Funding Black High-Growth Startups

Lisa D. Cook[a,b], Matt Marx[c,b], Emmanuel Yimfor[d]

[a] *Michigan State University*
[b] *NBER*
[c] *Cornell University*
[d] *University of Michigan*

December 1, 2022

Abstract

We analyze determinants of access to venture capital for Black founders of high-growth startups. We combine image- and name-processing algorithms with clerical review to identify race for over 100,000 startup founders "at risk" for venture funding. Black founders raise roughly one-third as much venture capital in the five years after founding vs. other startups formed in the same year, industry, and state. What explains the gap? We attribute about a third of the gap to four factors: Black startups have smaller founding teams; Black founders are less likely to have worked at the same companies or attended the same schools as investors who fund startups in the same industry and geography; Black startups are less likely to be located in geographies with plentiful venture capital, and Black startups are less likely to have a patent. We then bound our estimates of the funding gap and show that, to explain the gap, omitted variables would have to be nearly four times as important as the variables we fix. The funding gap is not statistically different from zero in later funding stages (post Series B), suggesting that some investors initially hold—but later amend—incorrect beliefs about Black-founded startups. We also exploit the hiring of Black partners and show that they are more likely to fund successful Black startups, consistent with segmented networks.

⋆ Lisa Cook, Federal Reserve Board and National Bureau of Economic Research; Matt Marx, Cornell University and National Bureau of Economic Research; Email: mmarx@cornell.edu; Emmanuel Yimfor, University of Michigan and Kenan Institute Distinguished Fellow; Email: eyimfor@umich.edu. We thank the Institute for Research and Innovation and Science, Mitsui Life Financial Research Center, and the Institute for Social Research at the University of Michigan for financial support and Steven Wu-Chaves for invaluable research assistance. Helpful comments were provided by Uday Rajan, Sugato Bhattacharyya, Erik Mayer, Josh Lerner, Johan Cassel, Sabrina Howell, Sophie Calder-Wang, Kelly Shue, Heather Tookes, James Weston, Camille Hebert, Alberto Teguia, conference attendees at the NBER SI Entrepreneurship meetings, and seminar participants at Harvard University, Duke University, The University of North Carolina, Pontificia Universidad Católica de Chile, The University of Michigan, Rice University, Carnegie Mellon, the Brookings Institution, the USPTO, PERC, and the FOM Research Group.

I. Introduction

At least since Schumpeter, economists have viewed entrepreneurship as a key vehicle for driving innovation and increasing economic productivity (Gennaioli, La Porta, Lopez-de Silanes and Shleifer (2013)). Most new ventures fail, but those that survive contribute disproportionately to job creation and often disrupt industries with breakthrough products and services (Puri and Zarutskie (2012), Haltiwanger, Jarmin and Miranda (2013)). Moreover, successful startups can create wealth for founders and owners and thus play an essential role in socioeconomic mobility (Quadrini, 2000).

By fueling socioeconomic mobility, entrepreneurship could help to address longstanding racial disparities in household wealth (Chetty, Hendren, Jones and Porter, 2020), at least to the extent that participation in entrepreneurship is representative of the nation's racial makeup.[1] Of course, not all forms of entrepreneurship are equally lucrative. Rubinstein and Levine (2020) show that unincorporated (i.e., self-employed) entrepreneurs earn considerably less than those who incorporate their businesses. Correspondingly, Sarada and Tocoian (2022) report greater social mobility for entrepreneurs who formally incorporate. Thus participation in higher-growth forms of entrepreneurship is more likely to help address income inequality, and the exclusion of underrepresented minorities from high-growth entrepreneurship could perpetuate, or even exacerbate, existing wealth gaps.

In this paper, we investigate the representation of Black founders in a particularly high-growth subset of incorporated entrepreneurship: startups backed by venture capital (VC).[2] VC-backed startups are among the highest-growth and most influential companies

[1] In the U.S., average household wealth for Whites is seven times higher than for Blacks. https://www.brookings.edu/blog/up-front/2020/12/08/the-black-white-wealth-gap-left-black-households-more-vulnerable/

[2] For purposes of our analysis, we group venture capital and angel investors together. Angels represent about 1/46th the volume of investment dollars of venture capitalists, and as we show, angels and venture capitalists exhibit nearly identical patterns of investment regarding Black founders. Therefore, to avoid wordiness we use "VC" throughout to refer to both venture capital and angel investments.

worldwide. Although less than 0.5% of all firms founded each year obtain VC funding, VC-backed startups contribute disproportionately to jobs, innovation, and wealth creation (Puri and Zarutskie, 2012; Kortum and Lerner, 2001; Haltiwanger, Jarmin and Miranda, 2013; Lerner and Nanda, 2020). In fact, VC-backed startups represent more than 50% of initial public offerings, 20% of acquisitions, and 89% of public-firm R&D expenditures. Unlike other investment professionals (such as bankers), venture capitalists are typically paid 20% of profits (and 2% of assets under management) from their investments, encouraging them to invest in the best ideas irrespective of the founder's race or gender. Moreover, venture capitalists specialize in financing firms with intangible assets. These assets cannot easily be pledged as collateral, so the firms must rely more on equity funding than on debt (Eisfeldt and Papanikolaou, 2014).

Despite many anecdotal accounts of Black entrepreneurs who have struggled to raise venture capital for their startups,[3] we are unaware of prior work that comprehensively characterizes the participation of Black founders in raising venture capital. Studies of Black entrepreneurs to date instead focus on a broader set of newly-founded companies. Although these include some high-growth companies, the studies' samples generally focus on small businesses. For example, Fairlie, Robb and Robinson (2022*a*) show evidence of differences in business outcomes (employment, sales, and closures) for Black-owned startups in a sample of both high-growth and non-high-growth startups. Other studies investigate the dynamics of Black founders in small-business (debt) lending (Blanchflower, Levine and Zimmerman, 2003; Hurtado and Sakong, 2022) and crowdfunding (Younkin and Kuppuswamy, 2018). All of these studies yield important findings, albeit in contexts that are less likely to yield high-growth ventures (such as those funded by venture capital).

[3] See, e.g., this article on venture capital fundraising difficulties encountered by Black founders (`https://www.csmonitor.com/Business/2021/0222/For-Black-owned-businesses-venture-capital-still-elusive`).

Studies of venture capital equity funding for high-growth startups have generally focused on the gender gap instead of race (see, among others, Ewens and Townsend (2020); Howell and Nanda (2019); Hebert (2020)). One reason for this disparity is that databases of high-potential ventures typically do not report race or ethnicity of founders, but often report gender.[4] Or, if the database does not report the founders' gender, one can predict gender from forenames with reasonable reliability.

We create a new dataset by classifying race for over 150,000 unique founders and investors of high-growth startups. For startups where PitchBook reports the company having been founded from 2000-2022 and with at least one founder, we match the founders/owners to a large online job platform and obtain profile photos from the platform, company web pages, and various social media sites. We classify the race of each founder/owner through a combination of algorithmic image and name classification methods followed by clerical review. This novel race disaggregation methodology performs better than existing methods. We identify substantially more Black founders than existing methodologies, which rely on name classification algorithms to identify Black founders and then use image verification to reduce false positives (Gompers and Wang (2017)).

For each startup, we calculate the proportion of founders that are Black. In our analysis, we include only founders for whom we have images that can be used to identify race. Although we found images for 90% of the founders in our sample, we condition our analysis on resume data and finding an image, to mitigate selection concerns related to who has public resume data or a public image. We also take advantage of rich resume data to calculate a proxy for each founder's exposure to individual partners that invest in the same industry sector and state.

[4] When some databases, such as Crunchbase, report race, the sampling and data-collection methods are not transparent. Thus, there are possible selection concerns, such as whether investors that report race are similar to investors that choose not to.

We begin by estimating the size of the gap in venture capital funding of Black entrepreneurs. We find that only 3.40% of startups in Pitchbook have at least one Black founder. Given that Blacks constitute 16% of the working-adult U.S. population in the 2020 census, Black founders are underrepresented among high-growth startups by a factor of nearly five. Whether we measure two, three, four, or five years after founding, Black-owned businesses raise about one-third as much venture capital as other startups formed in the same year, in similar industries, and in similar locations.

About a third of this gap can be attributed to four factors. First, Black-owned startups have smaller founding teams. Second, Black founders are less likely to have worked at the same companies, or to have attended the same schools, as investors who might have funded their startups. Third, Black startups tend to be located outside of private-equity hubs where venture capital is easily accessed. Fourth, Black-owned startups are considerably less likely to have a patent.

Interestingly, we find that the gap in non-debt funding exists entirely within the venture capital segment. There is no discernible difference in funding raised from other non-debt sources (i.e., accelerators, equity crowdfunding, and grant programs such as the Small Business Innovation Research and the Small Business Technology Transfer programs). We provide a simple theoretical framework to highlight how the gap in funding—or the expectation of a gap—could influence the supply of Black founders in high-growth entrepreneurship. We highlight the influence of both supply-side and demand-side factors.

What explains the gap in venture capital funding for Black entrepreneurs? It could result from at least three different mechanisms. First, investors may provide less funding to Black startups because of bias, which could be driven by "taste-based" discrimination, biased beliefs, inaccurate stereotypes, or even organizational routines (such as sourcing deals from within the investor's network, which might not include Black founders (Gompers, Gornall, Kaplan and Strebulaev, 2020; Small and Pager, 2020)). Second, investors may use race as a proxy for unobserved variables they believe are positively related to future success but negatively associated with Black founders. In doing so, investors could "statistically" discriminate against Black founders (Phelps (1972); Arrow (1973)). Third, investors may provide less funding to Black founders because they observe variables that are not typically captured in databases such as PitchBook. The key difference between the second explanation and the third is that in the third, investors observe the omitted variable but we (the researchers) do not.

First, we directly assess whether omitted variables play a role, applying the Oster (2019) test to bound our estimates of the funding gap. We assume that omitted variables are just as likely to explain the gap as our controls and still estimate a large funding gap after doing so. We then use the Oaxaca and Ransom (1994) decomposition to show that our controls explain 31%-62% of the funding gap (depending on the specification). The estimates show that, for our estimate of the funding gap to be zero, any omitted variables would have to be nearly four times more important than our controls.

Second, we explore the possibility that Black-owned startups are of lower quality. We do so in a subsample where we can observe a coarse proxy for initial quality: startups that file for a patent. Not all patent applications are granted, so we can use issuance as an indicator of the quality of the invention underlying the startup. In this subsample, we replicate the gap in venture funding for Black-owned startups. Moreover, we establish that Black-owned startups' granted patents are of similar quality, whether measured by forward citations to granted patents, reliance on scientific literature, or time to grant.

Third, we exploit time-series variation in fundraising to show that the early-stage gap in VC funding for Black-owned startups dissipates over time. We interpret this dynamic reversal as possible evidence of investors' biased beliefs becoming disconfirmed as per Bohren, Imas and Rosenberg (2019).

Fourth, we conduct an "outcome test" in which we find that when examining marginal venture-backed startups (i.e., those that do not raise venture capital until more than three years after funding), Black-owned startups are no less likely to experience an attractive liquidity event once accounting for observables. This differs from the unconditional picture, where Black-owned startups appear less likely to be acquired. It may be that investors form inaccurate stereotypes about the likelihood of success for Black startups (Bordalo, Coffman, Gennaioli and Shleifer (2016)). Nevertheless, we are cautious about drawing strong inferences from this test, which infers the source of bias by comparing the success of the marginal Black-founded startup to the success of the marginal non-Black startup, but we only have a rough proxy for marginal startups. Therefore, we perform further tests to improve our interpretation of the patterns from the data.

Fifth, we show that the gap is not common to all venture capitalists but rather varies by the race of the lead VC partner, with Black startups being more likely to receive venture funding from Black lead partners *within* the same investment firm. If the funding gap were heavily influenced by statistical discrimination, we would expect a more uniform likelihood of Black founders being funded or a uniform likelihood of Black founders' success, conditional on their receiving funding, across all investors (Anwar and Fang (2006)). We find that neither is the case. On the other hand, if homophily were behind this pattern, we would expect investments made by Black partners in Black-owned startups to be less successful, as Black partners would pay the price for their distaste of non-Black startups. We find the opposite to be the case, suggesting that Black partners are instead leveraging their expertise, credibility, and networks to select (high quality) underrepresented entrepreneurs.

A. *Related Literature*

Our paper is related to the literature on the funding gap between Black and non-Black founders in other settings. Bates and Bradford (1992) report that minority-owned businesses and particularly Black-owned businesses have less access to venture capital financing. Park and Coleman (2009) find that Black-owned businesses have lower lines of credit than White-owned firms and firms owned by other minorities, even though they have comparable demand. Bates, Bradford and Jackson (2018) suggest that higher capital-search costs for minority-owned businesses explain the funding gap and find evidence that capital providers get higher returns from minority-owned projects—evidence, in their view, of taste-based discrimination. Fairlie, Robb and Robinson (2022*a*) point out that Black-owned businesses are able to raise only a small fraction of the outside equity, such as from VC and angel investors, that white-owned firms raise. Unlike our paper, however, these papers use survey data that combine high-growth, innovation-driven startups with self-employed individuals and small and medium startups, many of which are not eligible for venture funding. Self-employed individuals and founders of high-growth startups differ on many dimensions (Rubinstein and Levine (2020)), and any results of a sample that includes both are likely driven by the self-employed, as there are many more self-employed individuals than high-growth startups. As a result, these papers' estimates of the funding gap are difficult to generalize. We focus on high-growth startups, leveraging founder and investor characteristics to explain the funding gap.[5]

[5] The paper with data most similar to ours is Åstebro, Rafih and Serrano (2022), which also uses PitchBook and employs names and photos to categorize 5,090 founders. However, there are substantial differences. First, whereas we identify Black-owned startups specifically, their paper determines only whether the startup has at least one non-white founder (i.e., the race of the non-white founder is not reported). Second, we categorize all startups in PitchBook that were formed between 2000 and 2020, whereas they limit their sample to startups that raised at least $1 million in funding from 2010-2020. Third, the geographies are entirely non-overlapping, as we focus on the U.S. while they focus on Europe. Therefore, the results of the two papers are difficult to compare.

The evidence on a funding gap involving non-venture-capital funding is mixed. On the one hand, Ginther, Schaffer, Schnell, Masimore, Liu, Haak and Kington (2011) find that, after controlling for relevant applicant characteristics such as educational background and previous research awards, African Americans are less likely to receive NIH funding than White researchers. Ginther, Basner, Jensen, Schnell, Kington and Schaffer (2018) note that Black applicants have fewer papers and citations and that this difference could explain a substantial amount of the grant funding gap. However, such patterns in publishing and citations have also been shown to be influenced, at least in part, by racial discrimination. Younkin and Kuppuswamy (2018) find that Black men are less likely to raise money from crowdfunding sources because the quality of their product is perceived to be low. On the other hand, Smith and Viceisza (2018) report no significant differences in the number of offers by race or ethnicity in a TV pitch competition. Forscher, Cox, Brauer and Devine (2019) point out that there is little to no bias in the *initial* rounds of NIH R01 grant proposals, but they acknowledge possible bias at other stages. We contribute to this research by showing that, among high-growth startups that are "at risk" for venture funding, Black founders raise as much non-VC funding as other founders.

More recently, Ewens and Townsend (2020) show evidence of gender bias amongst angel investors. Male investors express interest in male-led startups even though male-led startups do not outperform female-led startups. Howell and Nanda (2019) show that networking frictions might explain the gender financing gap, as male participants in new venture competitions are more likely to proactively reach out to VC judges after the competition. Hebert (2020) shows that female-founded firms raise 27% less external equity overall, but the gap reverses in female-dominated sectors (i.e., female entrepreneurs become more likely to raise funding than male entrepreneurs). Gornall and Strebulaev (2020) use a randomized field experiment to show that investors do not discriminate against female or Asian entrepreneurs when evaluating unsolicited pitch emails. Our paper extends this line of inquiry by relating the funding gap amongst female founders to the gap amongst Black founders of innovation-driven startups.

The plan for this paper is as follows. Section II shows a simple framework for understanding the implications of the funding gap and other pre-startup frictions for entry into high-growth entrepreneurship. Section III shows our empirical strategy. Section IV shows how we construct our sample. Section V presents our findings on the ability of Black founders to raise non-debt funding, and Section VI concludes.

II. Conceptual Framework

This framework, a simplification of Hsieh, Hurst, Jones and Klenow (2019), illustrates how variation in the availability of capital by race and human capital pre startup formation might influence the entry of Black founders into high-growth entrepreneurship.

Suppose an agent's decision to enter into entrepreneurship is characterized by the following utility function:

$$U = (1 - \tau_r^f) F \epsilon ln(I) - (1 + \tau_r^I) I, \tag{1}$$

Where r is the agent's race, F is the amount of funding available to each entrepreneur, ϵ is the agent's idiosyncratic talent (or intrinsic utility) for entrepreneurship (drawn randomly from a power law distribution that is not race-specific), I is the agent's investment in the skills required to become a successful entrepreneur (education, past startup experience, initial wealth to test early ideas, networking, etc.), and τ_r^f is a race-specific fundraising deficit, capturing differences in access to F by race that are attributable to (a lack of) efforts by providers of funding. These compose the classical sources of discrimination, both statistical and taste-based. In addition to capturing the classical sources of discrimination, τ_r^f captures possibly entirely *unintentional* discrimination embedded in organizational practices. Small and Pager describe this as "institutional" discrimination. Such discrimination might be especially important in venture capital, where less than 28% of deals are sourced from outside the partners' network (Gompers, Gornall, Kaplan and Strebulaev (2020)).

τ_r^I is the race-specific cost of acquiring the skills required for success in entrepreneurship. It captures the fact that it might be harder for agents of a particular race to enter elite colleges, network with successful entrepreneurs, or get hired by prominent startups. To simplify things, we represent each agent's utility from her outside option (working for a public firm, working for the government, etc.) as $\overline{O}$, so that the agent chooses to become an entrepreneur as long as utility from entrepreneurship is greater than the outside option. One could also think of $\overline{O}$ as the minimum utility threshold required to qualify for F (or $(1-\tau_r^f)F$).

Given ϵ, τ_r^f, τ_r^I, and F, the agent will choose I to maximize utility and will enter entrepreneurship as long as her utility exceeds her utility from the outside option. Given the simple functional form we assume, an agent of race r will choose I to equate the marginal cost and marginal benefit of acquiring the skills required for success in entrepreneurship. Formally, the agent will choose I^* such that:

$$I^* = \frac{(1-\tau_r^f)F\epsilon}{(1+\tau_r^I)}. \tag{2}$$

Given the agent's choice of I^*, indirect utility is:

$$U^* = (1-\tau_r^f)F\epsilon\left[Ln\left(\frac{(1-\tau_r^f)F\epsilon)}{(1+\tau_r^I)}\right)-1\right]. \tag{3}$$

From this simple framework we can see that entry into entrepreneurship is a function of endowed talent for entrepreneurship (ϵ), barriers in acquiring the skills required to become an entrepreneur (supply-side factors), and barriers in fundraising (demand-side factors).

Given that the utility from entrepreneurship must exceed the outside option, an agent will only become an entrepreneur if:

$$U^* \geq \overline{O}. \tag{4}$$

Now we derive some implications of this simple framework to fix ideas on the different forces that might generate equilibrium statistics on representation in high-growth entrepreneurship by race.

First, two agents of different races with the same value of ϵ would face different entry decisions depending on the magnitude of τ_r^I and τ_r^f. Figure 1 makes this point visually by showing a simulation for a population with two races, Black and non-Black. We assume that 15% of the population is Black and that talent for entrepreneurship is drawn from a power law distribution that is not race specific. The threshold vertical lines are dependent on τ_r^f, τ_r^I, F, and $\overline{O}$. Innate ability (intrinsic utility) for entrepreneurship, ϵ, is drawn from a power law distribution whose density is given by $f(\epsilon, a) = a\epsilon^{a-1}$, where we set a to 0.2 for illustration. The distribution is centered at 10 with a standard deviation of 5. The dashed lines represent the threshold for entry into entrepreneurship, which varies by race because of the combined effect of τ_r^f and τ_r^I. For illustration, we set $F = 1$, $\tau_r^f = 0$, τ_r^I

= 0.1, and the threshold for entry $\overline{O} = 18.03$, the 84th percentile of the distribution of U^* when there are no frictions ($\tau_r^I = \tau_r^f = 0$). We pick this value so that 16% of the population enters into entrepreneurship, which matches U.S. statistics on the proportion of working adults in entrepreneurship. The fact that Black founders' representation in entrepreneurship is lower than their proportion in the population can be explained by either of these frictions.

[Insert Figure 1 About Here.]

Second, Figure 2 further illustrates how entry into entrepreneurship varies as a function of τ_r^f and τ_r^I. Panels A and B show that τ_r^f, τ_r^I, or both could generate lower entry into entrepreneurship by Black founders. When we consider the effect of supply-side frictions (τ_r^I), we hold demand-side frictions (τ_r^f) fixed, and vice versa.

[Insert Figure 2 About Here.]

Third, Figure 3 shows that lower skill acquisition is a rational response to demand-side frictions—or to expectations of these frictions. In other words, potential Black entrepreneurs who anticipate having trouble raising venture capital, whether due to exclusion from preferential networks or other forms of discrimination, may elect not to invest in developing the sort of skills to place themselves in the pipeline that is visible to investors. We show that "effective ability" varies between Black and non-Black entrepreneurs as a function of τ_r^f and τ_r^I, even though the innate ability for entrepreneurship (ϵ) is not a function of race.

[Insert Figure 3 About Here.]

III. Empirical Strategy

For most of our analysis, we rely on Poisson regressions to explain the amount of external funding a startup raises as a function of the proportion of its founders that are Black. Our choice is driven by the fact that some startups in our sample do not raise any external non-debt funding and thus have zero as their dependent variable. Cohn, Liu and Wardlaw (2021) show that Poisson regressions likely provide consistent estimates in this setting.

Our goal is to quantify the extent to which Black founders of high-growth startups face difficulties in raising external non-debt financing, and to examine possible explanations. We estimate the following reduced form equation using Poisson regression:

$$\begin{aligned}\text{Funding Raised}_i = \exp[&\alpha_1 + \beta_1 \mathrm{P(Black)}_i + \beta_3 \mathrm{P(Female)}_i \\ &+ X'\gamma + \lambda_j + \omega_s + \eta_t + \epsilon_{it}]\end{aligned}$$

Or equivalently

$$\begin{aligned}\ln(\text{Funding Raised}_i) = \;&\alpha_1 + \beta_1 \mathrm{P(Black)}_i + \beta_3 \mathrm{P(Female)}_i \\ &+ X'\gamma + \lambda_j + \omega_s + \eta_t + \epsilon_{it},\end{aligned} \tag{5}$$

The dependent variable, *Funding Raised*, is the cumulative amount of non-debt funding a startup receives two, three, four, or five years following company formation. *Funding Raised* comprises capital from venture capital firms and other sources such as accelerators, crowdfunding (proceeds from product or equity crowdfunding), grants, and the Small Business Innovation (SBIR) and Small Business Technology Transfer (STTR) programs. The unit of observation is a startup (i) founded in year (t). *P(Black)* is the proportion of founders that are Black; *P(Female)* is the proportion of founders that are female. λ_j, ω_s, and η_t are indicators for the startup's industry, headquarter state, and year of company formation, respectively. X is a vector of other control variables, such as the number of founders, the proportion of founders that are serial founders, the proportion of founders that attended elite schools, whether the startup obtained a patent within five years of company formation, and the startup's network score (see section C for more detail).

Our hypothesis, informed by anecdotal evidence and various news reports, is that $\beta_1 < 0$. The identification challenge lies in quantifying β_1 and explaining *why* $\beta_1 < 0$. We consider three main reasons.

First, investors may provide less funding to Black startups because of bias. Such bias has several possible sources. One possible source is taste-based discrimination. According to this view, investors *consciously* dislike working with Black founders and expect Black founders to "compensate" them for this distaste by accepting less funding (or a lower valuation) than non-Black founders—despite the Black founders' having the same probability of future success. Another possible source is biased beliefs (Bohren, Imas and Rosenberg, 2019). According to this view, investors simply underestimate Black founders, at least initially. Yet another possible source of bias is institutional discrimination (Small and Pager, 2020). According to this view, certain organizational practices, such as habitually selecting investments based on referrals from people within an investor's network, prevent Black founders from entering investor networks and make it harder for them to raise funding. Consistent with a heavy use of networking, Gompers, Gornall, Kaplan and Strebulaev (2020) show that less than 28% of venture capital deals are sourced from outside the VCs' networks.

Second, investors may associate race with an unobserved variable(s), X_1, that is positively related to future success but negatively related to Black founders. This unobserved variable is related to τ_r^I in the model. For example, investors might suspect that it is harder for Black founders to be exposed to successful entrepreneurs or to make the connections that are required in order to secure purchase orders from corporations. According to this view, the investors “statistically discriminate” against Black founders, using race as a proxy for the unobserved variable they associate with success. This discrimination, in turn, reduces the amount of funding that investors provide to Black-owned startups. Implicit in the statistical discrimination theory is the notion that the investors’ beliefs are correct—i.e., that Black-owned startups indeed have worse outcomes, on average, than similar non-Black startups (Phelps (1972), Arrow (1973)).

Third, the sign of β_1 might be driven by a variable that investors observe (like Black founders’ demand for equity funding) but that we empirical researchers do not. To the extent that this “omitted variable,” X_2, is positively associated with Black founders and negatively associated with fundraising, it might confound our estimates of equation 5. This explanation differs from the second explanation in that investors actually *observe* the omitted variable, as opposed to merely suspecting that it exists.

We formalize these competing explanations using the following system of equations:

$$\begin{aligned} \ln(\text{Funding Raised})_i = \alpha_1 + \beta_1 \text{P}(\text{Black})_i + \beta_3 \text{P}(\text{Female})_i \\ + X'\gamma + \lambda_j + \omega_s + \eta_t + \epsilon_i, \end{aligned} \tag{6}$$

$$\begin{aligned} \ln(\text{Funding Raised})_i = \alpha_2 + \rho \text{P}(\text{Black})_i + \delta_1 X_1 + \delta_2 X_2 \\ + \beta_3 \text{P}(\text{Female})_i \\ + X'\gamma + \lambda_j + \omega_s + \eta_t + \epsilon_i, \end{aligned} \tag{7}$$

$$\text{P}(\text{Black})_i = \alpha_3 + \gamma_1 X_1 + \gamma_2 X_2 + \epsilon_i, \tag{8}$$

$$\beta_1 = \rho + \delta_1 \gamma_1 + \delta_2 \gamma_2. \tag{9}$$

Although Equation (7) is the reduced-form Poisson regression we would like to run (i.e., the correct one), Equation (6) is the regression we actually run, because we do not know X_1 and X_2. We can derive (9), the omitted variable bias formula, by combining (6), (7), and (8) to show how β_1 is a combination of the three forces discussed above. Thus, if our hypothesis that $\beta_1 < 0$ is correct, it could be due to bias, ρ, "statistical discrimination," $\delta_1\gamma_1$, or an "omitted variable," $\delta_2\gamma_2$. Our identification strategy cannot convincingly rule out omitted variables. Instead, we rely on direct tests of compelling omitted variables and apply the Oster test to quantify the possible influence of omitted variables on our estimates of the funding gap—β_1 in the reduced form estimation and τ_r^f in the model. Further, we use outcome and cross-sectional tests to gauge the relative importance of ρ relative to $\delta_1\gamma_1$.

A. *Omitted Variables versus Statistical Discrimination and Bias*

A.1. *Demand for Funding*

In our first test, we assess whether Black founders have a lower demand for external funding relative to non-Black founders. To the extent that Black founders anticipate being discriminated against, we hypothesize that they should have a lower ex ante demand for *all* forms of external financing. Consistent with this, Fairlie, Robb and Robinson (2022*a*) show that Black entrepreneurs often avoid applying for bank funding because they anticipate being denied a loan.

We implement this hypothesis by testing whether Black founders are less likely to raise VC vs non-VC funding. A sharp difference between the two funding sources would cast doubt on demand-side factors as an explanation for the funding gap.

A.2. *Quality of the Idea*

Our second test focuses on the quality of the idea. Underrepresentation in funding of Black entrepreneurs may arise because investors expect that their business ideas are of lower quality. Of course, evaluating the ex ante quality of a business plan is not straightforward (Scott, Shu and Lubynsky, 2020), so, in this case, we limit our inquiry to a context where we can more closely locate the point of departure: technology-based ventures that filed a patent early on.[6]

Using patents, we can test the extent to which the inventions underlying Black vs. non-Black founders' ventures differ in quality. Specifically, we proxy for quality by testing whether Black founders are less likely to have their patents granted, how quickly the patents are approved (assuming that hard-to-evaluate ideas take longer for approval), and the extent to which patents garner forward citations (conditional on the patent being granted). If these signals are present and investors rely on them when funding startups, they may help explain why Black founders raise less funding.

A.3. Quantifying the Impact of Omitted Variables

Next, we bound our estimate of the funding gap using tests that account for the potential impact of omitted variables (Oster (2019)). The Oster test allows us to bound our estimate of the funding gap by examining how the coefficient and R-squared change as controls are added to the regression model. We estimate the bias-adjusted coefficient of the funding gap as follows:

$$\beta^* = \widetilde{\beta} - \delta[\beta^o - \widetilde{\beta}]\frac{R_{max} - \widetilde{R}}{\widetilde{R} - R^o}. \tag{10}$$

β^* is the bias-adjusted estimate of the funding gap. R_{max} is the maximum R-squared a researcher might hope to achieve from a regression that explains the amount of funding

[6] Of course, there is more to a business plan than a patent alone. Shane 2000 describes seven different ventures based on a single 3-D printing invention at MIT that was licensed separately. Nonetheless, we contend that the quality of that underlying invention is assessable in this context.

a startup raises using controls; $\widetilde{R}$ is the R-squared from the regression of VC funding on the proportion of founders that are Black with controls; and R^o is the R-squared without controls. Similarly, $\widetilde{\beta}$ and β^o are estimates of the funding gap with and without controls. δ is the assumed relationship between observed controls and unobserved variables.[7] Following Oster (2019), we calculate R_{max} as 1.3 times the maximum R-squared achievable from a regression with controls and assume that $\delta = 1$, so that any unobservable (to us) variables that are important for investors' allocation decisions are just as important as the variables we account for. We also solve equation 10 to obtain the maximum value of δ that one would have to assume in order for our estimates of the funding gap to be zero.

While we cannot completely rule out that our estimates of the funding gap are driven by omitted variables, the methodology from Oster (2019) helps provide some bounds on how unobservables (to us) could impact our estimates, and on the size that unobservables would have to be in order to explain away our estimates of the funding gap.

B. Statistical Discrimination versus Bias

After testing the relative importance of omitted variables versus statistical discrimination or bias, our next set of tests attempt to quantify the relative importance of statistical discrimination and bias.

B.1. Post-Investment Outcomes

To evaluate the relative importance of statistical discrimination versus other bias sources, our first test focuses on outcomes. If the funding gap results from statistical discrimination, we hypothesize (as theory predicts) that startups with a high proportion

[7] This further assumes that the variables for which we account are orthogonal to the omitted variables that correlate with the funding gap, akin to the two principal components of variables that explain the amount of venture funding a startup raises.

of Black founders will be less likely to be successful. However, if the funding gap results from taste-based bias or inaccurate stereotypes that investors do not update, we expect—consistent with the outcome test (Becker, 1993)—that firms with a high proportion of Black founders will be *more* successful due to the higher threshold they have to overcome to obtain funding. To correctly approximate the theory, the outcome test should be based on comparisons of the marginal, and not the average, Black vs. non-Black founded startups.

To understand the problem that may arise from comparing averages, suppose that there are two easily distinguishable types of Black entrepreneurs: those who have a 3% chance of success and those who have a 65% chance. Similarly, assume that non-Black entrepreneurs have either a 3% or 55% chance of success.[8] If VCs, in a race-neutral manner, fund individuals who are at least 10% likely to be successful, then investments in Black startups will be successful 65% of the time, whereas investments in non-Black startups will be successful only 55% of the time. In such a case, even though the selection process is race-neutral, the inferences from the outcome test suggest a bias on the part of the VCs. Thus, this infra-marginality problem may render estimates using averages uninformative about the extent of bias (Ayres (2002)).

We (crudely) approximate the margin by focusing on startups that took a long time (more than three years) to raise their first round of venture capital funding when we compare outcomes; however, we admit that our inferences may be tainted by this approximation. When we run the outcome test, we effectively assume that conditional on raising venture funding many years after startup formation, there is no difference in the distributions of risk by founder race, which, admittedly, is a strong assumption. To draw robust inferences on how bias might influence the funding gap, we, therefore, supplement

[8] We assume the weights on the different chances of success are such that the average rate of success is equal across Black and non-Black startups.

the outcome test with two other tests.

B.2. *Follow-on Funding*

Our next test of the source of bias leverages the Bohren, Imas and Rosenberg (2019) prediction that biased beliefs might lead investors to fund Black founders at a lower rate, at least initially. We posit that, following positive project updates, investors will update their *biased* priors and provide larger or equal amounts of funding to Black founders in follow-on rounds. We implement this prediction by taking advantage of the staged nature of venture funding. Specifically, we run equation 5, where the dependent variable is the likelihood and amount of funding raised at an early stage (Series A and B) and a late stage (Series B or later). If investors hold biased beliefs and then update them, we expect the funding gap to disappear or even reverse during the later stages of funding.

B.3. *Investor Heterogeneity*

Our final test to evaluate the relative importance of different sources of bias uses the ethnicity of lead partners to exploit heterogeneity across investors. Our hypothesis builds on the Anwar and Fang (2006) theory that statistical discrimination is more likely if venture capitalists are monolithic in their investment behavior. Note that most managing partners of venture capital funds get 2% of the fund's size in fees and 20% of the profits from investments, regardless of their race (Ivashina and Lerner (2019)). Thus, the race of the founder, in principle, should not affect the likelihood of an investment or the success of the investment for investors of *all races* when there is no relative bias against Black founders. However, if there is a relative bias, then the race of the founder could have an effect. For example, Black partners might be more likely than other investors to fund Black founders (or to fund successful Black founders).

IV. Data

A. Sample Construction

Our goal is to study the extent of disparities in funding for Black founders of high-growth startups, and to explore the mechanisms driving these disparities. To our knowledge, no such study has previously been conducted. The only available dataset of which we are aware is the Crunchbase Diversity Spotlight, in which investors self-reported their portfolio companies that were either Black-founded or Black-led. We, therefore, undertook an effort to classify a set of high-growth startups that are Black-owned. Our approach involves classifying not startups but rather *individual founders*, then inferring the status of the startups from those founders. To execute this approach, we restrict our sample to startups where we can reliably determine the race of at least one founder, and to founders whose race can be reliably determined. Were we to, for example, include founders whose race could not be classified, we might miss some Black founders and classify their startups as non-Black. Our approach introduces some selection (founders must have resume information and a publicly available image to be included), but it minimizes false negatives and false positives.[9] To further minimize error, we restrict our time period of inquiry to an epoch when we can glean the most information possible about individual founders.

We start with PitchBook, which (based on our own comparisons) we believe to be the most complete and up-to-date repository of information about high-growth startups and their founders, at least in the post-2000 era. PitchBook covers not just companies that raised venture capital but also companies "at risk" of doing so, including those that raised accelerator funding, equity crowdfunding, and SBIR/STTR or other types of grants.

[9] See Table A.2 for a comparison of startups that we include and startups that we exclude from our sample. Based on the value of the startup at exit, we conclude that the included startups are more likely to be successful than the excluded ones, suggesting that our estimates are likely a lower bound of the funding gap.

PitchBook also contains data on founders, CEOs, and other executives associated with these startups and posts the LinkedIn URLs for the vast majority of them. Our PitchBook data are current through June 6, 2022. (For full details on PitchBook sampling, see Section A.A.2.) Although the PitchBook personnel files include a wealth of information (including dates of employment at the PitchBook companies, and educational background), the LinkedIn URL is a gateway to much more, including—crucially—profile pictures. We therefore limit our inquiry to *founders for whom we can retrieve a LinkedIn profile and profile picture.* Using publicly available LinkedIn pages and various web sources, we found profile pictures for about 90% of the founders we searched for.[10]

The profile picture is used to determine race, in three steps. First, we use an image-processing algorithm to classify founders by skin tone (see section A.A.4 for details). Second, we use name classification algorithms to distinguish between races with similar skin tones—for example, Blacks and dark-skinned Asians. Third, we add a clerical review to the classification process to reduce errors. Specifically, we manually verify that each founder who is flagged as Black by our image-processing algorithm is indeed Black. To accomplish this, we use a combination of the founder's picture, affiliation with Black groups on LinkedIn, and self-identification as a Black founder in her or his LinkedIn profile, as well as various news sources and crowdsourced lists of Black founders.[11] The advantage of using image recognition in addition to name algorithms is illustrated in Figure 4. The figure shows that we would have wrongly classified 2,313 Black founders as non-Black (false negatives) had we relied solely on name prediction algorithms.

[Insert Figure 4 About Here.]

[10] To that end, we first obtained the list of all founders of these startups from PitchBook by searching for the keywords "founder" or "owner" in job titles, then manually inspected the results to make sure they were correct.

[11] Here is an example of a crowdsourced list of Black founders.

B. Matching PitchBook to USPTO

In a mechanism test, we evaluate the quality of the startup's "idea" within the subset of startups that file patents with the U.S. Patent & Trademark Office. For each startup in PitchBook, we obtain the complete history of the startup's name changes. Next, we merge these startups on name and state where they are headquartered to data on all assignees in the USPTO database as of September 2022. We focus on assignees that applied for a patent (but did not necessarily obtain one). When an assignee has multiple applications, we keep the first application filed. If multiple applications are filed on the same day, we keep the application that was eventually granted or that generated the most forward citations. We further restrict the set of matches to assignees that were formed no more than five years before their first patent application. The restriction on the founding year allows us to identify young startups, whose financial constraints are likely to be more salient (Hadlock and Pierce (2010)). See section A.A.4 for a more in-depth discussion of the matching process.

V. Results

A. Summary Statistics

Table 1 presents the summary statistics of our sample for the different variables used in the analysis. Panel A is at the startup level, and Panel B is at the founder level. The first fact that stands out is that only 3.4% of high-growth startups have at least one Black founder. Given that about 16% of the U.S. population of working adults is Black, Black founders are underrepresented among high-growth, innovation-pursuing startups by nearly a factor of five. There has been slight growth in the share of Black-founded startups over time, as we show in Figure 6.

[Insert Figure 6 and Table 1 About Here.]

Some variables are related to the amount of capital raised from different sources. In this respect, note that Black founders raise less funding in the five years after founding, both from venture capital (VC) and non-VC sources, when we do not condition on observables.[12] Non-VC sources include crowdfunding, accelerators, incubators, and grant funding. Table 1 also shows that in our sample, Black startups are less likely to IPO or be acquired—at least when we do not condition on observables.

The trend for venture capital is visible in Figure 7. We see that Black founders raise less funding in the five years following startup formation across different industry sectors (Figure 8) and geographies (Figure 9). Figure 9 shows that the gap in funding between startups with vs. without Black founders is largest in areas with a large supply of venture financing (California, Massachusetts, and New York). Further, Figure 10 shows that the distribution of funding in the five years following startup formation is shifted to the left, suggesting that the gap in venture capital funding is not driven by outliers.

[Insert Figure 7, Figure 8, Figure 9, Figure 10 About Here]

A critical component of our analysis is the "quality" of the founder. We proxy this with indicator variables equal to one if the founder graduated from a top-20 university or is a serial founder. (See Appendix D for a list of top schools we include in our analysis.) Our data in Panel B of Table 1 shows that Black founders are slightly less likely to be serial founders but are equally likely to have graduated from top schools. In a later analysis, we will decompose how much of the funding gap is likely to be driven by differences in human capital before the startup formation.

[12] Note that we use "venture capital" inclusive of both traditional venture capital as well as angel investors, as these two types of investors exhibit quite similar investment patterns regarding Black-owned startups. The ratio of venture capital dollars to angel-investor dollars is approximately 46:1 in our data.

B. Black Startups and Fundraising

In Table 2 we begin to explore the dynamics of Black founders and raising venture capital. We estimate equation 5 using Poisson maximum likelihood, except that our dependent variable is an indicator for whether the startup raised at least one dollar of funding from venture capitalists 2, 3, 4, and 5 years after founding. The unit of observation is a startup formed between 2000 and 2020.[13] All regressions include state (where the startup is headquartered), founding year, and industry fixed effects (the industry being one of seven sectors in PitchBook, as presented in the last seven rows in Panel A of Table 1). We control for the number of founders, the proportion of founders that are serial founders, the proportion of founders that attended elite schools, whether the startup obtained a patent within five years of company formation, and the startup's network score. (See section C for more detail.)

The estimates in Column (1) imply that, all else equal, increasing the proportion of Black founders from zero to one reduces the likelihood that a startup will raise venture capital funding over the next two years by 31% ($100 \times (e^{-0.38} - 1)$). Female founders face a deficit that is about two-thirds the magnitude of the one for Black founders, regardless of time horizon. By contrast, venture capitalists are much more likely to invest in startups with serial founders and with founders from top schools, with stronger networks, with patents, and with larger founding teams in general.

Table 3 refines this view to examine the total amount of VC funding the startup raises (estimating equation 5) in Panel A, and to compare this outcome variable with funding raised from sources other than venture capital in Panel B. The estimates in Panel

[13] A round qualifies as a venture capital round if it is classified as "Early Stage," "Late Stage," or "Seed funding" by PitchBook *and* the primary investors are venture capital funds with a limited partnership structure. We further require that PitchBook lists the investor's type as "Venture Capital," "PE/Buyout," "Growth/Expansion," "Corporate Venture Capital," "Other Private Equity," or "Not-For-Profit Venture Capital."

A closely resemble those of Table 2. All else equal, increasing the proportion of Black founders from zero to one reduces the amount of venture capital funding a startup can expect to raise over the next two years (column 1) by nearly two-thirds (64.5% = (100 $\times$ ($e^{-1.04} - 1$)). [14]

Given that the amount that venture capitalists are willing to invest in a company is intimately related to their valuation of the venture, two alternative hypotheses present themselves. First, perhaps the lower amounts raised in Panel A of Table 3 simply reflect VCs' opinion that these companies are less valuable. Appendix Table A.5 repeats the analysis of Panel A for the subset of startups whose pre-money valuation was at least $1. Even when we account for pre-money valuation, Black-owned startups receive substantially less venture funding. A second possible explanation for the funding gap is that investors put higher valuations on startups with Black founders and thus purchase smaller fractions of the companies, hence the lower funding. Figure 11 presents evidence against this hypothesis by showing that valuations for Black startups are lower, not higher, during our sample period.

[Insert Tables 2 and 3 About Here.]

[Insert Figure 11 About Here.]

However, when we turn to Panel B, we no longer see a gap in the funding of Black founders—at least, not within five years of founding. The dependent variable in Panel B is limited to non-VC sources of capital, including from accelerators, equity crowdfunding,

[14] As noted above, we use "venture capital" throughout the paper inclusive of angel investing, as angel investing represents approximately 1/46th the dollar volume of venture capital and exhibits similar dynamics regarding Black-owned startups, as shown in Appendix Table A.10. Whether examining 2-, 3-, 4-, or 5 years after founding, the amount of angel funding is decreasing in Black ownership, and the magnitude of the gap is nearly as large among angels as among venture capitalists. In unreported results, the coefficients for the venture-capital-only sample are nearly indistinguishable from Table 2.

and grants which include the Small Business Innovation Research (SBIR) program, and the Small Business Technology Transfer (STTR) program. (Note that Panel B does not include angel investors, which we examine in Appendix Table A.10). We interpret this difference in VC vs. the non-VC funding sources in Panel B as possible evidence that the demand-side explanation for the funding gap is weak on its own. To the extent that the Black founders are not applying for external financing for fear of being denied, we would expect to observe at least a somewhat similar pattern across VC *and* non-VC funding. That we do not see a fundraising deficit among non-VC sources of capital, suggests that a demand-based explanation is not the primary driver of the funding gap.

Also in support of this conclusion, we note that the venture-funding gap is not localized based on racial animus. In Appendix Table A.8 we revisit Table 2, interacting the fraction of Black founders with an indicator from Howell, Kuchler and Stroebel (2021) for counties with an above-median percentage of Google searches for racially charged words. This analysis is in the spirit of Fairlie, Robb and Robinson (2022*a*). They report that one reason Black founders raise less debt financing is that they expect to be denied a loan and show that this fear of denial is especially great in states with high racial animus. Although small-business loans are highly localized, venture capitalists also prefer to invest locally (Bernstein, Giroud and Townsend, 2016): therefore, if the gap we document is mostly driven by lower demand for external funding from Black founders, we might expect to see an even greater gap among founders who are located in regions with higher racial animus. Yet we do not find any such evidence from two to five years after founding. The estimated coefficients in columns (1-3) of Appendix Table A.8 are negative but imprecisely estimated, and the coefficient in column (4) is positive. This suggests that a lack of demand for venture funding from Black founders is not a likely explanation for the venture capital funding gap.

C. Oster Omitted variables test and Oaxaca-Blinder Decomposition

Given our discussion in section III of the possible influence of omitted variables on our estimates, in this section we bound our estimate of the funding gap where we account for the impact of omitted variables on our estimates. We follow Oster (2019) and calculate the lower bound using $R_{max} = 1.3 \times 0.288$ and $\delta = 1$. The maximum R-squared from a regression of the log amount of VC funding raised in the five years following company formation on the proportion of founders that are Black with controls is 0.288. Given that this test was proposed using linear models, we first regress *Ln(VC funding (5 yrs))* on *P(Black)* and controls from Table 3 to estimate the bias-adjusted coefficient and how important unobservable variables would have to be, relative to observables, $\widetilde{\delta}$, to explain away the funding gap. Of course, only firms that raised at least a dollar of VC funding in the five years following venture formation are included in this test. Panel A of Table 4 presents our results.

Following Oster (2019), we bound the funding gap between 142% and 70%. In column (4), we show that, for the funding gap to be zero, omitted variables would have to be nearly four times more important than the variables we control for.

Given the wide range of our estimates of the funding gap (our estimate without controls is one and a half times as large as our estimate with controls), we follow Oaxaca and Ransom (1994) and Fairlie, Robb and Robinson (2022*a*) and perform a decomposition to understand the influence of the controls on our estimates of the funding gap. Panel B of Table 4 shows the estimates of the pooled decomposition (see Fairlie, Robb and Robinson (2022*a*) for more details). We can explain between 31% and 62% of the difference in venture funding raised in the five years following company formation. If we focus on the second column, state, industry, networks, number of founders, and having a patent explain about a third of the gap. Note that we standardize all variables we consider to have a mean of zero and a standard deviation of one.

Black-founded startups could be less likely to have patents because they do not apply, or because they are more likely to be rejected conditional on applying for a patent. We explore patent applications more carefully in the next section.

[Insert Table 4 About Here.]

D. "Quality" of the Startup

Venture investors make investment decisions after carefully considering the individual companies, their founders, and the perceived quality of their ideas. Therefore, the differences in funding between Panels A and B of Table 3 could also (or rather) reflect different levels of due diligence between professional VC investors and non-VC sources of capital such as government review panels for SBIR/STTR, and accelerator boards. We thus repeat the exercise in a subsample of startups where we can observe a proxy (admittedly coarse) for the quality of the idea: startups that apply for a patent. Guzman and Stern (2020) employ patents as indicators for higher-quality startups; our objective is to use patent *applications* to distinguish patents filed from patents granted, also taking account of examination length and, for those patents that are eventually granted, the count of forward citations and the patents' reliance on science. We therefore use patent-examiner evaluations of the startups' patent applications—not all of which are granted—to investigate whether the evidence supports the notion that ideas from Black founders are of lower quality. If it is the case that patents submitted by startups with Black founders are lower in quality, this might help to explain the gap in VC funding of Black founders.

Appendix Table A.1 contains descriptive statistics for the subset of PitchBook-tracked startups that applied for a patent. Table 5 repeats the analysis of Table 3 for the subsample of PitchBook startups that applied for a patent, matched as described in Appendix A.A.4. The results resemble those of the full PitchBook sample, with Black-owned startups that filed a patent experiencing a VC funding deficit in the first five years after founding. The consistency in the VC gap between the full sample and this subsample makes it reasonable to ask whether the gap can be explained by quality differences in startups' patent applications.

[Insert Table 5 About Here.]

In Table 6 we compare four measures of quality for patent applications, depending on the ratio of Black founders in the startup. We control for firm age (the number of years between when the company was formed and when it applied for a patent), the number of founders, the network score of founders, the proportion of founders from top schools, the proportion of founders who are serial founders, and the proportion of female founders. We further include a fixed effect for the USPC class by application year, to control for variation in approval rates across different patent classes over time as well as the selection of Black founders into certain patent classes. The unit of observation in this test is the first patent application by a startup in our sample.[15]

In column (1), we explore whether patents from Black-owned startups were any less likely to be granted as of September 2022. From Table 2, we know that venture capitalists are 60% more likely to invest in a startup that has a patent, so the rejection of a patent application has substantial implications for garnering the support of investors (see also Hsu and Ziedonis (2013) and Farre-Mensa, Hegde and Ljungqvist (2020)). If patent applications from Black-owned startups were less likely to be granted, this could help to explain the gap in venture capital funding as it would point to a generally lower quality of underlying technical innovation among Black startups. However, we recover no such

[15] When a startup applied for multiple patents on the same date, we keep the most successful application—the application that was granted and that generated the most citations.

evidence in column (1) of Table 6.

In the remaining columns of Table 6, we consider the quality of the patents that are ultimately granted. Column (2) counts the number of forward citations to those granted patents through September 2022. Hirschey and Richardson (2004) find that investors are influenced by patents with higher citation counts, and although said counts are not visible to investors at the application stage, they nonetheless proxy for the quality and influence of an innovation. Including the USPC-class-by-application-year fixed effects, we again fail to find a difference between citation rates for granted applications by Black- and non-Black-owned startups.

A complementary measure of patent quality is reliance on the scientific literature, which has been correlated with multiple measures of value (Poege, Harhoff, Gaessler and Baruffaldi, 2019). Therefore, if we were to establish that patents filed by Black-owned startups are less reliant on science, this might help to explain venture capitalists' reluctance to invest. However, in column (3), we fail to find differences in the number of references to the scientific literature between Black-owned vs. other startups (Marx and Fuegi, 2020, 2022).

Finally, we consider the duration of the examination process (i.e., years from application to issuance) for patent applications filed by Black-owned vs. other startups. Of course, the examination process can be influenced by a variety of factors, including a) the quality of the invention, b) the quality of the application (independent of the underlying invention), c) the response time on the part of the applicant, d) and the response time of the examiner. Hence, examination length is at best a noisy indicator. But if patent applications from Black-owned startups were substantially worse, we might find that they have much longer examination times. However, as shown in column (4), we do not.

[Insert Table 6 About Here.]

D.1. Robustness of Patenting-Startup Subsample

Because PitchBook is more likely to cover startups that have raised some external financing, conditioning on coverage in PitchBook suggests that our estimates understate the magnitude of the funding gap for Black founders, as we likely miss startups that did not raise *any* external funding. To test the extent to which our estimates understate the true funding gap, we repeat our analysis using the same sample in Farre-Mensa, Hegde and Ljungqvist (2020), which also covers first-time assignees that applied for a patent.[16] Our estimates using that sample are in Appendix Table A.3. Consistent with our hypothesis, the funding gap is much larger in this sample. The estimates from Column (5) of Panel A imply that, all else equal over a five-year horizon, increasing the proportion of Black founders in a startup from zero to one decreases the amount of venture funding the startup can expect to raise by 90%. However, consistent with our analysis using the PitchBook sample, there is no funding gap when we look at non-VC funding.[17] We also repeat the test of patent outcomes using the sample in Farre-Mensa, Hegde and Ljungqvist (2020), which covers first-time assignees that applied for a patent between 2001 and 2009. Our estimates using this sample, shown in Table A.6, are virtually identical to what we find in the PitchBook-USPTO sample, suggesting that our results are not driven by how we constructed our sample or selection into PitchBook.

[16] We download their sample from the *Journal of Finance*'s website.

[17] We are less thorough in our classification of Black founders in this sample due to the larger sample size. To predict inventor race in this sample, we use NamePrism (also used in Egan, Matvos and Seru (2017)) to predict the probability that a founder is Black. Then, using the same procedure as in the main analysis, we download and process all images where the probability that the inventor is Black is 40% or greater. This procedure reduces the false positive rate (classifying a non-Black founder as Black), but likely has a high false negative rate (classifying a Black founder as non-Black). Thus, this coefficient is also likely to underestimate the true funding gap.

E. Statistical Discrimination and/or Bias

E.1. Statistical Discrimination and Post-Funding Outcomes

If statistical discrimination is the primary driver of the venture capital funding gap, we would expect Black-owned startups to be less likely to achieve an exit, given the lower amounts of funding they raise. For this test we attempt to focus on marginal startups, akin to consumers who are a high credit risk such as studied by Butler, Mayer and Weston (2022). Credit scores do not exist for new ventures, so use another proxy: for startups that raised venture capital, the number of years elapsed since founding until a round of venture capital was secured. Although it is possible that a new venture might intentionally delay fundraising, or might pivot from an initial business model based on bootstrapping to a capital-hungry one years later, in most cases we expect that high-potential ventures will seek external funding sooner rather than later. Indeed, Figure 12 indicates a clear correlation between the "funding delay" and the likelihood of a successful exit.

[Insert Figure 12 About Here.]

Therefore, in the interest of focusing on marginal startups we limit our analysis in Table 7 to those that raised venture capital later than three years after the company was formed. (This subset includes approximately 25% of startups that raised VC.) Whether accounting for founder observables in column (3) or not (cols. 1-2), or accounting for the amount of VC raised (col. 4), we are unable to detect differences in the likelihood of a successful exit by Black-owned startups. Keeping in mind from Appendix Table A.5 that Black-founded startups raise less venture capital even when controlling for team size, patenting, networks, serial founders, and the investors' own pre-money valuation of the startup, the findings of Table 7 are not consistent with taste-based discrimination being the primary driver of the funding gap. However, as we discussed in section III, our inference might be biased because we only have a coarse proxy for the marginal startup.

[Insert Table 7 About Here.]

E.2. Biased Beliefs and Dynamic Reversal in Follow-on Funding Rounds

Next, we analyze the extent to which biased beliefs explain the VC funding gap for Black-founded startups. This test leverages the staged nature of venture funding and the dynamic-reversal prediction from Bohren, Imas and Rosenberg (2019) discussed in Section III. Given that investments are typically staggered over time as a function of milestones, we hypothesize that although Black founders raise lower amounts in the first funding round, they should raise equal or higher amounts in later rounds as investors update their initially-mistaken beliefs about the prospects of Black-owned startups.

Table 8 presents estimates of the relationship between the proportion of a startup's founders that are Black and the likelihood and size of follow-on rounds. A unit of observation in this test is a startup that raised later-stage funding, hence the lower number of observations. We select the sample as such to examine fundraising dynamics over time for a fixed sample. The dependent variable in columns (1) and (2) is whether the startup raised any funding; columns (3) and (4) explore the magnitude of VC funding (with zero if the startup did not raise any).

[Insert Table 8 About Here.]

Columns (1) and (3) show that Black founders' early-stage funding—both in terms of likelihood and amount—is considerably smaller, even conditional on eventually raising later-stage funding. The gap is no longer visible in the later stages (conditional on raising seed *and* early-stage funding), which typically occur more than five years after founding—that is, following the analysis of Table 3. We see this pattern as consistent with investors dynamically reversing their priors regarding Black founders, as per Bohren, Imas and Rosenberg (2019).

Conversely, investors appear to reverse their priors regarding a more traditional signal for promising founders. The positive and statistically significant coefficient on *Serial Founder* in columns (1) and (3) indicate that these startups raise more venture capital in early stages, but not in later rounds (see columns (2) and (4)). This suggests that serial foundership may be a false flag of quality, perhaps because unreported exit values make it difficult to distinguish attractive exits from so-called "fire sales" (Puri and Zarutskie, 2012). Other signals remain more consistent over time: startups that have a patent at founding, startups with larger founding teams, and startups with higher network scores all raise more capital both in the early and the late stages.

Overall, the results of Table 8 suggest that VC firms' biased beliefs might drive not only the Black funding gap but also misallocation more generally among high-growth innovative startups. This is not entirely surprising, as venture investors make decisions under substantial uncertainty. As shown in Table 1, very few Black-owned startups in our sample ever achieve an IPO, so investors may lack salient examples of prominent, Black-led, successful startups. If these investors fail to account fully for observables (as in column (4) of Table 7), they are likely to form inaccurate negative stereotypes about startups with Black founders (Bordalo, Coffman, Gennaioli and Shleifer (2016)).

F. Cross-Sectional Heterogeneity

Table 9 repeats the tests in Table 3 with cross-sectional interactions to investigate which factors mitigate or exacerbate the funding gap. The dependent variable is the cumulative amount of venture funding a startup raises in the five years following its formation. We interact the proportion of founders that are Black with indicators for whether the startup is located in a private-equity hub' (California, Massachusetts, and New York), whether the startup is in the information technology sector (which comprises almost half of all startups), whether the startup has a patent, and the proportion of the startup's founders who are serial founders.

[Insert Table 9 About Here.]

Our investigation of this cross-sectional interaction is motivated by Table 4, which shows that these factors explain about 32% of the funding gap. Thus, it seems possible that these factors will mitigate the funding gap here. For example, competition amongst VCs in private equity hubs could reduce the potential for bias to affect the Black-founded startups, and the falling costs of firm entry thanks to Amazon Web Services, Shopify, and other platforms might reduce barriers to entry for Black founders of IT startups. However, we do not find that either of these is the case, as shown in columns (1) and (2). In column (3), we interact the percentage of founders who are Black with whether the startup has a patent. The Table 8 evidence that investors hold and then dynamically reverse their initially biased beliefs about Black entrepreneurs suggests that the investors' bias could be ameliorated by the presence of positive signals such as a patent (Hsu and Ziedonis, 2013). The estimated coefficient of interest in column (3) is consistent with this interpretation, as the funding gap is smaller for Black startups with a patent.

Every table to this point has shown that serial founders raise more venture capital (see also Nahata (2019)). Moreover, the dynamic-reversal test of Table 8 indicated that investors are positively biased toward serial founders in early-stage funding. To the extent that investors rely on previous entrepreneurial experience as a signal of quality, one would expect Black founders who have launched past startups to experience fewer frictions in fundraising. Although the result in column (4) is consistent with this hypothesis, the estimate is imprecise.

F.1. Investor Heterogeneity

If statistical discrimination explained the funding gap for Black-owned startups, we would expect venture investors to respond homogeneously to these firms. Venture capital investors—note that this section omits angel investors[18]—do not invest their own money but act as agents on behalf of limited partners, whose money they invest and to whom they have a fiduciary responsibility. In this section, we examine whether, among venture-capital firms, there is evidence of heterogeneous response by investor type. We hypothesize that if statistical discrimination plays a large role in explaining the funding gap, all VC firms will be equally likely to fund Black founders.

As described in Appendix A.A.3, we identified the race of the lead partners on the startup deals in our sample in order to examine whether the funding gap is homogeneous across investors of different races. Panel A of Table 10 presents our results. Across all models, it is evident that the gap in venture capital funding of Black-owned startups varies substantially with certain characteristics of the lead partner. When the lead partner is Black, they are more likely to back a Black founder, even when measured *within* the same venture capital firm. Thus, investors are not completely homogeneous with regard to which founders they fund. This is not what we would expect in the face of purely statistical discrimination (Anwar and Fang (2006)).

[Insert Table 10 About Here.]

The finding that Black lead partners are more likely to fund Black founders could be explained by a variety of mechanisms. One view might ascribe such patterns primarily to homophily: i.e., Black lead partners want Black entrepreneurs to succeed and therefore

[18] The analysis of Table 10 includes fixed effects for the investment firm. As such, the effect of a focal lead partner's race is identified relative to other lead partners in the firm. Given that angel investors invest not on behalf of limited partners and as part of a general partnership but are generally acting alone, they drop out of this analysis.

select on racial affinity even when it could mean compromising on quality. This argument is akin to the "cost of friendship" when investors choose syndicate partners based on ethnicity or social ties (Gompers, Mukharlyamov and Xuan, 2016). If this were true, we would expect Black lead partners to *underperform* investors of other races when they invest in Black entrepreneurs.

Another view might be that Black lead partners have a superior ability to identify and attract Black founders, whether due to unique professional and social networks or to shared experiences and background (Cornell and Welch (1996)). As one example, assuming that Black lead partners are more likely to have attended a historically Black college or university (HBCU) or to have friends who are alumni; they should share networks with potential founders from HBCUs. If this view predominates, then when Black lead partners invest in Black founders, they should *outperform* investors of other races.

We adjudicate between these possibilities in Panel B of Table 10. Our setup is identical to Panel A, except that the dependent variable is replaced with an indicator for an investment in a Black-owned startup that either completed an IPO or was acquired. Across all columns, Black lead partners are more likely to invest in a successful Black founder. This suggests that the higher likelihood of Black lead partners investing in Black-owned startups observed in Panel A is not driven by homophily.

VI. Conclusion

We document a significant gap in VC funding amongst high-growth innovative startups, with Black founders raising approximately one-third as much as others in the first five years of their startups' existence. This gap does not exist for non-debt funding from sources other than venture capitalists. Nor does it appear to be explained entirely by omitted variables; indeed, the omitted variables would have to be nearly four times as important as the controls (which explain between 31% and 62% of the gap) for the funding gap to be zero. We examine the subset of patenting startups to rule out initial quality as an explanation for investors' lower allocations to Black-founded startups. We find that, in Black-owned startups, patents are granted no less often, receive no fewer citations, and are no less based on science, relative to other startups. The marginal Black-owned startup is no less likely to have a successful exit than non-Black-owned marginal startups once accounting for observables. Our evidence that the funding gap dissipates in later stages of funding (i.e., after Series B) suggests that investors' initially biased beliefs dynamically reverse as they learn more about Black entrepreneurs' capabilities. Finally, we show that Black lead partners invest more often in Black entrepreneurs and are more successful when they do, consistent with segregated networks.

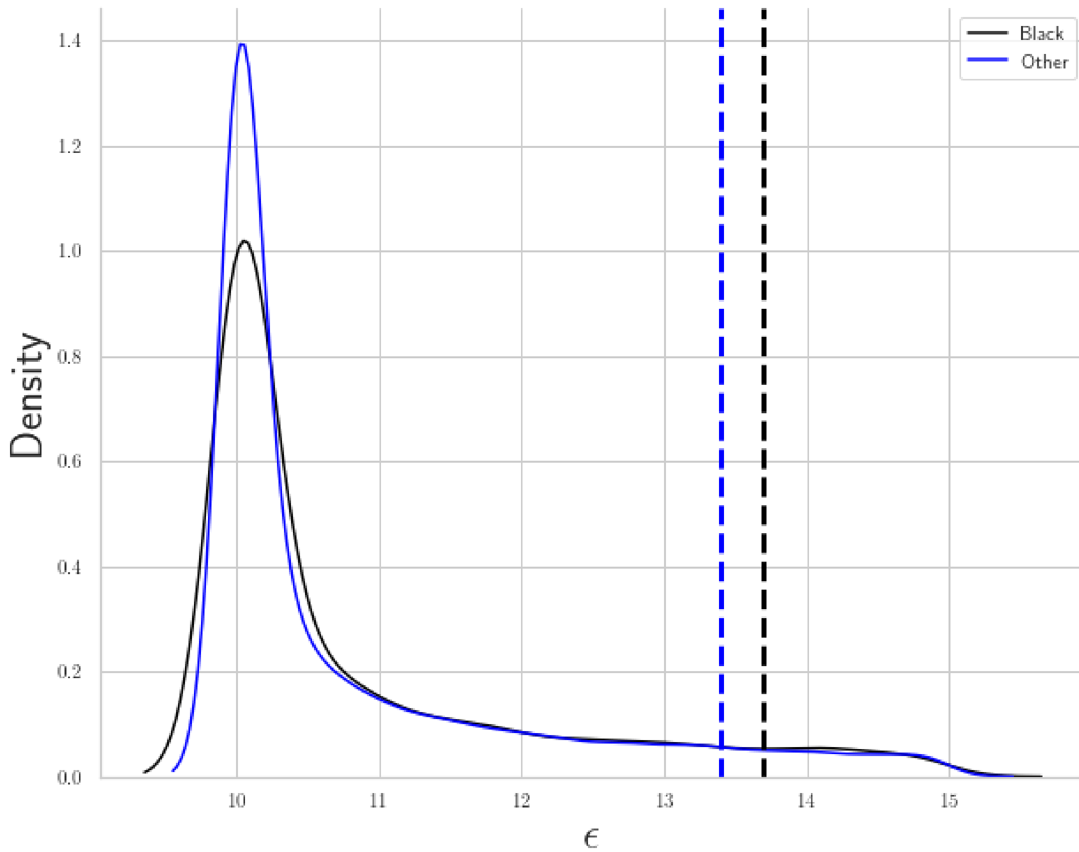
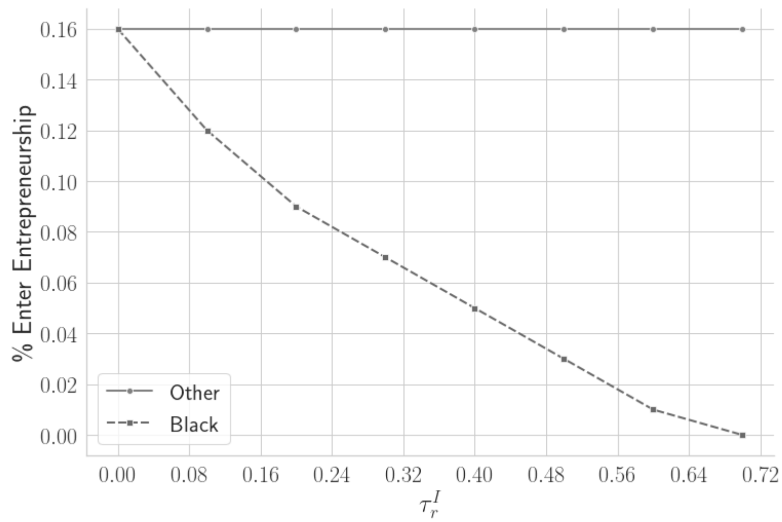
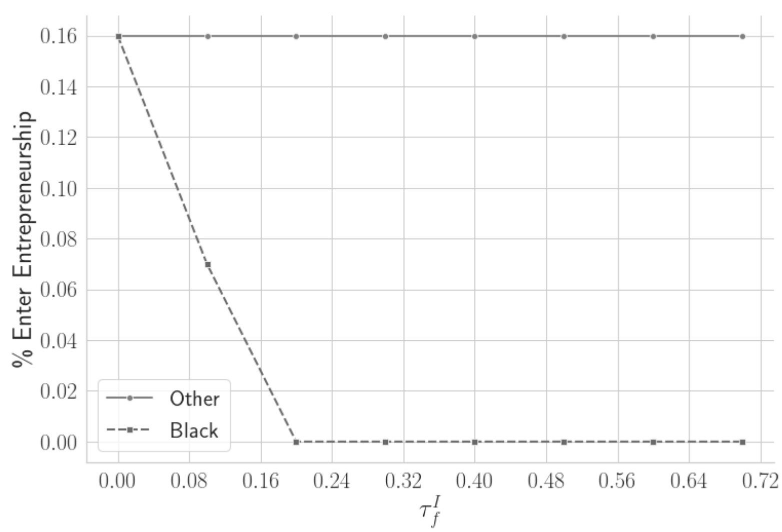


Figure 1: Threshold for Entry into Entrepreneurship by Race

This figure plots the hypothetical threshold of innate ability for entry into entrepreneurship by race that is implied by the model in section II. The figure is based on a simulated economy where 15% of the population is Black. Innate ability for entrepreneurship ϵ is drawn from a powerlaw distribution whose density is given by $f(\epsilon, a) = a\epsilon^{a-1}$, where we set a to 0.2 for illustration. We shift the distribution to have a mean of 10 and standard deviation of 5. The dashed lines represent the threshold for entry into entrepreneurship, which varies by race because of the combined effect of τ_r^f and τ_r^I. For this plot, we set $F = 1$, $\tau_r^f = 0$, $\tau_r^I = 0.1$. The threshold for entry, $\overline{O} = 18.03$, the 84th percentile of the distribution of U^* when there are no frictions ($\tau_r^I = \tau_r^f = 0$), so that 16% of the population enters into entrepreneurship. This matches U.S. statistics on the proportion of working adults in entrepreneurship.



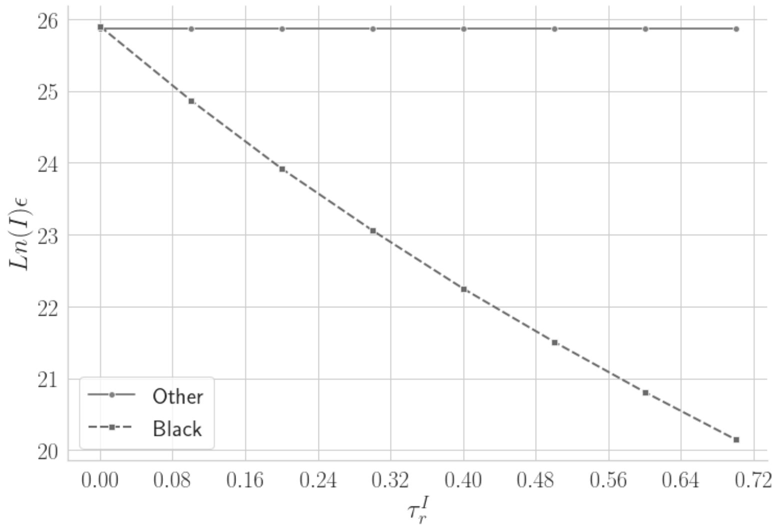
Panel A: Human Capital Investment



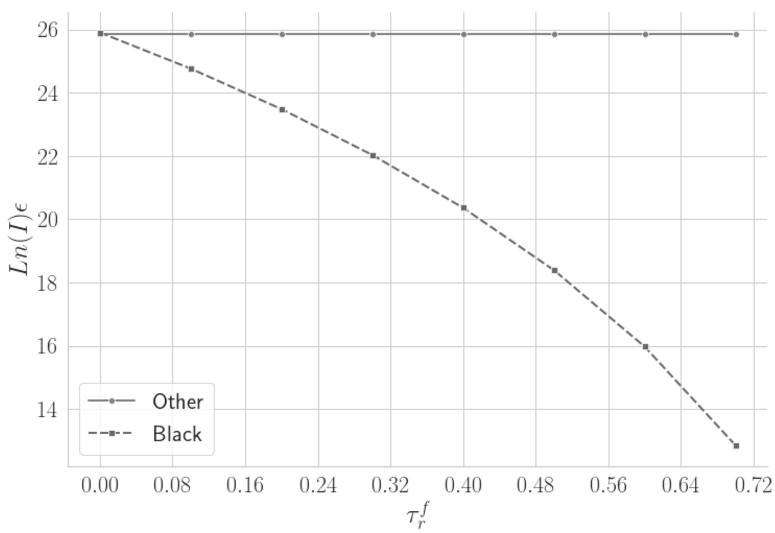
Panel B: Funding Gap

Figure 2: Frictions and Entry into Entrepreneurship by Race

This figure plots the effect of frictions in access to human capital (τ_r^I) and the funding gap (τ_r^f) on entry into entrepreneurship by race. These effects are implied by the model in section II. The figure is based on a simulated economy where 15% of the population is Black. Innate ability for entrepreneurship ϵ is drawn from a powerlaw distribution whose density is given by $f(\epsilon, a) = a\epsilon^{a-1}$, where we set a to 0.2 for illustration. We shift the distribution to have a mean of 10 and standard deviation of 5. For this plot, we set $F = 1$, $\tau_r^f = 0$ in Panel A, and $\tau_r^I = 0$ in Panel B. The threshold for entry, $\overline{O} = 18.03$, the 84th percentile of the distribution of U^* when there are no frictions ($\tau_r^I = \tau_r^f = 0$), so that 16% of the population enters into entrepreneurship.



Panel A: Human Capital Investment



Panel B: Funding Gap

Figure 3: Frictions and Effective Talent for Entrepreneurship

This figure plots the effect of frictions in access to human capital required to start high-growth startups (τ_r^I) and the funding gap (τ_r^f) on effective talent for entrepreneurship ($Ln(I)\epsilon$) by race. These effects are implied by the model in section II. The figure is based on a simulated economy where 15% of the population is Black. Innate ability for entrepreneurship ϵ is drawn from a powerlaw distribution whose density is given by $f(\epsilon, a) = a\epsilon^{a-1}$, where we set a to 0.2 for illustration. We shift the distribution to have a mean of 10 and standard deviation of 5. For this plot, we set $F = 1$, $\tau_r^f = 0$ in Panel A, and $\tau_r^I = 0$ in Panel B.

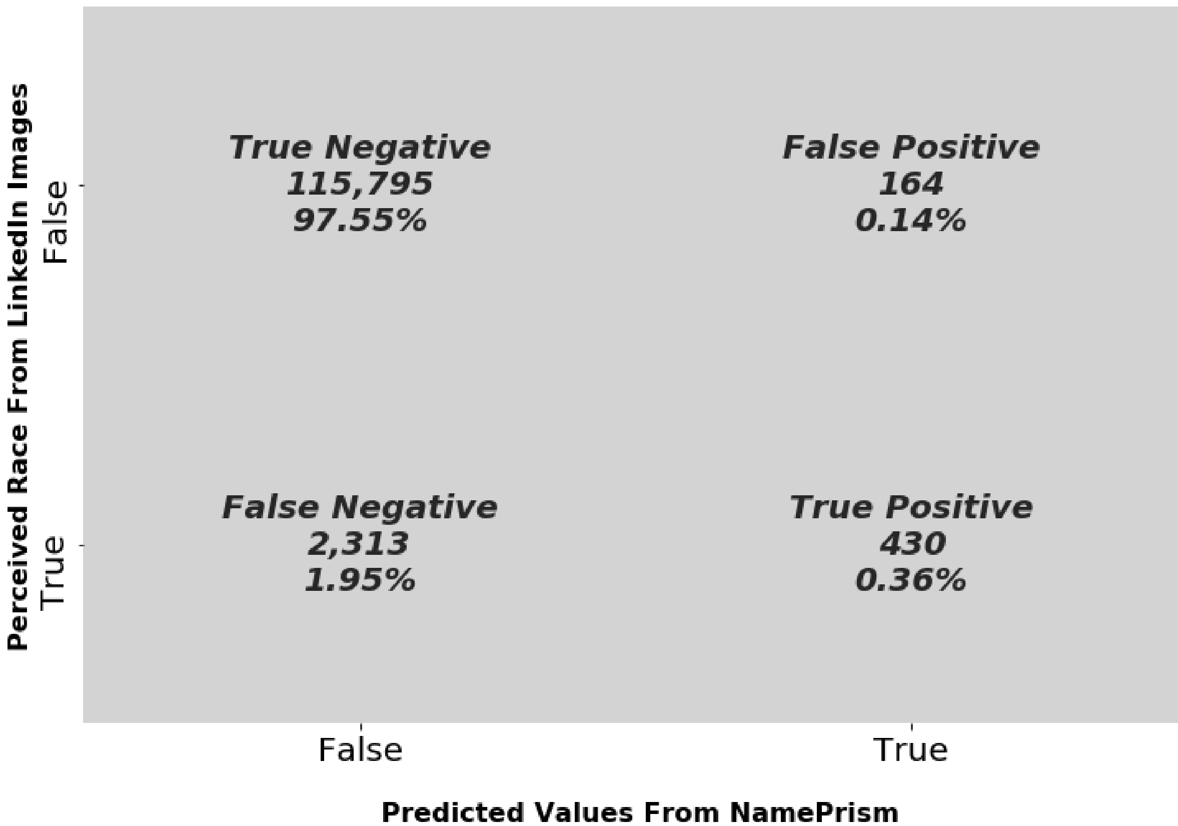


Figure 4: Perceived Race from Images versus Name Algorithms

This figure compares the classification of Black founders in our sample using perceived race from their images and the name prediction algorithm NamePrism, used in several published papers and developed by Ye, Han, Hu, Coskun, Liu, Qin and Skiena (2017). *False Negative* are the Black founders that we identified using images, which we would have missed if we had only used the predicted race by NamePrism, where a person is assigned to a race with at least a 50% probability. NamePrism takes the founder's first and last name as inputs and returns the probability that the founder is of a given race. See Appendix B for more detail on how we combine image- and name-processing algorithms and clerical review to develop our measure of perceived race.

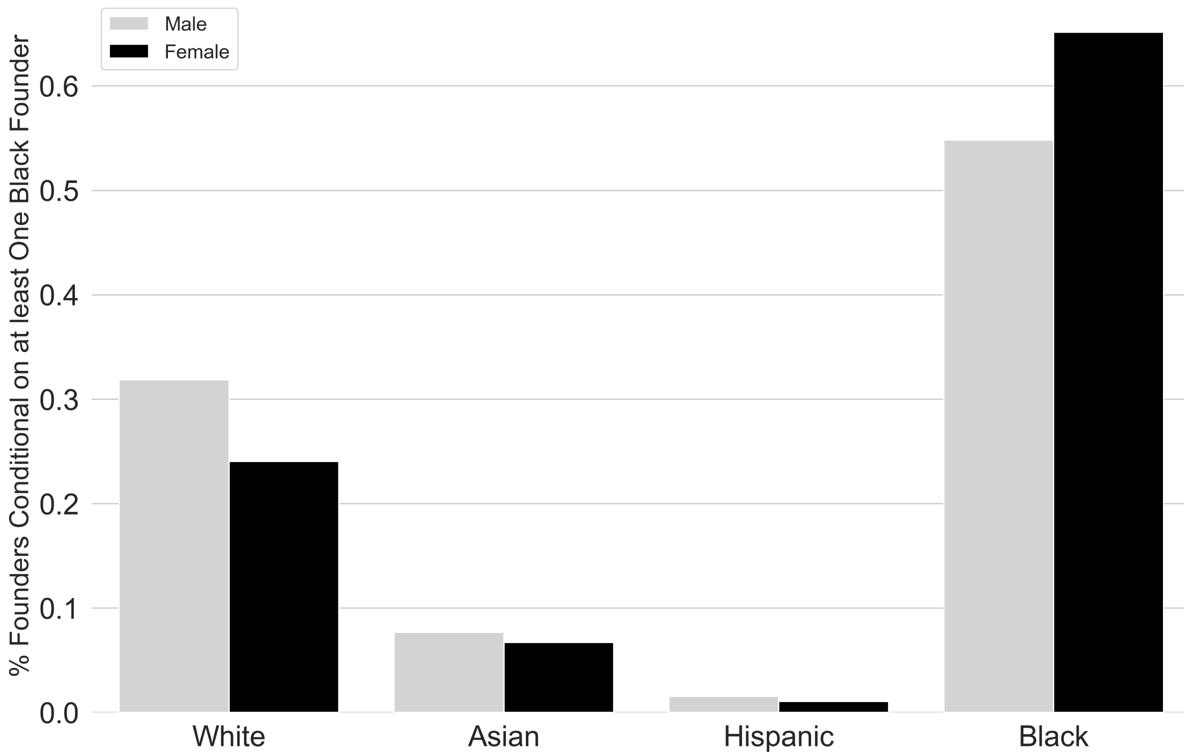


Figure 5: Racial Composition of Founding Teams with Black Founder

This figure shows the racial composition of founding teams with at least one Black founder, split by whether the Black founder is male or female. For each startup with at least one male or female Black founder, we calculate the proportion of co-founders that are White, Asian, and Hispanic. The black bars are for female Black founders and the grey bars are for male Black founders. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details. The black bar under White suggests that 30% of co-founders for female Black founders are White.

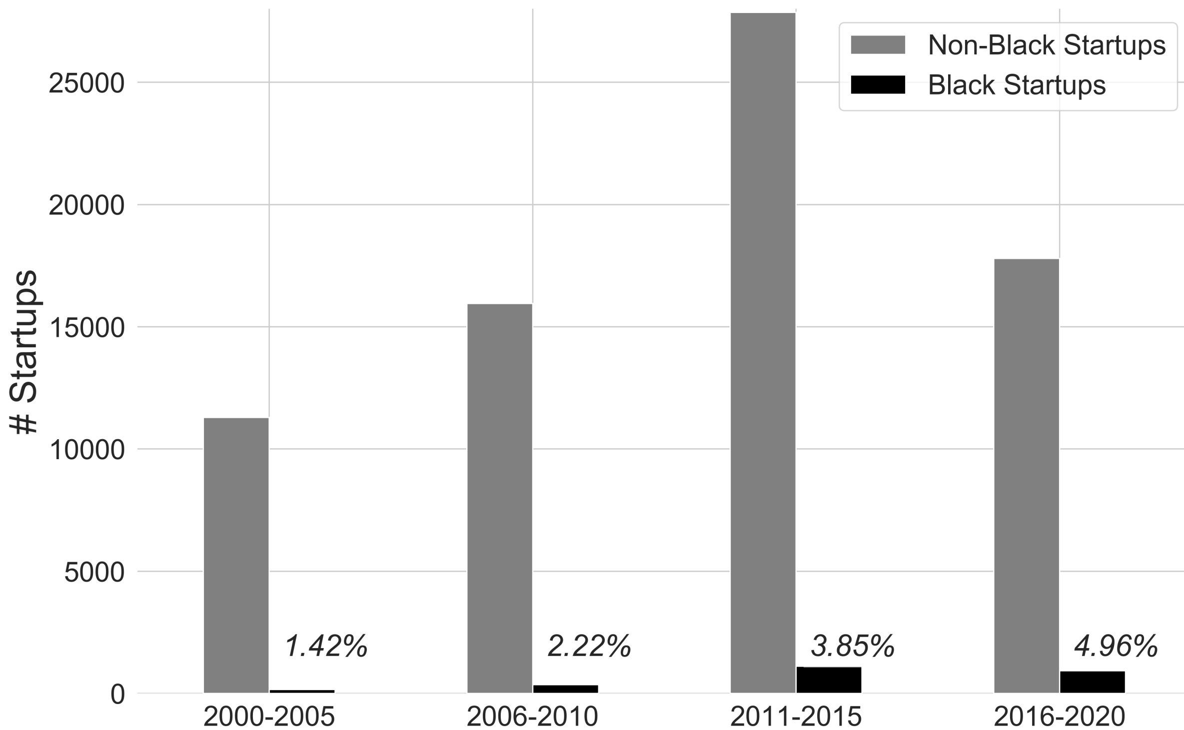


Figure 6: Count of Black and Non-Black Startups.

This figure plots the number of U.S.-based startups in our final sample, which comprises startups that were formed between 2000 and 2020. We plot the count of startups by whether the startup was formed by Black or non-Black founders. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details.

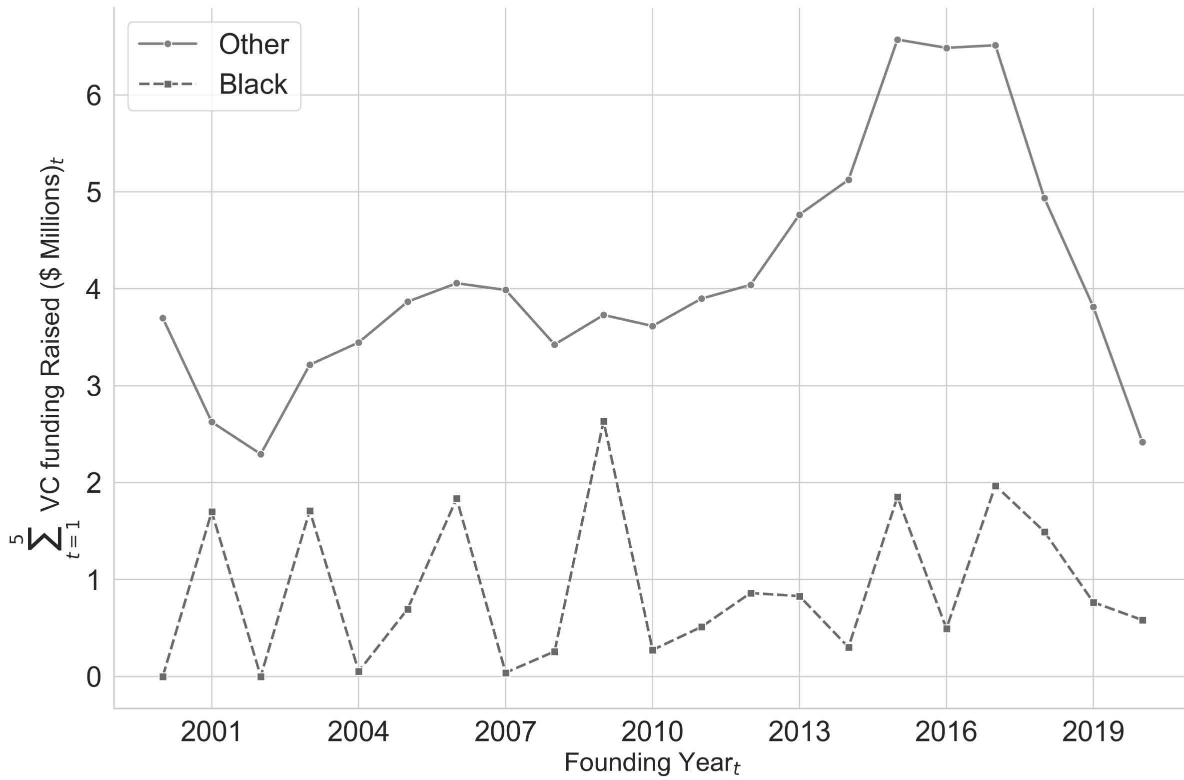


Figure 7: VC Funding Raised Five Years Following Startup Formation

This figure plots the average amount of VC funding raised by startups in our sample in the five years following company formation by race of the founder. We only include companies formed between 2000 and 2020. We define VC funding as rounds of funding raised from an investment firm running a fund with a limited partnership, where PitchBook classifies the round as "Early Stage," "Later Stage," or "Seed." Founding Year is the year the startup was formed. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details.

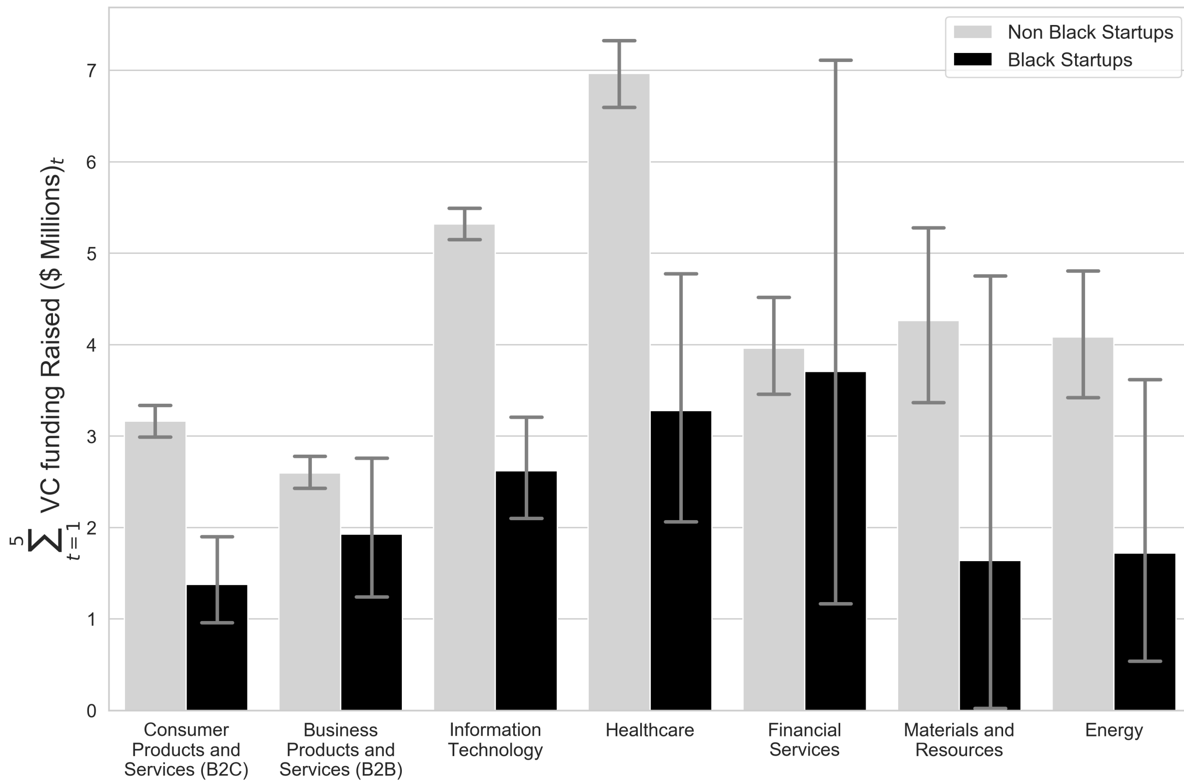


Figure 8: VC Funding Raised Five Years Following Startup Formation by Industry

This figure plots the average amount of VC funding that startups in our sample raised in the five years following company formation by industry and whether the startup has at least one Black founder. We define VC funding as rounds of funding raised from an investment firm running a fund with a limited partnership, where PitchBook classifies the round as "Early Stage," "Later Stage," or "Seed." Founding Year is the year the startup was formed. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details.

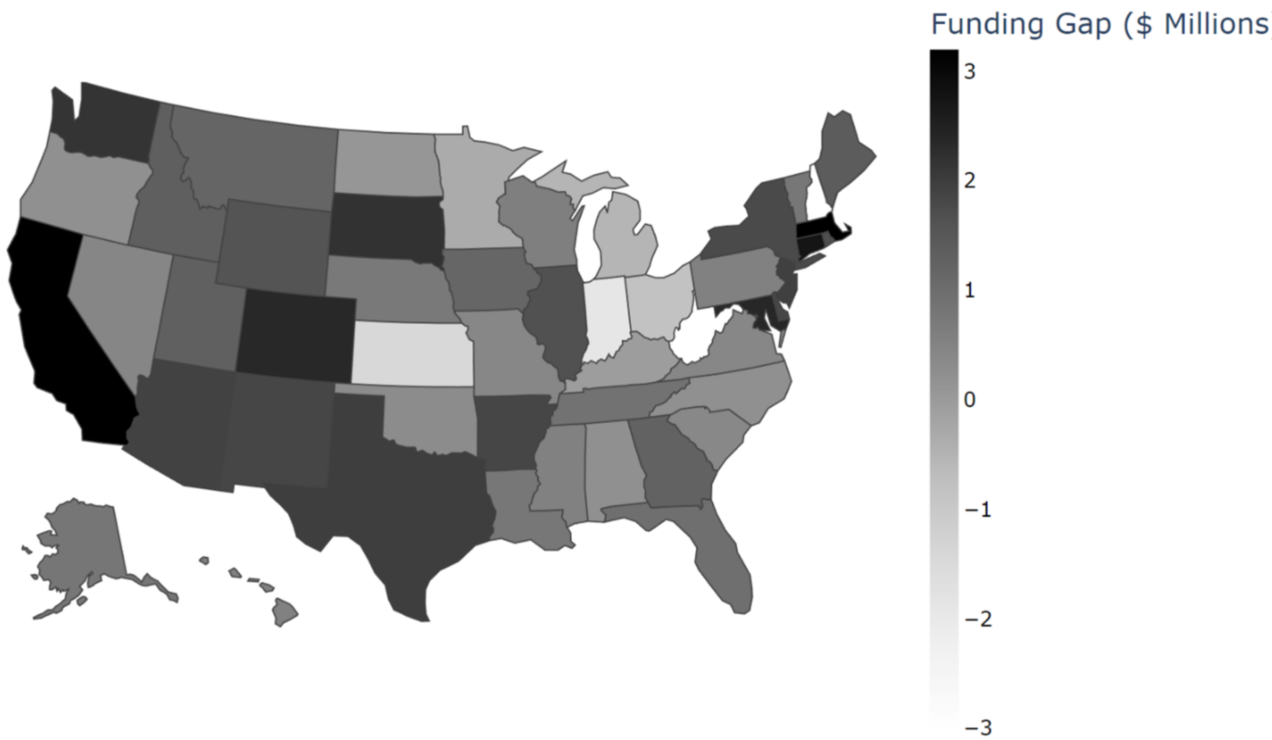


Figure 9: Difference in Mean VC Funding Raised Five Years Following Startup Formation by State

This figure plots the average difference in VC funding that startups raised in the five years following company formation for startups with no Black and at least one Black founder by state. We define VC funding as rounds of funding raised from an investment firm running a fund with a limited partnership, where PitchBook classifies the round as "Early Stage," "Later Stage," or "Seed." Founding Year is the year the startup was formed. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details.

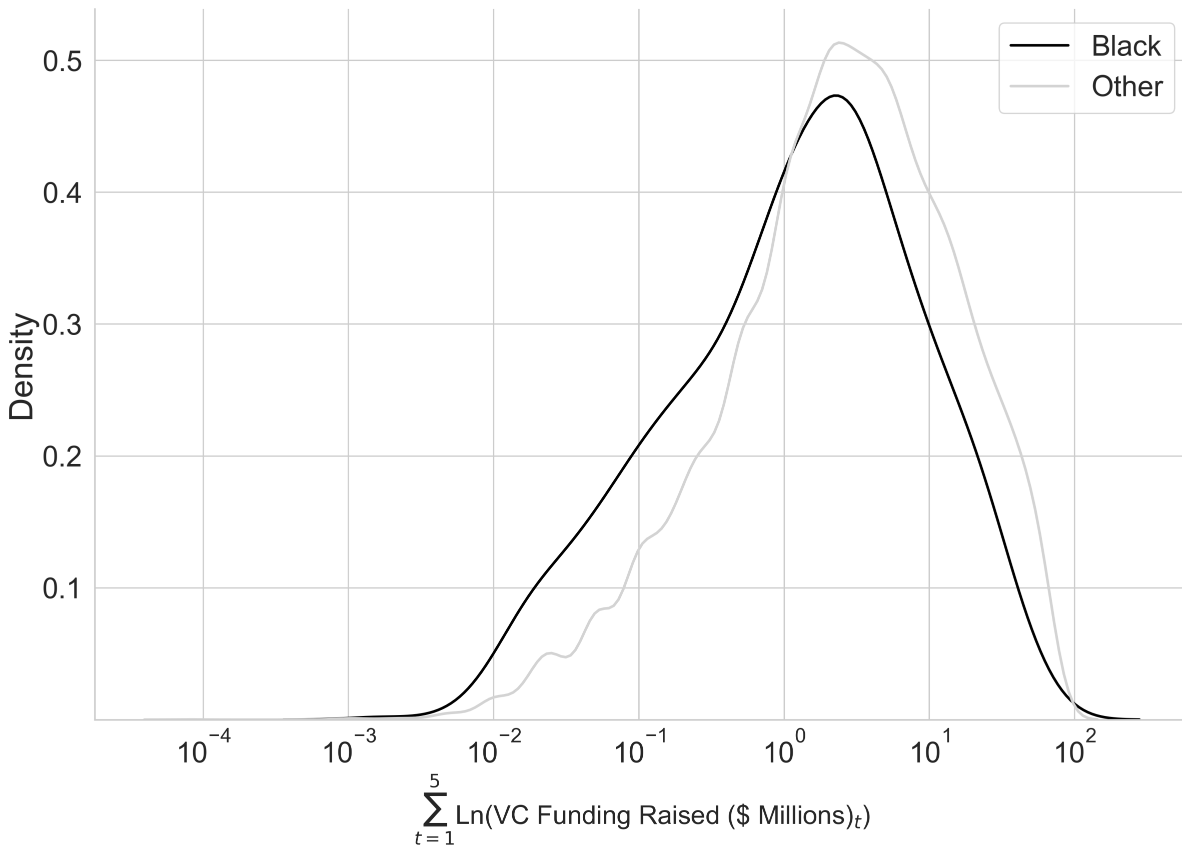


Figure 10: Distribution of Funding Raised in the First Five Years

This figure shows the distribution of funding raised in the first five years following startup formation, by whether the startup was formed by at least one Black founder. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details.

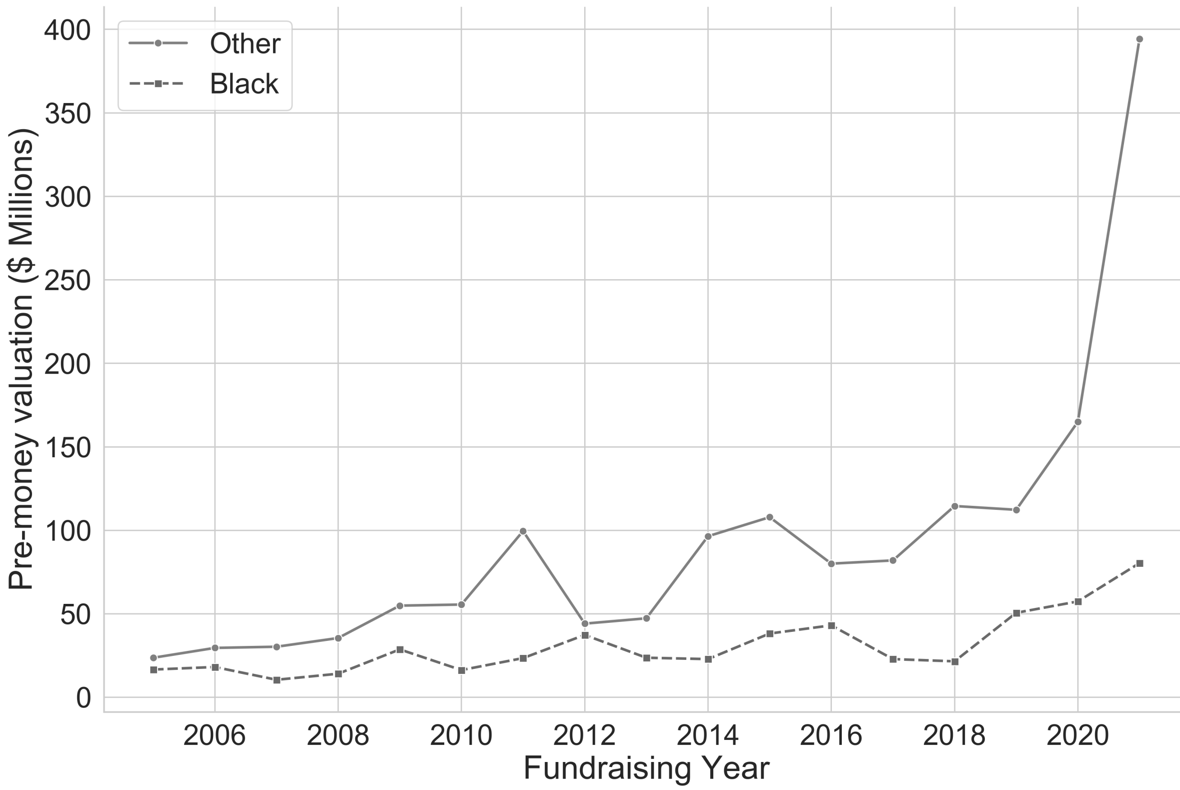


Figure 11: Pre-Money Valuations for Startups that Raised VC Funding

This figure plots the pre-money valuation for startups in our sample that raised at least one round of VC funding five years following company formation by race of the founder. The pre-money valuation is not available for all VC rounds in PitchBook and is only well populated after 2005, so we only include firms that raised VC funding between 2005 and 2021. We define VC funding as rounds of funding raised from an investment firm running a fund with a limited partnership, where PitchBook classifies the round as "Early Stage," "Later Stage," or "Seed." Fundraising Year is the year the startup raised VC funding. *Black* is an indicator for whether at least one of the startups founders are Black. We impute founder race using images, which we classify by combining image- and name-processing algorithms and clerical review. See Appendix B for more details. Pre-money valuation reflects how much venture investors valued the company just before making their investment.

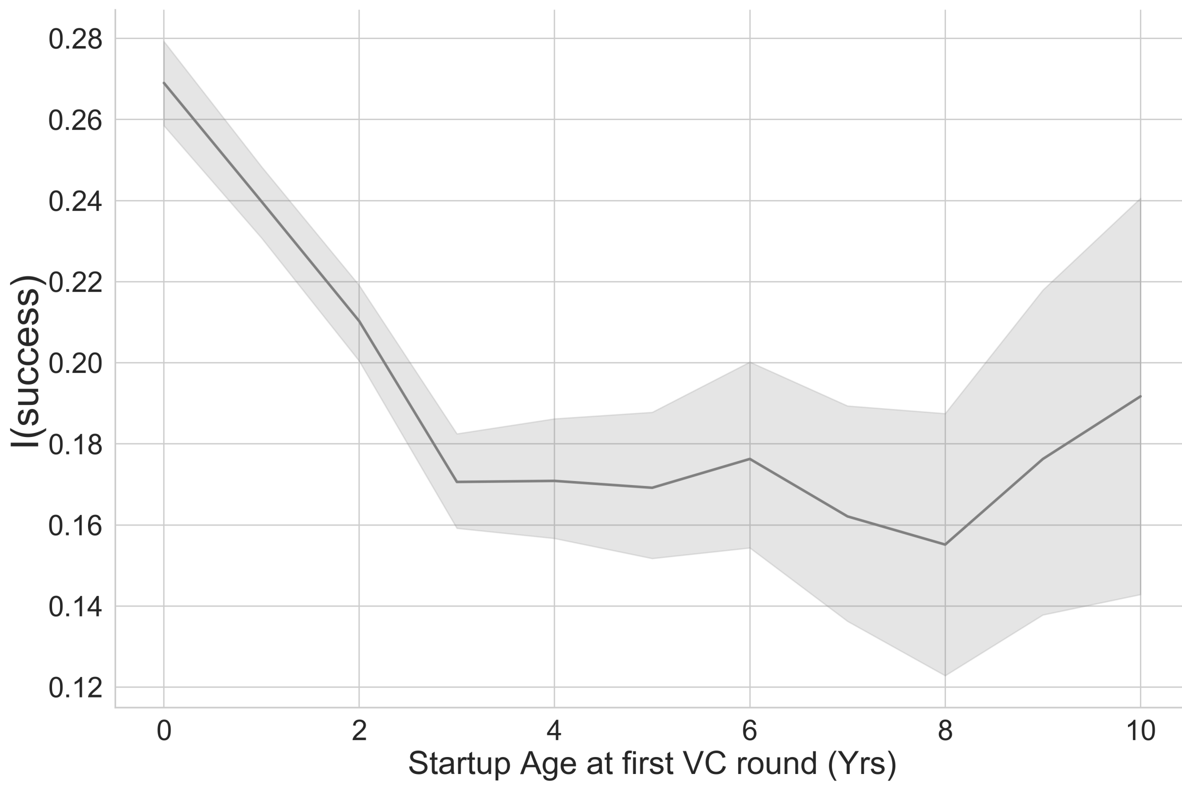


Figure 12: Startup success and time age at first VC-funding round

This figure plots the likelihood of success by the age of the startup when it first raised venture capital funding. Startup Age at first VC round is the difference between the year the startup was formed and the year the startup raised its first round of venture funding (VC). We define VC funding as rounds of funding raised from an investment firm running a fund with a limited partnership, where PitchBook classifies the round as "Early Stage," "Later Stage," or "Seed." *Success* is an indicator for whether the startup exited via an IPO or an acquisition by the second quarter of 2021.

Table 1: Characteristics of Startups

This table reports summary statistics for startups in PitchBook, formed between 2000 and 2020, where we could identify the race of at least one founder using images. *Black Owned* is an indicator that equals one if all startup founders are Black. *P(Black)* and *P(Female)* are the proportions of founders that are Black or female, respectively. We calculate this proportion only for the set of founders for whom we could identify race. *Year Founded* is the year the startup was formed. *I(PE Hub)* is an indicator that equals one for companies located in California, Massachusetts, or New York. *5yrs VC funding* is the total amount of funding that the startup raised from venture capital firms (firms classified in PitchBook as "Venture Capital," "PE/Buyout," "Growth/Expansion," "Corporate Venture Capital," "Other Private Equity," or "Not-For-Profit Venture Capital") in the five years following company formation. Similarly, *5 yrs Non-VC Funding* is the total amount of non-VC funding raised in the five years following company formation. Non-VC funding is funding raised from angel investors, accelerators, equity crowdfunding, and grants, which include the Small Business Innovation Research (SBIR) program and the Small Business Technology Transfer (STTR) program. *I(Patent)* is an indicator for startups that have at least one utility patent in the five years following company formation, according to the USPTO. *I(IPO)* is an indicator variable that equals to unity if the firm went public by the second quarter of 2021. *I(M&A)* is an indicator that equals one if the startup was acquired by the second quarter of 2021. *# Founders* is the number of startup founders. We identify founders by searching for the keywords "founder" or "owner" amongst executives associated with the startup. *I(Business Products and Services)*, *I(Consumer Products and Services)*, *I(Energy)*, *I(Financial Services), I(Healthcare)*, *I(Information Technology)*, and *I(Materials and Resources)* are indicators that equal one if the startup is in that industry sector. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. All continuous variables are winsorized at the 1% and 99% levels to minimize the influence of outliers.

	Black Owned		**Non-Black Owned**		
	N = 1,319		**N = 74,152**		
Panel A. Firm-level statistics	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
P(Black)	1.00	0.00	0.01	0.06	4698.72***
P(Female)	0.28	0.43	0.13	0.30	12.14***
Year Founded	2013.27	4.67	2011.54	5.15	13.29***
I(PE Hub)	0.36	0.48	0.48	0.50	−9.48***
# Founders	1.20	0.47	1.73	0.91	−40.16***
5yrs VC funding ($ Millions)	1.81	32.07	5.90	35.94	−4.58***
5yrs Non-VC Funding ($ Millions)	0.05	0.20	0.12	3.95	−4.31***
I(Has Patent)	0.02	0.15	0.05	0.22	−6.01***
I(IPO)	0.01	0.07	0.01	0.11	−3.19***
I(M&A)	0.09	0.29	0.24	0.43	−18.70***
I(Business Products and Services)	0.18	0.39	0.19	0.39	−0.62
I(Consumer Products and Services)	0.33	0.47	0.21	0.40	9.71***
I(Energy)	0.01	0.10	0.02	0.15	−3.91***
I(Financial Services)	0.03	0.17	0.04	0.20	−1.94*
I(Healthcare)	0.11	0.31	0.14	0.35	−4.24***
I(Information Technology)	0.33	0.47	0.39	0.49	−4.54***
I(Materials and Resources)	0.01	0.08	0.01	0.10	−1.67*

Table 1 - *continued* (Founder Statistics)

This table reports summary statistics for founders of startups in Panel A. This table only includes founders we could match to LinkedIn that had profile pictures allowing us to classify them by race. A unit of observation is a founder of a startup in Panel A above. *Black* is an indicator that equals one if the founder is Black. We classify a founder as Black using image- and name-processing algorithms and clerical review. *P(Skin Tone)* is the probability that a founder is Black, as computed by the image-processing algorithm. See Appendix B for more details. *Network Score* captures whether a founder attended the same school or worked in the same company as investors that funded companies in their industry and state. We only use information preceding startup formation to compute the network score. The score is the number of work and school pairs that are the same between the founder and partner that funded companies located in the same state and operating in the same industry, averaged over all partners in that industry-state dyad. For each founder-partner pair, we divide this overlap by the total number of unique work-school observations on the founder's resume and average over lead partners by weighting each observation by the number of deals involving the lead partner. See Appendix C for a more details. *I(Serial Founder)* is an indicator that equals one if the founder's LinkedIn profile indicated that they started another company whose name differs from and whose formation predates the startup that is the subject of our analysis. *(Top School)* is an indicator that equals one if the founder attended one of the top 20 universities, ranked by average SAT score of accepted freshmen in the year the startup raised funding (see Appendix D for the full list). *I(Founder-Inventor)* is an indicator for whether the founder was listed on a patent application assigned to a startup in the first five years following its founding. *# Prior Jobs* is the number of unique places where the founder worked before founding the startup. *I(Female)* is an indicator that equals one if the founder is female. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We winsorize all continuous variables at the 1% and 99% levels to minimize the influence of outliers.

	Black		**Non-Black**		
	N = 2,747		**N = 116,109**		
Panel B. Founder-level statistics	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
P(Skin Tone)	73.60	35.97	2.76	12.66	103.09***
Network Score	0.02	0.07	0.04	0.09	−11.78***
I(Founder-Inventor)	0.05	0.22	0.11	0.31	−13.05***
I(Serial Founder)	0.14	0.35	0.17	0.38	−4.33***
I(Female)	0.23	0.42	0.13	0.34	11.85***
# Jobs	2.32	2.69	2.22	2.40	1.87*
I(Has Bachelor)	0.54	0.50	0.53	0.50	0.79
I(Has MBA)	0.11	0.31	0.10	0.30	1.41
I(Has Masters)	0.14	0.34	0.14	0.35	−0.45
I(Has Ph.D.)	0.08	0.27	0.09	0.29	−2.82***
I(Top School)	0.17	0.38	0.17	0.37	0.63

Table 2: Association between Black Ownership and Likelihood of VC Funding (All PitchBook)

This table presents results from our analysis of the association between race and gender and funding raised in the five years following startup formation. We present coefficients from Poisson regressions run at the startup level, with standard errors in parentheses. The dependent variable, *I(Raised VC Funding)*, is an indicator for whether the company raised a round of VC funding 2, 3, 4, or 5 years following company formation. *P(Black)* is the proportion of founders that are Black. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

	I(Raised VC Funding)			
Dependent Variable:	Next 2yrs?	Next 3yrs?	Next 4yrs?	Next 5yrs?
	(1)	(2)	(3)	(4)
P(Black)	-0.385***	-0.327***	-0.282***	-0.271***
	(0.051)	(0.043)	(0.040)	(0.039)
P(Female)	-0.194***	-0.169***	-0.147***	-0.145***
	(0.021)	(0.018)	(0.017)	(0.016)
P(Serial Founder)	0.319***	0.302***	0.291***	0.277***
	(0.014)	(0.013)	(0.012)	(0.011)
P(Top School)	0.227***	0.225***	0.208***	0.205***
	(0.016)	(0.014)	(0.013)	(0.012)
Network score	1.407***	1.238***	1.152***	1.123***
	(0.063)	(0.056)	(0.052)	(0.049)
I(Has Patent)	0.475***	0.449***	0.440***	0.436***
	(0.019)	(0.016)	(0.014)	(0.013)
Ln(Count Founders)	0.423***	0.424***	0.421***	0.417***
	(0.011)	(0.010)	(0.009)	(0.009)
Observations	67695	68999	69764	70206
Log-likelihood	-43402.20	-47883.17	-50494.49	-52054.74
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Table 3: Association between Black Ownership and Funding Raised (All PitchBook)

This table presents results from our analysis of the association between race and gender and funding raised in the five years following startup formation. We present coefficients from Poisson regressions run at the (startup) level, with standard errors in parentheses. The dependent variable in Panel A, *VC Funding*, is the cumulative amount of VC funding the startup raised 2, 3, 4, or 5 years following company formation. In Panel B, the dependent variable is *Non-VC Funding*, the cumulative amount of non-VC funding the startup raised 2, 3, 4, or 5 years following company formation. Non-VC funding is funding raised from accelerators, equity crowdfunding, and grants, which include the Small Business Innovation Research (SBIR) program, and the Small Business Technology Transfer (STTR) program. *P(Black)* is the proportion of founders that are Black. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A:	**VC Funding**			
Dependent Variable:	Next 2yrs?	Next 3yrs?	Next 4yrs?	Next 5yrs?
	(1)	(2)	(3)	(4)
P(Black)	-1.036***	-1.089***	-1.058***	-1.010***
	(0.141)	(0.133)	(0.134)	(0.142)
P(Female)	-0.588***	-0.614***	-0.581***	-0.602***
	(0.052)	(0.051)	(0.051)	(0.051)
P(Serial Founder)	0.581***	0.565***	0.570***	0.563***
	(0.030)	(0.029)	(0.029)	(0.029)
P(Top School)	0.451***	0.462***	0.481***	0.495***
	(0.032)	(0.031)	(0.031)	(0.030)
Network score	2.973***	2.932***	2.906***	2.918***
	(0.116)	(0.112)	(0.112)	(0.111)
I(Has Patent)	0.914***	0.930***	0.931***	0.941***
	(0.038)	(0.035)	(0.034)	(0.032)
Ln(Count Founders)	0.662***	0.697***	0.749***	0.771***
	(0.025)	(0.024)	(0.023)	(0.023)
Observations	67695	68999	69764	70206
Log-likelihood	-201331.66	-294489.95	-392704.07	-482448.43
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Panel B:	**Non-VC Funding**			
	(1)	(2)	(3)	(4)
P(Black)	0.133	0.124	0.033	0.043
	(0.087)	(0.094)	(0.095)	(0.098)
P(Female)	0.009	0.017	0.009	-0.022
	(0.052)	(0.052)	(0.052)	(0.053)
P(Serial Founder)	-0.157***	-0.189***	-0.184***	-0.216***
	(0.049)	(0.050)	(0.051)	(0.051)
P(Top School)	0.379***	0.419***	0.391***	0.392***
	(0.047)	(0.046)	(0.046)	(0.046)
Network score	0.648***	0.974***	1.057***	1.176***
	(0.247)	(0.231)	(0.226)	(0.225)
I(Has Patent)	0.548***	0.645***	0.743***	0.738***
	(0.065)	(0.060)	(0.057)	(0.055)
Ln(Count Founders)	0.564***	0.566***	0.557***	0.577***
	(0.033)	(0.033)	(0.033)	(0.033)
Observations	57726	59718	60838	62158
Log-likelihood	-7359.57	-9980.11	-12166.31	-13888.63
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Table 4: How Important Are Omitted Variables?

Panel A presents coefficients from a bias-adjustment test proposed by Oster (2019). Given that this test was proposed using linear models, we first regress *Ln(VC funding (5 yrs))* on *P(Black)* and controls from Table 3 to estimate the bias adjusted coefficient and how important unobservable variables would have to be relative to observables, $\widetilde{\delta}$, to explain away the funding gap. Of course, only firms that raised at least a dollar of VC funding in the five years following venture formation are included in this test. Next, we estimate the bias adjusted coefficient of the proportion of Black founders on VC funding raised five years after startup formation, assuming unobserved variables are just as important as observed variables in explaining how much venture funding is raised, $\widetilde{\delta} = 1$. The bias adjusted coefficient in column (3) is computed as follows: $\beta^* = \widetilde{\beta} - \delta[\beta^o - \widetilde{\beta}]\frac{R_{max} - \widetilde{R}}{\widetilde{R} - R^o}$. β^* is the bias adjusted estimate of the funding gap. R_{max} is the maximum R-squared a researcher might hope to achieve from a regression that explains the amount of funding a startup raises using controls, $\widetilde{R}$ is the R-squared from the regression of VC funding on the proportion of founders that are Black with controls, and R^o is the R-squared without controls. Similarly, $\widetilde{\beta}$ and β^o are estimates of the funding gap with and without controls. In column (4) we compute how large unobserved variables would have to be relative to observed variables (δ) to explain away the funding gap. Panel B presents results from a Blinder-Oaxaca decomposition (following Fairlie, Robb and Robinson (2022*b*)) of the difference in the amounts of VC funding raised five years after startup formation by Black- and non-Black-founded startups. Here, Black is an indicator for whether *all* of the startup's founders are Black. Explanatory components decompose the mean differences into amounts explained by each independent variable, which we define in Table 1. When we decompose the Log (Difference) in funding, we condition on startups that raised at least some venture funding to avoid taking the log of zero. We standardize all variables in the decomposition to have a mean of zero and standard deviation of one.

Panel A: Oster (2019) Test ($R_{max} = 1.3 \times 0.288$)

	Baseline Effect (Std. error) $[R^2]$	Controlled Effect (Std. error) $[R^2]$	Identified Set	$\widetilde{\delta}$ for $\beta = 0$ given R_{max}
	(1)	(2)	(3)	(4)
P(Black)	-1.415*** (.093) [0.007]	-0.892*** (.091) [0.288]	[-1.415, -0.698]	3.798

Panel B: Blinder-Oaxaca Decomposition

	Dollar Difference (1)	Log(Difference) (2)
Venture Funding (5 yrs)		
No Black Founder	4.483	0.966
Has Black Founder	0.952	-0.562
Difference	3.531	1.529
Explanatory components		
Ln(Count Founders)	1.056	0.204
State X Year X Industry FE	0.231	0.072
Network Score	0.304	0.069
P(Female)	0.152	0.055
I(Has Patent)	0.234	0.036
P(Serial Founder)	0.183	0.012
P(Top School)	0.043	0.009
Total explained (controls)	2.205	0.475

Table 5: Association between Black Ownership and Funding Raised (Patent Sample)

This table presents results from our analysis of the association between race and gender and funding raised in the five years following a startup formation for the startups that filed at least one patent application in the five years following company formation. We present coefficients from Poisson regressions run at the startup level, with standard errors reported below in parentheses. The dependent variable, *VC Funding*, is the cumulative amount of VC funding the startup raised 2, 3, 4, or 5 years following company formation. . *P(Black)* is the proportion of founders that are Black. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A:	**VC Funding**			
Dependent Variable:	Next 2yrs?	Next 3yrs?	Next 4yrs?	Next 5yrs?
	(1)	(2)	(3)	(4)
P(Black)	-0.755**	-0.917***	-0.700***	-0.687**
	(0.320)	(0.296)	(0.265)	(0.275)
P(Female)	-0.478***	-0.408***	-0.355***	-0.345***
	(0.106)	(0.094)	(0.091)	(0.089)
P(Serial Founder)	0.383***	0.370***	0.374***	0.367***
	(0.048)	(0.044)	(0.044)	(0.043)
P(Top School)	0.233***	0.228***	0.269***	0.285***
	(0.049)	(0.045)	(0.044)	(0.043)
Network score	2.012***	1.990***	2.038***	2.052***
	(0.181)	(0.171)	(0.170)	(0.164)
I(Has Patent)	0.285***	0.307***	0.319***	0.343***
	(0.042)	(0.038)	(0.037)	(0.035)
Ln(Count Founders)	0.343***	0.337***	0.392***	0.423***
	(0.039)	(0.036)	(0.036)	(0.035)
Observations	10720	10998	11110	11187
Log-likelihood	-55311.31	-79530.35	-105522.17	-129039.55
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Table 6: Association between Black-Owned Assignees and Patent Outcomes

This table reports the estimated effect of the proportion of Black and female founders of a startup assigned a patent application on the likelihood the patent is granted, the number of citations the patent received, the number of scientific references, and the time between application and grant. The sample comprises assignees that applied for a patent between 2001 and 2021, where we could find at least one founder on Linkedin with a profile picture that allowed us to identify race. The dependent variable in Column (1), *I(Granted)*, is an indicator that equals one for startups whose patent application was ultimately granted. In Column (2), it is the number of citations the patent received (from subsequent patents) as of September 2022, (*Citations*). In Column (3), it is the number of references to scientific articles, *A Citations*, and in Column (4) it is the number of years between patent application and grant, *Years to Grant*. *P(Black)* is the proportion of founders that are Black. *Firm Age* is the number of years between when the firm was formed and when it applied for a patent. *Class X Year* denotes USPC class by application year fixed effects. We estimate Column (1) using a linear probability model (via maximum likelihood) and Columns (2), (3), and (4) using quasi-maximum likelihood Poisson models with robust standard errors. ^{g} denotes tests on the subset of applications that were granted. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(Granted)	Citations^g	A Citations^g	Years to Grant^g
	(1)	(2)	(3)	(4)
P(Black)	0.002	0.148	0.037	0.027
	(0.096)	(0.554)	(0.581)	(0.082)
P(Female)	-0.003	-0.309	0.089	-0.001
	(0.036)	(0.258)	(0.173)	(0.032)
P(Serial Founder)	-0.035	0.209**	0.414***	0.049**
	(0.024)	(0.098)	(0.114)	(0.022)
P(Top School)	0.043*	0.084	0.273**	0.062***
	(0.023)	(0.099)	(0.110)	(0.020)
Network score	0.217**	0.927***	1.402***	-0.107
	(0.099)	(0.333)	(0.459)	(0.084)
Ln(Count Founders)	0.064***	-0.087	0.407***	0.030*
	(0.017)	(0.071)	(0.088)	(0.016)
USPC Class X Year FE?	Yes	Yes	Yes	Yes
State X Year X Industry FE?	Yes	Yes	Yes	Yes
Observations	9308	4306	4306	4306
Log-likelihood	-8003.35	-32007.08	-26054.13	-7349.48

Table 7: Association between Black Ownership and Exits

This table investigates the relationship between the race of startup founders and startup outcomes for companies that raised their first VC round at least three years following company formation. We present coefficients from OLS regressions run at the startup level, with standard errors reported below in parentheses. The dependent variable, *I(Success)*, is an indicator that equals one if the startup exited via an acquisition or an IPO by Q2 2021. *P(Black)* is the proportion of founders that are Black. *Ln(Other Funding)* is the amount of funding raised from non-VC investors in the five years following company formation. *Ln(VC funding)* is the log of the total amount of VC funding raised in the five years following company formation. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(Success)			
	(1)	(2)	(3)	(4)
P(Black)	-0.019		-0.015	0.003
	(0.020)		(0.020)	(0.019)
P(Female)		-0.026***	-0.021**	-0.015
		(0.010)	(0.010)	(0.010)
P(Serial Founder)			0.037***	0.032***
			(0.010)	(0.010)
P(Top School)			0.016	0.011
			(0.010)	(0.010)
Network score			0.075	0.046
			(0.054)	(0.054)
I(Has Patent)			0.033**	0.026*
			(0.015)	(0.015)
Ln(Count Founders)			0.011	0.006
			(0.007)	(0.007)
Ln(VC Funding)				0.019***
				(0.002)
Observations	6310	6310	6310	6310
Adjusted R^2	0.065	0.065	0.070	0.084
State X Year X Industry FE?	YES	YES	YES	YES

Table 8: Association between Black Ownership and VC Funding Raised (Dynamic-Reversal)

This table investigates the association between race and the likelihood and amount of venture funding raised in follow-on rounds after seed funding. This table only comprises startups that raised a non-zero amount of late-stage funding to examine fundraising dynamics over time, holding the composition of startups fixed. *I(Early Stage)* is an indicator for startups that raised early-stage funding (Series A or B). *VC Funding ES* is the amount of early-stage funding the startup raised. *I(Late Stage)* is an indicator for startups that raised late-stage funding (Series C or later). *VC Funding LS* is the amount of late-stage funding the startup raised. *Ln(Seed Round)* is the log amount of seed funding the startup raised. *P(Black)* is the proportion of founders that are Black. We define all other variables in Table 1. In all columns, we restrict the sample only to startups that raised seed funding. In the Appendix A.A.1, we provide more details on the various stages of funding. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	I(Early Stage)	I(Late Stage)	VC Funding (ES)	VC Funding (LS)
	(1)	(2)	(3)	(4)
P(Black)	-0.099***	-0.018	-0.849***	-0.400
	(0.027)	(0.024)	(0.239)	(0.396)
P(Female)	-0.067***	-0.018	-0.564***	-0.817***
	(0.014)	(0.012)	(0.082)	(0.127)
P(Serial Founder)	0.045***	0.009	0.240***	0.106
	(0.011)	(0.009)	(0.051)	(0.080)
P(Top School)	0.053***	0.029***	0.289***	0.316***
	(0.012)	(0.010)	(0.054)	(0.081)
Network score	0.554***	0.222***	2.612***	2.377***
	(0.059)	(0.053)	(0.231)	(0.348)
I(Has Patent)	0.111***	0.093***	0.569***	0.392***
	(0.019)	(0.019)	(0.071)	(0.096)
Ln(Seed Round)	0.032***	0.060***	0.311***	0.365***
	(0.003)	(0.002)	(0.018)	(0.025)
Ln(Count Founders)	0.119***	0.094***	0.528***	0.733***
	(0.008)	(0.007)	(0.040)	(0.060)
Observations	15588	15588	15588	15588
Log-likelihood	-10056.67	-7868.89	-125102.79	-300292.31
State X Year X Industry FE?	YES	YES	YES	YES

Table 9: Association between Black Ownership and VC Funding Raised (Cross-Sectional Tests)

This table presents results from our analysis of the association between race and gender and VC funding raised in the five years following startup formation. We present coefficients from Poisson regressions run at the startup level, with standard errors reported below in parentheses. The dependent variable, *Ln(VC Funding)*, is the cumulative amount of VC funding the startup raised in the five years following company formation. The primary independent variables are interaction terms of *P(Black)*, the proportion of founders that are Black, and *I(PE Hub)*, an indicator for startups located in California, Massachusetts, and New York, or *I(Information Technology)*, an indicator for startups in the information technology sector. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	**VC Funding 5yrs**			
	(1)	(2)	(3)	(4)
P(Black) × I(PE Hub)	0.213			
	(0.251)			
P(Black) × I(Information Technology)		0.149		
		(0.285)		
P(Black) × I(Has Patent)			0.971**	
			(0.443)	
P(Black) × P(Serial Founder)				0.359
				(0.366)
P(Black)	-1.158***	-1.075***	-1.111***	-1.116***
	(0.169)	(0.188)	(0.147)	(0.163)
P(Female)	-0.602***	-0.602***	-0.602***	-0.602***
	(0.051)	(0.051)	(0.051)	(0.051)
P(Serial Founder)	0.563***	0.563***	0.563***	0.560***
	(0.029)	(0.029)	(0.029)	(0.029)
P(Top School)	0.495***	0.495***	0.495***	0.496***
	(0.030)	(0.030)	(0.030)	(0.030)
Network score	2.918***	2.919***	2.919***	2.918***
	(0.111)	(0.111)	(0.111)	(0.111)
I(Has Patent)	0.941***	0.941***	0.934***	0.941***
	(0.032)	(0.032)	(0.033)	(0.032)
Ln(Count Founders)	0.771***	0.771***	0.771***	0.771***
	(0.023)	(0.023)	(0.023)	(0.023)
Observations	70206	70206	70206	70206
Log-likelihood	-482439.74	-482443.44	-482360.07	-482430.07
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Table 10: Association between Lead Partner Race and VC Funding for Black Founders

This table investigates the association between the race of a lead partner and the proportion of deals involving the lead partner where at least one of the startup's founders is Black. Angel investors do not appear in this table. We present coefficients from OLS regressions run at the investor-startup level, with standard errors reported below in parentheses. This test comprises the lead partners that PitchBook associated with specific deals and the lead partner we matched to LinkedIn (and obtained pictures that allowed us to classify her or him by race). In Panel A, the dependent variable, *I(Invested in Black Founder)*, indicates whether the partner made at least one investment in a Black-founded startup. In Panel B, the dependent variable, *I(Successful Black Founder)*, indicates whether the partner made at least one investment in a successful Black-founded startup. Success indicates whether the startup exits via an IPO or acquisition by Q2 2021. *I(Black)* is an indicator that equals one if the lead partner on the deal is Black. We define *I(Female)*, *I(Asian)*, and *I(Hispanic)* analogously. The omitted category is white male partners. *I(Top School)* is an indicator for lead partners that attended a top 20 U.S. school (see Appendix D for the full list). *Ln(Experience (Yrs))* log difference between the year of the lead partner's first deal according to PitchBook and 2021. *Ln(# Investments)* is the log number of investments that the lead partner made as of Q2 2021. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A:	I(Invested in Black Founder)			
	(1)	(2)	(3)	(4)
I(Black)	0.085***	0.086***	0.086***	0.086***
	(0.022)	(0.022)	(0.022)	(0.022)
I(Female)		0.005	0.005	0.005
		(0.004)	(0.004)	(0.004)
I(Asian)			0.001	0.000
			(0.003)	(0.003)
I(Hispanic)				-0.018
				(0.014)
P(Serial Founder)	-0.004**	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
P(Top School)	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Network score	-0.028***	-0.028***	-0.028***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.007)
I(Has Patent)	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Count Founders)	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	79,064	79,064	79,064	79,064
Adjusted R^2	0.045	0.045	0.045	0.045
Industry X Year FE?	YES	YES	YES	YES
Investor FE?	YES	YES	YES	YES

Panel B:	I(Successful Black Founder)			
	(1)	(2)	(3)	(4)
I(Black)	0.012**	0.012**	0.012**	0.012**
	(0.006)	(0.006)	(0.006)	(0.006)
I(Female)		-0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.001)
I(Asian)			0.000	0.000
			(0.001)	(0.001)
I(Hispanic)				-0.002
				(0.002)
P(Serial Founder)	-0.001*	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
P(Top School)	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Network score	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
I(Has Patent)	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Count Founders)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(VC Funding)	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	79,064	79,064	79,064	79,064
Adjusted R^2	-0.027	-0.027	-0.027	-0.027
Industry X Year FE?	YES	YES	YES	YES
Investor FE?	YES	YES	YES	YES

REFERENCES

Anwar, Shamena, and Hanming Fang. 2006. "An alternative test of racial prejudice in motor vehicle searches: Theory and evidence." *American Economic Review*, 96(1): 127–151.

Arrow, K.J. 1973. "The theory of discrimination." In *Discrimination in Labor Markets.* 3–33. Princeton University Press.

Åstebro, Thomas, Ramzi Rafih, and Carlos J Serrano. 2022. "Venture Capital Financing in Europe: Gender and Ethnic Diversity in Founder Teams." *The Journal of Portfolio Management*, 48(9): 250–271.

Ayres, Ian. 2002. "Outcome tests of racial disparities in police practices." *Justice research and Policy*, 4(1-2): 131–142.

Bates, Timothy, and William D Bradford. 1992. "Factors affecting new firm success and their use in venture capital financing." *The Journal of Entrepreneurial Finance*, 2(1): 23–38.

Bates, Timothy, William D Bradford, and William E Jackson. 2018. "Are minority-owned businesses underserved by financial markets? Evidence from the private-equity industry." *Small Business Economics*, 50(3): 445–461.

Becker, Gary S. 1993. "Nobel lecture: The economic way of looking at behavior." *Journal of political economy*, 101(3): 385–409.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend. 2016. "The impact of venture capital monitoring." *The Journal of Finance*, 71(4): 1591–1622.

Blanchflower, David G, Phillip B Levine, and David J Zimmerman. 2003. "Discrimination in the small-business credit market." *Review of Economics and Statistics*, 85(4): 930–943.

Bohren, J Aislinn, Alex Imas, and Michael Rosenberg. 2019. "The dynamics of discrimination: Theory and evidence." *American economic review*, 109(10): 3395–3436.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2016. "Stereotypes." *The Quarterly Journal of Economics*, 131(4): 1753–1794.

Butler, Alexander W, Erik J Mayer, and James P Weston. 2022. "Racial Disparities in the Auto Loan Market." *The Review of Financial Studies.*

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. 2020. "Race and economic opportunity in the United States: An intergenerational perspective." *The Quarterly Journal of Economics*, 135(2): 711–783.

Cohn, Jonathan B, Zack Liu, and Malcolm Wardlaw. 2021. "Count data in finance." *Available at SSRN.*

Cornell, Bradford, and Ivo Welch. 1996. "Culture, information, and screening discrimination." *Journal of political Economy*, 104(3): 542–571.

Egan, Mark L, Gregor Matvos, and Amit Seru. 2017. "When Harry fired Sally: The double standard in punishing misconduct." National Bureau of Economic Research.

Eisfeldt, Andrea L, and Dimitris Papanikolaou. 2014. "The value and ownership of intangible capital." *American Economic Review*, 104(5): 189–94.

Ewens, Michael, and Richard R Townsend. 2020. "Are early stage investors biased against women?" *Journal of Financial Economics*, 135(3): 653–677.

Fairlie, Robert, Alicia Robb, and David T Robinson. 2022*a*. "Black and white: Access to capital among minority-owned start-ups." *Management Science*, 68(4): 2377–2400.

Fairlie, Robert, Alicia Robb, and David T Robinson. 2022*b*. "Black and white: Access to capital among minority-owned start-ups." *Management Science*, 68(4): 2377–2400.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist. 2020. "What is a patent worth? Evidence from the US patent "lottery"." *The Journal of Finance*, 75(2): 639–682.

Forscher, Patrick S, William TL Cox, Markus Brauer, and Patricia G Devine. 2019. "Little race or gender bias in an experiment of initial review of NIH R01 grant proposals." *Nature human behaviour*, 3(3): 257–264.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. 2013. "Human capital and regional development." *The Quarterly journal of economics*, 128(1): 105–164.

Ginther, Donna K, Jodi Basner, Unni Jensen, Joshua Schnell, Raynard Kington, and Walter T Schaffer. 2018. "Publications as predictors of racial and ethnic differences in NIH research awards." *PLoS One*, 13(11): e0205929.

Ginther, Donna K, Walter T Schaffer, Joshua Schnell, Beth Masimore, Faye Liu, Laurel L Haak, and Raynard Kington. 2011. "Race, ethnicity, and NIH research awards." *Science*, 333(6045): 1015–1019.

Gompers, Paul A, and Sophie Q Wang. 2017. "Diversity in innovation." National Bureau of Economic Research.

Gompers, Paul A, Vladimir Mukharlyamov, and Yuhai Xuan. 2016. "The cost of friendship." *Journal of Financial Economics*, 119(3): 626–644.

Gompers, Paul A, Will Gornall, Steven N Kaplan, and Ilya A Strebulaev. 2020. "How do venture capitalists make decisions?" *Journal of Financial Economics*, 135(1): 169–190.

Gornall, Will, and Ilya A Strebulaev. 2020. "Gender, race, and entrepreneurship: A randomized field experiment on venture capitalists and angels." *Available at SSRN*.

Granovetter, Mark S. 1973. "The strength of weak ties." *American journal of sociology*, 78(6): 1360–1380.

Guzman, Jorge, and Scott Stern. 2020. "The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US States, 1988–2014." *American Economic Journal: Economic Policy*, 12(4): 212–43.

Hadlock, Charles J, and Joshua R Pierce. 2010. "New evidence on measuring financial constraints: Moving beyond the KZ index." *The review of financial studies*, 23(5): 1909–1940.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda. 2013. "Who creates jobs? Small versus large versus young." *Review of Economics and Statistics*, 95(2): 347–361.

Hebert, Camille. 2020. "Gender stereotypes and entrepreneur financing."

Hirschey, Mark, and Vernon J Richardson. 2004. "Are scientific indicators of patent quality useful to investors?" *Journal of Empirical Finance*, 11(1): 91–107.

Howell, Sabrina T, and Ramana Nanda. 2019. "Networking frictions in venture capital, and the gender gap in entrepreneurship." National Bureau of Economic Research.

Howell, Sabrina T, Theresa Kuchler, and Johannes Stroebel. 2021. "Which lenders had the highest minority share among their Payment Protection Program (PPP) loans?" Working Paper.

Hsieh, Chang-Tai, Erik Hurst, Charles I Jones, and Peter J Klenow. 2019. "The allocation of talent and us economic growth." *Econometrica*, 87(5): 1439–1474.

Hsu, David H, and Rosemarie H Ziedonis. 2013. "Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents." *Strategic Management Journal*, 34(7): 761–781.

Hurtado, Agustin, and Jung Sakong. 2022. "The Effect of Minority Bank Ownership on Minority Credit."

Ivashina, Victoria, and Josh Lerner. 2019. "Pay now or pay later? The economics within the private equity partnership." *Journal of Financial Economics*, 131(1): 61–87.

Kortum, Samuel, and Josh Lerner. 2001. "Does venture capital spur innovation?" In *Entrepreneurial inputs and outcomes: New studies of entrepreneurship in the United States*. Emerald Group Publishing Limited.

Lerner, Josh, and Ramana Nanda. 2020. "Venture capital's role in financing innovation: What we know and how much we still need to learn." *Journal of Economic Perspectives*, 34(3): 237–61.

Marx, Matt, and Aaron Fuegi. 2020. "Reliance on science: Worldwide front-page patent citations to scientific articles." *Strategic Management Journal*, 41(9): 1572–1594.

Marx, Matt, and Aaron Fuegi. 2022. "Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations." *Journal of Economics & Management Strategy*, 31(2): 369–392.

Nahata, Rajarishi. 2019. "Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting." *Journal of Corporate Finance*, 58: 624–649.

Oaxaca, Ronald L, and Michael R Ransom. 1994. "On discrimination and the decomposition of wage differentials." *Journal of econometrics*, 61(1): 5–21.

Oster, Emily. 2019. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204.

Park, Yongjin, and Susan Coleman. 2009. "Credit rationing and black-owned firms: is there evidence of discrimination?" *Journal of Developmental Entrepreneurship*, 14(03): 255–271.

Phelps, Edmund S. 1972. "The statistical theory of racism and sexism." *The american economic review*, 62(4): 659–661.

Phillips, P Jonathon, Amy N Yates, Ying Hu, Carina A Hahn, Eilidh Noyes, Kelsey Jackson, Jacqueline G Cavazos, Géraldine Jeckeln, Rajeev Ranjan, Swami Sankaranarayanan, et al. 2018. "Face recognition accuracy of forensic examiners, superrecognizers, and face recognition algorithms." *Proceedings of the National Academy of Sciences*, 115(24): 6171–6176.

Poege, Felix, Dietmar Harhoff, Fabian Gaessler, and Stefano Baruffaldi. 2019. "Science quality and the value of inventions." *Science advances*, 5(12): eaay7323.

Puri, Manju, and Rebecca Zarutskie. 2012. "On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms." *The Journal of Finance*, 67(6): 2247–2293.

Quadrini, Vincenzo. 2000. "Entrepreneurship, saving, and social mobility." *Review of economic dynamics*, 3(1): 1–40.

Raffo, Julio. 2020. "MATCHIT: Stata module to match two datasets based on similar text patterns."

Rubinstein, Yona, and Ross Levine. 2020. "Selection into entrepreneurship and self-employment." National Bureau of Economic Research, London School of Economics and Political Science.

Sarada, and Oana Tocoian. 2022. "Entrepreneurship and the american dream: How far does the upward mobility ladder reach?"

Schumpeter, Joseph. 1911. "Theorie der wirtschaftlichen Entwicklung." In *Joseph Alois Schumpeter*. 5–59. Springer.

Scott, Erin L, Pian Shu, and Roman M Lubynsky. 2020. "Entrepreneurial uncertainty and expert evaluation: An empirical analysis." *Management Science*, 66(3): 1278–1299.

Serengil, Sefik Ilkin, and Alper Ozpinar. 2020. "LightFace: A Hybrid Deep Face Recognition Framework." 23–27, IEEE.

Shane, Scott. 2000. "Prior knowledge and the discovery of entrepreneurial opportunities." *Organization science*, 11(4): 448–469.

Small, Mario L, and Devah Pager. 2020. "Sociological perspectives on racial discrimination." *Journal of Economic Perspectives*, 34(2): 49–67.

Smith, Baylee, and Angelino Viceisza. 2018. "Bite me! ABC's Shark Tank as a path to entrepreneurship." *Small Business Economics*, 50(3): 463–479.

Ye, Junting, Shuchu Han, Yifan Hu, Baris Coskun, Meizhu Liu, Hong Qin, and Steven Skiena. 2017. "Nationality classification using name embeddings." 1897–1906.

Younkin, Peter, and Venkat Kuppuswamy. 2018. "The colorblind crowd? Founder race and performance in crowdfunding." *Management Science*, 64(7): 3269–3287.

Funding Black High-Growth Startups

Internet Appendix

Appendix A. Table of Contents

This Internet Appendix contains supplementary discussions and analyses, which we organize as follows:

10. Table A.5 repeats the analysis in Table 3 at a deal level, controlling for the pre-money valuation of the startup, which is available for about 50% of all deals.

11. Table A.6 repeats the analysis in Table 6 using the sample in Farre-Mensa, Hegde and Ljungqvist (2020).

12. Table A.7 repeats Table 3 for founders of other races.

13. Table A.8 repeats Table 3 with an interaction term for counties with high racial animus using google searches for racist terms.

14. Table A.9 tests whether access to government-supported programs targeting high-growth startups—the Small Business Investment Company (SBIC) and the State Small Business Credit Initiative (SSBCI)—vary by the race and gender of the startup founder.

15. Table A.10 estimates the funding gap separately for angel investments.

Appendix A. PitchBook Data

Appendix A.1. Overview of PitchBook and Definition of Funding Rounds

Formed in 2007, PitchBook researches and delivers data on funding rounds in private markets, including angel, grant, equity and product crowdfunding, accelerator/incubator funding, venture capital, private equity, M&A, and IPO transactions. PitchBook collects its data from regulatory filings (such as SEC Form D filings), credible news sources, press releases, and directly from companies, investors, and service providers. Of the funding rounds PitchBook tracks, we use the following types of non-debt funding rounds in our analysis:

1. **Accelerator/Incubator Backed:** Financing received as part of an accelerator or incubator program (cash or equity). These programs involve events where a company joins a temporary program that variably provides funding, office space, technological development, and/or mentorship, often in exchange for equity in the company. PitchBook's tracking criteria only include accelerators/incubators that take equity or give a cash disbursement as part of the program.

2. **Angel Round:** PitchBook defines financings as angel rounds if there are no PE or VC firms involved in the company to date and they cannot determine if any PE or VC firms are participating. In addition, if there is a press release that states the round is an angel round, it is classified as such. Finally, if a news story or press release only mentions individuals making investments in a financing, it is also classified as an angel round.

3. **Seed:** When investors and/or a press release state that a round is a seed financing, or if the round is for less than $500,000 and is the first round as reported by a

government filing (such as Form D), it is classified as a Seed round. If angels are the only investors, then a round is only marked as seed if it is explicitly stated.

4. **Early Stage:** Early stage is usually a Series A to Series B financing deal that occurred within 5 years of the company's founding date. If there is no series associated with the deal, and the deal occurred within 5 years of the company's founding date, PitchBook also categorizes the deal as early-stage VC.

5. **Late Stage:** A later-stage round of financing by a venture capital firm into a company. Later-stage is usually Series B to Series Z+ rounds and/or occurred more than 5 years after the company's founding date.

6. **Corporate Venture Capital:** Rounds where the investors in the rounds are part of established corporate venture capital arms or corporations making equity investments.

7. **Equity Crowdfunding:** Financing received from a crowdfunding platform where individuals provide venture or growth funding through the purchase of the target company's equities.

8. **Product Crowdfunding:** Financing received from a crowdfunding platform through which individuals have provided non-equity funding in exchange for companies' products, generally before they have been released to the market.

9. **Grant:** When a company receives financing that will not give the provider an economic interest or right in the assets or future cash flows of the company.

Appendix A.2. Constructing Our Test Sample

We begin with the direct data feed of all companies in PitchBook as of June 4, 2021, that are U.S. based (the startup is headquartered in a U.S. state) and were formed between January 2000 and December 2020: 138,859 companies. Of these companies, we were able to identify at least one founder for 102,476. We identify founders by keeping people with the keywords of "founder," "owner," or "founding" in their title description. Given that our study seeks to classify founders by race, we use LinkedIn to collect pictures and biographical information on founders. Of the 192,377 founders of interest for the 102,476 companies, PitchBook had LinkedIn urls for 163,329 founders. We searched for the images for the 133,075 founders, where all the founders of the startups had a Linkedin url. Thus, we started our search with 92,111 companies with LinkedIn profile url information on all founders.

Of these founders, we matched 118,856 founders (of 75,471 startups) to LinkedIn and collected images (from a variety of sources) for them. We combined image-processing algorithms, name-processing algorithms, and clerical review and classified 2,747 founders as Black. We also conditioned our analysis on founders with a usable profile picture, to eliminate selection coming from founders choosing to make images and biographical information public.

These steps led us to our final sample of 75,471 U.S.-based startups formed between 2000 and 2020 with at least one founder we could find on LinkedIn and for whom we were able to find a valid profile picture from various web sources, allowing us to classify the founder by race. From Table A.2, we see that the startups in our sample are younger (hence are less likely to have exited by the Q2 2021), raise more VC funding, and are more likely to succeed (using exit valuation, *Valuation*, as a measure of success) than the startups we exclude.

Appendix A.3. Identifying Lead Deal Partners

For each funding round involving the 75,471 startups in our final sample from the previous section, we kept the individual lead partners that PitchBook associates with each deal, who are members of the investment team that has represented the investor on deals. Of the 30,358 lead partners we identified, we had valid Linkedin URLs and were able to collect images we could use to classify race for 21,096. Of these lead partners, we matched 15,487 to an employer in a U.S. state, which PitchBook identifies as the lead partner's primary location. We mapped each lead partner into the following mutually exclusive categories: Black, White, Asian, and Hispanic. We further use PitchBook's classification of gender for each lead partner as determined by PitchBook's Data Operations team.

Appendix A.4. PitchBook and Patent Application Data

Appendix A.4.1. Applications by Small Entities

We start our sample construction using the publicly available patent data from the United States Patent and Trademark Office. Our dataset uses applications from January 2001 to December 2021. In line with the patenting literature, we focus our attention on regular utility patent applications, which account for over 90% of all patents. Given our focus on small businesses, we further restrict our attention to applications by small entities by keeping applications by assignees that the USPTO refers to as SMALL or MICRO. For these applications we only keep the assignee that was the first to be assigned the patent; then, we keep the first patent application by each assignee. When the first application involves multiple patent claims by the same assignee, we keep the application that was granted or with the largest number of forward citations.

For each application, we have the inventor(s), the date of the application, the final outcome of the application, the assignee, and the primary and secondary technology classification to which the application has been assigned.

Appendix A.4.2. Merging Micro-Entity Application Assignees to PitchBook

Matching the patent-application assignees to PitchBook companies is principally an exercise in cleaning assignee names, as PitchBook company names are rather well standardized (i.e., of suffixes such as "Company," "Inc.," etc.). Pre-grant application data since 2001 are obtained from patentsview.org. PatentsView assigns a unique assignee ID and performs some harmonization among assignee names but does not strip off suffixes as does PitchBook. Therefore, we perform two standardizations. First, we remove a leading "The" at the start of the company name. Second, we remove standard corporate suffixes,[19] doing so iteratively as some appear in sequence, with or without periods and optionally preceded by a comma. Any of these is removed *only* when appearing at the very end of the company name and when preceded by a space (and, optionally, by a comma before the space).

Once standardized, the assignee names from PatentsView are matched against the full list of PitchBook companies using Raffo's (Raffo (2020)) MatchIt package for Stata using default parameters. The resulting assignee-name/PitchBook-company matches are collected, duplicates are removed, and all with a similarity score above 93.5 are retained, with the additional constraint that the initial character matches exactly.

In a final step, we check that the founding year of the PitchBook company and the submission year of the patent application are within reason. For example, if the assignee was on a patent application filed in 2001 but the PitchBook company was formed in 2016, we likely have a false positive even with a high MatchIt similarity score. Although

[19] The full list we remove is inc gmbh mbh gbr gmbh co kg ag kgaa pte gmbh srl ag as aktien gesellshavgt ag as spa llc llc bh sa kb de xv oy ab mg ltd company limited corp incorporated corporated "companylimited" corporation company plc lc sro ne sl lp srl bv pvt bhd aps gmnbh ltda. Note that certain of these only appear when separated by periods. Importantly, "co" is not removed when preceded by "& " or "and," such as in "Tiffany & Co," for this is a distinctive part of the company name.

in theory patents should not have been applied for prior to the founding of the company, we allow for slight inaccuracy but no more than two years prior to founding.

Appendix B. Using Images and Names to Impute Race

Due to the ambiguity in using first and last names to classify founders and lead partners as Black, we instead use their images from LinkedIn and various web sources. We began this process by classifying images using several pre-trained image classifiers with python open-source code on Github. In particular, we used VGG-Face, Google FaceNet, OpenFace, Facebook DeepFace, DeepID, ArcFace, Dlib and SFace. These algorithms are all wrapped in the *DeepFace* package developed by Serengil and Ozpinar (2020).

Although experiments show that these algorithms outperform humans on facial recognition tasks (Phillips, Yates, Hu, Hahn, Noyes, Jackson, Cavazos, Jeckeln, Ranjan, Sankaranarayanan et al. (2018)), automated face recognition is not infallible and produces Type I and Type II errors, especially in classifying Black founders. Thus, we add name algorithms and clerical review to mitigate these errors. Type II errors mainly come from classifying light-skin blacks as non-Black, and Type I errors come from classifying dark-skin Asians of Indian descent as Black. When we cannot tell whether a light-skin founder is Black, we use affinity groups on LinkedIn, news reports, crowd-sourced lists of Black founders, and even attendance at an HBCU. We rely on names to reclassify dark-skin Asian founders. Specifically we use an algorithm developed by Ye, Han, Hu, Coskun, Liu, Qin and Skiena (2017) to reclassify dark-skin Asian founders using their first and last name. We also combined the name and image algorithms to classify founders/partners as Hispanic, Asian, and White, and use clerical review when the algorithms are inconclusive or disagree. The algorithms are inconclusive when the predicted probability that a founder/partner is of a given race is below 50%, and disagree when their predictions of race differ from each other.

Appendix C. Constructing the Network Score

We also construct a measure of links between founders and lead partners working for investment firms that funded companies in the same state and industry sector. We use resume information from LinkedIn for the founders (75,417) and lead partners (20,096—we do not condition of finding an image for the partner or her location as we do in the lead partner tests) in our sample. We keep resume information that pre-dates the year of company formation for each founder-lead partner pair. One caveat to note is that we are using future information (post company formation) on whether a lead partner funded a similar company. We assume that lead partners on future deals have the characteristics of potential lead partners at the time of company formation. Given referral-based hiring practices in the venture capital industry (Gompers, Gornall, Kaplan and Strebulaev (2020)), we think this assumption is likely valid.

To construct the network score, we first create a count of the number of universities and companies that the founder has in common with each lead partner that funded a company in the same industry and state. Then we divide this number by the number of unique universities and companies on the founder's resume. To consider a company or university in our network measure, the founder and lead partner must have overlapped for at least a year. Finally, we sum this measure over all lead partners, weighted by the number of investments each lead partner made as of Q2 2021, to get a measure of the founder's network. Formally, we define the network score as:

$$\text{Network Score}_f = \sum_p \frac{\text{Deals}_p}{\sum \text{Deals}_p} \left(\frac{\sum_u \sum_c I_{fpu} I_{fpc}}{\sum_u \sum_c} \right), \tag{C1}$$

where u indexes all the unique universities for each founder, c indexes companies, p indexes lead partners, and f indexes founders. So I_{fpu} takes a value of one when a founder and lead partner attended the same university and overlapped by at least one year. Deals_p is the total number of deals a lead parter was involved with as of Q2 2021. Our network score captures the potential strength of relations between founders and lead partners. We interpret a higher network score as implying that a founder is likely to know potential investors, but do not imply that the founder actually knows the investors. One can think of our measure as capturing the "weak ties" in Granovetter (1973).

Appendix D. Top Schools

Here is the list of the top 20 schools in our analysis, in alphabetical order:

1. Brown University
2. Carnegie Mellon University
3. Columbia University
4. Cornell University
5. Dartmouth College
6. Duke University
7. Harvard University

8. Massachusetts Institute of Technology
9. New York University
10. Northwestern University
11. Princeton University
12. Stanford University
13. University of California, Berkeley
14. University of California, Los Angeles (UCLA)
15. University of Chicago
16. University of Michigan
17. University of Pennsylvania
18. University of Texas at Austin
19. University of Southern California (USC)
20. University of Virginia
21. Yale University

Table A.1: Characteristics of Startups that Applied for a Patent

This table reports summary statistics for startups that raised some external financing and applied for an utility patent with the USPTO. The unit of observation is a startup. *Black Owned* is an indicator that equals one if any startup founder is Black, while *P(Black)* and *P(Female)* are the proportions of founders that are Black or female, respectively. *Age (Yrs)* is the number of years between when the startup was formed and when it applied for a patent. *I(PE Hub)* is an indicator that equals one for companies located in California, Massachusetts, or New York. *5yrs VC funding* is the total amount of funding that the startup raised from venture capital firms (firms classified in PitchBook as "Venture Capital," "PE/Buyout," "Growth/Expansion," "Corporate Venture Capital," "Other Private Equity," or "Not-For-Profit Venture Capital") in the five years follwing its patent application. Similarly, *5 yrs Non-VC Funding* is the total amount of non-VC funding raised following the startup's first patent application. Non-VC funding is funding raised from angel investors, accelerators, equity crowdfunding, and grants, which comprise funding from the Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs. *I(IPO)* is an indicator variable that equals to unity if the firm went public by the second quarter of 2021. *I(M&A)* is an indicator that equals one if the startup was acquired by the second quarter of 2021. *I(Business Products and Services)*, *I(Consumer Products and Services)*, *I(Energy)*, *I(Financial Services), I(Healthcare)*, *I(Information Technology)*, and *I(Materials and Resources)* are indicators that equal one if the startup is in that industry. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. All continuous variables are winsorized at the 1% and 99% levels to minimize the influence of outliers.

	Black Owned		**Non-Black Owned**		
	N = 237		**N = 12,344**		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
A. Firm-level statistics					
P(Black)	0.62	0.30	0.00	0.00	32.11***
P(Female)	0.14	0.30	0.09	0.25	2.36**
Year Founded	2012.37	3.91	2010.77	4.86	6.21***
I(PE Hub)	0.54	0.50	0.55	0.50	−0.56
# Founders	2.15	1.07	1.88	0.99	3.90***
5yrs VC funding ($ Millions)	12.28	75.69	16.14	64.60	−0.78
5yrs Non-VC Funding ($ Millions)	0.19	0.71	0.27	2.88	−1.48
I(Has Patent)	0.23	0.42	0.25	0.43	−0.83
I(IPO)	0.01	0.09	0.04	0.19	−4.59***
I(M&A)	0.15	0.36	0.24	0.43	−4.11***
I(Failed)	0.18	0.39	0.14	0.35	1.45
I(Business Products and Services)	0.17	0.38	0.14	0.34	1.44
I(Consumer Products and Services)	0.18	0.38	0.13	0.33	2.01**
I(Energy)	0.01	0.11	0.03	0.18	−2.89***
I(Financial Services)	0.01	0.09	0.01	0.11	−0.71
I(Healthcare)	0.22	0.41	0.26	0.44	−1.72*
I(Information Technology)	0.40	0.49	0.41	0.49	−0.37
I(Materials and Resources)	0.02	0.13	0.02	0.14	−0.23

Table A.1 - *continued* (Characteristics of Founders that Applied for a Patent)

This table reports summary statistics for founders of startups that raised some external financing and applied for a utility patent with the USPTO. A unit of observation is a founder of a startup in Table 1 above. *Black* is an indicator that equals one if the startup founder is Black. We classify a founder as Black using an image-processing algorithm and clerical review. *P(Skin Tone)* is the probability that a founder is Black, as computed by the image-processing algorithm. *I(Serial Founder)* is an indicator that equals one if the founder's LinkedIn profile indicated that they started another company whose name differs from the focal assignee and whose formation predates the current startup that is the focus of our analysis. *I(Top School)* is an indicator that equals one if the founder attended one of the top 20 universities. *I(Female)* is an indicator that equals one if the founder is female. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We winsorize all continuous variables at the 1% and 99% levels to minimize the influence of outliers.

	Black		**Non-Black**		
	N = 244		**N = 22,303**		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
B. Founder-level statistics					
P(Skin Tone)	71.70	36.74	2.73	12.04	29.37***
Network Score	0.04	0.08	0.05	0.11	−3.69***
I(Female)	0.16	0.37	0.10	0.30	2.68***
I(Serial Founder)	0.18	0.38	0.20	0.40	−1.03
I(Has MBA)	0.12	0.33	0.11	0.31	0.60
I(Has Masters)	0.16	0.37	0.19	0.39	−1.18
I(Has Ph.D.)	0.15	0.36	0.18	0.38	−1.25
# Jobs	2.31	2.50	2.37	2.46	−0.39
I(Founder-Inventor)	0.59	0.49	0.57	0.50	0.65
I(Top School)	0.25	0.43	0.23	0.42	0.89

Table A.1 - *continued*

This table compares statistics on startups in the PitchBook-USPTO sample to other startups in PitchBook. *Patent Sample* is an indicator that equals one if the startup is in the PitchBook-USPTO sample, and *Full Sample* is an indicator that equals one for startups in the full sample. We define all variables in Table 1. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We winsorize all continuous variables at the 1% and 99% levels to minimize the influence of outliers.

	Patent Sample		**Full Sample**		
	N = 12,581		**62,890**		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
C. Patent Sample versus full Sample					
P(Black)	0.01	0.09	0.03	0.15	−15.13***
P(Female)	0.10	0.25	0.14	0.31	−18.37***
Year Founded	2010.80	4.85	2011.73	5.19	−19.34***
I(PE Hub)	0.55	0.50	0.46	0.50	18.36***
# Founders	1.88	1.00	1.69	0.88	20.28***
5yrs VC funding ($ Millions)	16.06	64.83	3.78	26.08	20.92***
5yrs Non-VC Funding ($ Millions)	0.27	2.85	0.09	4.09	5.91***
I(Has Patent)	0.25	0.43	0.01	0.10	62.03***
I(IPO)	0.03	0.18	0.01	0.07	17.00***
I(M&A)	0.21	0.41	0.22	0.41	−0.60
I(Failed)	0.12	0.33	0.14	0.34	−4.03***
I(Business Products and Services)	0.14	0.34	0.20	0.40	−18.32***
I(Consumer Products and Services)	0.13	0.33	0.23	0.42	−28.45***
I(Energy)	0.03	0.18	0.02	0.14	8.57***
I(Financial Services)	0.01	0.11	0.05	0.21	−25.57***
I(Healthcare)	0.26	0.44	0.12	0.33	34.07***
I(Information Technology)	0.41	0.49	0.38	0.49	6.04***
I(Materials and Resources)	0.02	0.14	0.01	0.09	7.73***

Table A.2: Characteristics of Startups in Our Sample and Other Startups in PitchBook

This table compares statistics on startups in the PitchBook sample to other startups in PitchBook that are not in our sample because we could not match any founder to LinkedIn. A unit of observation is a startup formed between 2000 and 2020 that has a LinkedIn profile link for at least one founder. *I(IPO)* and *I(M&A)* are indicator variables that equal one if the company has gone public or been acquired as of the second quarter of 2021. *I(VC Funding)*, *I(Accelerator Funding)*, *I(Angel Funding)*, *I(Crowd Funding)*, and *I(Grant Funding)* are indicator variables that equal to one if the startup raised funding from the respective sources. *Year Founded* is the year in which the company was formed. *Valuation* is the value for which the company was acquired or its market capitalization at IPO. The final column reports the t-statistic for a test of differences in means of the different groups. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We winsorize all continuous variables at the 1% and 99% levels to minimize the influence of outliers.

	In Sample		**Others Startups**		
	N = 75,471		**16,640**		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
Full Sample versus other PitchBook startups					
I(IPO)	0.01	0.11	0.01	0.11	-0.70
I(M&A)	0.22	0.41	0.25	0.43	-8.19^{***}
I(VC Funding)	0.34	0.48	0.20	0.40	42.44^{***}
I(Accelarator Funding)	0.11	0.32	0.08	0.27	16.09^{***}
I(Angel Funding)	0.13	0.34	0.13	0.33	0.83
I(CrowdFunding)	0.04	0.19	0.04	0.19	0.18
I(Grant Funding)	0.07	0.26	0.08	0.27	-0.93
Year Founded	2011.57	5.14	2010.17	5.40	30.54^{***}
Valuation ($ Millions)	327.33	1786.29	256.19	939.85	1.88^{*}

Table A.3: Association between Black Ownership and Funding Raised (Same Sample as Farre-Mensa, Hegde and Ljungqvist (2020))

This table presents results from our analysis of the association between race and gender and funding raised in the five years following a startup's first patent application. We show coefficients from Poisson regressions run at the assignee level, with standard errors reported below in parentheses. We use the same sample that is used in Farre-Mensa, Hegde and Ljungqvist (2020). The dependent variable in Panel A, *VC Funding*, is the cumulative amount of VC funding the startup raised 2, 3, 4, or 5 years following the patent application. We get data on fundraising from PitchBook after merging the assignees in this sample to PitchBook on name and state and verifying all matches for accuracy. In Panel B, the dependent variable is *Non-VC Funding*, the total amount of non-VC funding raised 2, 3, 4, or 5 years following the patent application. Non-VC funding is funding raised from angel investors, accelerators, equity crowdfunding, grants, and the Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs. *P(Black)* is the proportion of inventors (where we could identify race) that are Black, and *P(Female)* is the proportion of inventors that are female. To predict inventor race in this sample, we first use NamePrism, an algorithm developed by Ye, Han, Hu, Coskun, Liu, Qin and Skiena (2017), to compute the probability that an inventor is Black. Then we downloaded and processed all images (using the same procedure as in the main analysis) where the probability that the inventor is black is 40% or greater. We use the Genderize.io algorithm to predict gender. *Ln(Count Investors)* is the log count of the number of inventors listed on the patent application. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by startup.

Panel A:	**VC Funding**			
Dependent Variable:	Next 2yrs	Next 3yrs	Next 4yrs	Next 5yrs
	(1)	(2)	(3)	(4)
P(Black)	-2.261	-2.776*	-2.642*	-2.856**
	(1.463)	(1.623)	(1.419)	(1.441)
P(Female)	-0.977*	-0.674	-0.675*	-0.376
	(0.541)	(0.435)	(0.404)	(0.484)
Ln(Count Inventors)	0.735***	0.699***	0.725***	0.663***
	(0.095)	(0.084)	(0.076)	(0.091)
Log-likelihood	-87619.36	-105571.02	-123939.25	-149849.93
Panel B:	**Non-VC Funding**			
Dependent Variable:	Next 2yrs	Next 3yrs	Next 4yrs	Next 5yrs
P(Black)	0.050	0.080	0.156	0.148
	(0.070)	(0.101)	(0.178)	(0.182)
P(Female)	0.006	-0.002	0.001	-0.000
	(0.013)	(0.030)	(0.031)	(0.033)
Ln(Count Inventors)	0.027***	0.035***	0.041***	0.047***
	(0.006)	(0.008)	(0.009)	(0.010)
Observations	33964	33964	33964	33964
Log-likelihood	-25200.65	-61214.70	-62724.37	-64639.86
Fixed Effects?	Class X Year	Class X Year	Class X Year	Class X Year

Table A.4: Association between Black Ownership and Funding Raised (Panel Regression PitchBook-Patent Sample)

This table presents results from our analysis of the association between race and gender and funding raised in the five years following a startup's formation. We show coefficients from Poisson regressions run at the startup-year level, with standard errors reported below in parentheses. The dependent variable in Panel A, *VC Funding*, is the total amount of VC funding raised each year. In Panel B, the dependent variable is *Non-VC Funding*, the total amount of non-VC funding raised each year. Non-VC funding is funding raised from accelerators, equity crowdfunding, and grants, which includes funding from the Small Business Innovation Research (SBIR) program. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by startup.

Panel A:	**VC Funding**			
	(1)	(2)	(3)	(4)
P(Black)	-1.285***	-1.217***	-1.037***	-0.909***
	(0.101)	(0.101)	(0.102)	(0.111)
P(Female)		-0.704***	-0.652***	-0.538***
		(0.038)	(0.039)	(0.043)
P(Serial Founder)				0.595***
				(0.025)
P(Top School)				0.480***
				(0.026)
Network score				2.868***
				(0.096)
I(Has Patent)				0.936***
				(0.028)
Ln(Count Founders)				0.765***
				(0.020)
Firm Age (yrs)				0.124***
				(0.004)
Observations	422592	422592	422592	422592
Log-likelihood	-796315.73	-791896.63	-746798.51	-688601.25
State FE?	NO	NO	NO	YES
Industry FE?	NO	NO	YES	YES
Year FE?	YES	YES	YES	YES

Table A.4 - *continued*

Panel B:	**Non-VC Funding**			
	(1)	(2)	(3)	(4)
P(Black)	0.223***	0.205***	0.291***	0.352***
	(0.059)	(0.059)	(0.060)	(0.063)
P(Female)		0.134***	0.092***	0.112***
		(0.032)	(0.034)	(0.037)
P(Serial Founder)				-0.191***
				(0.037)
P(Top School)				0.371***
				(0.034)
Network score				0.254
				(0.177)
I(Has Patent)				0.657***
				(0.045)
Ln(Count Founders)				0.572***
				(0.023)
Firm Age (yrs)				-0.145***
				(0.006)
Observations	422592	422592	422592	422592
Log-likelihood	-12000.51	-11998.68	-11752.55	-11559.33
State FE?	NO	NO	NO	YES
Industry FE?	NO	NO	YES	YES
Year FE?	YES	YES	YES	YES

Table A.5: Association between Black Founders and Funding Raised (Fixing Investor's Valuation)

This table reports estimates on the association between the proportion of a startup's founders that are Black and the amount of VC funding the startup raises in the five years following its formation. The unit of observation is a startup-deal, where the startup is a U.S.-based startup formed between 2000 and 2020. The dependent variable is *Ln(VC Funding)*, the amount of VC funding the startup raises in funding rounds within five years of when the company was formed. *Ln(Pre-money valuation)* is the log valuation of the startup just prior to the funding round. The number of observations is lower in this test than inTable 3 because we only use startups with pre-money valuation information that raised at least $1 of venture capital funding, so *Ln(VC Funding)* is well defined. *Year* in this table is the year the funding round was completed. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by startup.

	Ln(VC Funding)			
	(1)	(2)	(3)	(4)
P(Black)	-0.688***	-0.186***	-0.173***	-0.173***
	(0.120)	(0.057)	(0.054)	(0.054)
Ln(Pre-money valuation)		0.833***	0.817***	0.809***
		(0.004)	(0.004)	(0.004)
P(Female)				-0.053**
				(0.022)
P(Serial Founder)				0.050***
				(0.014)
P(Top School)				0.014
				(0.015)
Network score				0.178***
				(0.062)
I(Has Patent)				0.115***
				(0.018)
Ln(Count Founders)				0.069***
				(0.011)
Founding Year FE?	YES	YES	NO	NO
State X Year X Industry FE?	NO	NO	YES	YES
Observations	29986	29986	29986	29986
Log-likelihood	-52388.76	-34876.60	-32925.68	-32845.84

Table A.6: Association between Black Assignees and Patent Outcomes (Same Sample as Farre-Mensa, Hegde and Ljungqvist (2020))

This table reports the association between the proportion of Black and female inventors listed on a patent application and the likelihood the patent is granted, the likelihood the patent is abandoned, the time between the application and the grant, and the number of citations the patent received. We use the same sample of first-time patent applicants that is used in Farre-Mensa, Hegde and Ljungqvist (2020). The dependent variable in Column (1), *I(Granted)*, is an indicator that equals one for startups whose patent application was ultimately successful. In Column (2), it is an indicator for whether the patent application was abandoned, *I(Abandoned).* In Column (3), it is the number of citations the patent received as of 2017, (*Citations*), and in Column (4), it is the number of years between patent application and grant, *Years to Grant. P(Black)* is the proportion of inventors (where we could identify race) that are Black, and *P(Female)* is the proportion of inventors that are female. To predict inventor race in this sample, we first use NamePrism, an algoritm developed by Ye, Han, Hu, Coskun, Liu, Qin and Skiena (2017), to predict the probability that the inventor is Black. Then we downloaded and processed all images (using the same procedure as in the main analysis) where the probability that the inventor is black is 40% or greater. We use the Genderize.IO algorithm to predict gender. *Ln(Count Inventors)* is the log count of the number of inventors listed on the patent application. *Class X Year* denotes USPC class by application year fixed-effects. We estimate Columns (1) and (2) using linear probability models, and Columns (3) and (4) using quasi-maximum likelihood Poisson models with robust standard errors. ^{g} denotes tests on the subset of applications that were granted. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by application.

Dependent Variable:	I(Granted)	I(Abandoned)	Citations^{g}	Years to Grant^{g}
	(1)	(2)	(3)	(4)
P(Black)	0.086	-0.086	0.186	0.061
	(0.076)	(0.076)	(0.228)	(0.081)
P(Female)	-0.023*	0.023*	-0.084	0.031*
	(0.014)	(0.014)	(0.067)	(0.018)
Ln(Count Inventors)	0.012***	-0.012***	0.237***	0.029***
	(0.005)	(0.005)	(0.026)	(0.005)
Fixed Effects	Year	Class X Year	Class X Year	Class X Year
Observations	33964	33964	21672	21672
Log-likelihood	-19754.71	-19754.71	-182000.75	-37106.48

Table A.7: Association Between Black Ownership and VC Funding Raised (Cross-sectional Tests)

This table presents results from our analysis of the association between race and gender and VC funding raised in the five years following startup formation. We present coefficients from Poisson regressions run at the (startup) level, with standard errors reported below in parentheses. The dependent variable, *VC Funding 5yrs* is the cumulative amount of VC funding the startup raised in the five years following company formation. The primary independent variables are *P(Black)* the proportion of founders that are Black; *P(White)* (*P(Hispanic)*, *P(Asian)*), is the proportion of founders that are White (Hispanic, Asian). See the Appendix B for more details on how we classify founder race. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Dependent Variable:	**VC Funding 5yrs**			
	(1)	(2)	(3)	(4)
P(Black)	-1.010***			
	(0.142)			
P(White)		0.051		
		(0.032)		
P(Hispanic)			-0.326***	
			(0.113)	
P(Asian)				0.070**
				(0.034)
P(Female)	-0.602***	-0.613***	-0.613***	-0.617***
	(0.051)	(0.051)	(0.051)	(0.051)
P(Serial Founder)	0.563***	0.564***	0.566***	0.569***
	(0.029)	(0.029)	(0.029)	(0.029)
P(Top School)	0.495***	0.498***	0.494***	0.491***
	(0.030)	(0.031)	(0.030)	(0.031)
Network score	2.918***	2.934***	2.932***	2.939***
	(0.111)	(0.111)	(0.111)	(0.111)
I(Has Patent)	0.941***	0.944***	0.943***	0.943***
	(0.032)	(0.032)	(0.032)	(0.032)
Ln(Count Founders)	0.771***	0.775***	0.775***	0.773***
	(0.023)	(0.023)	(0.023)	(0.023)
Observations	70206	70206	70206	70206
Log-likelihood	-482448.43	-483621.28	-483458.96	-483588.85
State X Year X Industry FE?	Yes	Yes	Yes	Yes

Table A.8: Association between Black Ownership and Funding Raised (Racial Animus Founders)

This table presents results from our analysis of the association between the interaction of race and gender and racial animus and funding raised in the five years following a startup's formation. We show coefficients from Poisson regressions run at the startup level, with standard errors reported below in parentheses. *Racial animus* is an indicator for counties with above-median google searches for racially charged words (see Howell, Kuchler and Stroebel (2021) for more detail). The number of observations is lower in this test than in Table 3 because we only use observations where we could geocode the startup's address to obtain the county where it is headquartered. The dependent variable, *VC Funding*, is the cumulative amount of VC funding the startup raised 2, 3, 4, or 5 years following the company's formation. *P(Black)* is the proportion of founders that are Black. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by startup.

Dependent Variable:	**VC Funding**			
	Next 2yrs	Next 3yrs	Next 4yrs	Next 5yrs
	(1)	(2)	(3)	(4)
I(Racial animus) X P(Black)	-0.146	-0.136	-0.017	0.080
	(0.310)	(0.287)	(0.288)	(0.304)
P(Black)	-0.873***	-0.930***	-0.955***	-0.942***
	(0.207)	(0.191)	(0.194)	(0.191)
I(Racial animus)	-0.401***	-0.415***	-0.421***	-0.420***
	(0.042)	(0.040)	(0.040)	(0.039)
P(Female)	-0.550***	-0.581***	-0.544***	-0.564***
	(0.055)	(0.053)	(0.053)	(0.053)
P(Serial Founder)	0.546***	0.536***	0.538***	0.528***
	(0.031)	(0.030)	(0.030)	(0.030)
P(Top School)	0.438***	0.451***	0.469***	0.480***
	(0.033)	(0.032)	(0.031)	(0.031)
Network score	2.735***	2.701***	2.695***	2.717***
	(0.120)	(0.115)	(0.115)	(0.114)
I(Has Patent)	0.878***	0.890***	0.891***	0.901***
	(0.038)	(0.035)	(0.033)	(0.032)
Ln(Count Founders)	0.595***	0.629***	0.681***	0.702***
	(0.026)	(0.024)	(0.024)	(0.024)
Observations	57158	58272	58994	59386
Log-likelihood	-180068.48	-263250.25	-352193.99	-433072.24
State, Year, and Industry FE?	Yes	Yes	Yes	Yes

Table A.9: Association between Black Startups and Government-Backed Venture Funds

This table presents results from our analysis of the association between race and gender and the likelihood that a company raises funding from a government-backed venture capital fund. The dependent variable, *I(SBIC/SSBCI)*, is an indicator that equals one if a Small Business Investment Company (SBIC) or a fund backed by the State Small Business Credit Initiative (SSBCI) invested in the company. These funds use federally subsidized funds to invest in companies. We show coefficients from OLS regressions run at the startup level, with standard errors reported below in parentheses. *P(Black)* is the proportion of founders that are Black, and *P(Female)* is the proportion of founders that are female. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level. We cluster standard errors by startup.

Dependent Variable:	**I(SBIC/SSBCI)**			
	(1)	(2)	(3)	(4)
P(Black)	-0.464**		-0.411*	-0.301
	(0.220)		(0.221)	(0.221)
P(Female)		-0.513***	-0.503***	-0.411***
		(0.121)	(0.122)	(0.122)
P(Serial Founder)				0.444***
				(0.137)
P(Top School)				-0.035
				(0.136)
Network score				1.905**
				(0.750)
I(Has Patent)				0.354
				(0.259)
Ln(Count Founders)				0.555***
				(0.104)
Observations	74265	74265	74265	74265
Adjusted R^2	0.041	0.041	0.041	0.041
State, Year, and Industry FE?	Yes	Yes	Yes	Yes

Table A.10: Association between Black Ownership and Angel Funding Raised

This table presents results from our analysis of the association between race and gender and funding raised in the five years following startup formation. We present coefficients from Poisson regressions run at the (startup) level, with standard errors in parentheses. The dependent variable in Panel A, the dependent variable is the about of angel funding the startup raises in the two, three, four, and five years following company formation. *P(Black)* is the proportion of Black founders. We define all other variables in Table 1. $^{***}p < 0.01$ denotes significance at the 1% level, $^{**}p < 0.05$ denotes significance at the 5% level, and $^{*}p < 0.10$ denotes significance at the 10% level.

Panel A:	**Angel Funding**			
Dependent Variable:	Next 2yrs?	Next 3yrs?	Next 4yrs?	Next 5yrs?
	(1)	(2)	(3)	(4)
P(Black)	-0.938***	-0.898***	-0.871***	-0.814***
	(0.256)	(0.214)	(0.206)	(0.188)
P(Female)	-0.749***	-0.644***	-0.560***	-0.554***
	(0.093)	(0.083)	(0.080)	(0.076)
P(Serial Founder)	0.121	0.052	0.088	0.094
	(0.119)	(0.100)	(0.089)	(0.084)
P(Top School)	0.061	0.062	0.028	0.030
	(0.112)	(0.095)	(0.087)	(0.082)
Network score	0.573	0.160	-0.015	0.126
	(0.375)	(0.336)	(0.319)	(0.303)
I(Has Patent)	0.439***	0.513***	0.533***	0.597***
	(0.103)	(0.094)	(0.086)	(0.086)
Ln(Count Founders)	0.004	0.011	0.021	0.057
	(0.073)	(0.062)	(0.057)	(0.054)
Observations	59772	61373	62703	63442
Log-likelihood	-22517.10	-28267.27	-32757.93	-35866.22
State X Year X Industry FE?	Yes	Yes	Yes	Yes