Is There Racial Discrimination in Private Placements?

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Comments welcome

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Abstract

We examine whether entrepreneurs with different racial backgrounds raise capital successfully. After controlling for measures of firm and offering quality, we find that Black (Hispanic) entrepreneurs have 7% (5%) lower funding success rate and raise 38% (50%) (or $2.3 million ($3 million)) less capital than White entrepreneurs, on average. This effect appears to be partly due to investors discounting the credentials of minority entrepreneurs, rather than due to their firms facing greater information asymmetry. Our evidence suggests that the discrimination in this market is taste-based, not merely statistical.

Keywords: Raising Capital; Private Placements; Entrepreneurial Finance; Racial Discrimination

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1. Introduction

It is well known that entrepreneurs of color are glaringly underrepresented in entrepreneurship. Gompers and Wang (2017) find that among venture capital (VC)-backed entrepreneurs from 1990-2016, less than 1% are Blacks, and about 2% are Hispanics. According to recent data from the Kauffman Foundation, more minorities are starting businesses.[1] But minority entrepreneurs often struggle to attract early-stage funding for their firms. Black and Hispanic founders in the US raised only about 2.4% of the total venture capital raised between 2015 and 2020.[2] This paper examines whether this racial disparity also exists in the private placement market, which has grown substantially in size and importance; if so, we attempt to find its causes.

New businesses tap a variety of sources for capital. The most used types of capital are personal and family savings (64%), bank lending (17%), and personal credit cards (9%). Venture capital is available to only about 0.5 percent of entrepreneurs (see, e.g., Hwang, Desai, and Baird, 2019). Moreover, startup firms tend to have limited access to bank loans because these loans are limited by (a) the amount of equity, which many talented entrepreneurs lack due to limited personal and family wealth, and (b) demonstrated earning power of the business, which startups have yet to

[1] See Ricketts, J. "In Praise of Today's Entrepreneurs." *Wall Street Journal*, November 4, 2019.

[2] See Tweh, B. "A New Push for Diversity in Funding Tech Startups; The idea: Tech entrepreneurs of color get venture and angel money from investors of color." *Wall Street Journal*, October 22, 2020. See also http://about.crunchbase.com/wp-content/uploads/2020/10/2020_crunchbase_diversity_report.pdf

achieve. Therefore, lack of access to capital is a primary barrier that entrepreneurs face. The private placement market offers an important avenue to entrepreneurs for raising capital. But when access to capital is tied to factors unrelated to the quality of the business, such as ethnic, racial or gender bias, it hinders the flow of capital to many promising entrepreneurs. This paper focuses on racial bias as one such barrier to raising capital.

It is important to study minority entrepreneurs' access to capital in the private placement market for several reasons. First, access to capital is a crucial determinant of entrepreneurship (Kerr and Nanda 2011; Simoes et al. 2016), which is an engine of economic growth. Second, minority entrepreneurship promotes economic development in minority communities (Bradford and Osborne, 1976) and minority families (Bradford, 2003). Third, the private placement market has become one of the most important capital markets. During recent years, the total capital raised in private markets has even outpaced that raised in public markets. For example, in 2017, public markets raised $2.1 trillion in the U.S., while private markets raised over $2.4 trillion. Almost 70% of the latter amount was raised via private placements, i.e., sales of unregistered securities through private offerings, mostly to accredited investors.[3] Thus, we focus on the largest private capital market, namely private placements, which has information on entrepreneurs who try to raise funds, and identify funding outcomes for minority entrepreneurs.

In the private placement market, startups raise capital from angel investors, other individual investors and venture capitalists. Angel investors provide personal funds in return for an equity stake in the venture. VCs typically choose high-risk, high-return investments that could lead to an

[3] The rest was raised via initial coin offerings, crowdfunding and debt sales to large investors. See Eaglesham, J. & Jones, C. "The fuel powering corporate America: $2.4 trillion in private fundraising." Wall Street Journal, April 2, 2018.

IPO or acquisition. The research question we ask is whether there is racial disparity in this market. If there is a disparity, we attempt to shed some light on its sources and causes. Systematic evidence on this issue can improve our understanding of minority entrepreneurs' financial decision-making. A better understanding of this issue is also important for the participants in this market, (i.e., investors, entrepreneurs, and middlemen such as brokers, dealers, and finders) as well as policymakers and regulators.

Using a comprehensive set of private placements, we investigate the outcomes of private fundraising led by entrepreneurs of color. We identify firm and issue characteristics contributing to inequality and examine whether correlated characteristics are the primary source of racial disparities. We then examine the initial funding gap between minority and White entrepreneurs, after we control for industry, location, year, firm age, firm revenue, types of securities offered, duration of offering, and other firm and issue-specific determinants of the amount of capital raised.

Our analysis yields three main sets of results. First, we find large racial differences in the source of capital, the amount of capital sought, and the duration of fundraising. Compared to White-led startups, minority startups are more likely to offer debt-type securities, have smaller offering amounts, and make offerings that last for over a year. Second, we find racial differences in capital raising outcomes. We find that Black (Hispanic) entrepreneurs have 7% (5%) lower funding success rate and raise 38% (50%) (or $2.3 million ($3 million)) less capital than White entrepreneurs, on average. Third, we examine the channels that lead to racial differences in access to capital.[4] We find that credential discounting partially explains the racial gap in small business

[4] Motivated by Fairlie, Robb, and Robinson (2022), we use the term access to capital to capture the amount of capital raised, understanding that this quantity is an equilibrium capital market outcome affected by both supply-side and demand-side factors.

financing, which supports the taste-based discrimination theory. Finally, we provide some evidence that information asymmetry does not explain the racial gap in financing. This finding does not support the statistical discrimination theory.

Our analysis is subject to three identification concerns. First, lower funding to minority-led projects may simply be due to these projects being of lower quality. While we have no information about *project quality* due to the lack of SEC disclosure requirement, we partially address this issue by controlling for measures of *firm and offering quality* such as firm revenue, firm age, offering duration and types of securities offered. Second, our analysis may be subject to a selection concern because we only analyze projects that are actually proposed by entrepreneurs. Our study is based on the premise that any barriers minority entrepreneurs face in accessing this market are relatively small, so selection should be less of a concern. The third concern is about omitted variables measuring firm and entrepreneur characteristics. We try to mitigate it by matching each minority-owned firm with a majority-owned firm with similar firm and offering characteristics. We then obtain average treatment effects from the matched sample to draw inferences based on contemporaneous outcomes of financing in minority vs. White-owned firms. Our main conclusions remain the same in this analysis.

Our paper contributes to three strands of the literature on entrepreneurial finance and discrimination. First, it contributes to the emerging literature on gender and racial discrimination in entrepreneurial finance (see Ewens, 2022 for an excellent review). Ewens and Townsend (2020) find evidence of gender-matching between investors and entrepreneurs: male investors express less interest in female entrepreneurs, and vice versa. Fairlie, Robb, and Robinson (2022) find that Black entrepreneurs are less likely to apply for loans because they expect to be denied credit even when they have good credit histories. Chatterji and Seamans (2012) find that expansion of credit card availability improves Black entrepreneurs' entry into entrepreneurship, and this effect is strongest in areas with historically high rates of racial discrimination. Bates Bradford and Jackson (2018) find that minority-owned businesses have lower access to equity capital despite higher financial returns than White-owned businesses. Cassel, Lerner, and Yimfor (2022) find that Blacks and Hispanics have difficulty raising first-time private capital funds (i.e., venture capital, buyout, and growth investment groups), and are punished more harshly for poor performance in their follow-on fundraising. On a peer-to-peer lending platform, Pope and Sydnor (2011) find that Black borrowers are less successful in raising debt than Whites, and pay higher interest rates when they do. Our paper adds to this literature by showing that racial discrimination also seems to exist in the private placement market.

Second, the paper contributes to the broad literature on ethnic and racial disparity in economics and finance (see, e.g., Richard, Murthi, and Ismail, 2007). Ambrose, Conklin, and Lopez (2021) find that minorities pay more in mortgage broker fees than similarly qualified Whites. Bertrand and Mullainathan (2004) find that résumés with Black names receive lower callback rates from employers than do those with White names. Agan and Starr (2017) find that online job applicants with Black-sounding names have a substantially lower response rate after the introduction of policies that prohibited employers from asking about job applicants' criminal records. Lacking this criminal record data, employers appear to rely on exaggerated impressions of racial differences in felony conviction rates. Kumar, Niessen-Ruenzi and Spalt (2015) find that U.S. mutual fund managers with foreign-sounding names have lower fund flows and experience lower increase (greater decrease) in flows following good (bad) performance. Edelman, Luca, and Svirsky (2017) find that Airbnb hosts are less likely to accept guests with Black names than those with White names. But Guo, et al. (2021) find no significant racial differences in CEO pay in S&P

1500 firms. Our paper adds to this literature by showing that race also matters in the private placement market.

Third, this paper contributes to the literature on the determinants of success in funding small businesses. Petersen and Rajan (1994) find that small businesses with close ties to an institutional creditor have greater access to financing. Bernstein, Giroud and Townsend (2016) find that entrepreneurial firms significantly connected to VCs are more likely to raise financing for their projects. Bernstein, Korteweg and Law (2017) show that information about the founding team is an important determinant of entrepreneurial financing success. Sørensen (2007) finds that VC-backing helps young firms reach the next stage by going public. Our paper adds to this literature by showing that entrepreneurs' race also seems to matter for funding success.

The paper proceeds as follows. Section 2 discusses the related literature and develops our main hypothesis. Section 3 details the data and sample. Section 4 presents our baseline results. Section 5 presents identification and robustness checks. Section 6 concludes.

2. Literature Review and Hypothesis Development

Most explanations for discrimination in the literature center around two main competing, but not mutually exclusive, theories: taste-based discrimination and statistical discrimination (see Ewens, 2022 for a review). The main determinant of discrimination in the taste-based theory is inter-ethnic bias (Becker, 1971). In our context, the theory assumes that investors have a disutility from investing in minority-led firms, which leads them to invest less in these firms, even if means sacrificing some returns. On the contrary, statistical discrimination theory argues that any observed disparity in funding outcomes between the races is simply a rational behavioral response to uncertainty. Given the extreme information asymmetry in entrepreneurial finance, investors use race as a correct signal of productivity (Phelps, 1972; Arrow, 1973). We attempt to separate between the two theories based on our findings on the channels of observed discrimination, which we discuss later in this section.

Jacquemet and Yannelis (2012) investigate differences in callback rates between applicants with résumés that have Black or White-sounding names, and fictitious names combining elements of various East European last names. Black résumés as well as résumés with fictitious names received significantly fewer invitations for job interviews than White résumés and there was no difference between the first two groups.

Kaas and Manger (2012) study the odds of native German and Turkish students to get an internship in Germany. They create one set of false applications providing reference letters from prior employers and one set of applications without any letter. They find that the racial disparity reduces and becomes insignificant when applicants provide additional information through reference letters and interpret this as evidence in favor of statistical discrimination. One commonly used strategy to investigate statistical discrimination is to vary the amount of information provided on quality. The underlying idea is that providing more information reduces uncertainty among decision makers about quality.

Relatedly, other studies suggest that adverse selection due to information asymmetry can cause small minority firms to fail to obtain financing. A large literature shows that small firms have difficulty raising capital because of information asymmetry with potential investors (see, e.g., Chan, Siegel and Thakor, 1990; and Gompers 1995). Investors are reluctant to invest in startups because they have less information about the issuer's prospects than the issuer does (e.g., Sufi, 2007). Similarly, Hildebrand, Puri, and Rocholl (2017) find that without financial intermediaries to reduce information asymmetry, lead investors can wrongly place higher bids on low quality issues.[5] Chen (2017) also shows that adverse selection is a first-order barrier to crowdfunding and can lead to market failure. Dorff (2014) finds that promising startups that can raise capital from professional investors (e.g., VCs) do not use crowdfunding, and leave the crowdfunding market to unpromising ventures. The information asymmetry channel implies that racial differences in capital raising should reduce when the issuer provides additional information on firm quality, which can help reduce information asymmetry. Evidence in favor of this channel would support the statistical discrimination theory.

Sometimes, racial differences exist even when additional information is provided. Bertrand and Mullainathan (2004) examine racial discrimination in the labor markets of Boston and Chicago. They find that résumés with Black-sounding names are less likely to receive callbacks than résumés with typical white-sounding names. Apart from race, they vary the quality of résumés (low versus high). They find that while Whites with higher quality résumés were more likely to get an invitation for a job interview than Whites with lower quality résumés, this effect is absent among Black candidates. This finding suggests that more information regarding minority applicants' skills does not always reduce racial discrimination. Bertrand and Mullainathan explain this as lower returns to credentials for Blacks and measure credentials using résumé-quality. If lower returns to credentials is the channel driving discrimination, we expect high-quality minorities to have lower success in raising capital than high-quality Whites. This channel also implies that high-quality entrepreneurs should have higher success in raising capital than low-

[5] A large literature analyzes the way financial intermediaries such as VCs overcome information asymmetry (e.g., Chan, 1983; Lerner, 1995; Gompers, 1995).

quality entrepreneurs, but this differential should be greater for Whites than minorities. Evidence for this credential discounting channel would support the taste-based discrimination theory.

3. Data and Key Variables

3.1. Data sources and sample selection

Firms can offer and sell securities legally without registering with the SEC through a Regulation D exemption via rules 504, 505 or 506 by filing a Form D with the SEC. Beginning March 16, 2009, Form D must be filed electronically. We use these Form D filings to analyze the private placement market in the US.

Panel A of Table 1 illustrates our sample selection process. To minimize measurement error and capture a representative set of startups seeking capital, we focus on first-time fundraisers over the 2008-2019 period. We begin with the earliest Form D filed by an issuer, excluding pooled investment funds. We only keep the primary issuer when multiple issuers jointly file a Form D. We eliminate offerings by firms located outside the US, and drop public firms (i.e., firms currently listed on NYSE or Nasdaq, and firms that filed any 10-Q or 10-K reports with the SEC) because we analyze fundraising efforts by small, entrepreneurial businesses. We retain only Form Ds filed over 2009-2019 because electronic Form D filing became mandatory beginning in March 2009. Our final sample includes firm-level observations on 96,574 unique firms over 2009-2019.

We also attempt to analyze three investment outcomes following a fundraising campaign. The first outcome is an indicator equal to one if a startup had a successful exit via an initial public offering (*IPO*). The second outcome is an indicator equal to one if a startup had a successful exit by being acquired (*Acquired*). The third outcome is an indicator equal to one if a startup has gone bankrupt (*Bankrupt*). The three outcome measures, the first two positive and the third negative, are motivated by the venture capital literature (see, e.g., Gompers et al., 2010; Nanda, Samila and Sorenson, 2020). The data we use for these measures is described in Appendix B. Table 2 shows that the mean values of *IPO*, *Acquired* and *Bankrupt* variables are 0.00, 0.01 and 0.00, respectively. Given the lack of incidence of these outcomes in our sample, we do not analyze these outcomes further.

3.2. Identifying ethnicity

The names of an issuer's related persons and their relationships to the issuer are recorded in item 3 of Form D. Relationships are either executive officer, director, or promoter (i.e., company shareholder at the time of incorporation). We obtain the names of executive officers (EOs) who are natural persons.[6] We classify the race of the entrepreneurs based on the last names and geographic location of their EOs,[7] using Imai and Khanna's (2015) Bayesian race prediction method. This method combines the Census Bureau's Surname List[8] with various information from geocoded voter registration records to produce probability estimates of individual-level race and ethnicity. By combining an individual's last name with their geographic location, the method

[6] We omit a few cases where the EO listed is an institution or firm.

[7] EOs are typically the entrepreneurs themselves, given that the firms in our sample are quite small, with an average of 1.3 (2.5) EOs in minority-owned (White-owned) firms.

[8] Released in 2007, the list contains the percentage of individuals who are White, Black or Latino for each surname occurring at least 100 times in the 2000 Census. The list contains a total of 151,671 names, representing about 90% of the U.S. population in the 2000 Census. Imai and Khanna supplement this list with the Census's Spanish Surname List, which contains 12,500 common Latino surnames, about half of which are on the 2007 Census Surname List.

produces fairly reliable predictions of race and ethnicity.[9] Based on about nine million voter registration records from Florida that identify self-reported ethnicity, Imai and Khanna find that their method has a false positive rate for Blacks (Latinos) of 6% (3%) and a true positive rate above 80%. This method is similar to the methodology that regulators and the courts use to determine consumers' race and ethnicity (see, e.g., Consumer Financial Protection Bureau, 2014; United States Department of Justice, 2010). Following Ambrose, Conklin, and Lopez (2020), we classify an entrepreneur's race to that of the group with the highest predicted probability.

3.3. Variable construction

We use four key independent variables that partition the data into four subsamples based upon the variables *Minority, Black, Hispanic*, and *Asian.* First, *Minority* equals one if the firm has any Minority EOs (Black, Hispanic, and Asian), zero otherwise (*All White* executive officers). This variable allows us to perform the analysis collectively for all minority groups, with Whites as the reference group, to determine whether any minority disparity exists. Second, the *Black* dummy variable equals one if firm *i* has any Black EO, zero otherwise, and so forth. Note that the *All White* observations are the same in each subsample and serve as the reference group that represents firms with White EOs only.

We use two dependent variables to test whether a private offering is successful: (1) offering *Success Rate* = total amount sold/total amount offered; and (2) *Ln(Sold)* = ln (1+total amount sold).

[9] Blacks and Whites often share the same last names for historical reasons. For example, a Johnson can be either White or Black. But a Johnson from Jackson, MS is highly likely to be Black, while a Johnson from White Plains, NY is highly likely to be White. This is the basic intuition behind Imai and Khanna's algorithm. This is less of an issue with Hispanics, whose last names tend to be quite distinct from Whites and Blacks.

We control for offering and firm characteristics according to the previous literature. For example, previous studies find that startups with successful fundraising tend to be concentrated in certain states, especially California and New York (e.g., Stangler, Tareque, and Morelix, 2016; Nanda and Rhodes-Kropf, 2013). Our set of control variables includes an indicator of an issuer located in California or New York, team size, offering amount, offering duration, firm age, revenue, indicators for the types of securities offered, and an indicator of an offering made in connection with a business transaction (e.g., merger, acquisition, or exchange offer). The regressions include industry, state of firm location, and year fixed effects.

3.4. Summary statistics

Panel B of Table 1 shows the number of private offerings conducted under Regulation D for top 5 industries and top 5 states by Minority and all White issuers. The sample labeled "Minority" includes firms with any Black, Hispanic, or Asian EOs, while "All White" includes firms with all White EOs. Panel B shows almost no difference in industry and location between Minority and White entrepreneurs. Not surprisingly, the latter are quite dominant, with 9 to 23 times higher frequencies than minority entrepreneurs across the top 5 industries or states. The 'other technology' industry is the largest, and California is the largest state for both groups of entrepreneurs. Figure 1 shows a heatmap that documents that roughly the Eastern half of the country and the West Coast have some of the highest densities of private offerings. Figure 2 plots minority fund-raising rates by industry, and plots the regression coefficients of industry fixed effects and their 95% confidence intervals from estimating the regression:

$$nonWhite_{i,t} = \alpha_0 + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

in which the variables are for a firm *i*. The variable *Minority* equals one if firm i has any minority (i.e., Minority) EO, and zero otherwise. Fixed Effects is a vector of year, industry, and state fixed effects with robust standard errors. We see that the rates of minority entrepreneurs seeking capital is higher in coal mining, computers, construction, energy conservation, lodging and conventions, and tourism and travel services industries; the rates are lower in airlines and airports, commercial banking, environmental services and insurance industries.

Table 2 presents summary statistics of the variables used in the regressions. We identify the race and ethnicity of 94% of the firms' EOs in our sample that equals 115,420 individual EOs. Among the first-time fundraisers identified, 1% have at least one Black EO, 1% have a Hispanic, 4 percent have an Asian, and 94% have all White EOs. Thus, the overwhelming majority of entrepreneurs are White.

Figure 3 shows the number of unique issuers that raise capital in private markets. The black (gray) bar represents the number of unique first-time fund-raising firms that have any Minority (White) EOs. Figure 3 also shows a similar pattern of White dominance in the private placement market. The number of firms with all White EOs is at least ten times larger than those with any Minority EO.

Table 3 compares the characteristics of offerings by Minority and All White entrepreneurs in first-time offerings by a firm. The sample is partitioned based on the *Minority* variable. The table reports mean and median values for the two groups, and *t*-statistics and *p*-values of the differences between them. For the dollar variables, the *t*-statistics are based on the natural logarithm of one plus the dollar value. To reduce the effect of outliers, we winsorize all dollar variables at the 1st and 99th percentiles, and observe that on average, minorities tend to raise ($Sold) less than do Whites ($2.7 million vs. $6.2 million). Minority (i.e., non-White) firms have lower revenue, a longer offering duration, and more debt offerings. Minority-owned firms are also younger and have smaller teams than majority-owned firms. Further, minority firms are more likely to be located in California or New York, offer an indefinite amount, and disclose their revenue than are firms with all White EOs.

Figure 4 shows the average success rate of private offerings led by Minority and all-White firms. Panel A shows significant racial differences in success rates for each firm revenue category. As revenue increases, the financing success rate also increases for both groups of firms with revenue between $1 million and $5 million. However, the success rate for Minority issuers with revenue above $5 million is significantly lower than that of Whites in the same revenue range.[10] This evidence may imply that investors tend to discount minorities with high credentials. We explore this issue further in section 4.2. Panel B shows no discernible racial differences in success rates for each firm age category. Thus, we find little evidence that mature firms have higher rates of financing success for either minorities or Whites.

4. Regression Results

4.1. Minority small business financing

In this section, we examine the outcomes of minorities' small business financing using first-time private offerings using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t} \quad (1)$$

[10] This may be partly due to a small sample size for this group. We tackle this issue by using a matching approach to compare the two groups in the same revenue category in section 5.

in which the variables are for a firm *i* for a given time *t*. The dependent variables are: (1) Success Rate = (Total amount sold/Total offering amount), and (2) Ln(Sold) = ln(1+Total amount sold). *Minority* is a dummy variable that equals one for minorities, and zero otherwise. For example, in column for Blacks, Minority refers to *Blacks*. *Control* is a vector of firm i's controls: Revenue fixed effects for revenue range variable, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects for security type (equity, debt, securities to be acquired, and other types), year, industry, and state. The *t*-statistics in parentheses are based on robust standard errors.[11] Appendix A defines the variables.

Table 4 presents estimates from cross-sectional OLS regressions of our two measures of financing success: Success rate and Ln($Sold). The main explanatory variable of interest is the race of the firm's EOs. We find that Black and Hispanic entrepreneurs have lower financing success rate and raise less capital than do Whites. In terms of economic magnitude, Blacks (Hispanics) have a 7% (5%) lower funding success rate than do Whites, and they raise substantially less capital. The total amount sold is approximately 38% lower ($= e^{-0.48} - 1$) in offerings by Blacks than by Whites. The average dollar amounts Whites sold ($Sold) is $6,107,923 in the regression sample in column (2). So Black entrepreneurs raise $2.3 million less than White entrepreneurs. Similarly, Hispanics raise about 49.8% less ($= e^{-0.69} - 1$) capital than Whites, who raised an average of $6,118,881 in the regression sample in column (4). So Hispanic entrepreneurs raise about $3 million less capital than White entrepreneurs.

[11] Our results are similar when standard errors are clustered by state.

4.2. Information asymmetry or credential discounting?

We next explore reasons why minorities raise less capital and thus, have a less successful offering. As discussed in section 2, minority entrepreneurs may have less success obtaining financing because investors are less familiar with these firms, resulting in greater information asymmetry. We expect information asymmetry to be greater with firms that do not disclose their revenue in Form D filings. Accordingly, we measure the degree of information asymmetry using the variable $DiscloseRevenue$ that equals one if firm *i* reports revenue, and zero otherwise.[12] We then re-estimate the regressions in Table 4 by interacting this variable with *Minority*:

$$y_i = \alpha_0 + \alpha_1 Minority_i \times DiscloseRevenue_i + \alpha_2 DiscloseRevenue_i + \alpha_3 Minority_i + \beta Control_i + \delta Fixed\ Effects_i + \varepsilon_i$$

Table 5 shows the results. Contrary to the prediction of the information hypothesis, the success rate for Blacks and Hispanics is even lower when they disclose their revenue, which should reduce information asymmetry between issuers and investors. Thus, we conclude that providing information on firm quality that may reduce information asymmetry does not help Black and Hispanic entrepreneurs achieve success in financing. Note that the self-reported revenue figures in Form D filings may not be audited, although we know whether the firm has an auditor. The market appears to put less trust in revenue disclosures by Black and Hispanic entrepreneurs.

Another potential form of investor bias might be discounting minority-led startups' credentials. To investigate this issue, we re-estimate equation (1) after adding terms that represent the interaction between the minority entrepreneur indicator and the dummy variables that represent

[12] While this is not a complete test of this channel, it provides some evidence on this issue based on available data.

startup credentials, measured using revenue categories. The minority indicator is for the missing revenue category, i.e., revenue not disclosed.

Table 6 shows the results. In the Black columns, we find a significantly negative coefficient on the interaction terms of Minority with Revenue ($25 million to $100 million) and Revenue (>$100 million), indicating that high quality Black firms experience significantly lower returns to credentials. This finding is consistent with Bertrand and Mullainathan's (2004) results, who find that employers are less responsive to the quality of résumés for job applicants with Black-sounding names. The patterns for Hispanics are generally similar. Thus, these findings suggest that investors discount high quality minority firms compared to similar White firms. Interestingly, it shows that success rates do not differ (or differ less) between minorities and Whites for firms with lower revenues but get significantly larger for firms with higher revenues, a pattern which is also visible in Panel A of Figure 4. These findings suggest that high-profile minorities get less appreciation than they deserve.

4.3. Role of brokers

Brokers can help fundraising by minority entrepreneurs in several ways. For example, another potential form of investor bias might be minority-led startups' communication costs. Minority-led startups may have less success in financing because of higher communications costs with mainstream investors. While it is hard to measure the degree of communication barrier between minority entrepreneurs and investors, financial intermediaries such as brokers can help reduce the communication barrier because most brokers are White. So, we should observe minority offerings that use brokers to be more successful. We identify brokers' race using the same procedures that we use to identify EOs' race. We find that only 0.1% of brokers are identified as minority. So, we decide that examining broker race in our context is not useful, as it does not have sufficient variation to derive any meaningful inference. However, this homophily can offer insight into White brokers' role in working with minority clients.

We measure brokers' effectiveness in private offerings using dollar value of brokerage fees (sales commission and finder's fees). Specifically, we test whether paying higher brokerage fees for private placements increases the success of minority offerings. So we re-estimate the regressions in Table 4 by interacting the total fees paid to brokers, which is the sum of sales commissions and finders' fees, with an indicator for minority offerings. Table 7 shows that paying larger brokerage commission increases the success rate of financing and the amount of capital raised. The effect of brokerage fees is insignificant for Hispanics. For Black entrepreneurs, paying larger commissions has a perverse effect: it lowers their financing success rate!

4.4. The number of investors

We next explore whether more investors lead to greater offering success for firms led by minority entrepreneurs compared to those with observably similar White entrepreneurs. Using the number of investors who invested in the offering, we re-estimate the regressions in Table 4 by interacting the number of investors with an indicator for minority offerings. Table 8 shows that both Black and Hispanic entrepreneurs raise more capital when the number of investors increases. These findings suggest that Black and Hispanic startups benefit from having a larger number of investors.

5. Robustness Checks

In this section, we attempt to address three identification concerns. The first concern is that lower funding to minority-led projects may simply be due to these projects being of lower quality. Unfortunately, we have no information about project quality because the SEC does not require any disclosure in Form D filings about the projects to be funded. However, we partially address this issue by controlling for measures of firm and offering quality such as firm revenue, firm age, offering duration and types of securities offered.

The second concern is about selection. The issue is whether minority entrepreneurs face barriers to accessing this market. If so, we are only analyzing projects that are actually proposed by entrepreneurs. Our study is based on the premise that any barriers minorities face in accessing this market are small. If so, selection is less of a concern.

The third concern is about omitted variables. There are differences between minority and White-owned startups on several variables such as location, industry, business size, and the amount of capital raised. In addition, minority and White entrepreneurs differ in education, wealth, and several other aspects on which we have no data. We try to mitigate this concern by matching each minority firm with a White-owned firm with similar firm and offering characteristics. We then obtain average treatment effects from the matched sample to draw inferences based on contemporaneous outcomes of financing in minority vs. White-owned firms. Specifically, we use a nearest-neighbor matching method using the following covariates: Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects for security type (equity, debt, securities to be acquired, and other types). We do this matching in the same Revenue category in the same year and the same industry. Table 9 reports the results. Panel A reports the model-adjusted difference in means and ratio of variances between the treated and untreated for each covariate. Panel B reports the average treatment effect (ATE). We consistently find that Blacks (Hispanics) have a 7% (4%) lower funding success rate than Whites, and they raise substantially less capital. Both effects are statistically significant.

6. Discussion and Conclusion

Entrepreneurs of color are glaringly underrepresented in entrepreneurship, and they often struggle to attract early-stage funding for their startups. While the finance industry, institutional and individual investors, and regulators and policymakers are making efforts to reduce the racial gap, knowledge of its full extent and nature in the private capital market for entrepreneurs of color is quite limited. This study attempts to fill this gap in the literature.

We examine whether minority entrepreneurs raise capital successfully using all first-time private placements via Form D offerings over 2009-2019. We find that Black and Hispanic entrepreneurs have less success in financing and raise less capital than do Whites. Blacks (Hispanics) have a 7% (5%) lower funding success rate than Whites do, which translates into these minorities raising 38% (50%) less capital, or \$2.3 million (\$3 million) less compared to the mean amount raised by Whites. We find that low returns to these minorities' credentials partly explains the racial gap in small business financing, while information asymmetry does not. Our study calls for continued efforts to improve minorities' experience in private capital markets.

A possible reason for the racial difference in raising funds may be the fact that the finance industry, which provides the capital that fuels small businesses, remains White. For example, the chief executives of the largest American banks are mostly White men, as are the leaders of asset managers, private-equity firms, and hedge funds. Of the approximately 100,000 executives at financial firms in 2018, only 2,644 were Black and 3,682 Hispanics, according to the US Equal Employment Opportunity Commission.[13] As one potential solution to help minority entrepreneurs, a story in the *Wall Street Journal* suggests that entrepreneurs of color receive angel financing from investors of color. Angeles Investors, a nationwide group of Hispanic business executives who make angel investments in Hispanic-owned tech startups, has committed seed money to seven companies in amounts that average about $150,000. In addition, individual angel investors attempt to enhance minority-owned businesses. For example, Jay-Z, a rapper and entrepreneur created a $10 million fund for minority-owned startups.[14] Numerous stories in the business media refer to efforts to help combat racism. To reduce the racial gap and increase funding opportunities for minority entrepreneurs, some giant public firms are launching several projects in response to the national debate about systemic racism over George Floyd's killing in 2020. For example, Apple invested $10 million in Harlem Capital, a New York early-stage venture-capital firm, to support its investments in 1,000 companies with diverse founders.[15] Banks are also starting to focus on expanding access to enhance minority-owned small businesses. In a high-profile push, JPMorgan recently committed $30 billion to an effort to promote minority-owned small businesses.[16] The

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[13] See Hoffman, L., and Pulliam, S. "Wall Street Knows It's Too White. Fixing It Will Be Hard." *Wall Street Journal,* July 2, 2020.

[14] See Monga V. "Jay-Z Joins Push to Boost Minority-Owned Cannabis Businesses." *Wall Street Journal,* January 20, 2021.

[15] See Needleman, S.E. "Apple to Open Developer Academy, Provide Funding for Minority Entrepreneurs; Moves are part of tech giant's $100 million pledge to fight against racism after the killing of George Floyd." *Wall Street Journal,* January 13, 2021.

[16] See McCaffrey, O. "JPMorgan Unveils $30 Billion Push to Bridge Racial Wealth Gap." *Wall Street Journal,* October 8, 2020.

reasons for the diversity gap in private capital markets, and potential solutions for reducing it, are surely issues that merit further research.

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Figure 1

Geography of Private Offerings

The graph shows the heatmap of annual number of private offerings over 2009-2019. The figure shows the number of unique issuers that raise capital in private markets through Form D filings.

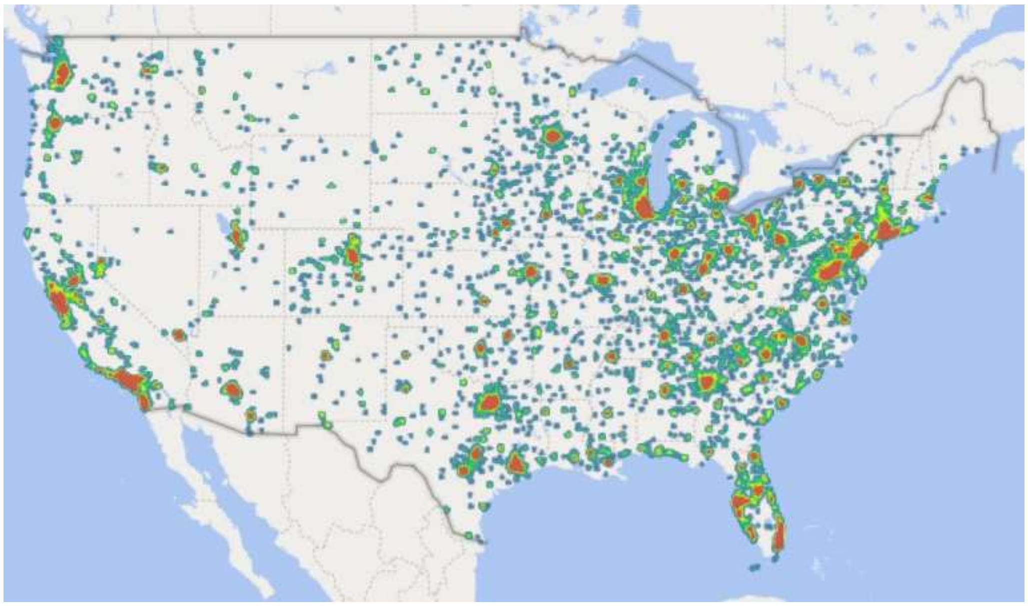


Figure 2

Minority fund-raising rates by industry

The figure plots Minority fund-raising rates by industry. The fund-raising rates are defined as the regression coefficients of industry fixed effects and 95% confidence intervals from estimating a regression: $Minority_{i,t} = \alpha_0 + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$
where the variables are for a firm i for a given time t. *Minority* equals one, if firm i has any Minority executive officer; it equals zero otherwise. Fixed Effects is a vector of fixed effects of year, industry, and state. Robust standard errors are obtained.

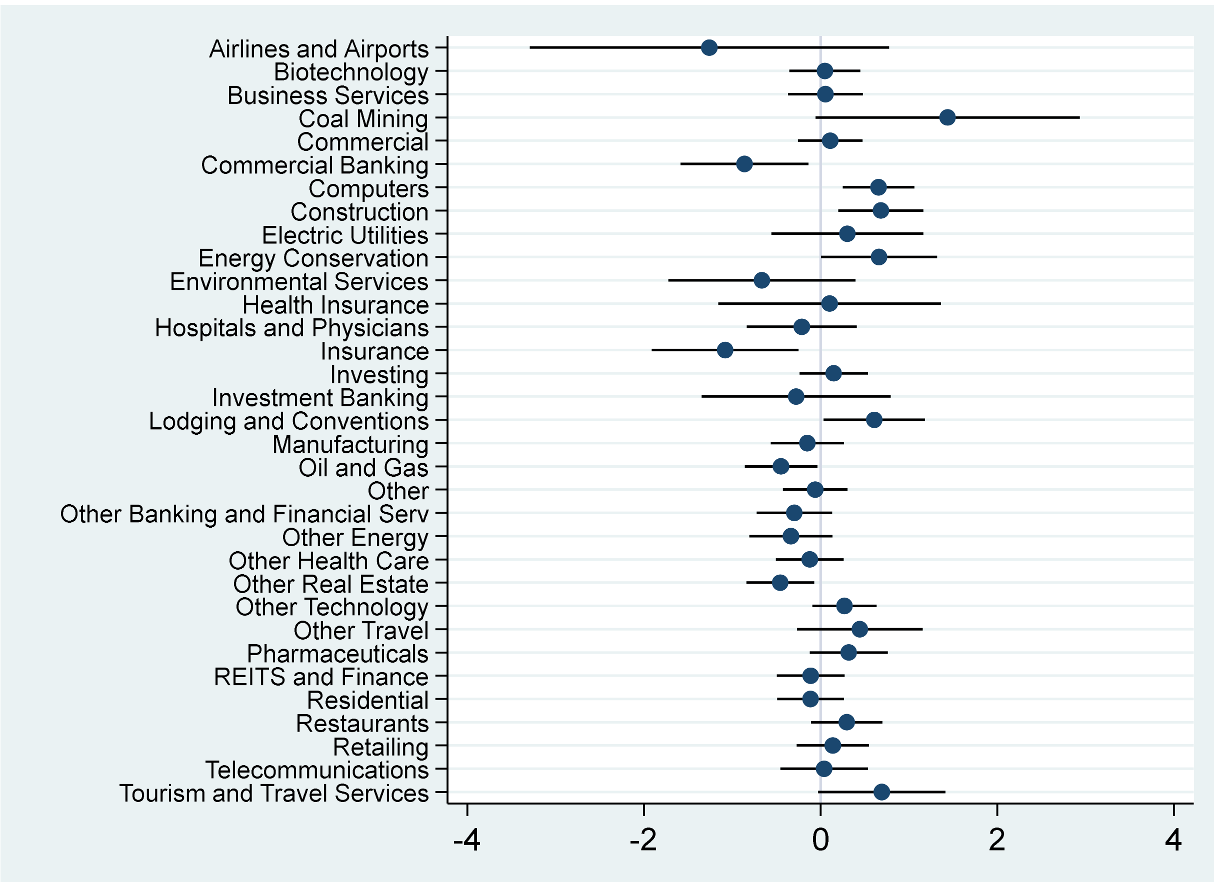


Figure 3

Minority Fund Raiser

The figure shows the annual number of unique issuers that raise capital in private markets in a transaction exempt from registration through Form D filings over 2009-2019. The sample selection procedure is described in Table 1. Black bar represents the number of unique first-time fund-raising firms through Form D filings with any Minority (Black, Hispanic, Asian) executive officer. Gray bar the number of unique first-time fund-raising firms through Form D filings with all White executive officers.

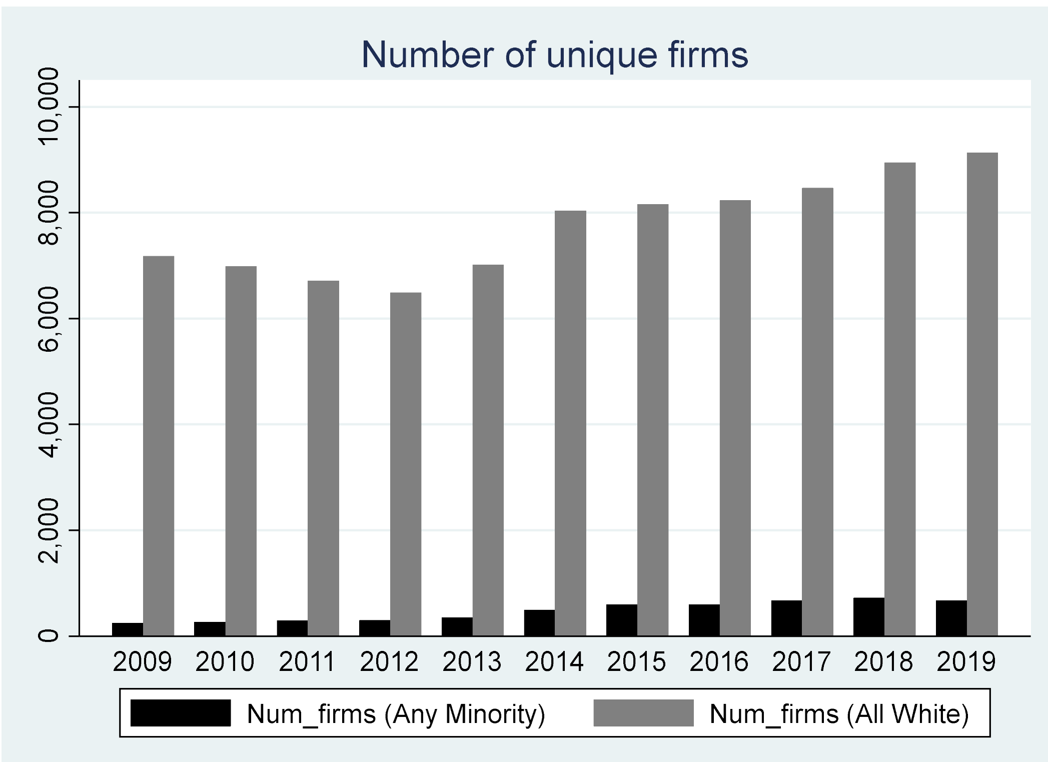
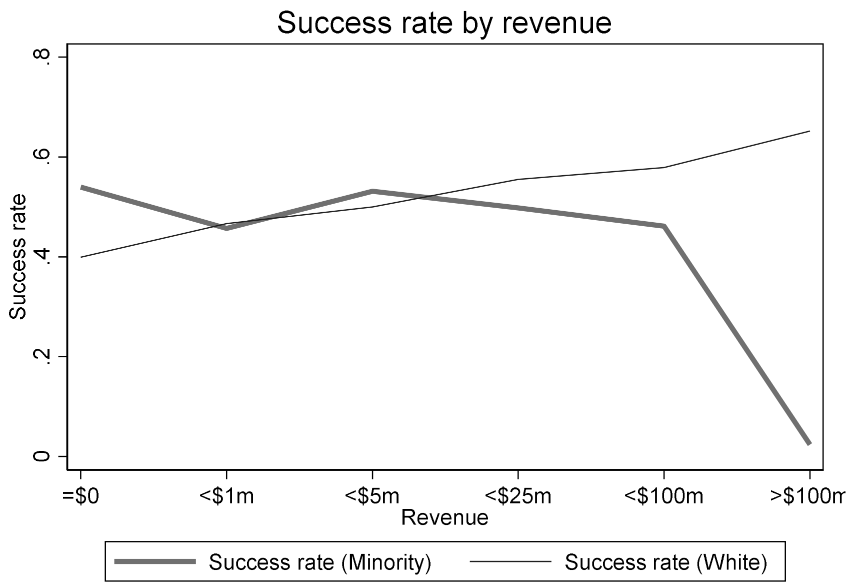


Figure 4

Success Financing Rate

The graph shows the averages of success rate of private offerings led by any Minority firm or by all White firm. Appendix A defines the variables.

Panel A: Success rate by revenue



Panel B: Success rate by age

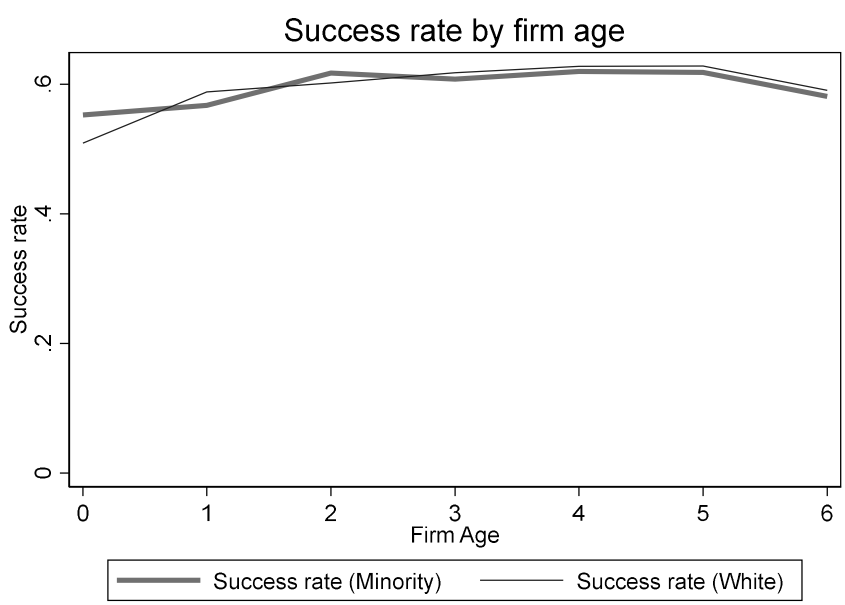


Table 1

Private Placements

The table shows private offerings filed via Form D filings with the SEC. Panel A shows the steps in our sample selection procedure. Panels B and C show the number of firms offering private placements by Top 5 industry and state by Minority status, respectively.

Panel A: Sample selection process

Sample Selection	
Earliest filed electronic Form D filings over 2008-2019 (Electronic filing of Form D with SEC required since March 16, 2009)	177,418
Exclude pooled investment funds	108,109
Keep only the primary issuer when multiple issuers jointly file a Form D	106,282
Keep firms located in the United States	101,096
Drop firms listed in NYSE and Nasdaq	99,673
Drop firms filed any 10Q or 10K reports	96,799
Keep filings made over 2009-2019	96,574
Private Placement Sample (at firm level)	**96,574**

Panel B: Top 5 Industry and State by Minority Status

Minority			All White			
Industry	Freq.	Percent	Industry	Freq.	Percent	$Freq_w/Freq_{nw}$
Other Technology	1260	24.17	Other	17400	20.38	13.8
Other	963	18.48	Other Technology	15617	18.3	16.2
Commercial	641	12.3	Commercial	8088	9.48	12.6
Residential	293	5.62	Other Real Estate	6023	7.06	20.6
Other Real Estate	225	4.32	Residential	5156	6.04	22.9
State	Freq.	Percent	State	Freq.	Percent	$Freq_w/Freq_{nw}$
CALIFORNIA	1776	34.08	CALIFORNIA	16014	18.76	9.0
TEXAS	616	11.82	NEW YORK	8883	10.41	14.4
NEW YORK	499	9.57	TEXAS	8835	10.35	17.7
DELAWARE	246	4.72	FLORIDA	3873	4.54	15.7
FLORIDA	215	4.13	MASSACHUSETTS	3610	4.23	16.8

Table 2

Summary Statistics of Regression Variables

The table reports summary statistics of the main variables used in this study over 2009-2019. Observations are at the firm level. Appendix A provides variable definitions.

				Quantiles		
Variable	n	Mean	S.D.	0.25	Mdn	0.75
Executive Officer (EO) Race Unknown	96574	0.06	0.24	0.00	0.00	0.00
IPO	96574	0.00	0.03	0.00	0.00	0.00
Acquired	96574	0.01	0.11	0.00	0.00	0.00
Bankrupt	96574	0.00	0.01	0.00	0.00	0.00
Offering_is_indefinite	96574	0.07	0.26	0.00	0.00	0.00
DiscloseRevenue	96574	0.38	0.48	0.00	0.00	1.00
Ln(Investor)	96574	1.74	1.34	0.69	1.61	2.64
Duration	96574	0.08	0.27	0.00	0.00	0.00
BusinessTransaction	96574	0.04	0.20	0.00	0.00	0.00
CA_NY	96574	0.30	0.46	0.00	0.00	1.00
Equity	96574	0.81	0.39	1.00	1.00	1.00
Debt	96574	0.14	0.35	0.00	0.00	0.00
Right to acquire	96574	0.10	0.30	0.00	0.00	0.00
Other security	96574	0.08	0.27	0.00	0.00	0.00
Ln(Firm Age)	96574	0.63	0.68	0.00	0.69	1.10
Revenue	96574	0.66	1.05	0.00	0.00	1.00
Success Rate	89757	0.56	0.43	0.06	0.65	1.00
Ln(Sold)	96574	10.94	5.76	10.60	13.12	14.73
Ln(Offering)	89757	14.43	1.94	13.30	14.51	15.54
Ln(Fee)	87557	0.74	2.75	0.00	0.00	0.00
Ln(Team Size)	90570	0.68	0.61	0.00	0.69	1.10
Minority	90570	0.06	0.23	0.00	0.00	0.00
Black	85995	0.01	0.09	0.00	0.00	0.00
Hispanic	86356	0.01	0.11	0.00	0.00	0.00
Asian	89088	0.04	0.20	0.00	0.00	0.00
All White	90570	0.94	0.23	1.00	1.00	1.00

Table 3

Descriptive Statistics

This table compares the characteristics of first-time offerings made by Minority and White entrepreneurs using Form D filings over 2009-2019. The sample is divided based on the *Minority* variable, which equals one, if a firm has any Minority executive officer; it equals zero, otherwise. The table reports means, medians, *t*-statistics and *p*-values of the differences between the two groups. For dollar variables, *t*-statistics are based on the natural logarithm of one plus the dollar value. To reduce the effect of outliers, we winsorize all dollar variables and the number of investors at the 1st and 99th percentiles.

	Minority	White	Mean			Median		
	N	N	Minority	White	t-stat	Minority	White	p-value
Success Rate%	4775	79592	55.18	55.17	0.01	62.15	62.24	0.69
Sold$	5212	85358	2,735,534	6,164,539	-5.36	326,001	500,000	0.00
Offering$	4775	79592	7,866,673	11,100,000	-14.53	1,500,000	2,000,000	0.00
Fee$	4778	77420	4,210.24	8,441.13	-2.56	0.00	0.00	0.03
Investor	5212	85358	10.76	13.64	-7.94	3.00	4.00	0.00
Revenue when disclosed	2303	31737	0.53	0.76	-10.87	0.00	0.00	0.00
Duration	5212	85358	0.10	0.08	6.79	0.00	0.00	0.00
Equity	5212	85358	0.80	0.81	-0.85	1.00	1.00	0.39
Debt	5212	85358	0.16	0.14	3.95	0.00	0.00	0.00
To_be_acquired	5212	85358	0.11	0.11	0.42	0.00	0.00	0.67
Other	5212	85358	0.06	0.08	-4.26	0.00	0.00	0.00
BusinessTransaction	5212	85358	0.02	0.04	-8.21	0.00	0.00	0.00
Firm Age	5212	85358	1.23	1.48	-8.73	1.00	1.00	0.00
CA_NY	5212	85358	0.44	0.29	22.21	0.00	0.00	0.00
Team Size: # EOs	5212	85358	1.29	2.47	-48.29	1.00	2.00	0.00
$Offering_is_indefinite	5212	85358	0.08	0.07	4.52	0.00	0.00	0.00
DiscloseRevenue	5212	85358	0.44	0.37	10.14	0.00	0.00	0.00

Table 4

Minority Small Business Financing

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer's race. The sample includes first-time fund raisers using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

where the variables are for a firm i for a given time *t*. The dependent variable in column (1) is *Success Rate* = (Total amount sold / Total offering amount); in column (2), Ln(Sold) = ln(1+Total amount sold). Each reported variable in the row of Minority is a dummy variable that equals one when true, and zero otherwise. For example, in column of Black, Minority reports $Black$ dummy variable that equals one, if firm *i* has any Black executive officer; it equals zero, if having all White executive officer. *Control* is a vector of firm i's controls: Revenue fixed effects, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type). $Fixed\ Effects$ is a vector of fixed effects of year, industry, and state. The t-statistics in parentheses are based on robust standard errors. Appendix A defines the variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Black		Hispanic	
	SuccessRate	Ln(Sold)	SuccessRate	Ln(Sold)
	(1)	(2)	(3)	(4)
Minority	-0.07***	-0.48***	-0.05***	-0.69***
	(-4.33)	(-4.95)	(-4.29)	(-3.79)
Controls	Yes	Yes	Yes	Yes
Revenue FE	Yes	Yes	Yes	Yes
Security type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	80163	80163	80519	80519
Adjusted R^2	0.18	0.18	0.18	0.18

Table 5

Information Asymmetry

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer race. The sample includes first-time fund raisers using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} \times DiscloseRevenue_{i,t} + \alpha_2 DiscloseRevenue_{i,t} + \alpha_3 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

where the variables are for a firm *i* for a given time *t*. The dependent variable in column (1) is *Success Rate* = (Total amount sold / Total offering amount); in column (2), Ln(Sold) = ln(1+Total amount sold). For example, in column of Black, Minority reports $Black$ dummy variable that equals one, if firm i has any Black executive officer; it equals zero, if having all White executive officer. $DiscloseRevenue$ equals one if firm *i* reports revenue, zero otherwise. *Control* is a vector of firm i's controls: Revenue fixed effects, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type). $Fixed\ Effects$ is a vector of fixed effects of year, industry, and state. The t-statistics in parentheses are based on robust standard errors. Appendix A defines the variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Black		Hispanic	
	SuccessRate	Ln(Sold)	SuccessRate	Ln(Sold)
Minority× DiscloseRevenue	-0.10***	-1.89***	-0.07***	-1.29***
	(-3.15)	(-3.94)	(-2.62)	(-3.56)
Minority	-0.02	-0.26	-0.02	-0.07
	(-0.88)	(-0.88)	(-1.27)	(-0.31)
DiscloseRevenue	0.08***	-0.28	0.08***	-0.23
	(2.81)	(-0.64)	(2.80)	(-0.53)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	80163	80163	80519	80519
Adjusted R^2	0.18	0.18	0.18	0.18

Table 6

Lower Returns to Credentials

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer's race. The sample includes first-time fund raisers using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} \times Revenue_{i,t} + \alpha_2 Revenue_{i,t} + \alpha_3 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

where the variables are for a firm i for a given time t. $Revenue$ is fixed effects of a categorical variable of revenue. *Control* is a vector of firm i's controls: Revenue fixed effects, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type). $Fixed\ Effects$ is a vector of fixed effects of year, industry, and state. The t-statistics in parentheses are based on robust standard errors. Appendix A defines the variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Black		Hispanic	
	SuccessRate	Ln(Sold)	SuccessRate	Ln(Sold)
Minority×Revenue(=$0)	-0.09**	-1.62***	-0.09***	-1.56***
	(-2.39)	(-2.81)	(-3.03)	(-3.54)
Minority×Revenue(($0 to $1m)	-0.13***	-2.01***	-0.03	-0.79
	(-2.64)	(-2.87)	(-0.94)	(-1.48)
Minority×Revenue($1m to $5m)	-0.08	-2.30*	0.02	0.75
	(-0.92)	(-1.73)	(0.23)	(0.68)
Minority×Revenue($5m to $25m)	-0.08	-1.73	-0.15*	-4.48***
	(-0.58)	(-0.67)	(-1.96)	(-2.79)
Minority×Revenue($25m to $100m)	-0.29***	-10.48***	-0.05	-5.39
	(-9.27)	(-24.30)	(-0.19)	(-1.17)
Minority×Revenue(>$100m)	-0.44***	-17.37***	-0.32***	-3.15
	(-11.23)	(-30.59)	(-5.82)	(-1.33)
Minority	-0.02	-0.26	-0.02	-0.07
	(-0.88)	(-0.88)	(-1.27)	(-0.31)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	80163	80163	80519	80519
Adjusted R^2	0.18	0.18	0.18	0.18

Table 7

Role of Brokers

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer's race. The sample includes first-time fund raisers using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} \times BrokerFee_{i,t} + \alpha_2 BrokerFee_{i,t} + \alpha_3 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

where the variables are for a firm i for a given time t. The dependent variable in column (1) is *Success Rate* = (Total amount sold / Total offering amount); in column (2), Ln(Sold) = ln(1+Total amount sold). Each reported variable in the row of Minority is a dummy variable that equals one when true, and zero otherwise. For example, *Minority* equals one, if firm *i* has any minority, Black, or Hispanic executive officer; it equals zero, if having all White executive officer. $BrokerFee$ equals ln(1+ sales commissions+ finders fees) when sales commissions and finders fees are not estimates. $Control$ is a vector of firm i's controls: Revenue fixed effects, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type). $Fixed\ Effects$ is a vector of fixed effects of year, industry, and state. The t-statistics in parentheses are based on robust standard errors. Appendix A defines the variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Black		Hispanic	
	SuccessRate	Ln(Sold)	SuccessRate	Ln(Sold)
Minority× BrokerFee	-0.02**	-0.21	-0.01	-0.11
	(-2.40)	(-1.40)	(-0.88)	(-0.71)
Minority	-0.06***	-0.88***	-0.05***	-0.60***
	(-3.63)	(-3.57)	(-3.83)	(-3.24)
BrokerFee	0.01***	0.11***	0.01***	0.11***
	(21.79)	(13.46)	(21.87)	(13.51)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	72784	72784	73092	73092
Adjusted R^2	0.18	0.20	0.18	0.20

Table 8

The Number of Investors

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer's race. The sample includes first-time fund raisers using Form D filings over 2009-2019. We use the following specification:

$$y_{i,t} = \alpha_0 + \alpha_1 Minority_{i,t} \times Investor_{i,t} + \alpha_2 Investor_{i,t} + \alpha_3 Minority_{i,t} + \beta Control_{i,t} + \delta Fixed\ Effects_{i,t} + \varepsilon_{i,t}$$

where the variables are for a firm i for a given time *t*. The dependent variable in column (1) is *Success Rate* = (Total amount sold / Total offering amount); in column (2), Ln(Sold) = ln(1+Total amount sold). Each reported variable in the row of Minority is a dummy variable that equals one when true, and zero otherwise. For example, *Minority* equals one, if firm *i* has any minority, Black, or Hispanic executive officer; it equals zero, if having all White executive officer. $Investor$ equals ln(1+ total number of investors already invested). *Control* is a vector of firm i's controls: Revenue fixed effects, Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type). $Fixed\ Effects$ is a vector of fixed effects of year, industry, and state. The t-statistics in parentheses are based on robust standard errors. Appendix A defines the variables. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Black		Hispanic	
	SuccessRate	Ln(Sold)	SuccessRate	Ln(Sold)
Minority× Investor	0.02	0.80***	0.01	0.53***
	(1.50)	(4.89)	(1.34)	(3.72)
Minority	-0.04**	-1.48***	-0.03**	-0.74***
	(-2.51)	(-5.25)	(-2.05)	(-3.11)
Investor	0.19***	2.96***	0.19***	2.96***
	(127.86)	(129.58)	(127.92)	(129.64)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	80163	80163	80519	80519
Adjusted R^2	0.47	0.56	0.47	0.56

Table 9

Robustness Checks

The table presents estimates from cross sectional OLS regressions of measures of success of private offerings and the issuer's race. We use a nearest-neighbor matching method based on covariates of *Control*: *Control* is a vector of firm i's controls: Firm Age, $Offering, Duration, BusinessTransaction, Team Size, CA_NY, and fixed effects of security types (equity, debt, securities to be acquired, and other type) and in the same Revenue category in the same year and same industry. Panel A reports the model-adjusted difference in means and ratio of variances between the treated and untreated for each covariate. Panel B reports the average treatment effect (ATE).

Panel A: Differences in covariates

	Black				Hispanic			
	Standardized differences		Variance ratio		Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
Firm Age	-0.23	-0.06	0.83	0.89	-0.14	-0.16	0.83	0.71
$Offering	-0.23	-0.21	1.14	0.61	-0.26	-0.17	1.19	0.61
Team Size	-1.27	-0.94	0.28	0.43	-1.01	-0.78	0.41	0.54
Duration	0.09	-0.20	1.46	0.25	0.09	-0.17	1.40	0.36
BusinessTransaction	-0.10	-0.24	0.58	0.14	-0.13	-0.22	0.48	0.16
CA_NY	-0.14	-0.17	0.90	0.87	0.07	0.00	1.05	1.00
Equity	0.01	0.26	0.99	0.61	-0.10	0.17	1.14	0.73
Debt	-0.03	-0.25	0.95	0.55	0.02	-0.14	1.04	0.73
To_be_acquired	-0.11	-0.23	0.77	0.53	-0.01	-0.14	0.99	0.69
Other	0.02	-0.15	1.10	0.49	0.07	-0.14	1.27	0.53

Panel B: Average treatment effect

	Dep. Variable	Coef.	p-value	Number of obs.
Black vs White	Success Rate	-0.07	0.01	30,105
Hispanic vs White	Success Rate	-0.04	0.06	38,774
Black vs White	Ln(Sold)	-0.94	0.03	30,105
Hispanic vs White	Ln(Sold)	-0.71	0.02	38,774

Appendix A
Variable Definitions
The table defines the variables used in the study. The data come from Audit Analytics Private Placement Database.

Variable	Definition
Revenue	This indicates Revenue Range disclosed Item 5, Form D = 0 if revenue range is not disclosed. = 1 if revenue range is "No Revenues" = 2 if revenue range is "$1 - $1,000,000" = 3 if revenue range is "$1,000,001 - $5,000,000" = 4 if revenue range is "$5,000,001 - $25,000,000" = 5 if revenue range is "$25,000,001 - $100,000,000" = 6 if revenue range is "Over $100,000,000"
Ln(Offering)	Ln(1+the dollar amount of the securities being offered. Item 13, Form D)
Ln(Investor)	Ln(1+the total number of investors who have already invested in the offering. Item 14, Form D)
Duration	=1 if the issuer intends the offering to last more than one year, zero otherwise. Item 8, Form D
Security Types	Types of securities offered
Equity	=1 if type(s) of securities offered is Equity, zero otherwise. Item 9, Form D
Debt	=1 if type(s) of securities offered is Debt, zero otherwise. Item 9, Form D
Right to Acquire	=1 if type(s) of securities offered is Option, Warrant or Other Right to Acquire Another Security or Security to be Acquired Upon Exercise of Option, Warrant or Other Right to Acquire Security.
Other	=1 if type(s) of securities offered is Pooled Investment Fund Interests, Tenant-in-Common Securities, Mineral Property Securities, or Other.
BusinessTransaction	=1 if the offering is in made in connection with a business combination transaction., zero otherwise. Item 10, Form D
Success Rate	(Total amount sold / Total offering amount)
Ln(Sold)	Ln(1+ the dollar amount of the securities sold. Item 13, Form D)
Ln(Fee)	Ln (1+ sales commission + finders' fees) when they are not estimates. Item 15 of Form D.
Ln(Firm Age)	Ln(1+filing year – year of incorporation)
Ln(Team Size)	Ln(1+the number of executive officers)

CA_NY	= 1 if issuer is located in California or New York, zero otherwise.
Offering_is_indefinite	= 1 when total offering amount = 0 or when total offering amount is "Indefinite".
DiscloseRevenue	= 1 if firm reports revenue, zero otherwise
Minority	= 1 if firm has any minority executive officers (Black, and Hispanic), zero if having no minority (All White executive officers)
Black	= 1 if firm has any Black, zero if having no Black (All White)
Hispanic	= 1 if firm has any Hispanic, zero if having no Hispanic (All White)
Asian	= 1 if firm has any Asian, zero if having no Asian (All White)
White	= 1 if firm has any White, zero if having no White (All Minority)
Year Fixed Effects	Dummy variable for filing year
State Fixed Effects	Dummy variable for state of firm's current business address information, as disclosed Item 2 of Form D.
Industry Fixed Effects	Dummy variable for industry, as disclosed in Item 4 of Form D.

Appendix B

Data used to measure investment outcomes after fundraising

We use three databases from Audit Analytics to construct our three measures of investment outcomes following a fundraising campaign: *IPO*, *Acquired* and *Bankrupt.* The initial public offerings dataset covers all US IPOs since 2000. Data points include IPO information disclosed in registration forms filed before the IPO (e.g., S-1, S-1/A, SB-1, SB-1/A, N-1, N-1/A, S-4, S-4/A, S-11, S-11/A, F-1, F-1/A). The variable IPO_i equals one for a given firm i that went public after it sought capital via a private placement. We also obtain data on IPOs from Securities Data Company (SDC) Platinum. But we chose to use the data from SEC filings because the SDC database contains fewer IPOs than the former. From the SDC database, we first select all offerings involving equity (common stock, convertible, equity pipeline and registrations, and private equity). Then we select all the data ranging from 2000 to 2021. We apply data filtering to obtain issuers in the US. Then, we merge firms with IPOs from this SDC database to Form D issuers by name and the state where the issuer is located. We use both STATA and Python package and require at least 90% match rate of the name after first matching on state.[17] We are able to match about 100 Form D issuers with SDC (0.1% of Form D issuers), which is less than the number of Form D issuers that are identified using the IPO disclosures with the SEC. Also, our matching with the IPO disclosure is superior as it enables us to exactly match them using issuers' Central Index Key (CIK) number. The CIK number is used on the SEC's systems to identify corporations and individuals who have filed disclosure with the SEC.

[17] We use STATA package *matchit* and python package *fuzzywuzzy*.

The mergers and acquisitions database tracks current and historical M&A activity. It includes two different datasets: transaction-level summary and party-level detail. The transaction-level summary provides such details as transaction type and value. The party-level detail includes parties referred to as acquirer, target, and survivor, as well as the acquirers' most recent financial information before the deal commencement date. The party-level detail provides industry and financial data on all the parties named, including related parties such as parent and affiliate companies for each transaction, if available. The database also includes information on canceled transactions. The variable $Acquired_i$ equals one for a given firm *i* that is acquired in an M&A that closes after the firm sought capital via a private placement.

The bankruptcy notification dataset tracks bankruptcy declarations under Chapters 7, 11, and 15 by court and date disclosed since 2000. The data are collected by monitoring SEC filings and the US bankruptcy dockets located on PACER (US court electronic records). The variable $Bankrupt_i$ equals one for a given firm *i* that went bankrupt on bankruptcy end date (or begin date if the end date is missing).