NBER WORKING PAPER SERIES

VENTURE CAPITAL'S "ME TOO" MOMENT

Sophie Calder-Wang
Paul Gompers
Patrick Sweeney

Working Paper 28679
http://www.nber.org/papers/w28679

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2021

Support for this research was provided by the Division of Research at the Harvard Business School. Paul Gompers has invested in and consulted for venture capital firms. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Venture Capital’s “Me Too” Moment
Sophie Calder-Wang, Paul Gompers, and Patrick Sweeney
NBER Working Paper No. 28679
April 2021
JEL No. G3,J01,J16,J7,K31

ABSTRACT

In this paper, we document the historically low rate of hiring of women in the venture capital sector. We find that the high-profile Ellen Pao v. Kleiner Perkins gender discrimination trial had dramatic treatment effects. In difference-in-differences regressions, we find that the rate of hiring of female venture capitalists increased substantially after the trial and that the hiring was more pronounced in states that were more receptive to the exposure. We use the state-level mandated maternity benefits as an instrument for the receptivity to the treatment effects of the Pao Trial. We also show that the fraction of founders who are female increases after the Pao Trial, but that the increase is driven entirely by the hiring of female venture capitalists. There is no increase in the propensity of male venture capitalists to invest in female founders in the post-Pao Trial period.

Sophie Calder-Wang
University of Pennsylvania
sophiecw@wharton.upenn.edu

Paul Gompers
Harvard Business School
Baker Library 263
Soldiers Field
Boston, MA 02163
and NBER
pgompers@hbs.edu

Patrick Sweeney
Harvard Business School
Baker Library 280
Boston, MA 02163
psweeney@hbs.edu

1 Introduction

Despite tremendous strides in female labor market participation as well as increasing representation in many highly compensated sectors, venture capital remained immune to greater gender diversity. The rate of hiring of new senior venture capital professionals in the United States continually hovered around 8.5% and did not change noticeably from 1990 through 2015, hovering near 8% for two and a half decades. Beginning in 2015, however, we find a dramatic increase in the hiring of female venture capital investors. From 2015 onwards, the percentage of women hired in the venture capital industry increased by 50%. We explore one potential cause of this increase by exploring the role of the Pao v. Kleiner Perkins gender discrimination lawsuit in increasing awareness of gender issues in the venture capital industry. The suit, filed in 2012 went to trial in February 2015 and was decided by the jury on March 27, 2015. The high-profile trial was closely followed in the media and drew significant attention among venture capital firms in the United States.

Our paper identifies two main results. First, we show that the Pao Trial caused a significant increase in the hiring of female venture capitalists. Using a difference-in-differences analysis, we show that the Pao trial increased the hiring of female venture capitalists. Using Google search trends for the Ellen Pao trial as a measure of the exposure to the treatment, we find that states that were more attentive to the results of the trial are those that experienced the higher increases in female hiring. Using the level of state mandated maternity benefits as an instrument for the receptivity to exposure to the gender inequity issues in the venture capital industry exposed by coverage of the Pao Trial, we show that this receptivity had a dramatic impact on female hiring.

Second, we explore the financing of female founders. Many industry observers have argued that homophily in investing leads to gender funding biases and that hiring of more female venture capitalists is a prerequisite for increasing the number of female founders receiving venture capital. We show that the percentage of founders who are women increases in the 2015-2019 time period. We then explore whether this increase is driven by the increased representation of female venture capitalists in the industry or whether the Pao trial increased the propensity of male venture capitalists to invest in female founders or both. We show that the increase in percentage of female founders is driven by the hiring of female venture capitalists from 2015-2019. This increase in the financing of female entrepreneurs is directly tied to the increased prevalence of female venture capitalists (i.e., female venture capitalists are significantly more likely to invest in female entrepreneurs), not to an increased propensity of male venture capitalists to invest in female entrepreneurs. There is no increase in investments by men in female entrepreneurs after the Pao Trial and no effect of Google search trends or the level of state-mandated maternity benefits. Overall, our results are consistent with the view that exposure to important social issues can affect inherent bias in hiring, but the debiasing is dependent upon the receptivity to the exposure. The exposure effect of the Pao Trial, however, was specific to the gender bias in hiring of female investors, not a general exposure to gender bias issues broadly.

Two of the most striking patterns in labor economics in the past half-century have been the increase in female labor market participation along with the growing ethnic diversity of the American workforce. Given the rising rate of labor participation among females in all parts of the world, there has not been a larger factor affecting global labor supply and demand dynamics. As an example of the magnitude, female labor market participation in the US has nearly doubled since

1950, going from 33% to 57% in 2016.[1] Further, the overall US increase has been shared broadly across fields in the economy, including the professional fields of law, medicine, and business.

In this paper, we document a sharply contrasting phenomenon in the venture capital industry. After carefully documenting this contrasting trend, we examine potential labor supply explanations that could help explain the substantial underrepresentation of woman and the recent dramatic increase in female venture capitalists starting in 2015 by documenting the educational and career backgrounds of those who become venture capitalists. In particular, we show that schooling and work experience cannot explain the historically low representation of women in venture capital. The supply of women with backgrounds that are similar to male hires is much larger than the fraction of women hired into the venture capital industry. As such, we conclude that female labor supply cannot explain the relatively modest representation of women in the venture capital sector.

Our examination of the Pao Trial's effects is motivated by examining patterns of female participation in the venture capital industry compared to other highly-compensated professions. Figure 1 shows the evolution of female labor market participation in professional industries in the US along with total US female labor market participation. The figure shows the relative fraction of each category entering the labor force or a particular profession who are female. We believe looking at flow variables (i.e., fraction of those entering a profession who are female) is more relevant to changing participation barriers because the current stock of labor within a profession represents the historical experience with past barriers to entry. As can be clearly seen, total female entry into the labor market has stayed roughly constant over the 25 years: roughly 45-46% of the total US labor force has remained female. Moreover, while the professional fields of medicine and law started the period well below economy-wide levels of female participation (dark and light violet dashed lines,

[1] United States Bureau of Labor Statistics (2016) http://www.bls.gov/opub/ted/2000/feb/wk3/art03.htm , https://fred.stlouisfed.org/series/LNS11300002).

respectively), they both have a steady increase over time. In fact, not only have the female percentages fully converged, but at present, women's fraction entering law and medicine stand slightly above the economy-wide rates of 46.85%; 49.64% for medicine and 49.72% for law. From starting points of just 26.58% (for medicine) and 35.52% (for law) in the early 1990s, these increases represent substantial shifts in terms of economic magnitude in a short period of time. Figure 1 also shows the evolution of female entry into the venture capital industry. In stark contrast to other professional fields, women in began the early 1990s at much lower levels and did not show nearly the same convergence tendency, remaining at 8.61% during the 2010-2014 period. Starting in 2015, the hiring of female venture capitalists increased dramatically, averaging 14.23% for the period 2015-2019. This average, however, masks a year by year increase in this five year span of time. In 2015, the percentage of new venture capitalists that were women was 12.87%. That percentage increased steadily to 17.65% in 2019.

The historical low representation of women in venture capital is also in sharp contrast to other business sectors. Figure 2 compares the average rate of entry by women into venture capital over 2010-2019 (a period of time that includes the recent upswing in hiring, with the two largest finance and business-related professions for business school graduates over this time period: consulting and investment banking. Over the past decade, 11.42% of new hires in venture capital were women (from 2010-2014 8.61% of new hires were women). Over the same time period, 44.35% of new consultants were women and 33.85% of new investment bankers were women. Even relative to other highly sought after business jobs, female hiring in venture capital has lagged significantly.

One potential demand-side explanation for the lack of female hires into the venture capital industry is related to the notion of "homophily", which is the tendency of individuals to associate with similar others. As surveyed in McPherson, Smith-Lovin, and Cook (2001), the notion that "similarity breeds connection" has robust and profound effects in network structures of every type, including "marriage, friendship, work, advice, support, information transfer, exchange, co-membership, and other types of relationship." A direct implication of this "birds of a feather" phenomenon is that venture capitalists prefer to hire, invest in, or co-invest with those that are similar to themselves in characteristics such as gender and ethnicity.

Indeed, Gompers, Mukharlyamov, and Xuan (2016) show that co-investment patterns in venture capital are driven by social similarities, where venture capitalists who are more similar in terms of gender, ethnicity, school background, and work history are more likely to collaborate. They also show that this homophily driven collaboration reduces performance.[2] Moreover, Calder-Wang and Gompers (2020) find that this hiring bias can be mitigated when the existing male senior partners have daughters, i.e., having daughters increases the propensity to hire women into venture capital firms.

Since the typical venture capital firm is small in size, with a median of three partners in our dataset, hiring decisions are made infrequently. Further, expansion in the VC industry has occurred mostly at the extensive margin (i.e., the creation of new, small (three-partner) VC firms), as opposed to the intensive margin (existing firm expansion). This could be due to optimal scale considerations given the output (e.g., the information collection, processing, etc. could work best in small nimble teams), or due to inefficiencies (e.g., industry-wide equilibrium fee structures provide incentives to maintain small teams). Thus, aggregate new hiring in this industry is driven by the aggregated decisions of small teams. From social psychology, small groups are both more likely to be homophilous and more likely to have biases aggregate into expressed decision-making (Klocke

[2] Cohen, Frazzini, and Malloy (2008) show that homophily also works at the school ties level in the investment management arena between buy side analysts and CEOs.

(2007)). Thus, a slight preference over certain demographic characteristics could aggregate into a sustained overall lack of diversity at an *industry* level.

Put differently, in a firm making a single new hire, a slight gender preference may result in the hiring of a man over a woman. Even though the gender preference can be thought of as a continuous variable and any slight bias could be small, the hiring outcome is binary. In this setting, even a very small bias towards hiring someone of the same gender or ethnicity could lead to persistent low representation from those groups not already in the venture capital industry. The aggregation of such binary outcomes across firms can result in the overall lack of diversity across an entire industry.

Our conjecture is that the high-profile nature of the Pao Trial, the fact that it was widely covered in the broadcast and print media, potentially exposed venture capitalists to the issues of females in the sector. As such, this exposure potentially "de-biased" hiring and led to an increase in the propensity of firms to hire women. We test the exposure hypothesis by looking at how "exposed" states were to the Pao Trial by looking at the state-level time series of Google search trends for the "Ellen Pao Trial". This approach is similar to the approach taken by Kearney and Levine (2015) who look at the effect of MTV's *16 and Pregnant* television show on teen pregnancy rates. They look at Google search trends as a proxy for exposure to the content of the show. In the context of our setting, we find considerable heterogeneity in terms of search intensity towards the Pao Trial across states with the dramatic peak in search intensity in March 2015. Google search trends are reflective of the attentiveness to a particular issue and, as such, measure exposure to a particular event. We show in our difference-in-differences setting, that after the court decision, states with higher Google search trends for "Ellen Pao Trial" had the largest increase in hiring of female venture capital investors.

Given that there may be concern that Google search trends are somehow endogenous, we examine the difference-in-differences using an Instrumental Variables approach. We use the state-level mandated maternity benefits as an instrument for Google search trends for the Pao Trial. The reduced-form regressions show a significant positive relationship between state mandated maternity benefits and an increase in female hiring after the Pao trial. Similarly, the first stage of the IV regression shows a strong predictive relationship between the state-level mandated maternity benefits and Google search trends for the Pao Trial. Finally, the second stage results indicate that exogenous exposure to the Pao Trial is associated with an increase in female venture capital hiring.

Our final set of analyses look at the effect of hiring more female venture capitalists in response to the Ellen Pao Trial verdict on investments in female-founded companies. We find that the fraction of venture capital-backed companies that are founded by women increases after the Pao Trial. This increase, however, is directly tied to the increase in hiring of female venture capitalists. Female venture capitalists are significantly more likely to fund female-founded companies. This is true controlling for industry and state as well. When we examine the propensity to invest in female founders after the Pao Trial, we find that male venture capitalists do not change their propensity subsequent to the verdict. Hence, the Pao Trial served as an exposure reducing bias in the hiring of female venture capitalists, but did not carry over into investing in more female-founded companies.

The remainder of the paper is organized as follows: Section 2 describes how we construct the dataset for entrepreneurs and venture capitalists. Section 3 describes the time-series trends and industry patterns along the dimensions of gender. Section 4 discusses the Pao Trial and examines its effects on the hiring of female venture capitalists. Section 5 examines whether the hiring of more female venture capitalists increased investments in female entrepreneurs and whether exposure to the Pao Trial changed men's investments into female founded companies. Section 6 concludes.

2 Data Construction

The core data used in this paper are derived from several different sources. We start with *VentureSource*, a database that contains detailed information on venture capital investments. Our data cover the period from 1990 through mid-2019. We start our analysis in 1990 because the data become reasonably comprehensive at that point in time. For each portfolio company, we have the identities of the individuals involved with the firm including founders, venture capital investors, angel investors, board members, and early hires. We focus on the portfolio company founders as well as the venture capitalists on the board of directors. Throughout the paper, we will refer to company founders as "entrepreneurs". In addition to information about the people involved in the company, we also have information on the portfolio company's location and industry. A founder enters the data in the year in which they receive their first round of financing.[3] A venture capitalist enters the data in the year they make their first investment for which they sit on the board of directors.

For each individual entrepreneur and venture capitalist in the dataset, we collect a broad range of biographical information such as gender, ethnicity, education, and prior job experience. We collect this information from a variety of sources, including a leading online resume website, web searches, SEC filings, and news articles. The education information includes the academic institution attended along with the specific type of degree granted. Degree types include undergraduate, postgraduate non-business (Ph.D., M.S., J.D., and M.D.), and postgraduate business (MBA). For prior job experience, we record the company names as well as job titles.

Entrepreneur and venture capitalist genders are primarily determined based on first names. In the cases of unisex names, we determine gender by reading news articles and web pages

[3] We do not have information on founding dates, hence, we time entry as the time of first funding.

mentioning or containing pictures of the individual. To identify ethnicity, we use the name-matching algorithm developed by Kerr and Lincoln (2010) to determine the most likely ethnicity based on their first and last names. Due to the ambiguity in identifying Black names, anyone who was classified as White is then searched on the Internet for photos based upon the full name, the company name, and the company location. The Black designation is then based upon a review of the photos. Individual entrepreneurs and venture capitalists are classified into six non-overlapping ethnic groups: White, East Asian, South Asian, Latinx, Black, and all others. In this paper, we group East Asian and South Asian as Asian. Our overall match rates for both gender and ethnicity exceed 99%.[4]

In this paper, we choose to focus on entrepreneurs that have received venture financing. Although this by no means captures the full spectrum of entrepreneurs, venture financing remains an important source of entrepreneurial capital. For instance, Kaplan and Lerner (2010) found that more than 60% of true IPOs had venture financing. Considering only 1/6 of 1% of all companies are venture-backed, this represents a powerful source of high potential, fast-growing, innovative companies. Further, venture-backed companies also have a large impact on the overall economy. Gornall and Strebulaev (2015) found that companies previously backed by VCs account for 44% of the research and development spending among US public companies. Thus, the demographic trends of entrepreneurs who had access to venture capital represent those of a vital source of economy-wide innovation.

We determine the investment outcome using *VentureSource* and Refinitiv's SDC database, and S&P CapitalIQ. Finally, we use historical copies of Pratt's Guide to Private Equity and Venture Capital Sources and Pitchbook to manually code the locations of venture capital firm offices.

---

[4] For entrepreneurs, 108 (0.3%) of them are missing gender and 189 (0.4%) of them are missing ethnicity. For VCs, 25 (0.2%) of them are missing gender and 40 (0.4%) of them are missing ethnicity.

3 Gender Trends for Venture Capital

3.1 Summary Statistics

Table I provides a summary of the data for both entrepreneurs and venture capitalists in our sample aggregated across the entire period from 1990 to mid-2019. Overall, we have data on 13,571 venture capitalists with a similar gender breakdown: 90.9% are men and 9.0% are women.[5] This type of gender segregation has been documented anecdotally in the popular press. Gompers, Mukharlyamov, Weisburst, and Xuan (2020) documented that nearly 80% of venture capital firms had never hired a female investor.[6] [7]

We also examine the time series changes in the entry into venture capital for women in our data. For venture capitalists, because we can only identify a venture capitalist when they take a board seat at a portfolio company given our data source, the entry date is recorded as the first time they do so.[8] We cannot observe when the individual was actually hired at the venture capital firm. Similarly, because typically only partner level venture capitalists get to sit on boards of a portfolio company, we only observe senior hires.

Compared to measuring the diversity of the entire stock of venture capitalists, we focus here on measuring their entry rates. We choose to do this not only because it is challenging to observe the stock (it is hard to observe when a venture capitalist retires), but also because the entry rate is a more direct measure to track the changes in demographic trends. The stock of venture capitalists will represent the sum of all the past barriers to entry and differences in supply. However, one must

---

[5] Note that the percentages don't add up to 100% because a small fraction of entrepreneurs and venture capitalists with gender ambiguous names could not be found on web searches.

[6] Moreover, we will see later that the female venture capitalists on average make fewer deals than their male counterparts, representing 7.0% of the board seats taken up by venture capital investors.

[7] No other survey or popular press article has ever looked at the entire population of venture capitalists. Most accounts have been relatively small, cross sectional surveys done for popular media consumption.

[8] Since the average venture capitalist in our sample sits on the board of four startup companies, we only record the entry of the venture capitalist based on their first deal.

take necessary precautions while comparing it with other stock variables such as the labor force proportions.

As described in the introduction, Figure 1 plots the gender breakdown of entering venture capitalists from 1990 to mid-2019 (averaged over every five years) and shows that female investors have made little progress over the first 25 years. Over this period, women represent more than 45% of labor force participants. Meanwhile, the proportions of entering female venture capitalists remained extremely low. For women venture capitalists (VCs), the rate was around 6% in the early 1990s and rose to around 9% in the late 1990s, but stayed at that level until 2015, displaying no secular trends. In the most recent five year period, however, women represented 14.23% of new venture capital hires. In a sharp comparison, the proportion of women in high-skilled occupations such as medicine and law experienced dramatic increases during this period and are substantially higher in 2019.

3.2 Industry Patterns

In this section, we examine the industry patterns of gender representation within the venture capital sector. These patterns may help identify critical mechanisms that affect diversity. In particular, female venture capitalists may have different patterns of industry investments. These differences may affect the propensity of venture capital firms to hire female investors depending upon industry cycles of opportunity. Venture-financed portfolio companies are classified into industries based upon *VentureSource* industry codes. We group companies into seven broad industry segments: Business and Financial Services, Consumer Goods, Consumer Services, Energy and Utilities, Healthcare, Industrial Goods and Materials, and Information Technology. These classifications are highly correlated with venture capital investor specialization found in Gompers, Lerner, Kovner, and Scharfstein (2010). We classify venture capitalists into industries based upon the industry of their first investment.

In Figure 3, we see pronounced variations of gender diversity across different industries for venture capitalists. In the entire sample, women represent 9.0% of all venture capitalists. We categorize venture capitalists based upon the industry of their first investment. Certain industries have substantially more women investors. In particular, women represent 12.0% of venture capitalists in the Healthcare industry and 13.1% of investors in Consumer Goods. On the other hand, women venture capitalists are only 7.2% of Information Technology investors, the smallest percentage in what is the largest venture capital-backed industry. These patterns are consistent with anecdotal accounts of women pursuing more entrepreneurial opportunities in companies that focus on the consumer.

We next turn to the backgrounds of venture capitalists in our sample. In particular, we start by looking at the educational background of male and female venture capitalists. In Table III we see that many liberal arts colleges represented for undergraduate degrees for both male and female venture capitalists. Harvard, Stanford, and the University of Pennsylvania are the top 3 undergraduate colleges for both male and female venture capitalists, while the top 20 colleges represent 37.7% of all undergraduate institutions for men and 32.1% for women. The list of undergraduate institutions for men and women are virtually identical. Undergraduate majors shows some small differences between men and women. Economics and business are the top two majors for both men and women, but engineering/electrical engineering/computer science represent the next category of majors for men while biology/finance/chemistry are the next most common majors for women. This is consistent with the higher percentage of female investors in the Healthcare industry.

For those who obtain post-graduate degrees, 56% have an MBA. Unlike undergraduate institutions, MBAs are highly concentrated in a small number of programs. The concentration of the top 20 MBA programs among all MBAs is 74.8% for both men and women: Harvard Business School alone accounts for 21.8% of the MBAs for male venture capitalists and 20.7% of MBAs for female venture capitalists. The top five business schools, Harvard, Stanford, University of Pennsylvania, Columbia, and Chicago/Northwestern, account for more than half of all MBAs.

Among the non-MBA graduate institutions that we see in Table IV, the list looks quite similar to the MBA institutions with 45.6% of degrees represented by the top twenty universities for men and 50.5% for women. Stanford, Harvard, MIT, University of Pennsylvania, and Columbia are the top four institutions. Among non-MBA graduate degrees, Table VII shows that law and medicine represent nearly half of the non-MBA graduate degrees for male venture capitalists, but only 32.8% of graduate degrees for women.

The work experience of venture capitalists also shows some difference from the experience of entrepreneurs in Table VIII. Investment banks, private equity, and other venture capital firms make up more than half of the top 20 past employers for both men and women. This includes Goldman Sachs, Morgan Stanley, Merrill Lynch, Citigroup, and Lehman Brothers, suggesting that the analytical skills developed in financial firms are potentially seen as useful for the evaluation of investment opportunities. We also find a large number of consulting firms including McKinsey, Bain, Ernst and Young, and Accenture among the top employers. The remaining top 20 employers are large technology companies like Microsoft, IBM, Cisco, and Google. Overall, the number of former employers is quite high and the top 20 past employers account for 10% of all venture capitalists.

As a quick test of whether labor supply has limited the number of women entering venture capital, we tabulated data on women with training and backgrounds matching the venture capital industry. As we saw, venture capitalists tend to have MBA degrees and experience in investment banking or consulting. Overall, the fraction of MBA degrees granted to women has increased from around 35% in 1990 to 39% in 2019. Meanwhile, for Harvard Business School (as a proxy for top MBA programs) the fraction of MBAs granted to women grew from 27% in 1990 to 42% in 2019. Similarly, the fraction of women in occupations relevant to venture capital is quite high. Figure 2 shows that the percentage of those entering the investment banking industry who are women averaged 33.85% over the last decade. Meanwhile, the fraction of those taking a position in consulting who were women over the same period of time was 46.8%.

In short, for the venture capital industry, the number of women who have obtained the relevant educational degrees as well as the relevant job experience has remained substantially higher than the fraction of new venture capital investors who are women.[9] Overall, the evidence argues against a purely labor supply explanation for the low female levels in venture capital.

4 Ellen Pao Trial

The prior section documented that women are dramatically underrepresented in the venture capital sector and that their entry did not change dramatically from 1990 to 2015, but started to increase dramatically starting in 2015. In this section we explore whether the publicity around the Pao Trial led to a treatment effect that brought gender issues to the surface and led to increased hiring of female venture capitalists. We start by providing a brief history of the trial and then explore in a difference-in-differences setting whether the trial had a causal effect on hiring.

[9] Again, one must take caution here in interpreting the occupation data. Since it represents the stock of employees, we cannot differentiate entries from exits when it comes to their respective attribution to the overall changes.

4.1 Effects on Hiring of Venture Capitalists

4.1.1 Trial History

Ellen Pao was hired by Kleiner Perkins Caufield Byers in 2005 to be Chief of Staff for John Doerr, a Managing Director of the firm. Kleiner Perkins, established in 1972, is one of the oldest and most successful venture capital firms in Silicon Valley having backed successful startups including Genentech, Sun, AOL, Amazon, and Google. Believing she had been passed over for promotion while similar male colleagues had been advanced, Pao filed a gender discrimination lawsuit against Kleiner Perkins on May 10, 2012.

While most gender discrimination lawsuits settle prior to a court hearing, the Pao Trial was heard in San Francisco County Superior Court starting in February 2015. The trial gained significant media attention in both broadcast and print media. The testimony of many of Silicon Valley's star investors only increased the attention on the trial. The verdict was announced on March 27, 2015 and found for Kleiner Perkins, concluding that they had not discriminated against Pao. After the verdict, many industry pundits provided views that the lawsuit would increase the focus of women's issues in venture capital and technology. The effect of this focus, however, was in significant disagreement. Some believed that the high-profile trial might reduce the hiring of women as venture capital firms worried about the potential for similar legal actions. Others, however, forecast that the trial would lead to greater awareness of women's issues and would lead to greater hiring of women in the industry.

4.1.2 Diff-in-Diffs Ordinary Least Squares

Our first set of tests looks at a simple difference-in-differences setting to establish whether the Ellen Pao Trial was associated with an increase in the hiring of female venture capitalists.

Because the lawsuit was filed in early 2012 but not decided until early 2015, we define our pre-period as the four years from 2008 through 2011. Similarly, our post period is defined as 2015 through mid-2019. During the pre and post-periods, we identify the hiring of 3,635 venture capitalist.

We are interested in the differential effect of the Pao Trial on hiring depending upon the receptivity of the venture capitalist to coverage of the trial. To measure exposure to the Trial, we look at Google search trends for Ellen Pao. Google search trends tracks the frequency of search for different words or phrases relative to all searches over time and by region/state. A recent paper by Levy and Mattsson (2020) used Google search trends as to identify the treatment effects of exposure to the #MeToo movement across 30 OECD countries and its relation to reporting of sexual crimes. Levy and Mattsson argue that Google search trends for #MeToo measures the receptivity to the social movement, hence is a good measure of the treatment effect. They find that in OECD countries, Google search trend ratings are positively related to the increase in reporting of sexual crimes. We use a similar motivation to look at differential treatment effects of the Pao Trial.

Google search trends for Ellen Pao peak in mid-2015 with little coverage before and after the verdict in the trial, as shown in Figure 5. We use state level Google search trends to identify treatment effects in our difference-in-differences results. The state with the highest relative search intensity was California whose Google search trends rating is set to 100. The top five states are, in order, California, the District of Columbia, Washington, Massachusetts, and Nevada. The lowest state in terms of Google search trends is Mississippi, with a rating of 11. The next lowest states, in order, are Alabama, Maine, Tennessee, and Wisconsin.

Figure 6 illustrates a stylized difference-in-difference analysis where the percentages of female hired diverged after the Ellen Pao trials depending on the intensity of the Google search interest. More specifically, we divide states into above or below median levels of Google search interests and plot the percentages of female hires over time. Prior to the trial, there is little observable difference between these two groups of states. However, after the trial, there appears a noticeable divergence in terms of the percentages of female hires in venture capital.

In Table IX we run simple OLS regressions of whether the hire was a female on a variety of controls. Our base specification in column 1 regresses the gender of the hire on an interaction term between the state level Google search trend and a dummy variable for the post-Pao period. This specification allows the treatment effect of exposure to the Pao Trial to vary by state. The intensity of the treatment effect is measured by Google search trends ratings. We find that the interaction term is positive, i.e., states with a higher Google search trend for the Pao Trial have a larger increase in the hiring frequency for women in the post-Pao period. The standard deviation of the Google search trend is 16.5, so a one standard deviation increase in the Google search trend is associated with a 1.15% increase in hiring of female venture capitalists in the post period. Given that women were 8.4% of venture capital hires in the pre-period, this represents a 14% increase in hiring of female investors.

We add a variety of state and firm-level controls to the regressions to test the robustness of our result. First, controlling for the size of the venture capital market may be important in understanding hiring dynamics. Venture capital firms in states with larger venture capital markets may be under a greater spotlight and may therefore feel the pressure to respond to scrutiny from the Pao Trial. To control for venture capital market size, in regressions (2) to (6) with include a variable which is the number of venture capital investments made in that state during the ten years preceding the pre-Pao period, i.e., from 2002-2012. Moreover we normalize vc size by state poplulation

Our summary statistics above demonstrated that female venture capitalists were disproportionately represented in certain industries. For example, in the past decade, Consumer Goods and Consumer Services have become more important sectors of the venture capital industry. As such, controlling for industry focus of the venture capital hire may be important. In regressions

(3) through (6) we include dummy variables for the industry of the first investment of the venture capital hire. The results are unaffected by included these industry fixed effects.

Similarly, hiring of female venture capitalists may be related to venture capital firm characteristics. Larger and older venture capital firms may have different hiring practices and may be more likely to actively seek diversity. We control for the same set of firm-level controls that Calder-Wang and Gompers (2020) use in their hiring results. As such, we include venture capital firm age (defined as the age (in years) at the time of the hiring event) and partner count (the number of venture capitalists affiliated with the venture firm that has made at least one investment over the prior three years).. In regressions (4) to (6) we control for various sets of these venture capital-firm level controls. None of these firm level controls alter the main difference-in-differences result, that treatment effects of the Pao Trial media coverage led to an increase propensity for venture capital firms to hire women. We do find that older venture capital firms (defined as the age of the firm in years at the time of the hiring event) is positively related to the propensity to hire a female venture investor. This is true even once you control for the number of existing partners, hence age in the regression is not a proxy for firm size.

4.1.3 Reduced Form and Instrumental Variables

Given concerns about the measurement problems of Google search trends as it relates to the Pao Trial, in this section we pursue an instrumental variables framework to estimate the effect of the trial on hiring of female venture capitalists. A potential instrument in the context of our experimental design is a variable that would be correlated with the treatment effect of the trial, i.e., sensitivity to gender bias issues brought into focus through coverage of the trial, but uncorrelated with search intensity driven by factors that might drive interest in legal issues in venture capital generally. The reasoning on identification of such an instrument is analogous to Kearney and Levine's (2015) use of local area MTV ratings from the period before the airing of *16 and Pregnant*.

In our setting, we use the level of state-manded maternity benefits as an instrument for Google search trends in response to the Pao Trial. A variety of research has examined the role of maternity benefits on the choice of employment for women. Dustmann and Schonberg (2012) provide evidence that an expansion in maternity benefits has a strong impact on mothers' return to work after childbirth. Similarly, Gottlieb, Townsend, and Xu (2016) look at changes in Canadian maternity benefits and the choice of women to start businesses. In our view, the state-level of mandated maternity benefits proxies for how receptive individuals in that state are to issues of women in the workplace. The Pao Trial is likely to have a higher impact on venture capitalists attitudes in states with high levels of benefits. Therefore, we look at whether state-level variations in the mandated maternity/family leave benefits as an instrument for the treatment effect of the Pao Trial.

We obtain the benefit scores from the National Partnership for Women and Families that grades each state's laws concerning paid job protection, family and maternity leave, and flexible use of sick leave. The five states with the highest grades are New York, Rhode Island, New Jersey, Connecticut, and Washington D.C. that have an average score of 127. The sates with the lowest grade (0): Arizona, Georgia, South Carolina, Alabama, Indiana, Michigan, Mississippi, Nebraska, Oklahoma, South Dakota, and Wyoming. Our first set of regressions in Table X are reduced form using the state-mandated maternity benefits instead of the Google search trends variable in Table IX. We find that the interaction of state maternity benefits with the Post-Pao variable is positive and significantly related to hiring of female venture capitalists. This indicates that in states with great maternity benefits that are mandated, hiring of female venture capitalists went up more after the Pao Trial verdict in 2015. Once again, we include a variety of controls (as in Table IX) and none of the additional controls affects inferences our difference-in-differences effects. The standard deviation of the maternity score is 41.2 implying that a one standard deviation increase in the maternity score for a state increases the hiring of female venture capital investors by 2.2%, a 26% increase from the pre-Pao period average rate of female hires of 8.4%.

We now turn to our instrumental variables specification. In this setup, we instrument for Google search trends interacted with our Post-Pao dummy variable. The first stage is estimated by equation (1)

$$Google\ \times PostPao = Maternity\ Score\ \times\ PostPao + State\ Level\ Controls + Firm\ Level\ Controls + \epsilon$$

We continue to use size of the venture capital market as well as a variety of firm level controls. As can be seen in Panel A of Table XI, Maternity x Post-Pao is a strong predictor of Google x Post-Pao. When we include the size of the venture capital market, we also see that it is positively related to Google x Post-Pao indicating that it is a useful control in the first stage regressions. In regression (1), a one standard deviation increase in state-mandated maternity benefits is associated with a 24.5 increase in the Google search trend rating.

Larger venture capital markets (in terms of number of deals from 2002-2012 in that state) are associated with a higher Google search trend rating. Given that the Pao Trial was a major issue in the venture capital industry, it makes sense that a larger venture market would be associated with a greater Google search trend rating. We saw in the reduced form regression in Table X, however, that the size of the venture capital industry was not related to the probability of hiring a female venture capital investor in the Post-Pao period. Even so, controlling for the size of the venture capital market, the state-level mandated maternity benefits is still significantly related to the Google search trend rating. A one standard deviation increase in mandated maternity benefits is associated with an increase in the state's Google search trend rating by 18.3.

The second stage regressions in Panel B show that the instrumented state Google search trend rating is positive and significantly related to the propensity to hire a female venture capitalist in the post-Pao period. The size of the coefficient on $\widehat{Google} \times PostPao$ in the IV is of similar magnitude to the OLS results in Table IX providing support for Google search trends measuring the exposure treatment. When we add in the additional firm level controls, the results remain robust. We do find that older venture capital firms do have a higher propensity to hire female venture capitalists, but no other firm-level control is associated with hiring of woman.

Our IV results gives us comfort that we are identifying a causal impact of the Pao Trial. The Pao Trial exposed venture capital firms to the issues of woman in the venture capital industry. Venture capitalists in states in which firms were more receptive to this exposure were more significantly affected by the trial and were more likely to increase their propensity to hire a female investor. Google search trends is a direct measure of the exposure, but the component of the exposure that is related to the receptiveness is instrumented by the state-level of mandated maternity benefits. This is exactly the same approach as taken by Kearney and Levine (2015) with the MTV show *16 and Pregnant* and by Levy and Mattsson (2020) with the #MeToo movement.

4.2 Effects on Investments in Female Entrepreneurs

4.2.1 Female Entrepreneur Trends

One common reason given for hiring more female venture capitalists is that there are many female entrepreneurs who lack access to capital, either because they are starting companies in industries that are not the focus of male venture capital investors or because there is homophily in investing (i.e., men generally tend to invest in men.) In this section, we look at the downstream effects of the increase in female venture capitalists in the post-Pao period. We start by documenting trends in gender representation among venture capital-backed entrepreneurs. We then examine whether male venture capitalists tilt their portfolios more to male founders and whether female venture capitalists tilt their portfolio towards female founders. Finally, we ask whether the fraction of founders who are female increases after the Pao-Trial, whether that increase is exclusively due to more female venture capitalists or whether men increased their propensity to *invest* in female founders after the Pao trial.

Figure 6 presents the time series of women as a percentage of all founders of venture capital-financed companies. From 1990 through 2009, the fraction of female founders was always below 8% and showed little time trend. There was a meaningful increase in female founders from 2010-2014 to 10.5% and another increase for 2015-2019 to 13.0% of all venture capital-backed founders.

We are also able to tabulate the percentage of male and female founders in the portfolios of male and female venture capitalists in the pre-Pao period and the Post-Pao period. In the pre-Pao period, female venture capitalists had 11.9% of their founders who were women. Male venture capitalists had 7.2% of their founders who were women. This difference clearly indicates potential gender homophily in picking investments by venture capitalists. In the post-Pao period, the percentage of female founders in the portfolio of female venture capitalists increased to 15.0% while the percentage of female founders in male venture capitalists increased to 8.8%. Given that the industry composition may have shifted between the two periods, it is hard to determine whether the increase in portfolio weights is potentially associated with the Pao-trial treatment or is related to other factors. In the next section, we explore a difference-in-differences framework to test the hypothesis.

4.2.2 Diff-in-Diffs Effects

We next look at the gender of the founders for investments by venture capitalists pre- and post-Pao Trial. We use a similar framework to the one we used to examine the hiring of female venture capitalists. In particular, we look at whether the exposure to the Pao Trial as measured through Google search trends affected the propensity to invest in female founded companies. Given that gender homophily likely influences the choice of male and female venture capitalists in terms of founders, we control for whether the venture capitalists is male or female.

In Table XIV we report the second stage of our IV regressions. Our first stage is estimated in the same way as in Table XI. The main result can be seen in column (1). We see that female venture capitalists have a 5.5% greater propensity to invest in female founders. This is 75% higher than the propensity of male venture capitalists to invest in female founders. The constant term in (1) can be viewed as the baseline probability that a male venture capitalist investing in a female founder, i.e., 7.1%. We also see that the propensity to invest in female founders did not increase after the Pao Trial. Google x Post-Pao is small and insignificant.

In column (2) we include the treatment effect (Google x Post-Pao) interacted with Female. The coefficient is small and insignificant (and negative). Google x Post-Pao remains small and insignificant as well. Therefore, even when we separate out the treatment effect for male and female venture capitalists, we do not find any effect on either gender in terms of propensity to invest in female founders. Thus, the increase in female founders financed by venture capitalists after the Pao Trial is entirely driven by the increase in the fraction of venture capitalists who are female.

In columns (4)-(6) we include industry of the founder's company as well as a variety of controls for venture capital firm characteristics. First, industry effects do not change the increased propensity of female venture capitalists to invest in female founders. Even controlling for industry, women are more likely to invest in female founders. We find that older and larger venture capital firms are less likely to invest in female entrepreneurs. .

5 Conclusion

In this paper, we document the historically low rate of hiring women in venture capital and how a major gender-discrimination lawsuit in venture capital has impacted these firms' subsequent hiring decisions. We used Google search trends as a potential measure of the exposure to the event. We found strong evidence that exposure to the trial likely resulted in a material increase in the percentages of women hired in venture capital. We used state-level maternity scores as an instrument to address potential measure problems and find continued support for the causal impact. Lastly, we find the increased hiring of women in VC likely resulted in an increased amount of capital allocated to women founders.

Our research contributes to a growing literature on the economic implications of diversity and inclusion in firms. We provide measured, quantitative evidence towards how changes in firm diversity could be brought about by increased awareness of the relevant issues in an important segment of the capital market. Given that venture capital plays a crucial role in allocating equity capital towards entrepreneurship and innovation, our findings are relevant for ensuring that financial capital become accessible for all aspiring entrepreneurs despite their demographic backgrounds.

References

Abramowitz, A., and K. Saunders, "Ideological Realignment in the U.S. Electorate", *The Journal of Politics*, 60, (1998), 634-652.

Barro, R., "Education and Economic Growth," *Annals of Economics and Finance*, 14-2(A), (2013) 277-304.

Bertrand, M., and S. Mullinathan, "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," *American Economic Review* 94, (2004), pp. 991-1013.

Bohnet, I., A. van Geen, and M. Bazerman, "When Performance Trumps Gender Bias: Joint Versus Separate Evaluation," *Management Science* 62, no. 5 (May 2016): 1225–1234.

Calder-Wang, S., and P. Gompers, "And the Children Shall Lead: Gender Diversity and Performance in Venture Capital," forthcoming in the *Journal of Financial Economics* (2020).

Calvo-Armengol, A., and M. Jackson, "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 94 (3), (2004)

Cohen, L., A. Frazzini, and C. Malloy, "The Small World of Investing: Board Connections and Mutual Fund Returns," *Journal of Political Economy,* 116 (2008), 951–979.

Dustmann, C., and U. Schonberg, "Expansions in Maternity Leave Coverage and Children's Long-Term Outcomes," American Economic Journal: Applied Economics, 4 (2012), 190-224.

French, K. R., and J. M. Poterba, "Investor Diversification and International Equity Markets," *American Economic Review*, 81 (1991), 222–226.

Granovettor, M. "The Strength of Weak Ties," *American Journal of Sociology*, 78, (1973), pp. 1360-1380.

Gompers, P., A. Kovner, J. Lerner, and D. Scharfstein, "Performance Persistence in Entrepreneurship," *Journal of Financial Economics* 96, pp. 18-32.

Gompers, P., J. Lerner, and D. Scharfstein, "Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999," *Journal of Finance*, 2 (2005), 577 – 614.

Gompers, P., V. Mukharlyamov, and Y. Xuan, "The Cost of Friendship," *Journal of Financial Economics*, 119 (2016), 626–644

Gompers, P., V. Mukharlyamov, E. Weisburst, and Y. Xuan, "Gender Effects in Venture Capital," forthcoming in *Journal of Financial and Quantitative Analysis* (2020).

Gornall, W. and I. Strebulaev, "Financing as a Supply Chain: The Capital Structure of Banks and Borrowers," Working Paper (2015).

Gottlieb, J., T. Richard, and T. Xu, “Experimenting with Entrepreneurship,” University of British Columbia working paper, (2016).

Goldin, C., and C. Rouse, “Orchestrating Impartiality: The Impact of ‘Blind’ Auditions on Female Musicians,” *American Economic Review*,90(4) (2000): 715-741.

Gruber, J., “The Incidence of Mandated Maternity Benefits,” *American Economic Review*, 84(3), 1994, p. 622-641.

Hirsch, B., and D. Macpherson, "Union Membership and Coverage Database from the Current Population Survey: Note," *Industrial and Labor Relations Review*, 56, (2003), 349-54.

Hunt, G., “Laboring for Rights: Unions and Sexual Diversity Across Nations,” Philadelphia: Temple University Press, (1999).

Hsieh, C. T. and E. Hurst, C. Jones, P. Klenow, “The Allocation of Talent and U.S. Economic Growth,” *NBER Working Paper*, No. 18693 (2013). Latest Update as of 2018.

Jasso, G., D.S. Massey, M.R. Rosenzweig and J.P. Smith. “The New Immigrant Survey 2003 Round 1 (NIS-2003-1) Public Release Data.” March 2006. Retrieved September 10, 2018. Funded by NIH HD33843, NSF, USCIS, ASPE & Pew. http://nis.princeton.edu.

Kaplan, S. N. and J. Lerner, “It ain’t broke: The past, present, and future of venture capital,” *Journal of Applied Corporate Finance* 22(2) (2010), 36–47.

Kearney, M., and P. Levine, “Media Influence on Social Outcomes: The Impact of MTV’s *16 and Pregnant* on Teen Childbearing,” *American Economic Review* 105(12): 3597-3632.

Kerr, W. R., and W. F. Lincoln, “The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention,” *Journal of Labor Economics,* 28 (2010), 473–508.

Kerr, W. R., and M. Mandor, “Social Networks, Ethnicity, and Entrepreneurship,” Harvard Business School Working Paper, (2015).

Klocke, U., “How to Improve Decision Making in Small Groups: Effects of Dissent and Training Interventions,” *Small Group Research*, June 2007 38: 437-468

Kossinets, G., and D. Watts, “Origins of Homophily in an Evolving Social Network,” *American Journal of Sociology* 115, no. 2 (September 2009): 405-450.

Layman G., and T. Carsey, “Party Polarization and Party Structuring of Policy Attitudes: A Comparison of Three NES Panel Studies,” *Political Behavior*, 24 (2002), 199-236.

Levey, R., and M. Mattsson, “The Effects of Social Movements: Evidence from #MeToo.” Yale University working paper. (2020).

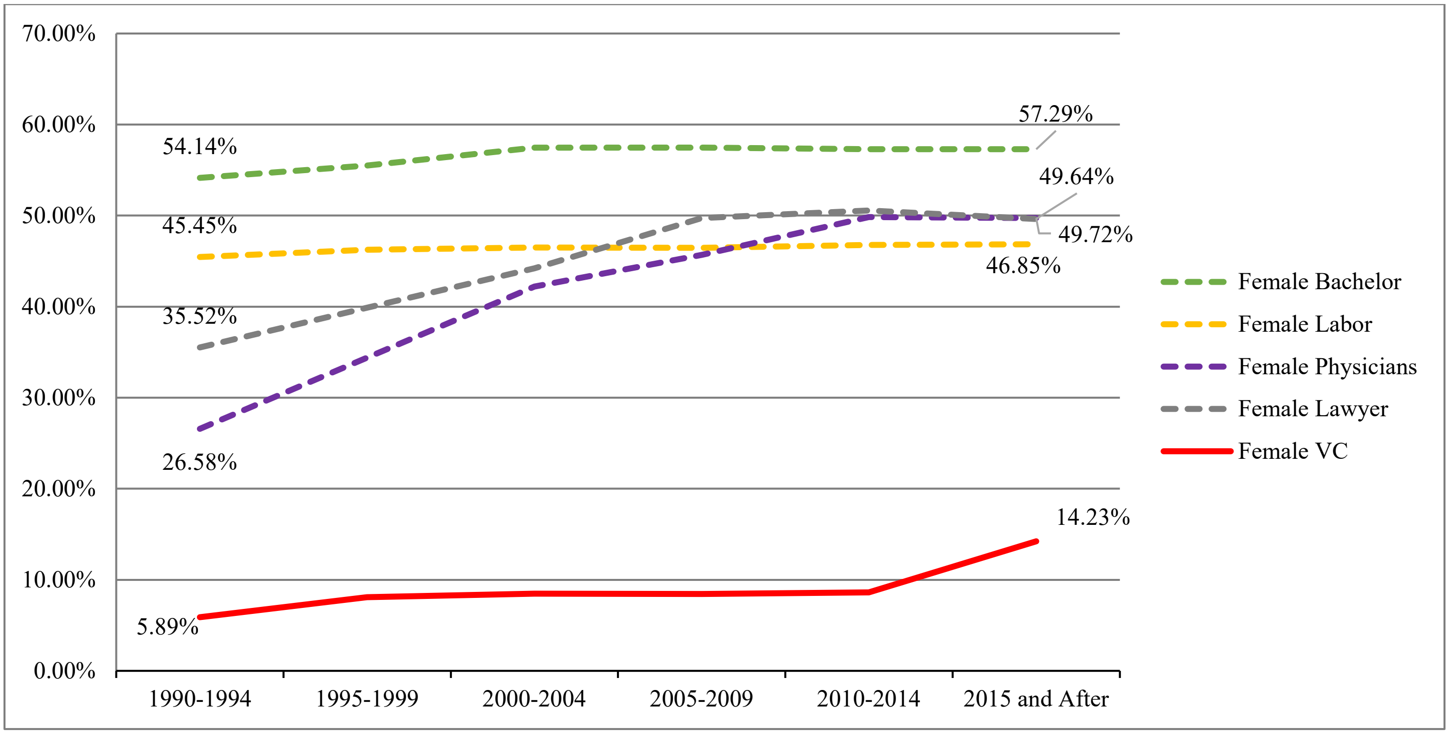
McPherson, M., L. Smith-Lovin, and J. M. Cook, “Birds of a Feather: Homophily in Social Networks,” *Annual Review of Sociology,* 27 (2001), 415–444.

Redbird, B., "The New Closed Shop? The Economic and Structural Effects of Occupational Licensure," *American Sociological Review*, 82(3) (2017), 600-624

Riegle-Crumb, C., C. Moore, and A. Ramos-Wada, "Who Wants a Career in Science or Math? Exploring Adolescents' Future Aspirations by Gender and Race/Ethnicity," *Science Education* 95 (2010), 458-476.

Figure 1: Female Ratio in Venture Capital, Law, and Medicine (1990-2019)

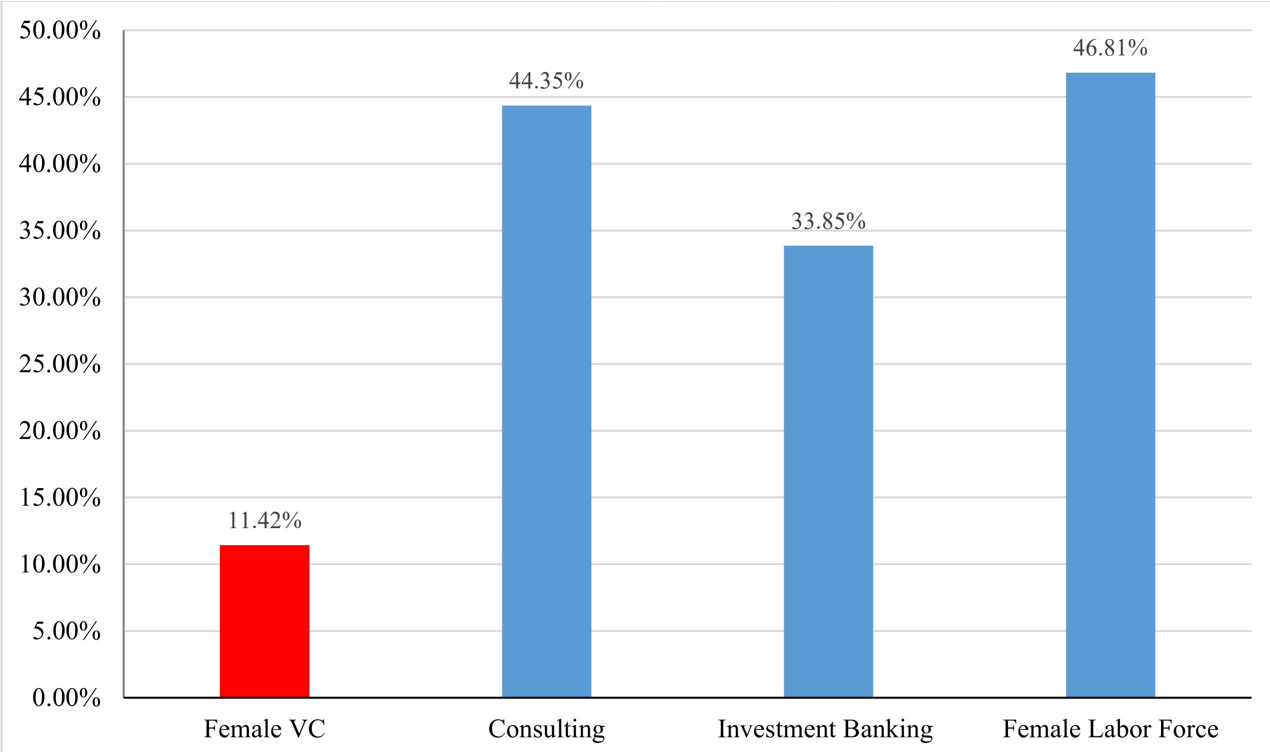
This figure compares female participation entry rates in venture capital from 1990 to 2019 to female entry rates in law, medicine and labor force.



Female Bachelor Data is retrieved from https://www.nsf.gov/statistics/degreerecipients/, bachelor degree conferred to female by year. Female Labor Force data is retrieved from http://www.bls.gov/cps/demographics.htm#women. Female lawyer/physician data is retrieved from http://www.census.gov/programs-surveys/acs/data/pums.html, female lawyers/physicians under 35 in 2000, 2005, 2010, and 2015. Female lawyer/physician in 1990 is estimated from female lawyer/physician between age 35 and 50 in 2000.
Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas and Matthew Sobek. IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, 2020.

Figure 2: Female Ratio in Financial Service Industry after 2010

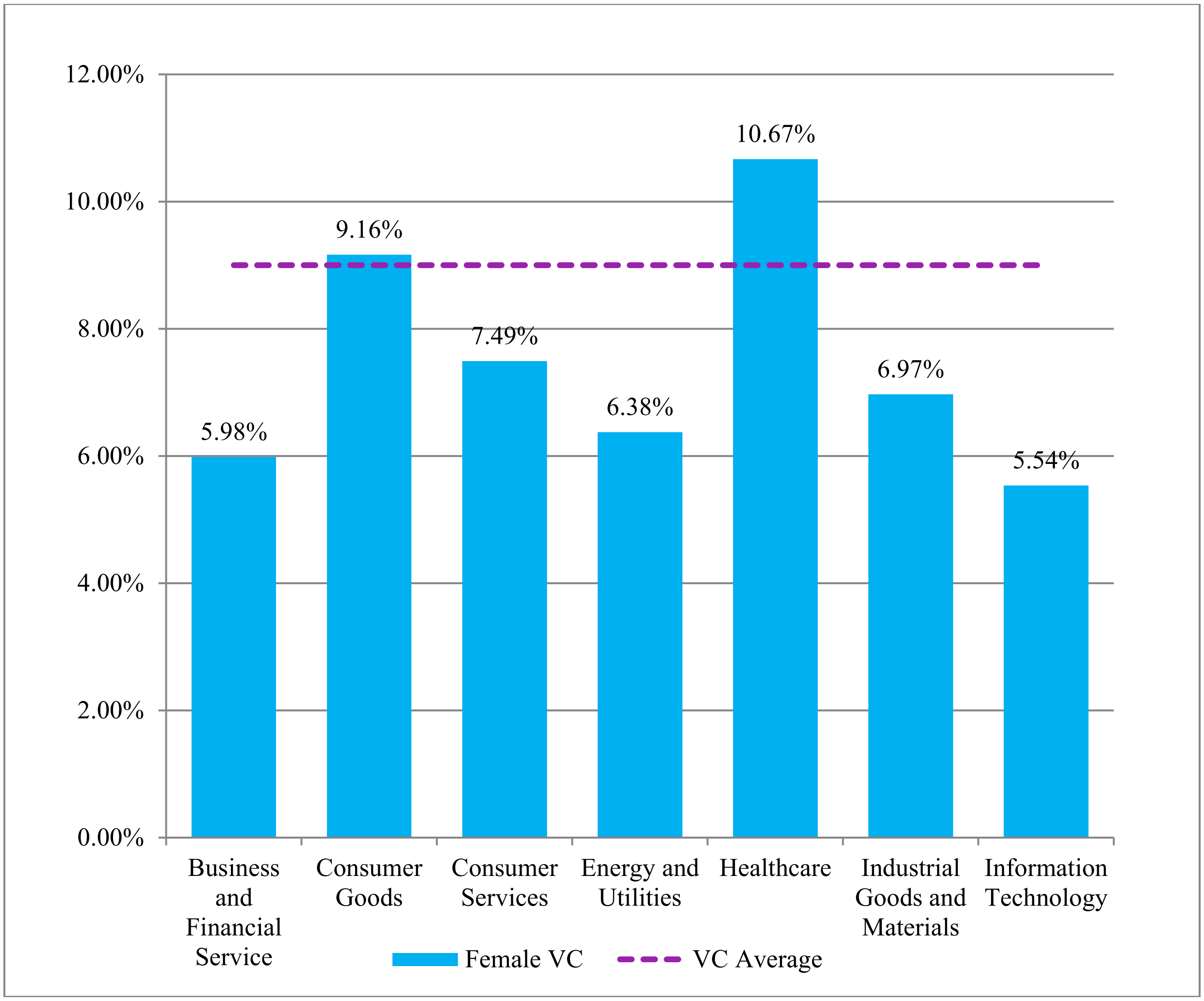
This figure compares female participation entry rates in venture capital from 2010 to 2019 to female entry rates in investment banking and consulting.



Data is retrieved from *https://www.eeoc.gov/eeoc/statistics/employment/jobpat-eeo1/index.cfm*

Figure 3: Industry Patterns of Female VCs

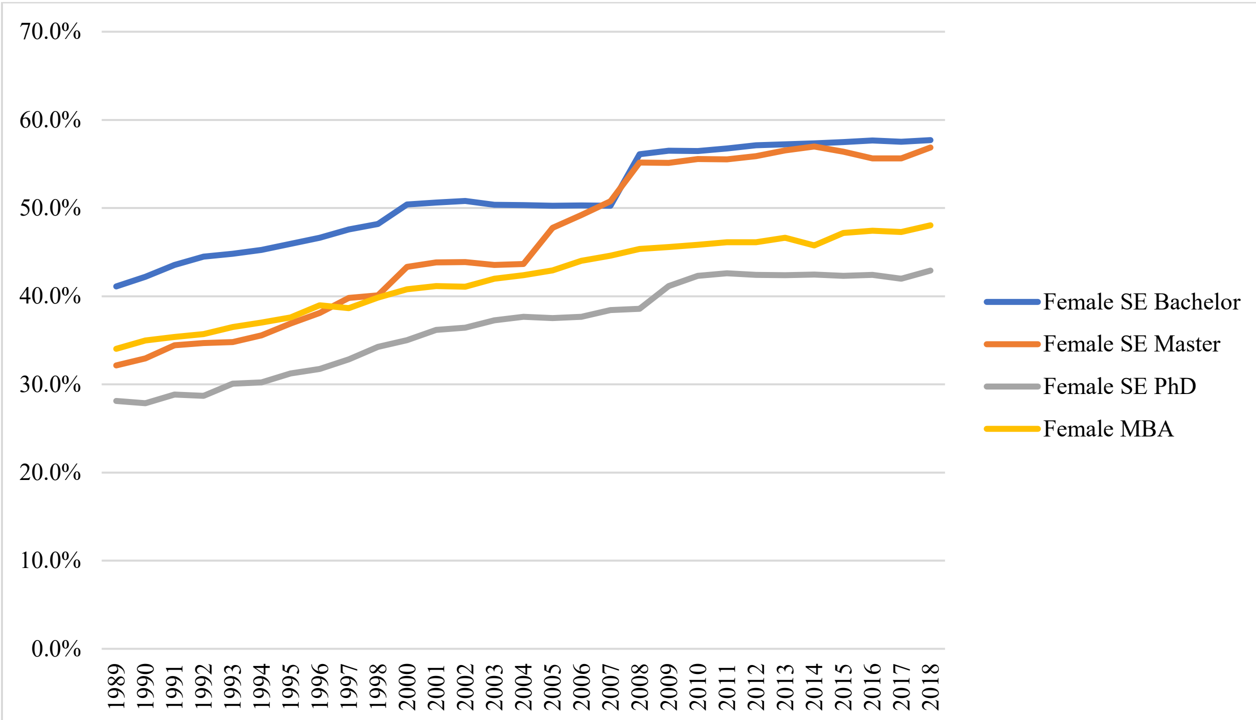
This figure looks at female participation rate in venture capital by industry.



Source: *VentureSource*

Figure 4: Female Degree Recipients in Science and Engineering and MBA

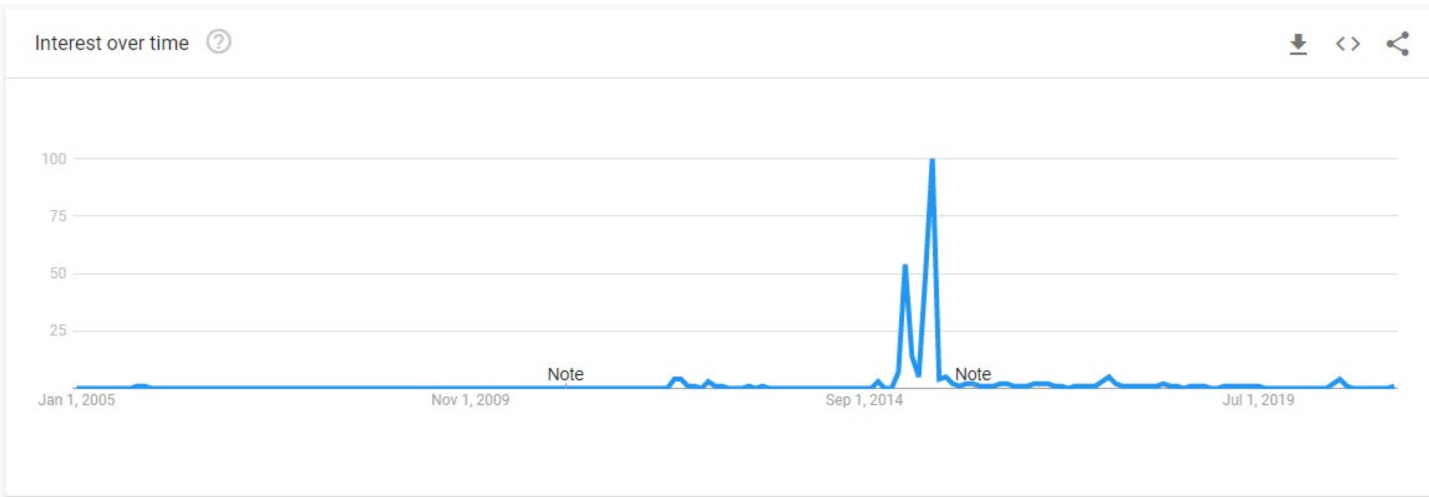
This figure plots the percentage of female science and engineering doctorate, master, and bachelor recipients as well as female MBA recipients.



Source: Female PhD, Master, Bachelor data is retrieved from *http://www.nsf.gov/statistics/degreerecipients/#tabs-1*. Female MBA data is retrieved from *National Center for Education Statistics*, Master's degrees conferred by degree-granting institutions, by sex, race/ethnicity, and field of study. *http://nces.ed.gov/programs/digest/2018menu_tables*.asp

Figure 5: Aggregate Google Search Interest of "Ellen Pao" Over Time

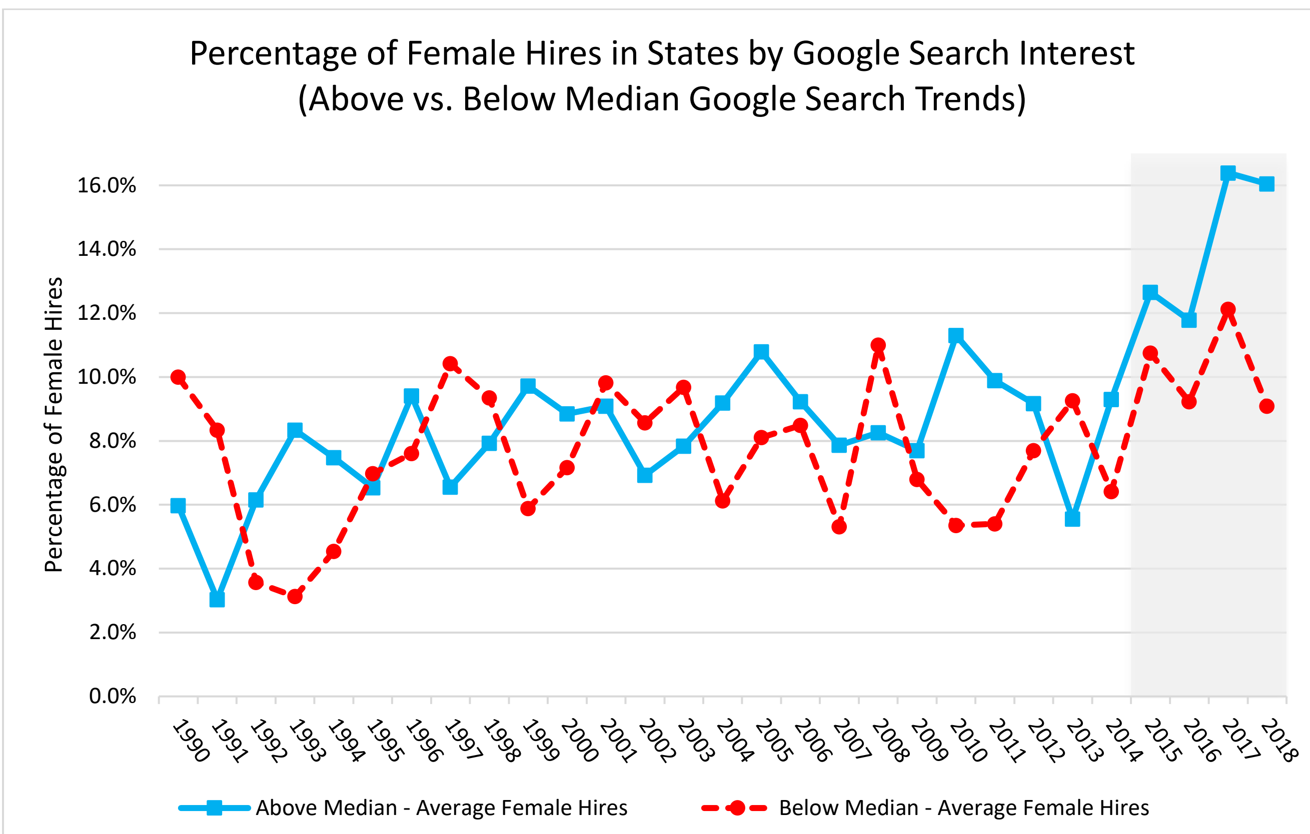
This figure plots the aggregate search interest on the key word "Ellen Pao" using Google Trends API.



Source: *Google Trends* (https://www.google.com/trends)

Figure 6: Percentage of Female Hires from Before and After Ellen Pao Trial by Google Trend

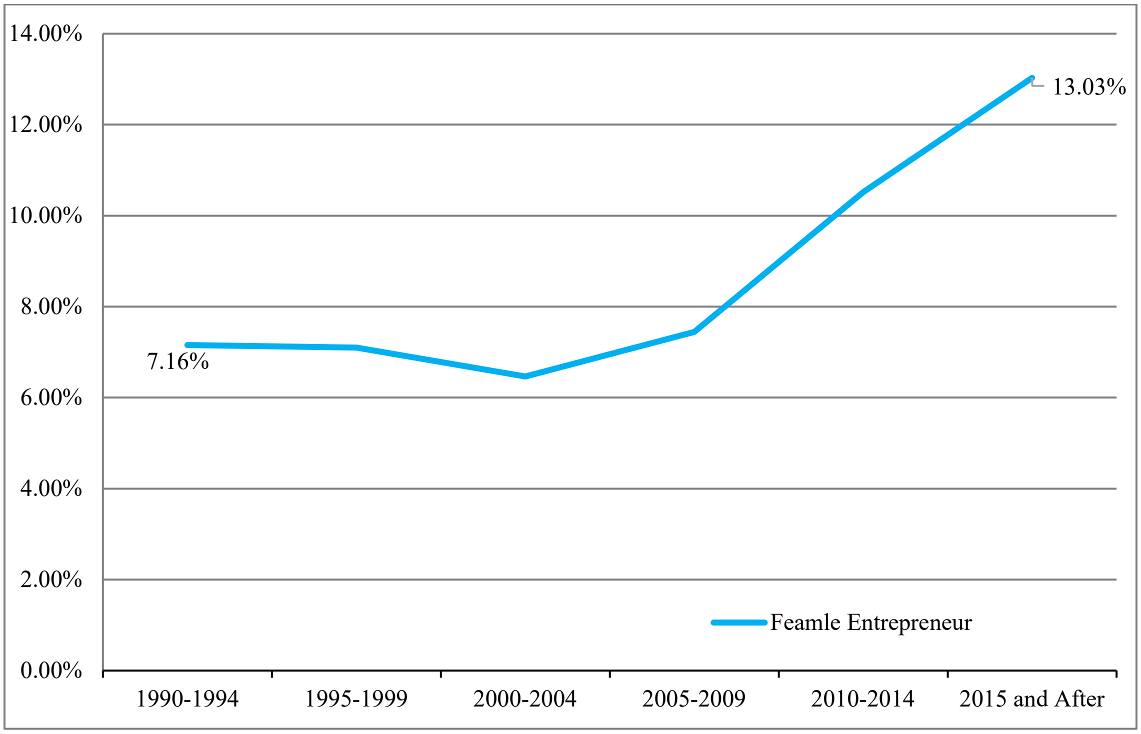
This figure plots time series of the percentage of female VC hires over time. The shaded area designates the time period after the Ellen Pao Trial.



Source: *Google Trends* (https://www.google.com/trends). Hiring data from *VentureSource*

Figure 7: Female Founders Time Series

This figure plots the percentage of female entrepreneurs from 1990 to 2019.



Source: *VentureSource*

Table I: Summary Statistics

This table reports summary statistics for the sample of US venture capitalists by gender from 1990 to 2019. There are a few people whose gender cannot be identified (less than 1%), hence the sum of gender/ethnicity category is slightly less than the total number of observations.

Venture Capitalist		
Gender	**Obs**	**% of total**
Male	12,325	90.69%
Female	1,224	9.01%
Total	13,571	100%

Source: *VentureSource*

Table II: Industry by Gender (Venture Capitalist)

This table summarizes VC industry by gender. The observation unit is VC deal-level. Non-US deals are excluded. Some deals cannot be matched to a specific industry, hence the sum of categories is slightly less than one.

Industry Group	Obs	Male	Female
Business and Financial Service	9,993	93.89%	5.98%
Consumer Goods	753	90.84%	9.16%
Consumer Services	5,566	92.38%	7.49%
Energy and Utilities	847	93.39%	6.38%
Healthcare	13,555	89.23%	10.67%
Industrial Goods and Materials	1,062	92.47%	6.97%
Information Technology	21,463	94.32%	5.54%
Total	53,248		

Source: *VentureSource*

Table III: Undergraduate Education (Venture Capitalists)

This table summarizes undergraduate education of venture capitalists in the sample by gender. The total number of degrees is less than the total number of VCs because some VCs are missing education history in our sample either due to they did not finish a certain degree or we cannot find it online.

Male Venture Capitalist			Female Venture Capitalist		
College	Count	Percent	**College**	Count	Percent
Harvard University	484	4.80%	Stanford University	55	4.49%
Stanford University	396	3.93%	Harvard University	54	4.41%
University Of Pennsylvania	336	3.33%	University Of Pennsylvania	47	3.84%
Princeton University	268	2.66%	Princeton University	28	2.29%
Yale University	263	2.61%	University Of California (Berkeley)	21	1.72%
University Of California (Berkeley)	234	2.32%	Yale University	20	1.63%
Dartmouth College	216	2.14%	Cornell University	17	1.39%
Cornell University	202	2.00%	University Of Virginia	16	1.31%
Duke University	169	1.68%	Duke University	15	1.23%
Massachusetts Institute Of Technology	163	1.62%	Georgetown University	15	1.23%
University Of Michigan	159	1.58%	Brown University	14	1.14%
University Of Virginia	150	1.49%	University Of Michigan	13	1.06%
Brown University	143	1.42%	Massachusetts Institute Of Technology	11	0.90%
University Of Ilinois (Urbana Champaign)	98	0.97%	University Of California (Los Angeles)	11	0.90%
University Of California (Los Angeles)	97	0.96%	University Of Illinois (Urbana Champaign)	11	0.90%
Georgetown University	91	0.90%	Columbia University	10	0.82%
Brigham Young University	84	0.83%	Dartmouth College	10	0.82%
Northwestern University	84	0.83%	Northwestern University	10	0.82%
Tufts University	83	0.82%	University Of North Carolina (Chapel Hill)	8	0.65%
Boston College	81	0.80%	Boston College	7	0.57%
Top 20 Total	3,801	37.71%	Top 20 Total	393	32.11%
	10,079			1,224	

Source: *VentureSource*

Table IV: Business School (Venture Capitalists) Continued

Male Venture Capitalist			Female Venture Capitalist		
Business School	**Count**	**Percent**	**Business School**	**Count**	**Percent**
Harvard University	1,181	21.81%	Harvard University	111	20.71%
Stanford University	615	11.36%	Stanford University	76	14.18%
University Of Pennsylvania	510	9.42%	University Of Pennsylvania	60	11.19%
Columbia University	244	4.51%	Columbia University	24	4.48%
University Of Chicago	229	4.23%	Northwestern University	20	3.73%
Northwestern University	210	3.88%	University Of Chicago	18	3.36%
Dartmouth College	127	2.35%	Yale University	13	2.43%
University Of California (Los Angeles)	111	2.05%	New York University	10	1.87%
New York University	108	1.99%	University Of California (Berkeley)	10	1.87%
Massachusetts Institute Of Technology	103	1.90%	University Of California (Los Angeles)	9	1.68%
University Of Virginia	94	1.74%	Cornell University	8	1.49%
University Of California (Berkeley)	91	1.68%	Dartmouth College	7	1.31%
University Of Michigan	85	1.57%	Massachusetts Institute Of Technology	7	1.31%
Duke University	73	1.35%	Boston University	5	0.93%
Insead	66	1.22%	Insead	5	0.93%
Yale University	50	0.92%	University Of North Carolina (Chapel Hill)	5	0.93%
Cornell University	42	0.78%	University Of Southern California	4	0.75%
Indiana University (Bloomington)	41	0.76%	Duke University	3	0.56%
University Of North Carolina (Chapel Hill)	38	0.70%	Indiana University (Bloomington)	3	0.56%
University Of Southern California	35	0.65%	University Of Virginia	3	0.56%
Top 20 Total	4,053	74.85%	Top 20 Total	401	74.81%
	5,415			536	

Source: *VentureSource*

Table V: Graduate School (Venture Capitalists) Continued

Male Venture Capitalist			Female Venture Capitalist		
Graduate School	**Count**	**Percent**	**Graduate School**	**Count**	**Percent**
Stanford University	361	8.63%	Stanford University	33	7.53%
Harvard University	266	6.36%	Harvard University	28	6.39%
Massachusetts Institute Of Technology	192	4.59%	Columbia University	18	4.11%
University Of Pennsylvania	116	2.77%	Massachusetts Institute Of Technology	13	2.97%
University Of California (Berkeley)	105	2.51%	New York University	13	2.97%
Columbia University	88	2.10%	Northwestern University	13	2.97%
New York University	79	1.89%	University Of Pennsylvania	13	2.97%
Yale University	78	1.86%	University Of California (Berkeley)	12	2.74%
Northwestern University	74	1.77%	Yale University	11	2.51%
Cornell University	70	1.67%	University Of Michigan	10	2.28%
University Of Michigan	67	1.60%	Johns Hopkins University	8	1.83%
Oxford University	59	1.41%	Cambridge University	7	1.60%
University Of Virginia	58	1.39%	Cornell University	6	1.37%
University Of Chicago	54	1.29%	Georgetown University	6	1.37%
University Of California (Los Angeles)	46	1.10%	Oxford University	6	1.37%
Georgetown University	43	1.03%	University Of Southern California	6	1.37%
Cambridge University	41	0.98%	University Of Virginia	6	1.37%
Duke University	37	0.88%	Boston University	4	0.91%
University Of Ilinois (Urbana Champaign)	37	0.88%	University Of California (Los Angeles)	4	0.91%
University Of London	37	0.88%	University Of Chicago	4	0.91%
Top 20 Total	1,908	45.61%	Top 20 Total	221	50.46%
	4,183			438	

Source: *VentureSource*

Table VI: Undergraduate Majors (Venture Capitalists) Continued

Male Venture Capitalist			Female Venture Capitalist		
Undergraduate Major	**Count**	**Percent**	**Undergraduate Major**	**Count**	**Percent**
Economics	829	11.83%	Economics	87	12.78%
Business	467	6.67%	Business	37	5.43%
Engineering	420	6.00%	Biology	29	4.26%
Electrical Engineering	321	4.58%	Finance	19	2.79%
Computer Science	222	3.17%	Chemistry	18	2.64%
Finance	219	3.13%	Computer Science	18	2.64%
Accounting	166	2.37%	Political Science	18	2.64%
History	155	2.21%	Political Science	18	2.64%
Mathematics	154	2.20%	Engineering	17	2.50%
Mechanical Engineering	139	1.98%	Electrical Engineering	14	2.06%
Biology	129	1.84%	English	14	2.06%
Chemistry	122	1.74%	Accounting	14	2.06%
Political Science	120	1.71%	Mathematics	12	1.76%
Science	115	1.64%	Chemical Engineering	11	1.62%
Physics	98	1.40%	Psychology	11	1.62%
Law	62	0.89%	Science	10	1.47%
Chemical Engineering	61	0.87%	Physics	8	1.17%
English	60	0.86%	Social Studies	8	1.17%
Government	57	0.81%	Law	7	1.03%
Psychology	57	0.81%	History	6	0.88%
Top 20 Total	3,973	56.72%	Top 20 Total	376	55.21%
	6,350			681	

Source: *VentureSource*

Table VII:Graduate Majors (Venture Capitalists) Continued

Male Venture Capitalist			Female Venture Capitalist		
Graduate Major	**Count**	**Percent**	**Graduate Major**	**Count**	**Percent**
Law	493	33.22%	Law	40	21.16%
Medicine	195	13.14%	Medicine	22	11.64%
Science	156	10.51%	Chemistry	13	6.88%
Electrical Engineering	141	9.50%	Biology	11	5.82%
Computer Science	77	5.19%	Electrical Engineering	9	4.76%
Engineering	66	4.45%	Science	8	4.23%
Chemistry	62	4.18%	Economics	7	3.70%
Business	58	3.91%	Computer Science	6	3.17%
Physics	53	3.57%	Public Administration	5	2.65%
Mechanical Engineering	39	2.63%	Engineering	5	2.65%
Biology	36	2.43%	Business	3	1.59%
Economics	35	2.36%	Finance	3	1.59%
Chemical Engineering	27	1.82%	International Relations	3	1.59%
Accounting	26	1.75%	Pharmacology	2	1.06%
Finance	23	1.55%	Physics	2	1.06%
Public Administration	15	1.01%	Mathematics	2	1.06%
Industrial Engineering	15	1.01%	Accounting	1	0.53%
Pharmacology	12	0.81%	Biochemistry	1	0.53%
Biochemistry	10	0.67%	Chemical Engineering	1	0.53%
International Relations	10	0.67%	Molecular Biology	1	0.53%
Top 20 Total	1,549	85.34%	Top 20 Total	145	76.72%
	1,645			189	

Source: *VentureSource*

Table VIII: Venture Capitalist Past Employment

This table summarizes employment history of venture capitalists in the sample by gender. The total number of past employers is less than the total number of VC because some people are missing employment history in our data and those are dropped.

Male Venture Capitalist			Female Venture Capitalist		
Past Employer	**Count**	**Percent**	**Past Employer**	**Count**	**Percent**
McKinsey & Company	142	0.74%	McKinsey & Company	18	0.91%
Morgan Stanley	118	0.61%	Morgan Stanley	15	0.76%
Goldman Sachs	114	0.59%	Goldman Sachs	13	0.66%
Merrill Lynch	83	0.43%	Citigroup	9	0.45%
Microsoft	79	0.41%	Ernst & Young	8	0.40%
Lehman Brothers	65	0.34%	Bain & Company	7	0.35%
Bain & Company	62	0.32%	Merrill Lynch	7	0.35%
IBM	62	0.32%	Google	6	0.30%
Deutsche Bank	59	0.31%	Microsoft	6	0.30%
Inc.	55	0.29%	Kleiner Perkins Caufield & Byers	5	0.25%
Credit Suisse	55	0.29%	Equity Capital Group	5	0.25%
JP Morgan	52	0.27%	JP Morgan	5	0.25%
Cisco Systems	49	0.25%	IBM	5	0.25%
Google	39	0.20%	Warburg Pincus	4	0.20%
Warburg Pincus	36	0.19%	Advent International	3	0.15%
New Enterprise Associates	35	0.18%	Apax Partners	3	0.15%
Summit Partners	29	0.15%	Battelle Ventures	3	0.15%
Apax Partners	27	0.14%	Bay City Capital	3	0.15%
Battery Ventures	24	0.12%	Bessemer Venture Partners	3	0.15%
Carlyle Group	23	0.12%	Deutsche Bank	3	0.15%
Top 20 Total	1,208	6.27%	Top 20 Total	131	6.62%
Sample Total	19,273		Sample Total	1,978	

Source: *VentureSource*

Table IX: Hiring Level Regressions

The dependent variable is a binary indicator of whether a given hire is a woman. *Google x Post* is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. *Size of VC Industry x Post* is the interaction between the number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Hire	(2) Female Hire	(3) Female Hire	(4) Female Hire	(5) Female Hire	(6) Female Hire
Google x Post	0.000694***	0.000283	0.000336*	0.000346*	0.000410**	0.000381**
	(0.000108)	(0.000219)	(0.000175)	(0.000176)	(0.000199)	(0.000186)
Size of VC Industry x Post		60.96**	53.59**	52.95**	52.76**	51.66**
		(23.06)	(20.71)	(20.52)	(21.78)	(21.61)
VC Firm Size				0.00000969	0.00000187	0.000161**
				(0.00000913)	(0.00000902)	(0.0000626)
VC Firm Age					0.000970**	0.000117
					(0.000369)	(0.000332)
Partner Count						-0.000109**
						(0.0000430)
Constant	0.0905***	0.0905***	0.932***	0.931***	0.923***	0.928***
	(0.00516)	(0.00490)	(0.00830)	(0.00835)	(0.00906)	(0.00830)
Industry FE	No	No	Yes	Yes	Yes	Yes
Observations	3635	3635	3624	3624	3624	3624

Table X: Hiring Level Regression Reduced Form

This table reports reduced form results of the hiring level sample. The dependent variable is a binary indicator of whether a given hire is a woman. Independent variables are the interaction between state mandated maternity and a dummy variable for the post-Pao period and the interaction between number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Hire	(2) Female Hire	(3) Female Hire	(4) Female Hire	(5) Female Hire	(6) Female Hire
Maternity x Post	0.000538***	0.000374***	0.000410***	0.000411***	0.000467***	0.000445***
	(0.0000420)	(0.000127)	(0.000108)	(0.000110)	(0.000123)	(0.000114)
Size of VC Industry x Post		32.76	25.52	25.82	24.24	23.43
		(19.72)	(18.15)	(18.32)	(19.21)	(18.50)
VC Firm Size				0.00000929	0.000000839	0.000157**
				(0.00000909)	(0.00000908)	(0.0000605)
VC Firm Age					0.00104***	0.000201
					(0.000387)	(0.000324)
Partner Count						-0.000107**
						(0.0000416)
Constant	0.0889***	0.0891***	0.938***	0.938***	0.931***	0.935***
	(0.00459)	(0.00469)	(0.00439)	(0.00437)	(0.00534)	(0.00414)
Industry FE	No	No	Yes	Yes	Yes	Yes
Observations	3635	3635	3624	3624	3624	3624

Table XI: Hiring Level IV Regressions

Panel A: This table reports regression result of female hires in the hiring level sample using a binary indicator of whether a given hire is a woman. $\widehat{Google\ x\ Post}$ is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. In the instrumental variable regression, the instrument is the interaction between state mandated maternity and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Hire	(2) Female Hire	(3) Female Hire	(4) Female Hire	(5) Female Hire	(6) Female Hire
$\widehat{\text{Google x Post}}$	0.000833***	0.000736***	0.000806***	0.000809***	0.000918***	0.000876***
	(0.0000634)	(0.000250)	(0.000212)	(0.000216)	(0.000241)	(0.000224)
Size of VC Industry x Post		11.97	2.747	2.985	-1.672	-1.314
		(26.50)	(23.84)	(24.10)	(25.67)	(24.57)
VC Firm Size				0.00000929	0.000000839	0.000157**
				(0.00000909)	(0.00000908)	(0.0000605)
VC Firm Age					0.00104***	0.000201
					(0.000387)	(0.000324)
Partner Count						-0.000107**
						(0.0000416)
Constant	0.0866***	0.0870***	0.936***	0.936***	0.928***	0.933***
	(0.00476)	(0.00501)	(0.00455)	(0.00454)	(0.00567)	(0.00437)
Industry FE	No	No	Yes	Yes	Yes	Yes
Observations	3635	3635	3624	3624	3624	3624

Table XI: Hiring Level IV Regression (Continued)

Panel B: This table reports the first stage results of the hiring level sample. The dependent variable *Google x Post* is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. The independent variables are the interaction between state mandated maternity and a dummy variable for the post-Pao period and the interaction between the number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Google x Post
Maternity x Post	0.595***
	(0.0779)
Size of VC Industry x Post	11106.3
	(37720.6)
Constant	6.210***
	(1.862)
Observations	3635

Table XII: Portfolio Level Regressions

The dependent variable is a binary indicator of whether a given founder of a portfolio company is female. *Google x Post-Pao* is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. Size of VC Industry x Post-Pao is the interaction between number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. *Female VC* is binary indicator of whether a given venture capital investors is a female. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Founder	(2) Female Founder	(3) Female Founder	(4) Female Founder	(5) Female Founder	(6) Female Founder
Female VC	0.0551***	0.0551***	0.0489***	0.0435***	0.0435***	0.0435***
	(0.0186)	(0.0189)	(0.0145)	(0.0134)	(0.0134)	(0.0136)
Google x Post	0.000255***	0.000282	0.000268	0.000292*	0.000300*	0.000304*
	(0.0000471)	(0.000218)	(0.000201)	(0.000165)	(0.000163)	(0.000157)
Size of VC Industry x Post		-3.900	-4.064	-6.812	-6.597	-6.653
		(27.72)	(27.85)	(22.78)	(22.60)	(22.53)
Google x Female VC x Post			0.000174	0.000126	0.000118	0.000119
			(0.000233)	(0.000220)	(0.000219)	(0.000218)
VC Firm Size				-0.000127*	-0.0000483	-0.0000644
				(0.0000680)	(0.0000997)	(0.000145)
VC Firm Age					-0.000558*	-0.000558*
					(0.000285)	(0.000285)
Partner Count						0.000124
						(0.000517)
Constant	0.0713***	0.0713***	0.0718***	-0.0819***	-0.0812***	-0.0819***
	(0.00403)	(0.00405)	(0.00402)	(0.0153)	(0.0153)	(0.0139)
Round FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	20807	20807	20807	20792	20792	20792
Adjusted R^2	0.005	0.004	0.004	0.020	0.021	0.021

Table XIII: Portfolio Level Regressions Reduced-Form: Maternity

This table reports reduced form results of the portfolio level sample. The dependent variable is a binary indicator of whether a given founder of a portfolio company is female. Independent variables are the interaction between state mandated maternity and a dummy variable for the post-Pao period. *Size of VC Industry x Post* is the interaction between number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. Female VC is binary indicator of whether a given venture capital investors is a female. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Founder	(2) Female Founder	(3) Female Founder	(4) Female Founder	(5) Female Founder	(6) Female Founder
Female VC	0.0545***	0.0544***	0.0544***	0.0415***	0.0415***	0.0415***
	(0.0185)	(0.0183)	(0.0183)	(0.0120)	(0.0120)	(0.0122)
Maternity x Post	0.000191***	0.000287	0.000287	0.000260	0.000266	0.000268
	(0.0000499)	(0.000225)	(0.000225)	(0.000196)	(0.000192)	(0.000188)
Size of VC Industry x Post		-18.32	-18.32	-16.26	-16.06	-16.10
		(37.61)	(37.61)	(33.67)	(33.15)	(33.05)
Google x Female x Post				0.000153	0.000146	0.000147
				(0.000221)	(0.000220)	(0.000218)
VC Firm Size				-0.000121*	-0.0000422	-0.0000537
				(0.0000707)	(0.000101)	(0.000144)
VC Firm Age					-0.000554*	-0.000553*
					(0.000285)	(0.000286)
Partner Count						0.0000891
						(0.000480)
Constant	0.0710***	0.0709***	0.0709***	-0.0893***	-0.0888***	-0.0892***
	(0.00407)	(0.00396)	(0.00396)	(0.0235)	(0.0232)	(0.0226)
Round FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	20807	20807	20807	20792	20792	20792
Adjusted R^2	0.005	0.005	0.005	0.020	0.021	0.021

Table XIV: Portfolio Level IV Regressions

Panel A: This table reports regression results of female founders in the portfolio level sample using a binary indicator of whether a given founder is a woman. *Google x Post* is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. In the instrumental variable regression, the instrument is the interaction between state mandated maternity and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Female Founder	(2) Female Founder	(3) Female Founder	(4) Female Founder	(5) Female Founder	(6) Female Founder
Female VC	0.0546***	0.0544***	0.0549***	0.0506***	0.0507***	0.0507***
	(0.0187)	(0.0183)	(0.0174)	(0.0159)	(0.0159)	(0.0161)
$\widehat{\text{Google x}}$ Post	0.000272***	0.000519	0.000520	0.000496	0.000507	0.000510
	(0.0000676)	(0.000409)	(0.000393)	(0.000354)	(0.000346)	(0.000340)
Size of VC Industry x Post		-31.06	-31.05	-28.21	-28.28	-28.40
		(47.65)	(47.82)	(42.60)	(41.88)	(41.52)
Google x Female VC x Post			-0.0000160	-0.0000903	-0.000100	-0.0000997
			(0.000298)	(0.000296)	(0.000298)	(0.000298)
VC Firm Size				-0.000122*	-0.0000422	-0.0000517
				(0.0000712)	(0.000102)	(0.000147)
VC Firm Age					-0.000562*	-0.000561*
					(0.000289)	(0.000290)
Partner Count						0.0000738
						(0.000489)
Constant	0.0712***	0.0708***	0.0707***	-0.0920***	-0.0915***	-0.0919***
	(0.00419)	(0.00397)	(0.00360)	(0.0229)	(0.0226)	(0.0218)
Round FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	20807	20807	20807	20792	20792	20792
Adjusted R^2	0.005	0.005	0.005	0.020	0.021	0.021

Table XIV: Portfolio Level IV Regressions (Continued)

Panel B: This table reports the first stage results of the portfolio level sample. The dependent variable *Google x Post-Pao* is the interaction term between the state level Google search trend and a dummy variable for the post-Pao period. The independent variables are the interaction between state mandated maternity and a dummy variable for the post-Pao period and the interaction between number of the number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012 and a dummy variable for the post-Pao period. Standard errors are clustered at state level. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Google x Post
Maternity x Post	0.524^{***}
	(0.0975)
Size of VC Industry x Post	26069.7
	(40222.4)
Constant	2.624^{**}
	(1.207)
Observations	20807
Adjusted R^2	0.839

Appendix Tables and Figures

Table A1: This table reports the regression results of the state-level Google search trend.The independent varibles are *Maternity Score* which is the the level of state-mandated maternity benefits and *Size of VC Industry* which is number of venture capital investments percapita made in that state during the ten years preceding the pre-Pao period from 2002-2012. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) levels.

	(1) Google	(2) Google	(3) Google
Maternity Score	0.312***		0.252***
	(0.0547)		(0.0460)
Size of VC Industry		57725.5**	19355.9
		(22385.5)	(22874.5)
Constant	25.98***	29.82***	25.84***
	(1.664)	(2.223)	(1.839)
Observations	48	48	48
R^2	0.597	0.420	0.621