Population-Level Evidence of the Gender Gap in Technology Entrepreneurship*

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Abstract

This paper investigates the entrepreneurship gender gap in technology industries. While digitization has created vast economic opportunities in the technology sector, it has also lowered many barriers to entry, reducing traditional frictions to entrepreneurship and thus potentially increasing opportunities for female founders. Using individual career histories from more than 600 million LinkedIn profiles, we study whether females exhibit a higher rate of founding in technology industries. We report three main results: 1) Females are only half as likely as males to found businesses in technology industries. 2) Although there are fewer females employed in tech industries, even when we use the gender gap in labor force participation as a baseline, the gender gap in tech entrepreneurship relative to the share of females employed in tech is wider than in other industries. 3) The larger gender gap in tech entrepreneurship relative to other industries is largely driven by lower likelihood of founding for females in lower positions in the organizational hierarchy: by contrast, females who reach the C-suite in technology sectors are actually 16% more likely to found firms than their female C-suite counterparts in non-tech industries. Together, these results paint a more nuanced picture of the gender gap, and provide important facts to inform policies intended to ameliorate the gender gap in tech.

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1 Introduction

A growing literature has sought to document and understand the "gender gap", the uneven distribution of opportunities between males and females in the economy and its economic implications (Duflo, 2012; Lambrecht and Tucker, 2019; Bohnet et al., 2015; Bertrand et al., 2010). Existing studies have proposed a variety of explanations for the existence of this gap, from frictions in the labor market (Goldin and Rouse; Levine and Rubinstein, 2017; Ewens and Townsend, 2019), differences in education (Card and Payne, 2017), or differences in preferences (Cook et al., 2018; Liang et al., 2018; Thebaud, 2015; Adams and Funk, 2012).

Female versus male participation in entrepreneurship is a potentially important signal of the gender gap (Howell and Nanda, 2019; Guzman and Kacperczyk, 2019; Lyons and Zhang, 2017; Gompers and Wang, 2017). Within entrepreneurship, there is evidence that the gender gap persists, even within developed economies where the gender gap in wages or professional development have declined (Global Entrepreneurship Monitor, 2017; Kaufman, 2018). One explanation for the existence of this gender gap is the presence of systemic frictions that prevent females from entering or advancing in particular industries and, in turn, founding businesses.

With the growth of digital technologies, a growing share of economic activity has moved to the technology sector. A unique and important characteristic of digital technologies is that digital technologies allow individuals to circumvent and reduce some of these frictions, allowing formerly under-represented groups to participate with a greater share. For instance, the shift from physical trading floors in financial markets to digital trading floors where trades were submitted from behind a computer led to higher female participation (Lambert, 2011). Similarly, the information technology (IT) revolution in India provided an avenue for advancement for individuals with previously restricted economic and societal opportunities (Arora and Athreye, 2002).

The potential for technology to reduce the gender gap in entrepreneurship is even more pronounced. Digital ventures typically require lower entry costs than brick-and-mortar ventures, so entrepreneurs are able to bootstrap (self-fund) their ventures. This may enhance opportunities for female founding, since external financing by venture capital (VC) has been identified as a potentially important obstacle for many female entrepreneurs (Levine and Rubinstein, 2017; Ewens and Townsend, 2019; Gompers and Wang, 2017). The digital distribution of technology products and services may equalize access to markets. Platforms such as app stores and peer-to-peer marketplaces widen the geographic reach of businesses and allow sellers to go beyond personal networks and local distribution channels, selling directly to customers (Bresnahan et al., 2014). The ability to transact online obscures gender, reducing the effect of systemic biases (Luca, 2017; Fisman and Luca, 2016). To the extent that systemic gender or racial biases creep into online channels

(Edelman et al., 2017), online platforms can take steps to obscure certain information in order to ensure that these characteristics are not visible on the platform (Fisman and Luca, 2016; Luca, 2017). STEM (Science, Technology, Engineering, & Mathematics) education, a potential pre-requisite for entering into technology industries, has seen growing female participation potentially reducing this gender gap.

Despite the growth of the promise of digital technologies, there is evidence that the gender gap in technology industries may persist. Studies of online marketplaces suggest that a substantial gender gap exists in the sharing economy, despite the role of the platform in mediating the interaction (Cook et al., 2018; Liang et al., 2018). Similarly, studies have found that the digitization of banking (shift from branches to online) has made it disproportionately more difficult for female entrepreneurs to get access to funding (Malmstrom and Wincent, 2018a,b). Industry reports suggest that only 3.8% of total VC dollars on average went to female founded firms over the period from 2014 until 2019 (Gene et al., 2019). Similarly, Guzman and Kacperczyk (2019) report that 22% of all new firms are founded by female entrepreneurs, but only 15% of firms in the IT Sector and 17% of firms in the e-commerce sectors have female founders. While digitization and the technology sector may be creating opportunities more broadly, it raises further questions as to whether this helps to reduce or increase the gender gap in entrepreneurship.

A major challenge to the existing studies on the gender gap is the lack of a baseline or reference group against which we can interpret the observed share of female entrepreneurship. We consider the female employees in an industry to be the risk set of entrepreneurs in the industry (as opposed to the entire population of females). For instance, if the share of female founders in an industry was equivalent to the share of female employees in that industry, then the source of any gender gap in entrepreneurship in that industry was driven by the gap in females entering that industry. Efforts to reduce the gender gap in this industry should focus on solving "pipeline" shortages. Alternatively, if the share of female founders in an industry was much lower than the share of female employees in that industry, this would suggest that the source of the gender gap in entrepreneurship in that industry comes in part from frictions within that industry. Policies to reduce the gender gap need to additionally consider factors that affect workplace advancement and female founding. Understanding these differences can help inform policies to address or account for this gender gap.

Our analysis is based on population level data acquired from LinkedIn through the Economic Graph Research (EGR) partnership. This allows us to study the population of more than 600 million individuals with public profiles on LinkedIn, their educational and employment histories, and shifts to entrepreneurship (if they occur). We systematically measure the gender gap in entrepreneurship (founding a business), across different industries, job positions held prior to founding, and education backgrounds. We focus primarily on founding events in the United States from 2005 to 2018. We find that while females represent 32% of the workforce in technology industries, they only represent 15% of founded firms. Therefore, the gender gap in founding is not simply a reflection of the baseline participation in technology industries. If tech entrepreneurship was simply a random draw from the tech workforce, we would expect 32% female founders. This would still reflect a gender gap, but it would not suggest that other mechanisms in tech are widening the entrepreneurship gender gap from the labor force participation baseline. In non-technology industries, the share of female-founded firms is approximately 36%, while the share of female employees is 49%. We find that females in tech are 50% less likely to found a venture than men in tech, while females in non-technology are only 23% less likely to found a venture than men in non-tech. This gap differs considerably across positions held prior to founding: females in junior positions in tech are 26 - 30% less likely to found than equivalently positioned females in non-tech industries. However, females from senior positions in tech are 16% more likely to found than equivalently positions females in non-tech industries. Furthermore, the share of males founding from senior positions in technology is 47% greater than males founding in non-technology industries.

This study contributes to the broader literature that has tried to document and understand the gender gap. The lack of baselines in existing studies limits the ability of researchers to interpret the magnitude of the gender gap and identify its sources. In contrast to earlier studies, we demonstrate how interpretation of the gender gap can change with respect to the baseline (risk-set) of people that may choose to become entrepreneurs. Our study is among the first to document the magnitude of the gender gap in technology industries and compare these magnitudes relative to different baselines in order to aid in interpreting these effects. This helps to highlight the problems associated with drawing conclusions about the gender gap without a benchmark and provides insights into the origin of the gender gap in digital entrepreneurship. In doing so, this study informs the broader literature on policies that may be used to reduce the gender gap, both in entrepreneurship and the economy more broadly (Lambrecht and Tucker, 2019).

2 Literature Review

The "Gender Gap" is the term commonly used to refer to unequal economic outcomes between men and women in the economy. These specific outcomes can include gender differences in income (Blau and Kahn, 1994, 2017; Card et al., 2015), the related question of the gender gap in top corporate positions, which may be an underlying factor influencing the gap in income (Matsa and Miller, 2011; Bertrand and Hallock, 2001; Bertrand et al., 2010; Kunze and Miller, 2017), and differences in education patterns which create differential paths for men and women early in their careers (Kahn and Ginther, 2017; Card and Payne, 2017). There is less work on the gender gap in entrepreneurship, with the recent study by Guzman and Kacperczyk (2019) and various industry reports (Gene et al., 2019; Monitor, 2019) being the exceptions.

A number of different and potentially reinforcing factors lead to the gender gap. One important issue is the presence of systemic frictions that prevent females from advancing in particular roles. For instance, academic research has documented the role of societal norms (Yang and Aldrich, 2014), familial pressures (Azmat and Ferrer, 2017), sorting into specific business areas (Thebaud, 2015; Guzman and Kacperczyk, 2019), educational topics (Card and Payne, 2017), the role of female superiors and cultural norms in facilitating this process (Abraham, 2017, 2019; Matsa and Miller, 2011; Nollenberger et al., 2016), and the role of gendered language (Wu, 2018) in shaping the gender gap.

While these studies have documented evidence of this for the gender gap in the broader economy, there is evidence that this also contributes to the gender gap in entrepreneurship (Markussen and Roed, 2017; Thebaud, 2015). Additionally, there a variety of entrepreneurship specific factors that may contribute to a greater gender gap in entrepreneurship. For instance, the need for venture-capital financing, which is largely male-dominated, can be a limitation for female founders, particularly when it comes to the decision of selecting which businesses should receive funding (Guzman and Kacperczyk, 2019; Scott and Shu, 2017). Additionally, many founders emerge from companies already within a particular industry (Sorensen and Fassiotto, 2011). Therefore, a lack of female employees within the industry may limit the risk set or likelihood of females that may transition into entrepreneurship.

With the growth of digitization and the rise in prominence of the technology sector, the costs of creating a businesses and have fallen and many traditional frictions or barriers to innovation may similarly dissipate (Goldfarb and Tucker, 2019; Greenstein et al., 2013). For example, digital platforms such as mobile application marketplaces have lowered the costs of creating a software application and bringing it to market, by providing much of the file storage, distribution, payment processing and rights enforcement that would previously have to be carried out by multiple parties (Miric et al., 2019; Bresnahan et al., 2014). One might expect that this democratized access to much of the infrastructure necessary to create a digital business could reduce the need for venture financing or the social networks and connections necessary to acquire funding or establish a distribution channel. This might lead researchers to observe a lower gender gap in technology industries.

However, empirical evidence of this phenomenon is quite limited. Evidence that does exist suggests that a large gender gap persists in technology industries as well. For instance, Kenney and Patton (2015) examine top management teams among Silicon Valley (SV) 150 and S&P 100 companies in 2013 and find that only 9% and 19% of executives were females, respectively. While there is overlap between these groups, the SV 150 captures a greater share of tech firms, suggesting that this gender imbalance within tech may be greater. Between 1996 and 2006, only 2.4% of CEOs within the software industry were females. The authors focus on initial public offerings (IPOs), which typically emphasize firms that acquired venture capital, rather than newly founded ventures. Guzman and Kacperczyk (2019) use business registration data and find that female founders are associated with lower performing IPOs, which is largely attributed to females' choices to found lower-growth potential ventures. This is their explanation for why only 10% of founders are female among the top 1% of high growth oriented firms. Given that technology is oriented towards high-growth ventures, this may suggest that the underlying differences are associated with a low concentration of females in digital entrepreneurship.

It is not clear that we should make inferences simply based on the absolute share of females, as this would be equivalent to assuming that the share of females "at risk" of becoming founders is 50% (i.e. there is a baseline of 50% share of females in the broader economy). The appropriate comparison would be the share of females within the "risk set" of individuals that could potentially found within technology industries. However, it is not clear, *a priori*, what this baseline should be be. For instance, the share of females working within the technology industry may provide a baseline, since a considerable share of foundings occur when individuals leave a company to found a company within a related industry. Many classical studies of entrepreneurial venture formation, particularly those looking at high growth clusters such as Silicon Valley, have found that individuals leaving incumbent firms in a sector are important sources of high-growth startups (Agarwal et al., 2004; Klepper and Sleeper, 2005; Bresnahan et al., 2001). This is particularly true when individuals feel that their superiors are not pursuing their ideas or that they are not progressing within the organization (Cirillo et al., 2013). At the same time, the share of females within any specific industry may prove a poor baseline, as only individuals from certain segments may transition to entrepreneurship. For instance, individuals in entry level positions may transition to entrepreneurship as a way to build experience early in their careers, while individuals in more senior positions may only transition to entrepreneurship to found high-growth ventures that would justify the opportunity costs of leaving their companies. Therefore, another relevant baseline is the share of females at various levels in the organizational hierarchy, which may better reflect the relevant set of individuals that might strike out to found a particular venture.

One challenge of comparing both founders and employees internal to an industry is the availability of data sources to allow this comparison. For example, data on founders can be gleaned from the census or business registration tax data, while data on individual positions, career histories, and education are difficult to match with this often anonymized data (Decker et al., 2014; Guzman & Kacperczyk, 2018). Studies of top-executive teams or firms that IPO often look at public firms to narrow the set of profiles to research. Those results are subject to several selection issues. While female founders in top founding teams often have longer trajectories with the focal firm than their male counterparts (Kenney and Patton, 2015), many firms also hire female employees prior to IPO to adjust their perception in financial markets (Chen et al., 2008). Alternatively, if male and female founders pursue fundamentally different businesses, then focusing on firms post-IPO would focus on the minority of female-founded businesses.

A number of recent studies have begun to use the data sources of prominent digital platforms to overcome the challenges of studying these dynamics. For instance, Brynjolfsson et al. (2017), Tambe (2014), Tambe and Hitt (2013) use data on engineers and their skills from LinkedIn to understand how the technical skills of engineers contribute to the value they contribute to the organization. Ge et al. (2016) consider the career trajectories of inventors based on their LinkedIn profiles and demonstrate the richness which this data provides above traditional patent based metrics of mobility. Kapur et al. (2016) explore the career trajectories of individuals and find which schools lead to the best career outcomes. Moallemi et al. (2017) consider the implications of promotion activities on individual promotions using LinkedIn data.

3 Data

We use data from the LinkedIn EGR partnership to study the population of US and global entrepreneurs and the trends in employment among the remainder of the workforce. The data contains all user-generated profiles on LinkedIn, approximately 600 million profiles. This data is anonymized and the identity of all individuals are protected. Data includes all information that appears on individuals' LinkedIn profiles. We use LinkedIn's gender designations, which employs their proprietary gender classification algorithm to infer gender from names. The algorithm can infer gender for approximately 90% of global observations and 95% of US observations. We omit individuals whose gender cannot be identified based on their names from our sample. We performed a robustness test in the analysis by testing whether the results of individuals with unknown gender were different. The observed values for those of unknown gender were between that observed for males and females, suggesting that these values were not systematically different, and the resulting measurement error was caused by an even distribution of gender neutral names. We defined industries based on a broad categorization provided by LinkedIn which groups the population of companies which exist in the economy (e.g., construction or healthcare; see Figure 1a for a breakdown). Technology is one of seventeen broad industries defined by in this dataset.[1]

We identify founders as individuals whose position contains the string "Founder" or "Founding" or "Entrepreneur."[2] We identify positions based on LinkedIn's clustering of user generated entries (e.g., Junior Assistant Manager of Operations) into standardized files (e.g., middle management). One limitation of this approach is that individuals self-select into LinkedIn and into reporting their employment history. This data more heavily samples from the general population of highly-skilled individuals, particularly in sectors such as technology (Zhu et al., 2019), and has been used in other studies looking at the career trajectories of

[1] We validated this classification by manually exploring a sample of the companies that were categorized as "technology" and found this classification to be an analog to high level IPC codes.

[2] We experimented with alternative definitions, including translation of these keywords into other languages, but we found that even internationally, the labels "founder" and "entrepreneur" were widely used.

highly-skilled individuals (Brynjolfsson et al., 2017; Tambe and Hitt, 2013; Tambe, 2014; Kapur et al., 2016; Moallemi et al., 2017).

4 Quantifying the Gender Gap in Entrepreneurship versus the Labor Force

What is the magnitude of the gender gap in entrepreneurship? We examine the 2000-2018 portion of all US LinkedIn profiles for which the industry category is not missing, yielding approximately 85.5 million profiles. We first focus on "founding events": the establishment of new firms reflected in an individual's LinkedIn profile.[3] Figure 1a plots the share of founding events by females within each industry, indicated by light blue dots. For the baseline, we plot the share of positions occupied by female employees within each industry, indicated by dark blue dots (see Appendix Figure D1 for the global gender gap by industry and Appendix Figure D3a for a non-US and global version of Figure 1a). This baseline (share of jobs occupied by females within the industry) is a an initial risk set of females that could become founders within that industry. If the percent of females founding firms in the industry is not very different from the percent of females occupying positions in the industry, then the source of the gender gap in founding is driven by the gender gap in industry participation. However, if the gender gap in founding differs from participation in the industry, it suggests that there are distinct factors affecting founding in addition to those that affect participation in the industry. As context, we see from Appendix Figure D2a and D2b that globally the gender gap is decreasing over time in tech and non-tech and for firms founded and jobs.

Figure 1a. *Shares of Firms Founded by Females and Jobs Occupied by Females by Industry*

Figure 1b. *Ratio of Shares of Female-Founded Firms to Shares of Jobs Occupied by Females*

We can see the importance of interpreting these baselines if we compare the technology industry to manufacturing (man) or government (gov). For tech, the share of female founding events is considerably lower than the share of female positions (15% vs. 32%). Alternatively, for manufacturing, the share of founding events by females is similarly low (15%), but the share of positions occupied by is lower (28%). Figure 1b plots the ratio of the shares in Figure 1a (see Appendix Figure D4 for a global version of Figure 1b), indicating that tech has the largest gender gap relative to its baseline, in spite of the fact that it has one of the lowest baselines for female employment across industries (third only to manufacturing and construction).

[3] Founding events are positions where an individual has listed either "founder" or "Entrepreneu" in their position name. Since this is based on the US sample of companies, the default language on these profiles is overwhelmingly English.

Overall, females account for 36% of founding events in non-tech industries but only 15% in tech. Comparison of the gender gap in founding to the female labor participation rate in each industry as a baseline suggests that the gender gap in tech entrepreneurship is driven by something more than the share of females employed in tech (i.e., a smaller risk set of founders).

An alternative measurement of the gender gap in entrepreneurship is the likelihood that any individual, male or female, ever becomes a founder within a particular industry.[4] The difference between comparing founders and founding events is that a single individual may be responsible for multiple founding events. In Figure 2, we present the share of female individuals that have ever founded in comparison to the share of founding events by females. We also show the comparison between employees vs. employee positions. We can see two broad patterns in comparing these groups. First, we find that the earlier results (Figure 1a) are consistent with the results at the population level (see Appendix Figures D3b and D3c).

Figure 2. *Share of Firms Founded by Females vs. Female Founders and Jobs Occupied by Females vs. Female Employees*

Figure 3. *Distribution of Serial Entrepreneurs within Female-Founded Firms vs. Male-Founded Firms by Industry*

Second, the share of founding events by females is lower than the share of females among founders. Given that the difference between these two metrics is the number of repeated founding events (serial founding), this implies that female founders are less likely to be serial founders. We explore this more directly by comparing the distribution of serial entrepreneurship within female-founded firms and male-founded firms (Figure 3). Looking at firms founded in tech, the share of female-founded firms that are founded by a serial entrepreneur who founded two firms is 0.5% lower than the share of male-founded firms founded by a serial entrepreneur who founded two firms. The share of male-founded firms by serial entrepreneurs with three firms is 70% higher than the share of female-founded firms by serial entrepreneurs with three firms. Serial founders are responsible for a higher share of male-founded firms, so serial entrepreneurship among males leads to greater differences in the observed gender gap if comparing the number of firms founded to the number of founders. Both founding events and founders are important metrics for understanding the connection between new ventures and serial entrepreneurship in quantifying a gender gap.

4.1 Gender Gap and Position Held Prior to Founding

We now turn to the positions held prior to founding, in order to get a clearer sense of the origins of the gender gap. The decision to found a company may be influenced by their current employment status and

[4]Here, we are assuming that individuals do not change gender within the sample studied.

the position that they currently hold. There are a variety of explanations for why individuals at different levels of professional seniority may choose to transition to entrepreneurship. Senior level professionals may have greater opportunity costs (e.g., lost wages from employment) if they shift to entrepreneurship. At the same time, the experience of these individuals may serve as a signal to potential financiers (e.g., VCs) and allow greater opportunities to found. Individuals early in their careers may resort to entrepreneurship due to a lack of alternative opportunities, or as a strategy to gain experience in order to pursue more lucrative opportunities in the labor market later on.

Since the probability of founding may depend on the positions held prior to founding, we explore the share of positions held prior to founding in Figure 4 for individuals in the US within technology-based industries (a non-tech version of Figure 4 is presented in Appendix Figure D5). The analysis presented here focuses on the founding events, so serial founders may be counted more than once. In order to track the sequence of positions in LinkedIn profiles, we use a 10% sample of US LinkedIn profiles from the 2005 - 2007 cohorts (i.e., their first job was in one of these years) tracked through 2018 for which industry and position categories were not missing, yielding approximately 4.9 million profiles (additional descriptive statistics about this sample are presented in Appendix Figures B1 and B2).

The distribution of positions held prior to founding gradually increases with seniority. Approximately 8% of founders found as their first job, while 16% found from CXO executive level positions. Approximately 36% of founders hold founding positions prior to founding, suggesting that serial founding represents an important share of individual transitions to entrepreneurship. Does the distribution of female founders follow similar patterns with regards to the seniority of founders?

Figure 4. *Share of Positions Held Prior to Tech Founding in US*

Figures 5a & 5b. *Shares of Firms Founded from Prior Position by Females and Shares of Jobs Occupied by Females, US Tech & Non-Tech*

We expand our analysis to consider the female share of founders that leave certain levels of employment to found a company, indicated by the dark blue dots in Figures 5a. To provide a baseline against which to interpret these values, we plot the share of females that occupy these positions, indicated by the light blue dots, which represents the "risk set" of individuals that may transition into entrepreneurship from that position.

These results highlight the challenges of interpreting the gender gap in entrepreneurship in the absence of a baseline. For instance, we find that females only represent approximately 15% of individuals founding companies after leaving lower level positions (First Job, Entry Level, or Senior Positions) and that percentage drops to 11% at the CXO level. However, the share of females occupying lower level positions (35%, 39%, and 37%, respectively) is considerably higher compared to females occupying Middle Management and CXO positions (29% and 22%, respectively). So the gender gap in entrepreneurship is smaller at the CXO level once we take into account the baseline of females holding CXO positions. By contrast, when we examine non-tech in Figure 5b, we observe that the fraction of founders coming from each position vary across positions, and that variation appears correlated with the fraction of jobs occupied by females in each position. In non-tech, the gender gap in entrepreneurship coming from each position is proportional to the baseline percentage of female employment in each position (with the exception of First Job), so the difference in the gender gap between the higher and lower level positions is not as severe.

The share of females within technology industries is consistently between 35 - 40% for entry level and senior positions. The share of females in STEM degrees is approximately 35% across Bachelors, Masters, and PhD degrees (see Appendix Figures C1 and C2), which suggests that the gender participation in technology industries is equivalent to the gender participation in tech education.

4.2 Summary of Descriptive Findings

By using rich population level career histories from LinkedIn, we are able breakdown the population of males and females that occupy certain positions and examine the transition to entrepreneurship in different industries. This generates a number of important findings. 1) The gender gap in tech (36% female employees) is larger than in non-tech (52% female). 2) The gender gap in tech is wider when we consider firms founded by women: 15% of tech vs. 36% of non-tech. 3) This gap is in part caused by the higher propensity of males to be serial founders relative to females. 4) The majority of founding events originate from individuals already in entrepreneurship or from CXO level positions. Females are more likely to occupy lower level positions prior to founding (approx. 15%), than CXO positions (11%). However, in comparison to the share of females occupying those positions, the relative share of females founding is only 40% of the females in those positions. Conversely for CXO positions, the relative share of females is 52% of the share of females in those positions. 5) The share of females in STEM education appears to be comparable to the share of females in entry level positions, suggesting that the gender gap in technology entrepreneurship is not solely a result of females in the pipeline of technology industries. It does perhaps point to an upstream issues with females entering into STEM areas, as well as a downstream issue with females in technology industries not transitioning into entrepreneurship.

5 Regression Results

While these descriptive analyses provide a benchmark for comparison, a limitation is that they do not control for multiple confounding factors such as experience, education, etc. To examine the existence of a gender gap in the rate of technology entrepreneurship, controlling for other variables such as education, experience, and unobserved changes over time, we move to a regression approach. We continue to use our 10% sample of US LinkedIn profiles from the 2005 - 2007 cohorts. The data has a panel structure with the unit of observation at the individual-year level. The dependent variable is whether an individual is a founder in a given year. We follow the cohort through 2018. Descriptive statistics and details of variable construction are provided in Appendix Table A1.

We estimate the following equation:

$$Pr(Founder = 1)_{it} = \alpha + \beta_1 Female_i + \beta_2 Technology + \beta_3 Female_i \times Technology_{it} + C\boldsymbol{\gamma} + \epsilon$$

We employ a linear probability model (LPM).[5] Results are consistent with logit and Cox proportional hazards models (see Appendix Table A2), but we present the LPM results for simplicity of interpretation.[6] The coefficient α captures the average annual probability that a male will be a non-tech founder. This is our baseline category. The terms β_1 and β_2 capture the difference from the baseline category in the annual probability of a female being a non-tech founder and of a male being a tech founder, respectively. The interaction coefficient β_3 captures the additional difference in the annual probability of a female being a tech founder, relative to the other categories. The set of controls $\boldsymbol{C}$ includes factors that might influence the probability of being a founder: education, time period, experience, and industry. The set of parameters $\boldsymbol{\gamma}$ captures the average differences of these factors from the baseline category. We also run separate regressions on particular groups in order to allow group-specific estimates (e.g., focusing only on the transition to founder by existing CEOs within technology industries).

Table 1 & 2. *Results of Regressions for Likelihood of Being a Founder*

Figure 6 & 7. *Predicted Probabilities for Regression Results*

In Table 1, Column 1 we present the results of the main interaction terms from our estimated equation. The intercept estimates that the annual probability of being a founder is low: males have a 0.7% probability of being a non-tech founder in a given year, but the coefficient on technology firms is so close to zero that

[5]Ordinary standard errors are reported, but results consistent with robust standard errors

[6]For the Cox model, we consider the first time founding a firm as the transition into a final state of being an entrepreneur. In the LPM and logit models, entrepreneurs may move out of founder state back into employee status.

we can generalize to say that males have the same probability of being tech or non-tech founders. Females are 0.2% less likely to be non-tech founders than males, and they are a further 0.2% less likely to be tech founders: females have only a 0.3% probability each year of being a tech founder. So the probability of females being tech founders is 58% lower than that for males, while the probability of females being non-tech founders is 28% lower than the probability for males.

Starting with Column 2, we introduce of year and cohort (year of entry into workforce) fixed effects in within all of these models to control for annual differences in the propensity to found that might result from macroeconomic dynamics. We also introduce experience controls (number of previous jobs, number of years of employment in current position). The intercept changes significantly, indicating the role that time and experience have on the probability of being a founder, but the female and tech industry coefficients remain unchanged.

In Column 3, we include education control variables (Bachelor, Masters, and Doctorate) as well as indicators for whether any of the degrees were in STEM fields and whether any are from highly prestigious institutions. These variables capture elements of individual ability, as well as access to funding and opportunities that may stem from university networks or the status associated with a degree from a top institution. The estimates indicate that only doctorates and degrees from top institutions increase the probability of being a founder. STEM lowers the annual probability, and no other degrees have an effect. However, once we introduce controls for the position held prior to founding in Column 4, the top institution effect disappears and a bachelor's degree now lowers the annual probability of being a founder.

Across Columns 1 through 4, as we introduce additional controls to our model, the coefficient on the female tech founder interaction effect remains relatively constant (0.2%). However, the intercept changes considerably as control variables are introduced, so the economic importance of this difference in the probability of being a founder changes over these different specifications. Therefore, in Figure 6, we plot the average annual probability of being a founder for different genders and industries across education, year, cohort, experience, and positions for the model in Table 1, Column 4. We observe that men are equally likely to be founders in tech and non-tech industries. However, the annual probability of having non-tech female founders is 23.3% lower than that for males, and they are half as likely as men to be tech founders.

In Columns 5-8, we run our regression separately on different groups: females and males in Columns 5 and 6, respectively, those working in tech, and in Columns 7 and 8, respectively. These regressions are equivalent to modeling interaction effects for gender and industry on all regressors, allowing us to estimate group-specific coefficients. Comparing Columns 5 to 6, we see that the increase in probability of being a founder from having a doctorate is less for females than for males. Overall, the results are consistent with those of Columns 1-4.

Figure 5 shows that there is a considerable difference in the baseline (risk set) of females in each position who could found a firm. The position held prior to founding may reflect the opportunities or opportunity cost that a founder faces. In order to explore these relationships more directly, we stratify the analysis by the positions held prior to founding, from Entry Level to CXO positions in Table 2. We present these results in Columns 1 through 4.

Given that the intercept varies considerably across these specifications, we again plot the average probability of founding for each group in Figure 7. We find that for individuals that hold entry level positions, the likelihood of males being technology and non-technology founders was similar (approximately 1% higher in tech). However, the likelihood of being a female tech founder was 26% lower than for being a female non-tech founder. Additionally, the likelihood of being a female tech founder was 28% lower than for male tech founders. Results for individuals that held senior positions prior to founding was comparable. However, if we look at males in middle management and especially CXO positions, being a tech founder is more likely than being a non-tech founder. Males from CXO positions are 47% more likely to be tech founders than non-tech founders, and females are 16% more likely to be tech founders than non-tech founders. However, relative to the probability of being a male tech founder, the probability of being a female tech founder is 36% lower than the probability of being a male tech founder conditional on coming from a CXO position. This suggests that the factors influencing the gender gap in tech entrepreneurship are related to career advancement in an industry.

6 Discussion and Interpretation of Results

In this paper, we document the gender gap within entrepreneurship and, specifically, the gender gap that exists within entrepreneurship in tech industries. Technology may reduce the the frictions that often prevent females from pursuing entrepreneurship. However, empirical measurement of the gender gap in technology entrepreneurship is limited. One issue that has not been considered by earlier studies is whether the gender gap in technological entrepreneurship is greater than the gender gap in the technology sector more broadly. In particular, we find that while females represent only a small share of technology founders, the relative baseline helps to contextualize this magnitude, indicating that the share of female founders in technology industries represents 2/3 of females in those industries, while in non-technology industries the ratio is 4/5.

To explore this directly, we estimate the rate of entrepreneurship (probability of founding in a given year for any individual) accounting for differences in education, temporal differences, and work experience. We find that the rate of entrepreneurship for females in technology is 50.3% lower than for males in technology industries, but 23.3% in non-technology industries. This provides evidence that while there is a gender gap in the economy more broadly, there exists an even greater gender gap relating to entrepreneurship in technology industries.

Importantly, for individuals in less senior positions, the difference between the rate of founding for males in technology and non-technology industries is similar (only 1.6% difference). Yet, the share of female founding in technology industries is approximately 9% lower in technology industries. Alternatively, for senior positions, such as CXO, the rate of female founding is 16% higher in technology industries, than in non-technology industries. However, the rate of males founding in technology industries is 47% more than in non-technology industries. While this confirms a gender gap, it also does suggest that technology industries, are associated with a greater absolute rate of entrepreneurship for females, even if it is lower in relation to the rate of founding by males.

These results provide important insights for contextualizing and understanding policies regarding the gender gap. For instance, the gender gap in STEM education maps closely to the gender gap in entry level and mid-management positions within the technology industry. Therefore, greater gender parity (lower gap) in education may help to close the gender gap that exists among those employed in technology industries. However, this would not necessarily account for the gender gap in entrepreneurship, as this remains considerably lower than the gender gap within the industry.

To the extent that high-growth entrepreneurship is a primary concern of policy makers, and that high-growth entrepreneurs come from more senior positions, then then it is perhaps encouraging that the rate of female entrepreneurship in technology industries is 16% higher than the rate of female entrepreneurship in non-tech industries. Alternatively, to the extent that entrepreneurship provides an opportunity for individuals in less senior positions to gain independence or experience, then the vast gender gap that exists within these industries, suggests that these opportunities are disproportionately being occupied by males, where males in these positions are 50% more likely to found than their female counterparts.

There may be a variety of mechanisms behind the origins of this gender gap. These may relate to differences in preferences or other frictions that do not exist within technology industries (Thebaud, 2015; Guzman and Kacperczyk, 2019; Gompers and Wang, 2017). The present study does not disentangle these mechanisms. Nevertheless, the fact that we observe a difference in the rate of entrepreneurship of females in technology industries, has implications for understanding the origin of the rate of entrepreneurship in technology industries and devise policies. These results also highlight nuance of interpreting the gender gap statistic, and the need to observe the "risk set" of individuals that can possibly found a business.

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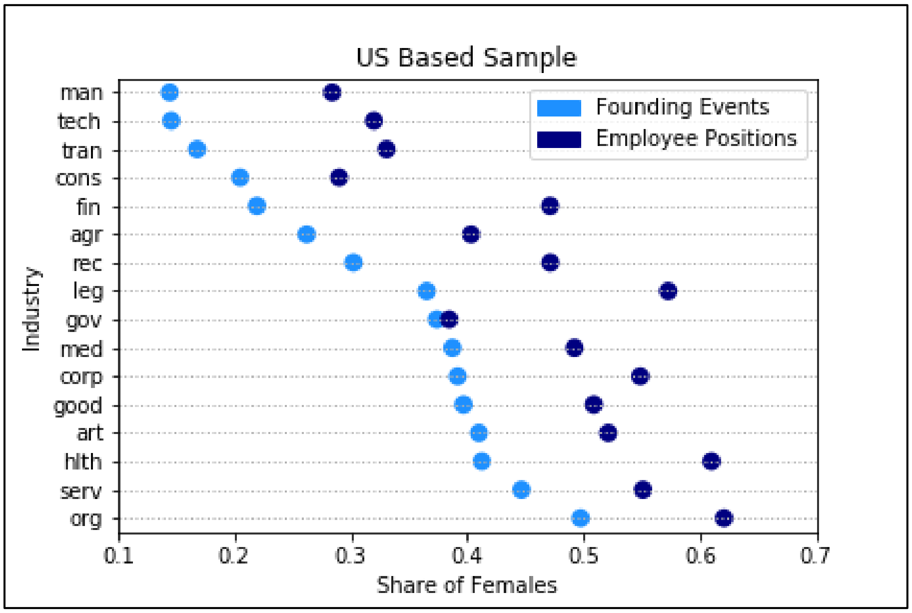
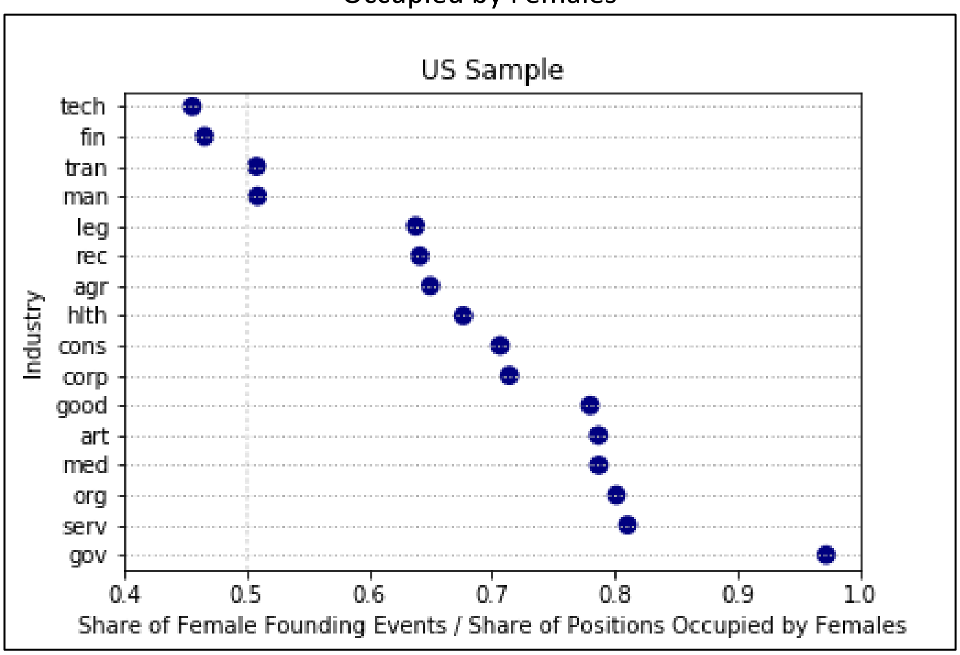
Figure 1a. Shares of Firms Founded by Females vs. Shares of Jobs Occupied by Females by Industry



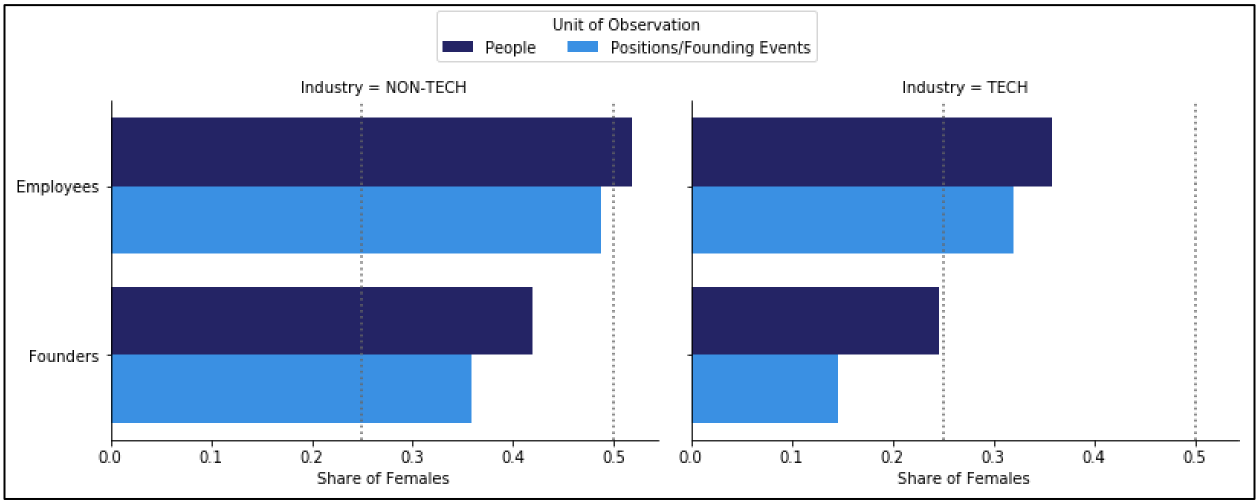
Note: This figure is based on the 2000-20018 portion of US LinkedIn profiles. The light blue dots represent the share of firms founded by female founders. The unit of observation is a founding event. The dark blue dots represent the share of jobs occupied by females. The unit of observation here is an employee position. The industries identified by LinkedIn are abbreviated as follows: tech = technology, man = manufacturing, tran = transportation, fin = finance, agr = agriculture, cons = construction, rec = recreation, med = media, corp = corporate, gov = government, leg = legal, good = goods, art = art, hlth = healthcare, serv = services, org = NGO. Category "undefined" is not shown.

Figure 1b. Ratio of Shares of Female-Founded Firms to Shares of Jobs Occupied by Females



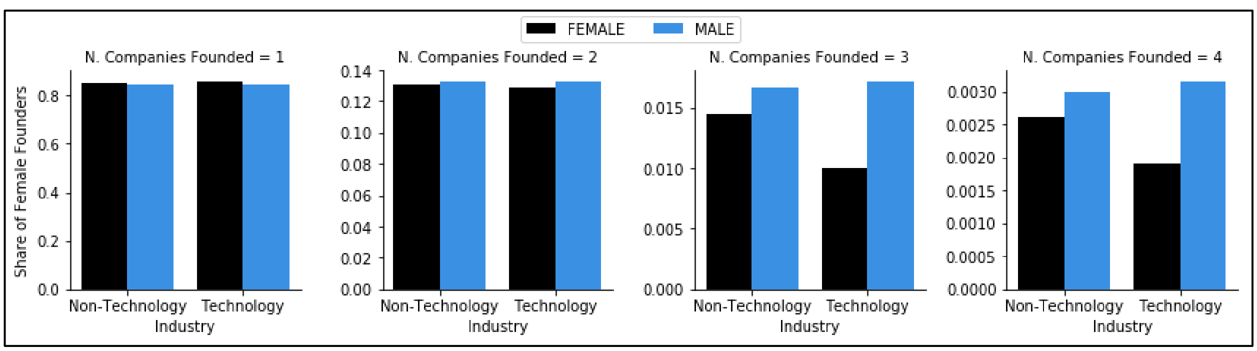
Note: This figure is the ratio between the two dots plotted in Figure 1a.

Figure 2. Share of Firms Founded by Females vs. Female Founders and Jobs Occupied by Females vs. Female Employees



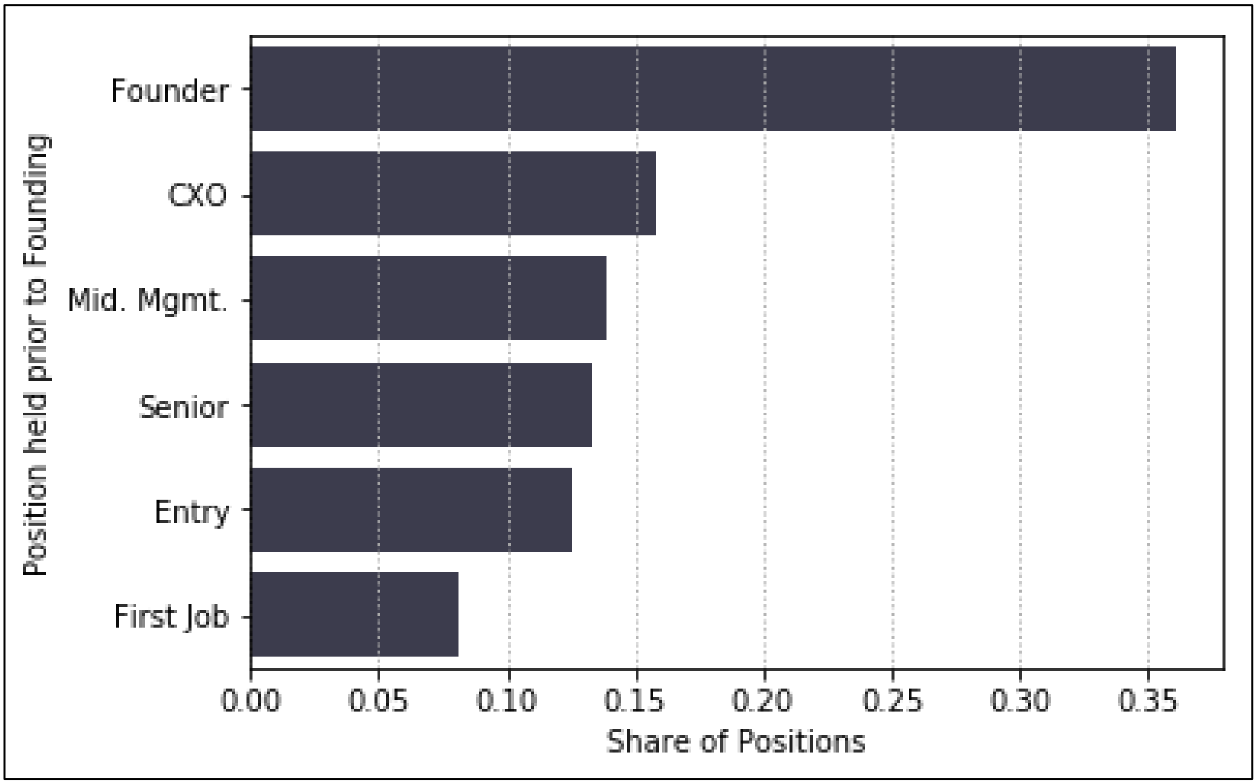
Note: This figure compares individuals vs. events based on the 2000-20018 portion of US LinkedIn profiles. The dark blue bars are the female share of employees or founders. The light blue bars are the female share of founding events or employee positions. The difference between the dark blue and light blue bars in the panel on the left indicates the level of employee churn (job changes) in tech and non-tech. The difference between the dark blue and light blue bars in the panel on the right indicates the amount of serial entrepreneurship (individuals that found more than one business).

Figure 3. Distribution of Serial Entrepreneurs within Female-Founded Firms vs. Male-Founded Firms by Industry



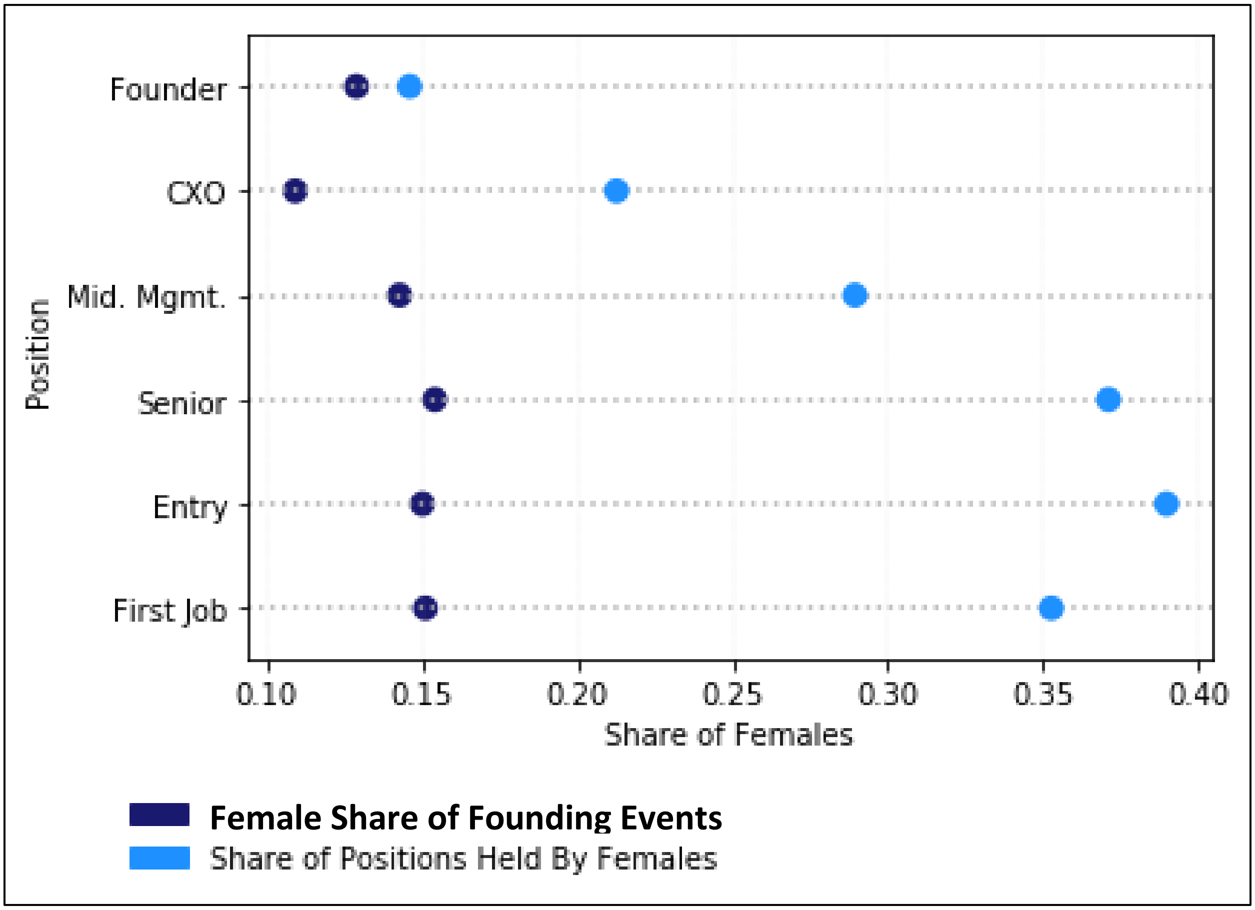
Note: This figure compares the distribution of entrepreneurs founding multiple ventures (1, 2, 3, or 4 or more) based on the 2000-20018 portion of US LinkedIn profiles. Approximately 80% of male-founded and female-founded firms are founded by non-serial entrepreneurs. However, as the level of serial entrepreneurship rises, serial entrepreneurs are responsible for a higher proportion of male-founded firms compared to female-founded firms. Each graph is shown on a different scale, as each successive group is only a fraction in absolute magnitude of the preceding graph.

Figure 4. Share of Positions Held Prior to Tech Founding in US



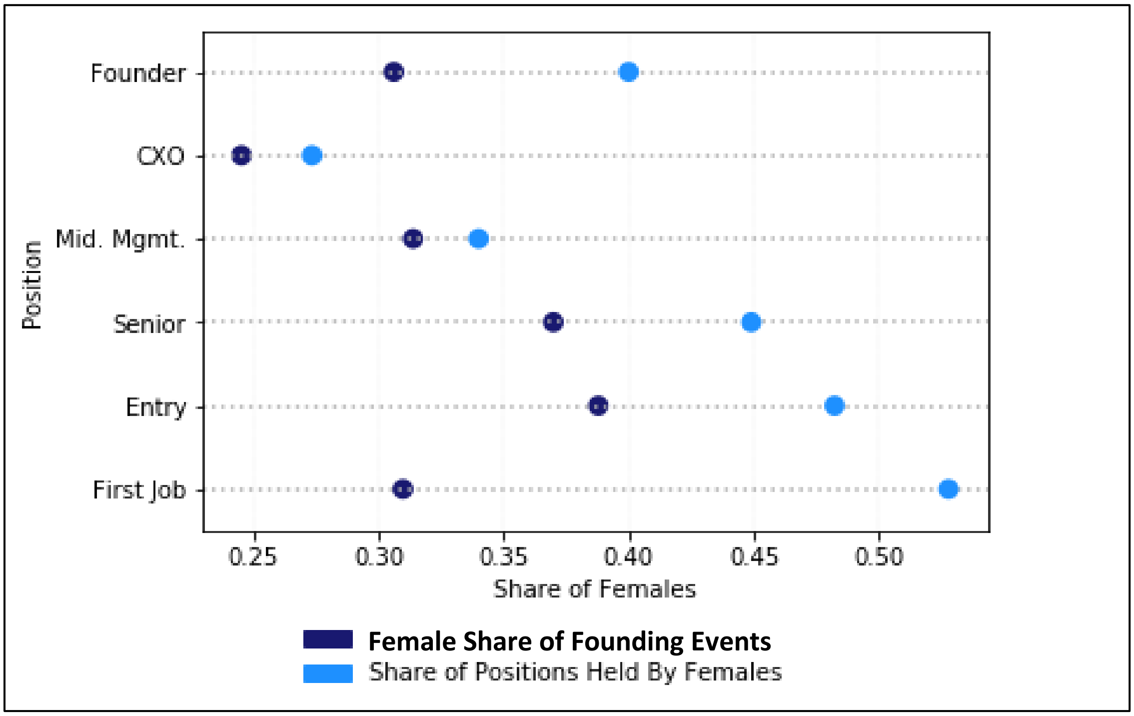
Note: This figure is based on all founding events identified in a 10% sample of US LinkedIn profiles from 2005-2007 cohorts (i.e., first job listed during these years) tracked through 2018. For each founding event, we identify the position held prior to that event. We present the distribution of founding events over those prior positions (bars sum to 1). Each group is mutually exclusive with the exception of "First Job", which overlaps partly with the entry level position variable. See Figure D3 for non-tech version of this figure.

Figure 5a. Shares of Firms Founded from Prior Position by Females vs. Shares of Jobs Occupied by Females, US Tech



Note: This figure is based on a 10% sample of US LinkedIn profiles from 2005-2007 cohorts (i.e., first job listed during these years) tracked through 2018. Dark blue dots represent the female share of all founding events preceded by another founding event, employment in a CXO, Middle Manager, Senior-, or Entry-level position, or founding event as the first job listed in the LinkedIn profile. Each group is mutually exclusive with the exception of "First Job", which overlaps partly with the entry level position variable. Light blue dots reflect the share of females that occupy those positions in the workforce. The light blue dots represent the risk set of females that could leave these positions in order to found a company. Comparing the dark and light blue dots reveals that despite variation in the share of females in positions, only a consistently small fraction of founders coming from each position are female. For example, of the people who left CXO positions to found a firm, 11% were women, whereas 21% of CXO positions are held by women. For entry level positions, although close to 40% are held by women, only 15% of founders coming from entry level positions are women.

Figure 5b. Shares of Firms Founded from Prior Position by Females vs. Shares of Job Positions Occupied by Females, US Non-Tech



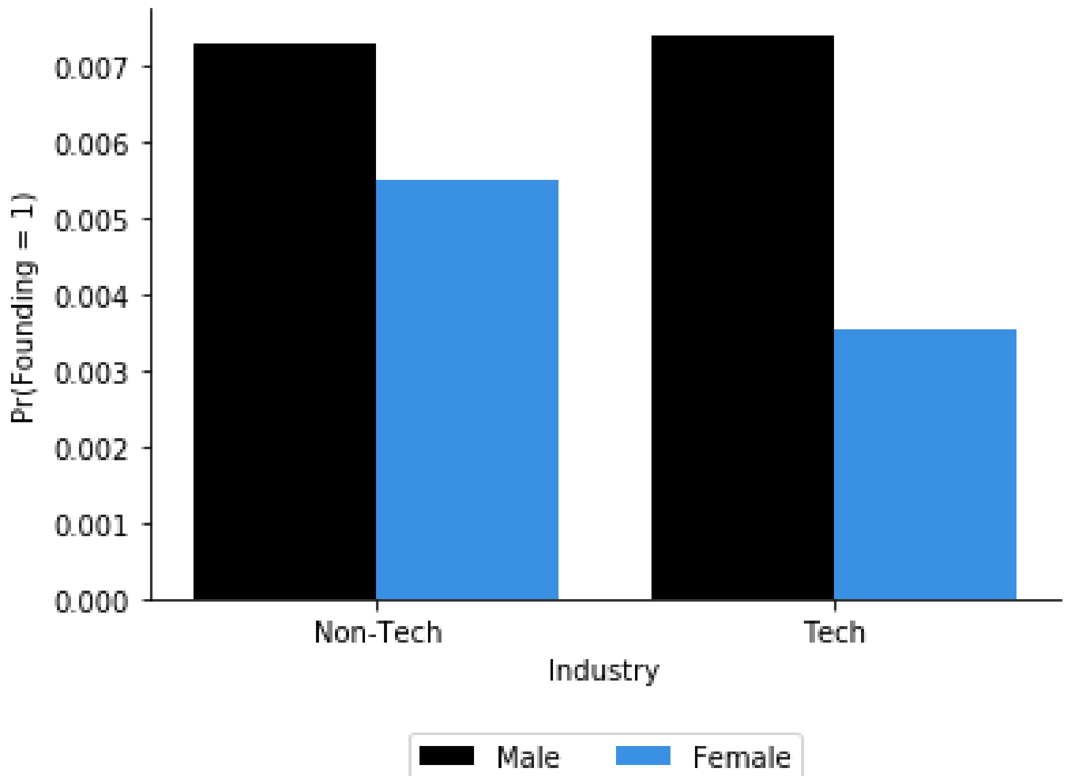
Note: This figure is based on a 10% sample of US LinkedIn profiles from 2005-2007 cohorts (i.e., first job listed during these years) tracked through 2018. Dark blue dots represent the female share of all founding events preceded by another founding event, employment in a CXO, Middle Manager, Senior-, or Entry-level position, or founding event as the first job listed in the LinkedIn profile. Each group is mutually exclusive with the exception of "First Job", which overlaps partly with the entry level position variable. Light blue dots reflect the share of females that occupy those positions in the workforce. The light blue dots represent the risk set of females that could leave these positions in order to found a company. Comparing the dark and light blue dots reveals that variation in the risk set in non-tech is correlated with the fraction of founders coming from each position, in contrast to the tech industry (Figure 5a).

Figure 6. Average Annual Probability of Being a Founder by Gender
(Table 1, Column 4)

Outcome: *Probability of Being a Founder for Each Individual in Each Year*
Controls: *Year FE, Cohort FE, Education, Experience, and Previous Position*

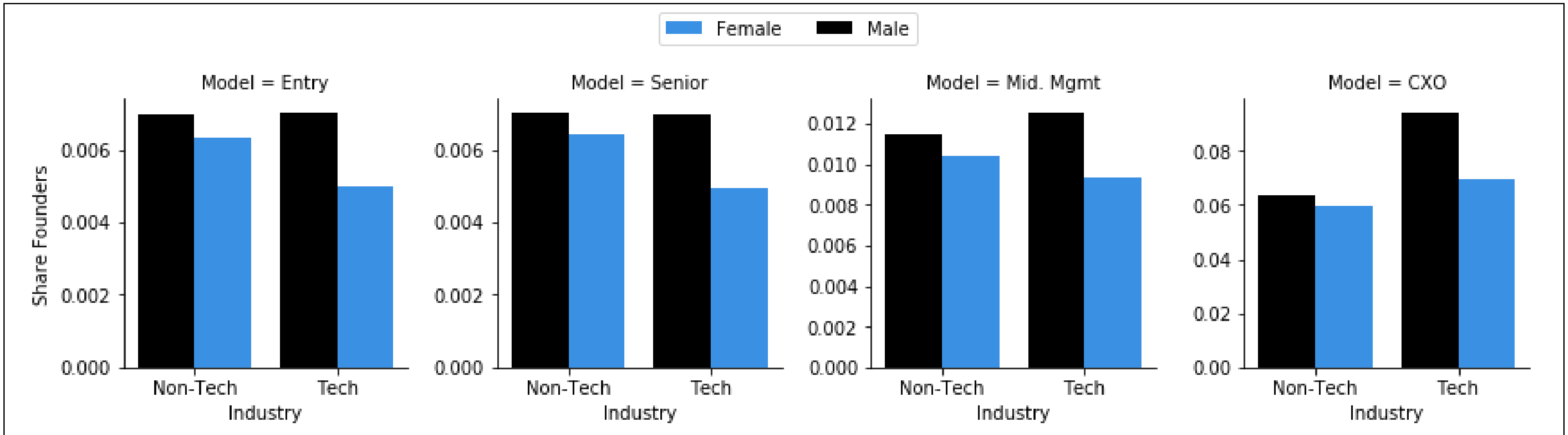
Key Comparisons:

- **Male Tech vs. Male Non-Tech:** *2% Higher in Tech*
- **Female Tech vs. Female Non-Tech:** *36% lower in Tech*
- **Female Non-Tech vs. Male Non-Tech:** *23% Lower for Females*
- **Female Tech vs. Male Tech:** *50% Lower for Females*



Note: These are the average of the predicted probabilities for each individual. Since this is based on an LPM, the differences in the bars are the equivalent to average marginal effects calculated for a logit model. Logit results shown in appendix.

Figure 7. Average Annual Probability of Being a Founder from Different Positions (Table 2).



Male Tech vs. Male Non - Tech			
1% Higher in Tech	*1% Higher in Tech*	*10% Higher in Tech*	*47% Higher in Tech*
Female Non-Tech vs. Male Non-Tech			
9% Lower for Females	*9% Lower for Females*	*9% Lower for Females*	*6% Lower for Females*
Female Tech vs. Male Tech			
28% Lower for Females	*30% Lower for Females*	*26% Lower for Females*	*14% Lower for Females*
Female Non-Tech vs. Female Tech			
26% Lower in Tech	*30% Lower in Tech*	*11% Lower in Tech*	*16% Higher in Tech*

Note: Differences in share based on 1 – [Pr (B) / Pr (A)].

Table 1. LPM Results of Panel Regression for Likelihood of Being a Founder

Sample: *2005 – 2007 Cohort (US Based, 10% Sample)*

Outcome Variable: Pr(Founder = 1) in a Given Year.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FULL SAMPLE				**FEMALE**	**MALE**	**Previous & Current Position in Tech**	**Previous Position in Tech**
Technology	-0.000***	-0.000	0.000	-0.000***	-0.003***	-0.000***		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Female	-0.002***	-0.002***	-0.002***	-0.001***			-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)
Female × Technology	-0.002***	-0.002***	-0.002***	-0.002***				-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)
Bachelors			-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000*
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Masters			-0.000**	-0.000***	-0.000***	-0.001***	-0.001***	-0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Doctorate			0.003***	0.003***	0.002***	0.003***	0.003***	0.007***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
STEM			-0.001***	-0.001***	-0.001***	-0.001***	0.001***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Top Institution			0.002***	0.000***	0.000***	0.000***	0.001***	-0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous Position	No	No	No	Yes	Yes	Yes	Yes	Yes
Intercept	0.007***	0.030***	0.029***	0.068***	0.058***	0.072***	0.080***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
N	76372157	76372157	76372157	76372157	34407758	41964399	8555496	1648132
R2	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.06
F	2237.23	13323.34	11041.01	30941.14	11632.62	20993.00	4294.39	3881.49

Standard errors in parentheses. (* p<0.1, ** p<0.05, ***p<0.01). Omitted categories: Male (Columns 1-4, 7-8), Non-Tech (Columns 1-6), 2005 cohort, 2005 year, Entry position.

Table 2. LPM Results of Panel Regression for Likelihood of Being a Founder
Sample: *2005 – 2007 Cohort (US Based, 10% Sample)*
Outcome Variable: Pr(Founder = 1) in a Given Year.

	(1)	(2)	(3)	(4)
Sample Position	**Entry**	**Senior**	**Mid. Mgmt.**	**CXO**
Technology	0.0001	-0.0001	0.0011***	0.0306***
	(0.0001)	(0.0001)	(0.0002)	(0.0014)
Female	-0.0007***	-0.0006***	-0.0010***	-0.0045***
	(0.0000)	(0.0001)	(0.0001)	(0.0009)
Female	-0.0014***	-0.0015***	-0.0022***	-0.0201***
× Technology	(0.0001)	(0.0002)	(0.0003)	(0.0029)
Bachelors	0.0007***	0.0006***	0.0012***	0.0118***
	(0.0001)	(0.0001)	(0.0001)	(0.0010)
Masters	-0.0002**	-0.0001	0.0004**	0.0008
	(0.0001)	(0.0001)	(0.0002)	(0.0013)
Doctorate	0.0019***	0.0022***	0.0033***	0.0056***
	(0.0001)	(0.0001)	(0.0002)	(0.0014)
STEM	-0.0006***	0.0001	0.0016***	0.0215***
	(0.0001)	(0.0001)	(0.0001)	(0.0011)
Top Institution	0.0010***	0.0018***	0.0026***	0.0162***
	(0.0001)	(0.0001)	(0.0001)	(0.0010)
Year FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Experience Controls	Yes	Yes	Yes	Yes
Intercept	0.0050***	0.0043***	0.0068***	0.0289***
	(0.0001)	(0.0001)	(0.0002)	(0.0017)
N	9718776	6801568	3181992	304346
R2	0.00	0.00	0.00	0.01
F	231.57	154.69	139.68	143.81

Standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01). Omitted categories: Male, Non-Tech, 2005 cohort, 2005 year.

A. Regressors & Logit

Table A1. Variable Construction and Descriptive Statistics

Variable	Mean	St. D.	Max	Min	Description
Founder	0.01	0.08	1	0	Indicator variable for whether the individual is a founder that year.
Female	0.48	0.50	1	0	Indicator variable for female
Technology	0.11	0.31	1	0	Indicator variable for technology industry
Bachelors	0.43	0.49	1	0	Indicator for whether individual has a bachelor degree.
Masters	0.20	0.40	1	0	Indicator for whether individual has a master's degree.
Doctorate	0.11	0.32	1	0	Indicator for whether individual has a doctorate degree.
STEM	0.17	0.37	1	0	Indicator variable for whether an individual has any degree in a STEM field.
Top Institution	0.16	0.37	1	0	Indicator whether individual has a degree from one of the top 15 universities according to the QS World University Rankings
Experience Control: Job Number	1.69	1.10	32	1	Number of jobs previously held by individual (since entry into workforce up to that year).
Experience Control: Years in Job	5.40	3.68	13	1	Number of years worked in current position.

Table A2. LOGIT Coefficient Results of Panel Regression for Likelihood of Being a Founder

Sample: *2005 – 2007 Cohort (US Based, 10% Sample)*

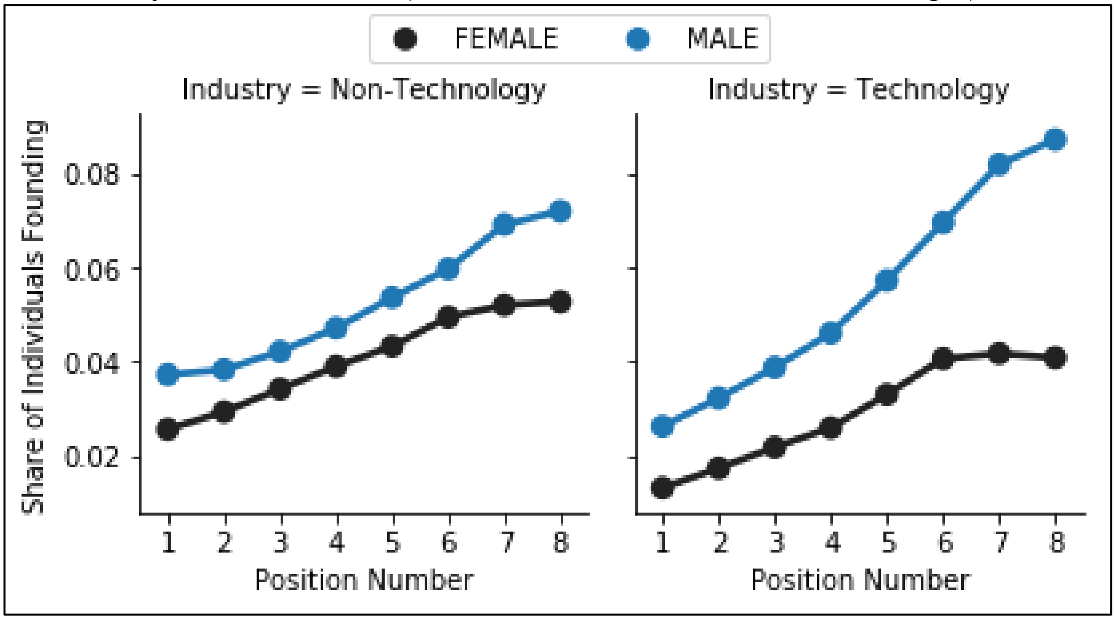
Outcome Variable: Pr(Founder = 1) in a Given Year.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		FULL SAMPLE			ENTRY	SENIOR	Mid Mgmt.	CXO
Technology	0.13***	0.13***	0.12***	0.07***	0.02	-0.01	0.12***	0.49***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Female	-0.22***	-0.22***	-0.23***	-0.23***	-0.13***	-0.11***	-0.12***	-0.10***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Female	-0.39***	-0.39***	-0.38***	-0.38***	-0.33***	-0.33***	-0.26***	-0.27***
× Technology	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)	(0.05)
Bachelors			0.27***	0.04***	0.14***	0.12***	0.15***	0.26***
			(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Masters			-0.16***	-0.16***	-0.03**	-0.01	0.04**	0.01
			(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)
Doctorate			0.31***	0.33***	0.32***	0.33***	0.30***	0.09***
			(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Degree in STEM			0.00	-0.04***	-0.11***	0.01	0.17***	0.36***
			(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Top Institution			0.38***	0.16***	0.18***	0.29***	0.28***	0.30***
			(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous Position	No	No	No	Yes	Yes	Yes	Yes	Yes
Intercept	-5.11***	-5.34***	-5.59***	-5.40***	-5.30***	-5.44***	-4.97***	-3.40***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
N	76372157	76372157	76372157	76372157	9718776	6801568	3181992	304346
Pseudo-R2	0.00	0.00	0.01	0.07	0.01	0.01	0.01	0.02

Standard errors in parentheses. (* p<0.1, ** p<0.05, ***p<0.01). Omitted categories: Male (Columns 1-4, 7-8), Non-Tech (Columns 1-6), 2005 cohort, 2005 year, Entry position.

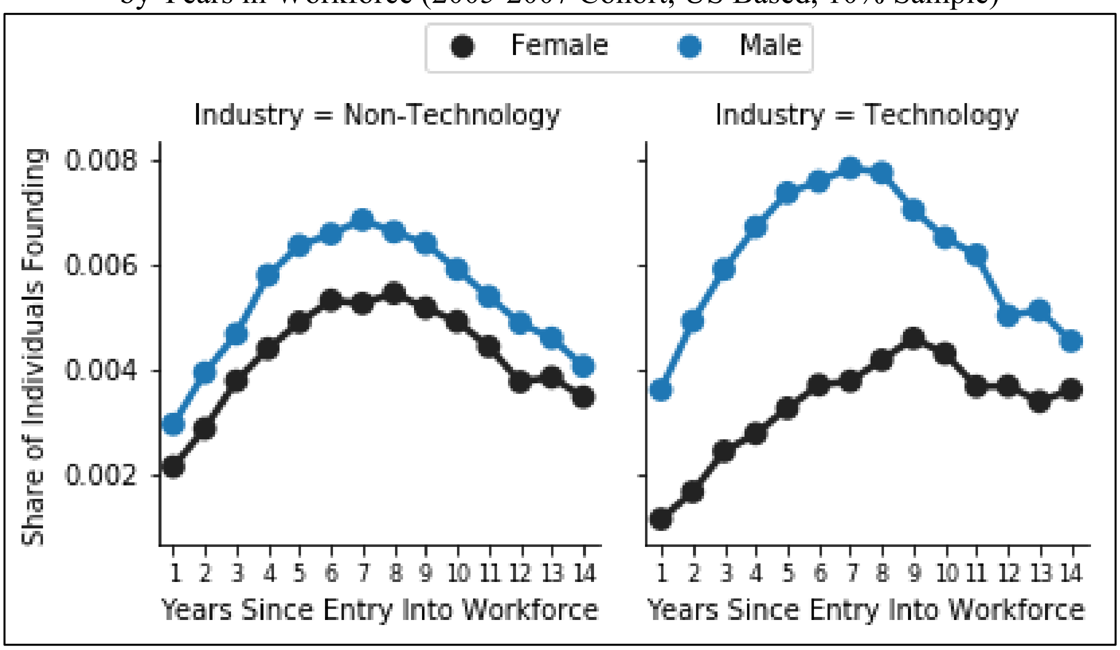
B. Additional Descriptive Results Regarding Career Progression and Founding

Figure B1. Share of Individuals Transitioning to Entrepreneurship by Position Number (2005-2007 Cohort, US Based, 10% Sample)



Note: Position number is the number of jobs held prior to founding. The right panel reveals a larger gender gap in tech entrepreneurship relative to non-tech that grows with the number of positions, particularly at positions 6 & 7.

Figure B2. Share of Individuals Transitioning to Entrepreneurship by Years in Workforce (2005-2007 Cohort, US Based, 10% Sample)



Note: The gender gap in tech entrepreneurship relative to non-tech is larger, particularly early in careers.

C. Descriptive Results Regarding STEM Participation

Figure C1. Overall Trend in Female Share of Degrees, Global

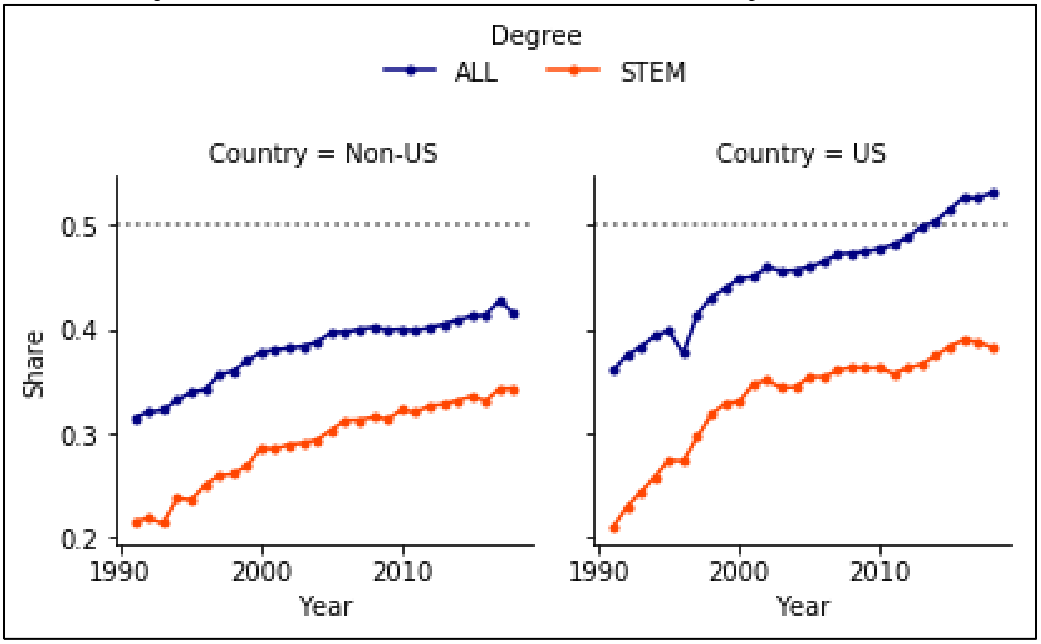
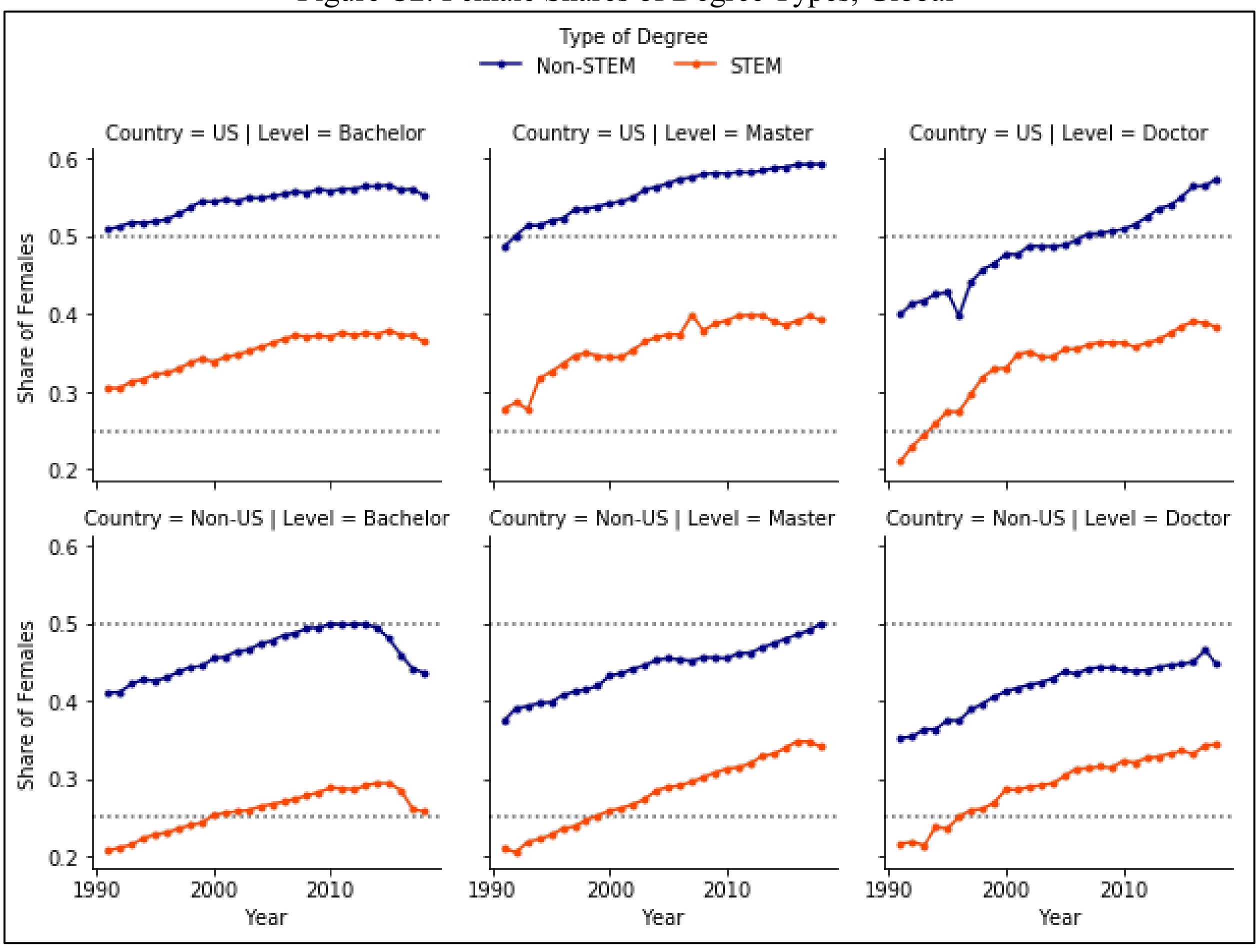
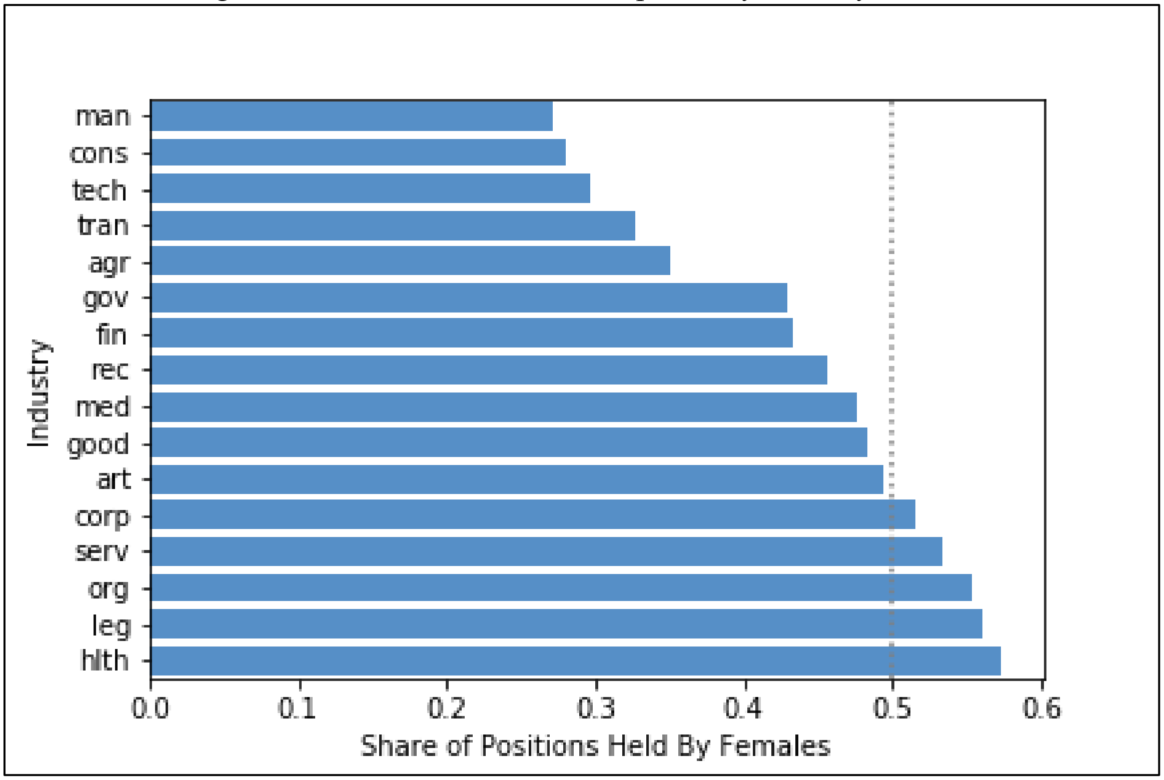


Figure C2. Female Shares of Degree Types, Global



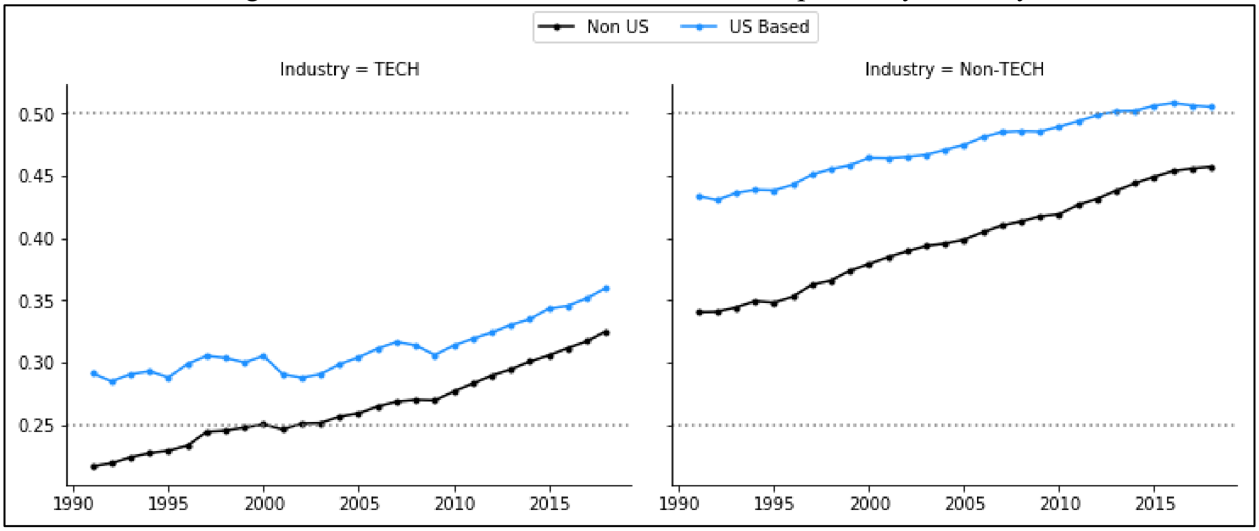
D. Supplementary Descriptive Results

Figure D1. Share of Female Participation by Industry, Global



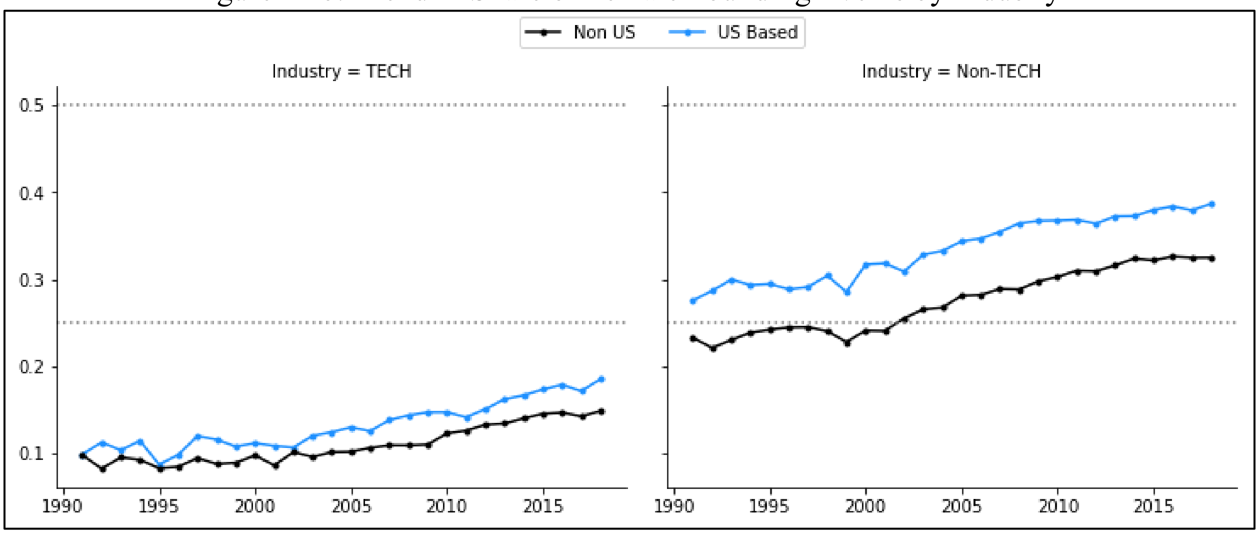
Note: Based on the 2000-2018 portion of global LinkedIn profiles, tech exhibits the third largest gender gap behind manufacturing and construction. The industries identified by LinkedIn are abbreviated as follows: tech = technology, man = manufacturing, tran = transportation, fin = finance, agr = agriculture, cons = construction, rec = recreation, med = media, corp = corporate, gov = government, leg = legal, good = goods, art = art, hlth = healthcare, serv = services, org = NGO. Category "undefined" is not shown.

Figure D2a. Trend in Share of Female Participation by Industry



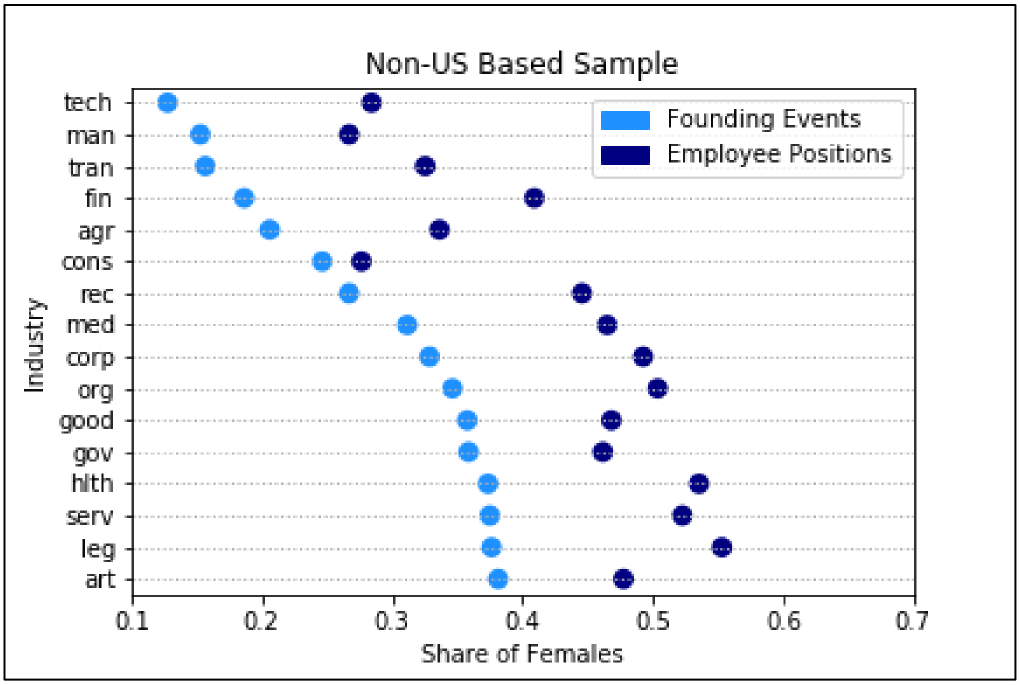
Note: Based on the global population of positions in LinkedIn profiles, the gender gap has been decreasing over time in tech & non-tech industries globally.

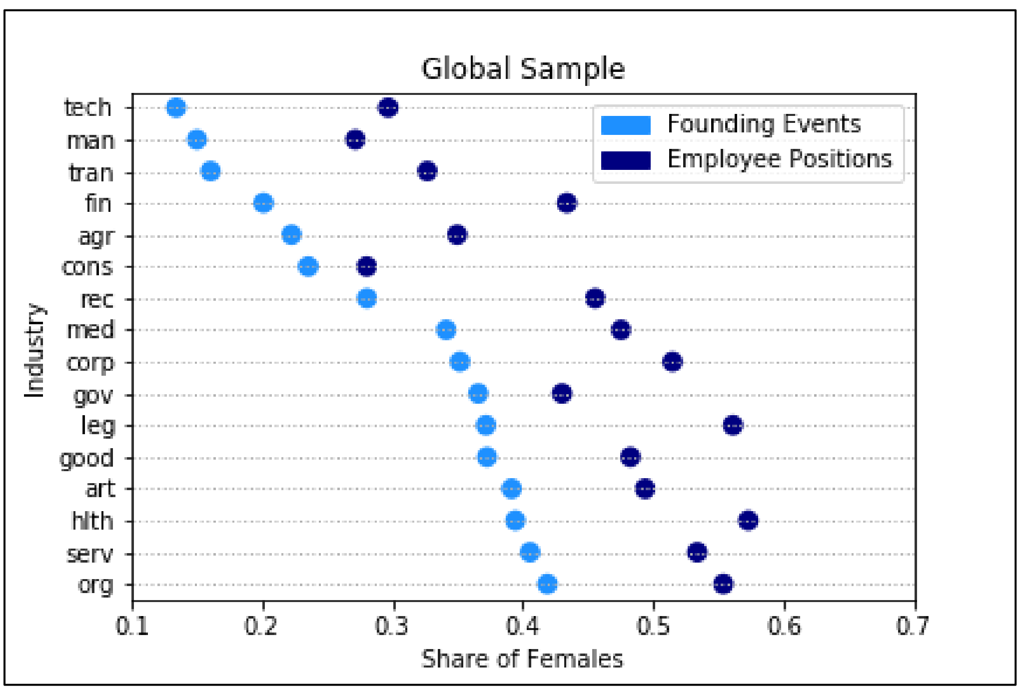
Figure D2b. Trend in Share of Female Founding Events by Industry



Note: Based on the global population of founding events in LinkedIn profiles, the gender gap has been decreasing over time in tech & non-tech industries globally.

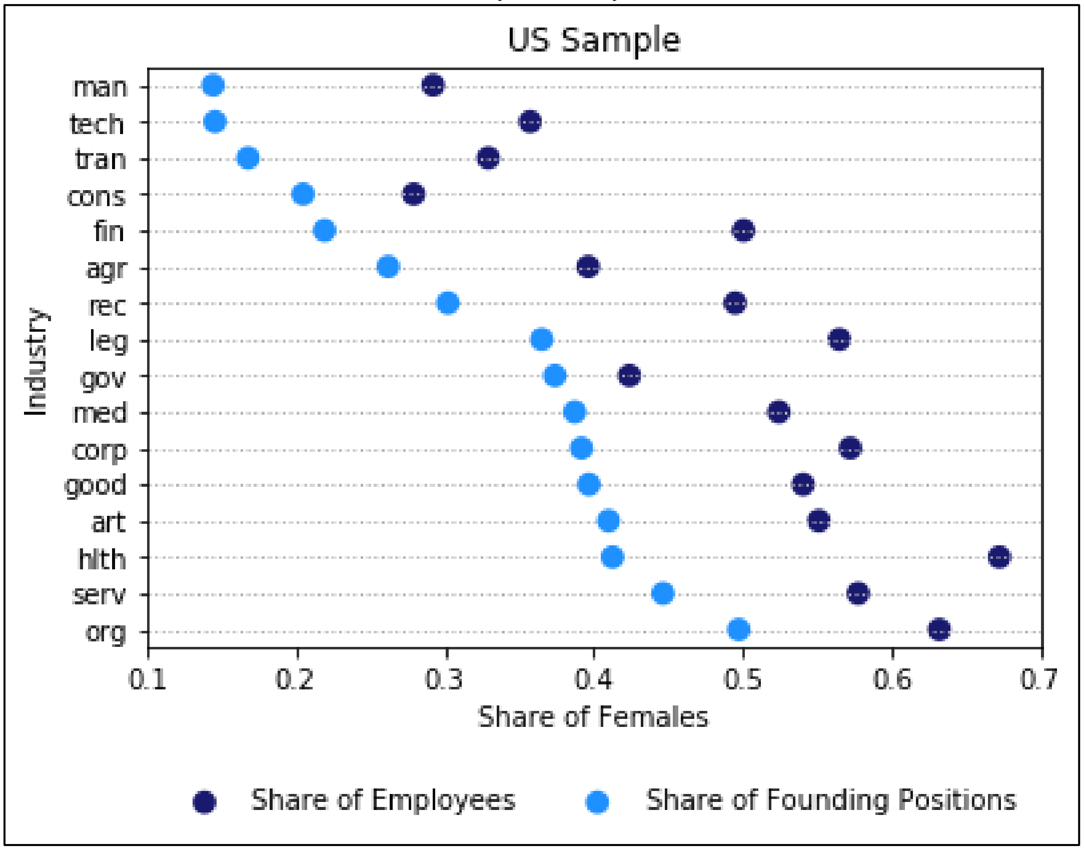
Figure D3a. Shares of Firms Founded by Females vs. Shares of Jobs Occupied by Females by Industry, Global





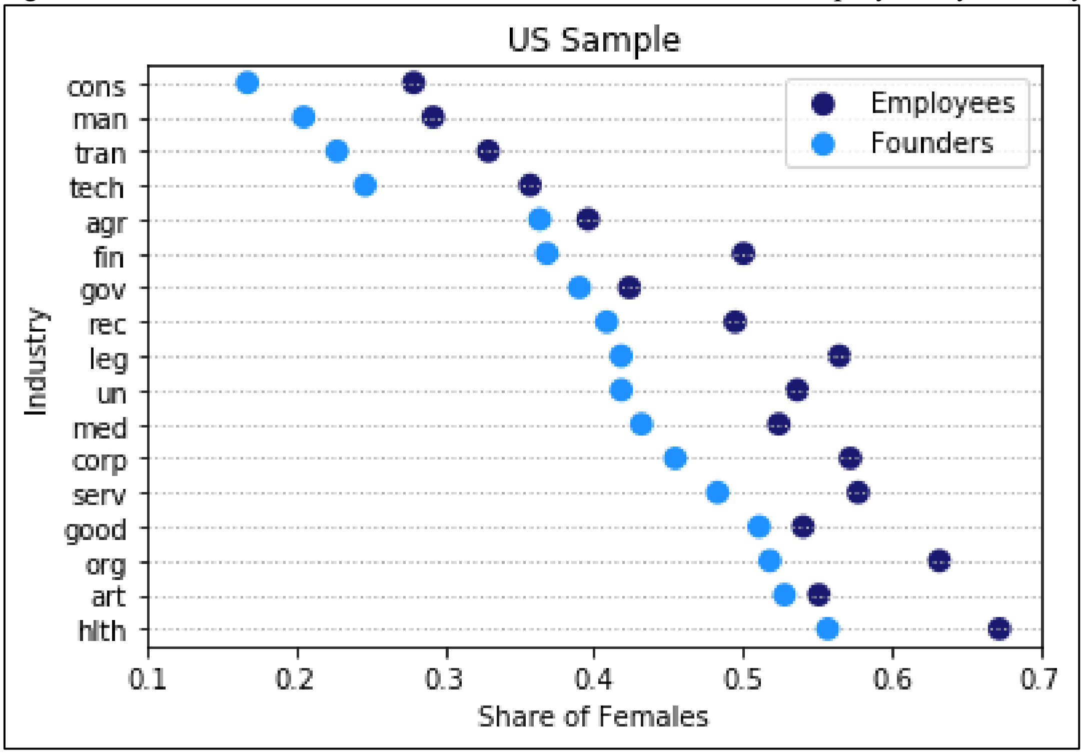
Note: These figures are based on the 2000-20018 portion of non-US and global LinkedIn profiles. The light blue dots represent the share of firms founded by female founders. The unit of observation is a founding event. The dark blue dots represent the share of jobs occupied by females. The unit of observation here is an employee position. The industries identified by LinkedIn are abbreviated as follows: tech = technology, man = manufacturing, tran = transportation, fin = finance, agr = agriculture, cons = construction, rec = recreation, med = media, corp = corporate, gov = government, leg = legal, good = goods, art = art, hlth = healthcare, serv = services, org = NGO. Category "undefined" is not shown.

Figure D3b. Shares of Firms Founded by Females vs. Shares of Female Employees by Industry



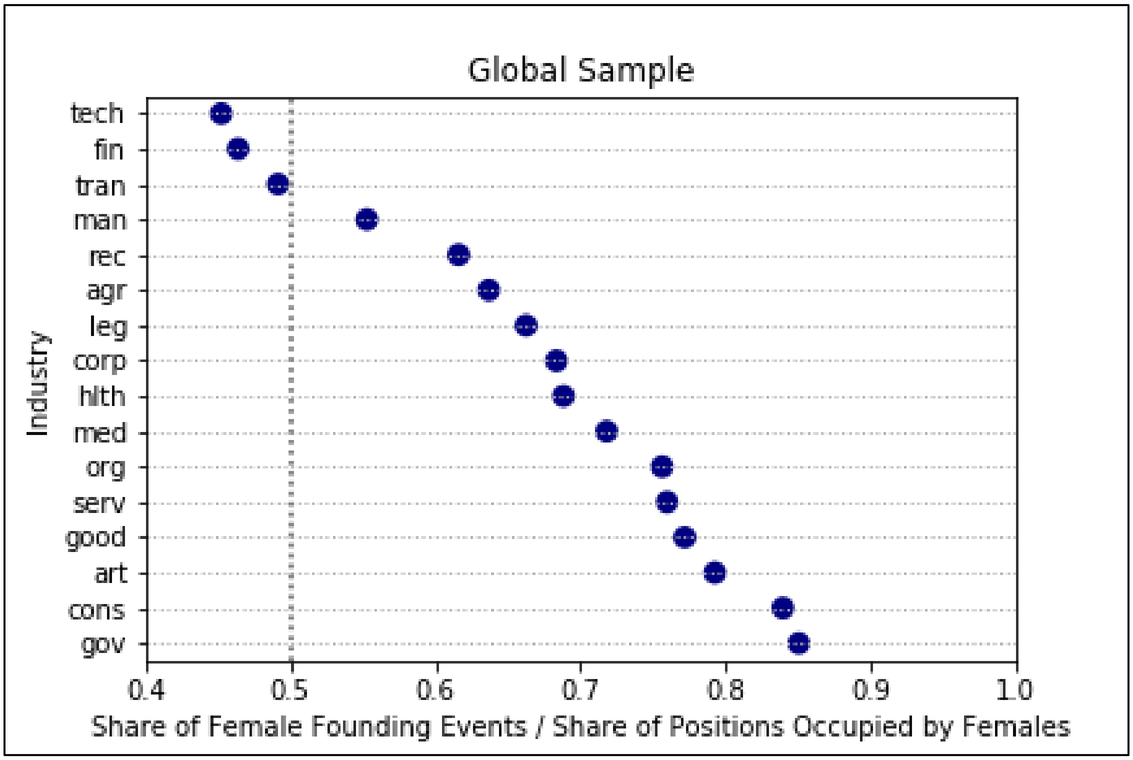
Note: This figure is based on the 2000-20018 portion of US LinkedIn profiles. The light blue dots represent the share of firms founded by females. The unit of observation is a founding event. The dark blue dots represent the share of employees in the industry who are female. The unit of observation is an individual. The industries identified by LinkedIn are abbreviated as follows: tech = technology, man = manufacturing, tran = transportation, fin = finance, agr = agriculture, cons = construction, rec = recreation, med = media, corp = corporate, gov = government, leg = legal, good = goods, art = art, hlth = healthcare, serv = services, org = NGO. Category "undefined" is not shown.

Figure D3c. Shares of Female Founders vs. Shares of Female Employees by Industry



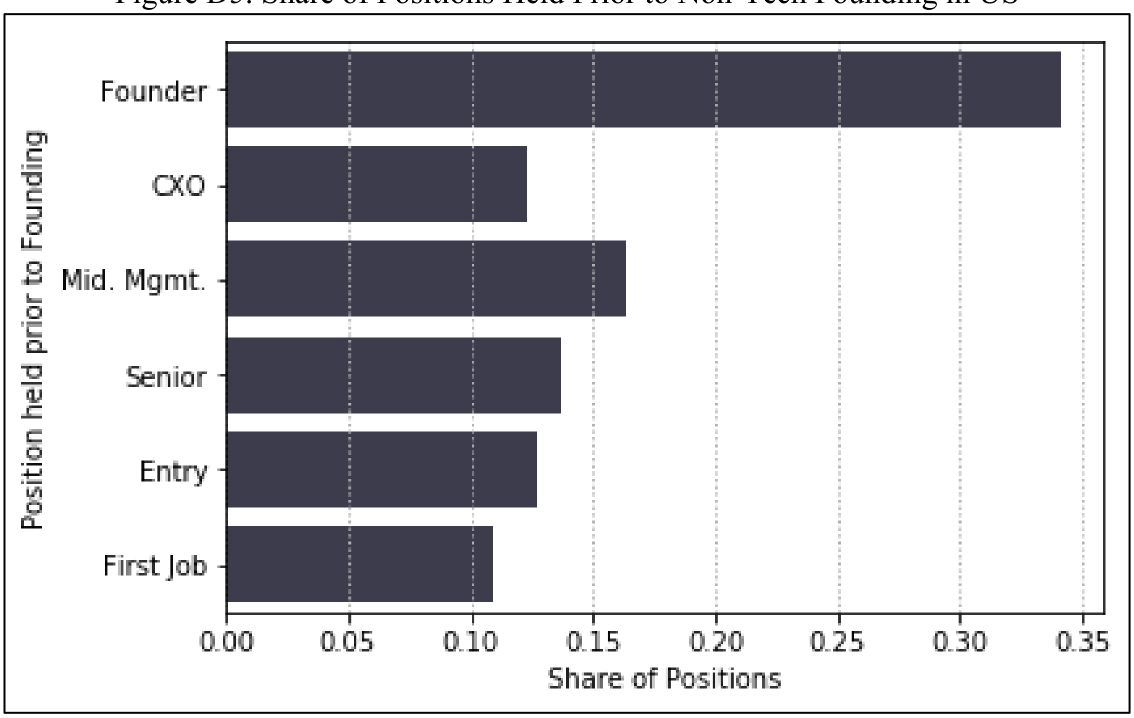
Note: This figure is a person rather than event/position based version of Figure 1. It is based on the 2000-20018 portion of US LinkedIn profiles. The light blue dots represent the share of founders who are female. The dark blue dots represent the share of employees in the industry who are female. In both cases, the unit of observation is an individual. The industries identified by LinkedIn are abbreviated as follows: tech = technology, man = manufacturing, tran = transportation, fin = finance, agr = agriculture, cons = construction, rec = recreation, med = media, corp = corporate, gov = government, leg = legal, good = goods, art = art, hlth = healthcare, serv = services, org = NGO. Category "undefined" is not shown.

Figure D4. Ratio of Shares of Female-Founded Firms to Shares of Jobs Occupied by Females



Note: This figure is the ratio between the two dots plotted in the lower panel of Figure D3a.

Figure D5. Share of Positions Held Prior to Non-Tech Founding in US



Note: This figure is based on all founding events identified in a 10% sample of US LinkedIn profiles from 2005-2007 cohorts (i.e., first job listed during these years) tracked through 2018. For each founding event, we identify the position held prior to that event. We present the distribution of founding events over those prior positions (bars sum to 1). Each group is mutually exclusive with the exception of "First Job", which overlaps partly with the entry level position variable.