direct information on the behavior of actors on the other side of the market. In these instances, it might be more difficult for job candidates to adjust their behavior over time, based on the information they receive about employers. Although our study is the first to account job application decisions across a sample of startups, empirically, it does not allow us to completely rule out other factors that may account for the differential job application patterns observed. Indeed, female-founded startups may be different from male-founded startups in ways that are unmeasured in the data. For example, although we account for the technology sector of the startup, more fine-grained distinctions relating to the exact types of technologies or products developed might influence the differential sorting of job applicants. Given the challenges of fully eliminating confounding factors in any field setting, future experimental work simulating a hiring context at a startup (and randomly assigning founders' profiles to otherwise identical startups) would be a valuable complement of our findings. Also, although our theoretical arguments in principle could apply to other dimensions of demographic homophily such as ethnicity, here we were unable to conclusively assess such dimensions. Like women, non-Asian minority workers tend to be significantly underrepresented in the startup labor market, and thus our theoretical arguments should similarly hold for these job-seekers. Although we lack a sufficiently large sample to assess these arguments with statistical precision, our findings relating to ethnic homophily are broadly consistent with the theory we developed: In case of Hispanics, we find that Hispanic workers are more likely to target firms with

Hispanic founders, although these firms do not disproportionally favor Hispanic candidates.[6] Future work could gather additional data on ethnic minority job-seekers to more conclusively assess the applicability of our arguments beyond the case of gender.

Finally, our findings pertain to software engineering positions at high-growth startups, in which technical programming skills are particularly important and relatively easy to observe in screening. Although we view this as a typical set of circumstances determining the matching for workers to "core" scientific-technical positions in high-tech startups (Baron et al., 2007), in other settings the match between an employer and employee may be less subject to objective criteria or be less influenced by urgency to hire. Under such circumstances, organizational selection processes might be more sensitive to various dimensions of social similarity between candidates and screeners (Rivera, 2011, 2012). Overall, our study sheds light on the distribution of minorities across startup jobs, by jointly considering the influence of candidate job search processes and startup hiring processes. A deeper understanding of not only processes that govern the creation of startup jobs but also the matching of workers to such jobs is critical in understanding the entrepreneurial economy.

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