Supply-Side Barriers in Black Patenting: Evidence from Innovative Firms

Marlène Koffi[a,b], Matt Marx[c,b], Emmanuel Yimfor[d]

[a] *University of Toronto*
[b] *NBER*
[c] *Cornell University*
[d] *Columbia University*

January 1, 2026

Abstract

Prior work has documented a substantial gap in high-growth entrepreneurship among Black founders, but the mechanisms underlying this gap remain elusive. Patents serve as "success markers" that help founders raise venture capital, so we explore whether this gap is explained in part by Black employees filing patents at lower rates, and if so, where in the process the disparity emerges. We find that the racial gap in patenting forms at the filing stage, not through downstream discrimination. Among employees at innovative firms (i.e., with at least 50 patents), Black workers patent at one-fifth the rate of colleagues in similar roles. Using quasi-random assignment of patent applications to examiners as an instrument, we rule out three demand-side explanations: patent approval rates are nearly identical; marginally-approved Black patents show no quality deficit in an outcome test; and patent grants are equally effective in propelling Black inventors toward high-growth entrepreneurship. Black inventors who do file have stronger credentials than peers, and Black employees are more likely to found startups despite patenting less. Our results point to a supply-side gap at the patent filing stage, not downstream discrimination.

⋆ Corresponding author: Emmanuel Yimfor, Columbia University and Kenan Institute Distinguished Fellow (emmanuel.yimfor@columbia.edu). We thank seminar participants at Washington University in St. Louis, UCLA, and the University of Minnesota, as well as participants at the 2026 ASSA meetings. All errors are our own.

I. Introduction

Understanding why racial minorities are underrepresented in high-growth entrepreneurship is a central question in the economics of innovation. In this paper, we focus on an oft-discussed yet difficult-to-study question: is there a gap in inventive activity, and what factors are responsible?

We find that the racial gap in patenting forms before anyone sees a patent application. Black employees at innovative firms file patents at one-fifth the rate of colleagues in the same occupation and company. When they do file, their applications are approved at identical rates, and their patents receive comparable citations. The gap is supply-side, not demand-side: it emerges at filing, not through discrimination in examination or differential returns to patents.

This finding matters because patents predict venture funding, and the gap in Black high-growth entrepreneurship remains large. Cook, Marx and Yimfor (2022) report that only 2.5% of entrepreneurs who raise venture capital are Black, four times lower than the Black share of the working population. Black founders who obtain funding receive less than half as much as others. Among the explanations is that Black entrepreneurs have fewer "success markers" that investors use as heuristics: patents, serial entrepreneurship, degrees from elite schools. These markers explain one-third to one-half of the racial gap. If patents matter for funding, understanding why Black employees patent less could help close the gap.

The patent disparity is striking. Only five percent of Black-owned startups have a patent compared with ten percent for others; founders of Black startups are half as likely to be listed as inventors. Patents attract investors for two reasons: they protect against imitation, and they signal technological value that is otherwise hard to verify. Several scholars have documented how patents help startups raise capital (Hsu and Ziedonis, 2013; Conti, Thursby and Rothaermel, 2013; Hoenig and Henkel, 2015; Farre-Mensa, Hegde and Ljungqvist, 2020). Guzman and Stern (2020) use patents to identify high-quality startups.

Given the connection between patenting and funding for high-growth entrepreneurship, we test three explanations for why Black employees patent less. *First*, supply-side factors: Black employees may file fewer applications even when holding similar positions at the same firms. *Second*, examination bias: applications may be filed at similar rates but denied more often. *Third*, differential returns: patents may yield less value for Black inventors, discouraging filing. We find evidence only for the first.

Making progress on this question is challenging for at least two reasons. Race is unavailable in patent or employment data, and name-based algorithms have double-digit error rates for Black individuals (Xie, 2022; Greenwald, Howell, Li and Yimfor, 2024). We address this by retrieving photos for 527,820 employees on LinkedIn and classifying race using a combination of name and facial-recognition algorithms (Cook, Marx and Yimfor, 2022). These employees come from 1,798 "innovative" firms (those with 50+ patents). We crosswalk employees to USPTO inventor records and to founder records in PitchBook, enabling us to observe both patenting and entrepreneurship outcomes. About one-third of all venture-backed founders worked at one of these innovative firms before launching their startups, making this a meaningful slice of the high-growth startup pipeline.

Our principal finding is that supply-side issues dominate. About 8.2% of employees at innovative firms are Black, but only 1.7% of inventors are, a 5.6× underrepresentation. Much of the raw gap reflects occupational sorting. Adding job title fixed effects reduces the gap by 64%; adding company fixed effects reduces it by another 29%. Black employees are concentrated in occupations and firms with lower patenting rates. But the residual within-firm, within-occupation gap of 6% points to barriers that operate after hiring.

Two additional patterns point to supply-side barriers rather than qualification gaps. First, Black inventors who do file applications have *stronger* credentials than their peers: higher rates of PhDs (12.5% vs. 11.6%), technical degrees (38.7% vs. 35.6%), and elite schooling (18.3% vs. 16.8%). This suggests Black employees clear higher bars to become inventors. Second, Black employees are actually *more* likely to found startups after joining innovative firms (by 38% relative to the mean), even as they patent less. Whatever suppresses Black patenting does not reflect lower entrepreneurial drive, but may still widen funding gaps given how heavily VCs weight patents when evaluating startups.

We then test demand-side explanations using an instrumental variables approach. Whether a patent is granted depends on the examiner assigned to evaluate it. We instrument for approval using quasi-random assignment of applications to examiners within art units (Williams, 2013; Aneja, Reshef and Subramani, 2024). The first stage is equally strong for Black and non-Black inventors.

We systematically rule out discrimination at three stages. At examination: approval rates differ by less than one percentage point, and power analysis rules out disparities exceeding 5% of the mean. At the margin: we use an outcome test (Becker, 1993). If examiners discriminated against Black inventors, marginally-approved Black patents would need to be stronger to clear the higher bar, and would therefore receive more citations than marginally-approved non-Black patents. We find no such difference. At returns: instrumenting for patent approval, we find no evidence that patents are less effective in propelling Black inventors toward entrepreneurship.

Why should patents facilitate entrepreneurship when the intellectual property belongs to the employer? The invention itself is the employer's, but the credential belongs to the inventor. We theorize that patents serve a signaling function. One in five inventors posts patents to their LinkedIn profile. If Black employees anticipated less signaling value, they might file less. But Black inventors are equally likely to post their patents.

Taken together, our findings point to a supply-side issue. Black inventors are not discriminated against in examination; their patents are not of lower quality; their patents are not less appreciated by investors. Rather, the gap emerges at filing. Although Black workers are underrepresented at innovative firms (8.2% vs. 12.0% of the workforce), the true gap emerges in the drop from 8.2% of employees to only 1.7% of inventors. Because patents serve as success markers that VCs use to evaluate founders, this pre-filing gap may propagate into the funding disparities documented by Cook, Marx and Yimfor (2022).

Our data allow us to identify where the gap forms, but not why. We cannot observe project assignments within firms. Black employees may be assigned to less patentable work, or may be less inclined to file when doing similar work. Disentangling these mechanisms remains a question for future research. Still, the policy implication is clear: interventions should focus upstream, ensuring equitable access to patentable projects within firms, rather than downstream at the examination stage.

II. Empirical Approach

In this section we outline our empirical strategy for measuring racial disparities in patenting and testing whether they arise from supply-side or demand-side factors. We first describe the creation of a novel dataset of hundreds of thousands of employees of "innovative" firms, which matches these employees to their inventor records and provides race. Then, we outline our identification strategy, which involves instrumenting for the likelihood a patent will be granted with the quasi-random assignment of patent examiners to applications.

A. *Data Construction*

To compare Black patenting rates vs. others and measure these inventors' transition to entrepreneurship, we need a large sample of workers at firms that are engaged in innovative activity (i.e., could reasonably be thought to be "at risk" of patenting). For those workers, we then need to determine their race, whether they filed patents at that firm, and also whether they left the firm to found a high-growth startup.

One approach to data construction would be to make use of administrative data, for example from the U.S. Census, which contains the race of company employees. One could then crosswalk firms in the Longitudinal Business Database to identify those that frequently file patents, and subsequently link individuals from the Longitudinal Employer Household Dataset (LEHD) to inventors on those firms' patents as in Babina and Howell (2024). Finally, one would need to link Census data to PitchBook or a similar source of high-growth entrepreneurial activity as in Lerner, Lithell and Phillips (2025).

However, the U.S. Census data are unsuitable for our task given the limited workplace information available in the LEHD. To compare patenting rates for Black vs. other workers, it is essential to account for the worker's role at the company. If for example, Black workers were more (less) likely to occupy technical roles at the company, we might incorrectly conclude that they are more (less) likely to patent when this could be explained by their role. Unfortunately, the LEHD does not contain information on job titles, only compensation. Instead, we turn to LinkedIn data, as captured by CoreSignal. CoreSignal's data resembles that of Revelio, which contains 90% of white-collar workers and is particularly representative of technical occupations (Hampole, Papanikolaou, Schmidt and Seegmiller, 2025), which aligns with our population of interest. Even though LinkedIn is not a universe like the LEHD, studies such as Gao, Ma and Xu (2022) have found similar results using LinkedIn and Census data.

CoreSignal also provides worker names, which we could use to predict race. But name-based algorithms alone have high error rates for Black individuals (Cook, Marx and Yimfor, 2022; Xie, 2022; Greenwald, Howell, Li and Yimfor, 2024). Instead, we classify race using photos and names. Below we describe our name and photo-based approach to determining race in the LinkedIn dataset, after first outlining our sampling of firms and employees.

A.1. *Sampling of employees at "innovative" firms*

Our aim is to benchmark patenting rates of Black vs. non-Black employees of firms that are involved with innovative activity, such that an employee could reasonably be said to be "at risk" of patenting. Our approach is to identify firms that were granted at least 50 patents during the period 2002-2019. We employed a multi-stage matching process. First, we matched patent assignees to companies in the CoreSignal database using company name and location. We standardized company names by removing common legal suffixes (e.g., "Inc", "LLC") and focusing on the most distinctive name components, then employed fuzzy matching algorithms with a similarity threshold of 90%. For companies with multiple potential matches, we leveraged state-level geographic information to improve matching precision. We then manually reviewed each match, yielding a total of 1,798 firms we refer to as "innovative."

CoreSignal contains 16.9 million employees at these firms. Classifying race from photos for all employees is prohibitively costly. We therefore construct a stratified sample. First, we restrict to employees with non-default LinkedIn profile photos (custom images rather than the generic avatar), yielding 9.3 million employees (55%). This restriction is necessary for photo-based race classification but introduces selection: employees who upload photos may differ from those who do not. Second, we restrict to employees who started between 2010–2023. Third, we draw a stratified sample with at least 500 employees per firm. This yields 527,820 unique workers across 758 companies

For these employees, we retrieve every employee during 2002-2019 and index their job title using a taxonomy from Lightcast (Tsvetkova, D'Amico, Lembcke, Knutsson and Vermeulen, 2024). Lightcast processes raw job titles from job postings, standardizing them into approximately 75,000 categories that help to place workers in similar, fine-grained job functions. This granularity is essential for our analysis: a "Machine Learning Engineer" is distinct from a "Frontend Developer," even though both are software engineers. Our fixed effects therefore compare Black and non-Black employees performing the same functional role at the same firm.

A.2. *Classifying race from photos*

Of the 527,820 employees in our stratified sample, we successfully download and classify race for 272,504 (44%). The remainder have expired photo URLs or failed downloads. We classify race using the methodology of Cook, Marx and Yimfor (2022), which combines facial recognition with name-based algorithms and achieves 94% accuracy across racial groups.

Photo-based classification reduces measurement error relative to name-only approaches. Name-based algorithms have high error rates for Black individuals (Cook, Marx and Yimfor, 2022; Greenwald, Howell, Li and Yimfor, 2024), which would attenuate our estimates of racial disparities.

Two concerns warrant discussion. First, employees with successfully classified photos differ from those without. Table A.1 reports the comparison. Employees with photos have more experience (9.3 vs 7.4 years), more education (6.1% vs 4.3% hold PhDs), and higher patenting rates (2.2% vs 1.3% file patents after joining). All differences are statistically significant.

This positive selection means our sample overrepresents high-achievers. For the racial gap estimates, the relevant question is whether selection differs by race. We cannot test this directly because race is unobserved for employees without photos. However, indirect evidence suggests our estimates are conservative. Among inventors in our sample, Black inventors have stronger credentials than White inventors: higher PhD rates (12.5% vs 11.6%), more technical degrees (38.7% vs 35.6%), and more elite schooling (18.3% vs 16.8%). This pattern suggests Black employees face stricter selection. If so, our estimated racial gap understates the true gap.

Second, the classifier may misclassify some individuals. We address this by restricting robustness checks to high-confidence classifications and excluding inventors with inconsistent race across multiple LinkedIn profiles (3.2% of matches).

A.3. Linking employees to patenting and entrepreneurial outcomes

Having established our sample of firms, employees, and race classifications, we now turn to outcomes: patenting and high-growth entrepreneurship. We constructed inventor-employee matches within each identified company using a multi-step process. First, we pre-filtered candidates by last name initial to reduce computational complexity. Second, we applied fuzzy string matching on both first and last names. For first names, we incorporated a nickname dictionary to account for common variations (e.g., "Robert" matching "Bob"). We weighted last name matching based on name frequency within each company, assigning higher weights to rare surnames to reduce false positives.

To ensure high match quality between patent records and LinkedIn profiles, we implemented several validation procedures. First, we verified temporal alignment by requiring that the inventor was employed at the assignee company around the time of patent application. Specifically, we kept only inventor-employer pairs where the patent application date fell within two years of the inventor's employment period at the assignee company according to LinkedIn data.

To avoid ambiguity, we restrict to one-to-one matches between USPTO inventor identifiers and LinkedIn profiles, retaining only cases where a single inventor matches a single profile. This yields 105,011 inventor-member pairs with validated race classification. We further restrict to inventors whose first patent application was filed at an innovative firm during 2002–2019, giving 43,908 first-time inventors. This inventor sample is constructed independently from the employee sample described above: we link USPTO records directly to CoreSignal profiles, then classify race for matched inventors.

A.4. Identifying Entrepreneurship Outcomes

To identify inventors who became entrepreneurs, we combined data from LinkedIn profiles and PitchBook. We defined entrepreneurship as founding a new company, which we measured through job titles as well as company founding dates. We classified an inventor as a founder if their job title contained founder-related terms (e.g., "founder," "co-founder," "founding partner") or ownership indicators (e.g., "owner," "proprietor") while excluding false positives such as "product owner" or "property owner."

We then matched these companies to PitchBook data to obtain additional information about the startups, including subsequent funding rounds and exit outcomes. To ensure accurate identification of new venture creation, we relied on founding dates reported in LinkedIn and imposed a temporal constraint requiring that the inventor joined the company within two years of its founding date. This restriction helps distinguish true founders from early employees or later-stage executives.

Our primary entrepreneurship outcome is whether an inventor founded any company following their patent application decision. We also constructed more selective measures capturing higher-impact entrepreneurship: (1) founding a startup at risk of venture funding (startup in PitchBook), and (2) founding a venture capital-backed startup. These graduated measures allow us to distinguish between different types of entrepreneurial activity, from small business creation to high-growth ventures. Our dataset is well-positioned to study the startup pipeline: about one-third of all venture-backed founders worked at one of these innovative firms before launching their startups.

Our analysis uses two samples. For employee patenting (Table III), we use 527,820 employees at innovative firms, of whom 230,262 have race classification. For patent examination and entrepreneurship (Tables IV–VIII), we link USPTO inventor records to CoreSignal profiles, yielding 105,011 inventor-member pairs with race. Restricting to first-time inventors at innovative firms yields 43,908 observations.

B. Examiner Leniency

A comparison of patent approval rates by race cannot establish discrimination because patent approval depends on application quality, which we do not observe. If Black inventors file lower-quality applications on average, we would observe lower approval rates even absent examiner discrimination. Conversely, if Black inventors must clear higher bars to file applications, their applications might be higher quality, masking discrimination.

We address this endogeneity using an instrumental variables strategy based on examiner assignment (Williams, 2013; Lemley and Sampat, 2012). Within USPTO art units (approximately 400 technology departments), applications are assigned to available examiners based on capacity and timing rather than application characteristics. Some examiners are systematically more lenient than their peers. This creates exogenous variation in approval likelihood that is orthogonal to application quality.[1]

We measure examiner leniency as the leave-one-out grant rate for each examiner, subtracting the art unit average for that year. Positive values indicate lenient examiners who grant more often than their peers; negative values indicate stricter examiners. The interquartile range of leniency spans approximately 10 percentage points, providing substantial variation for identification.

For the instrument to be valid, examiner assignment must be independent of inventor characteristics. We validate this assumption by testing whether leniency predicts inventor demographics, education, and experience conditional on art unit and filing year. The results,

[1] But see Righi and Simcoe (2019) and Feng and Jaravel (2020) for critiques of the limits of randomization.

reported below, show that examiner leniency is uncorrelated with inventor race and other observable characteristics.

III. Results

We present our main findings in three steps. First, we document the patenting gap controlling for occupation and employer. Second, we test for discrimination in examination using the examiner leniency instrument. Third, we examine whether patents differentially affect entrepreneurship outcomes by race.

A. The Patenting Gap

Black employees patent at dramatically lower rates than their colleagues. Table II Panel C establishes the central fact: only 0.34% of Black employees at research-active firms receive patents compared to 1.89% of others, a 5.6× gap. This disparity far exceeds the gap in representation. Black workers comprise 8.2% of employees at innovative firms but only 1.7% of first-time inventors (Panel A), a 4.8× underrepresentation. The question we address is where this gap originates.

The pattern points toward supply-side rather than demand-side explanations. Among first-time inventors who file patent applications, approval rates are virtually identical: 74.0% for Black inventors versus 74.4% for non-Black inventors (Panel C). Forward citations to granted patents are also similar (32.2 vs. 32.7). The gap forms before examination, not during it.

Black inventors who reach the patent application stage are, if anything, *more* qualified than their White counterparts. Panel B shows that Black first-time inventors hold advanced degrees at higher rates (12.5% PhD/JD/MD vs. 11.6%), have stronger technical backgrounds (38.7% CS/Engineering majors vs. 35.6%), and more frequently attended elite institutions (18.3% top-20 schools vs. 16.8%). The pattern suggests that Black employees do not fail to patent because they lack the credentials or qualifications to become inventors.

Entrepreneurship outcomes show no disadvantage for Black inventors. Among first-time inventors, 1.06% of Black inventors found VC-backed startups within five years compared to 0.92% of White inventors (Panel C). If discrimination in patent examination or entrepreneurship markets suppressed Black patenting, we would expect to observe lower downstream outcomes. We do not.

[INSERT TABLE II ABOUT HERE.]

These patterns motivate our empirical strategy. We first quantify the patenting gap using multivariate regression analysis with occupation and employer controls. We then test for discrimination in patent examination using both OLS specifications and an instrumental variables approach that exploits quasi-random assignment of applications to examiners. Finally, we examine whether patents have differential effects on entrepreneurship by race. Together, these analyses distinguish supply-side explanations (differential access to patent-generating opportunities within firms) from demand-side discrimination. We begin by formalizing the patenting gap.

A.1. Within-Firm, Within-Occupation Disparities

Table III quantifies the patenting gap while controlling for occupation and employer, the two primary channels through which Black employees might be sorted into lower-patenting positions. The sample includes 211,742 employee-job observations, where the unit of observation is an employee's first job at a research-active firm between 2010 and 2019. To test whether the patenting gap persists after controlling for occupation and employer, we estimate:

$$\text{Patented}_{ijkt} \times 100 = \beta \cdot \text{Black}_i + \gamma' X_i + \delta_t + \theta_j + \phi_k + \varepsilon_{ijkt}, \tag{1}$$

where i indexes employees, j indexes companies, k indexes Lightcast occupation titles, and t indexes start year. The dependent variable is an indicator for having any granted patent after the start date at the firm, multiplied by 100 for percentage point interpretation. The covariate vector X_i includes: an indicator for patenting before joining the firm, graduate degree indicators (Master's, MBA, PhD/JD/MD), CS/Engineering major, top school attendance, log years of prior experience, senior role experience, brand-name employer experience (Google, Apple, Microsoft, Amazon, or Meta), prior founder experience, and a female indicator. δ_t are start year fixed effects, θ_j are company fixed effects, and ϕ_k are Lightcast standardized occupation title fixed effects (approximately 75,000 categories based on job function). Standard errors are clustered by company.

[INSERT TABLE III ABOUT HERE.]

The raw gap is large, consistent with the descriptive statistics above. Column (1), with only year fixed effects, yields a coefficient of -0.47 percentage points (SE $= 0.04$), representing 24% of the 2% mean patenting rate.

Column (2) adds Lightcast occupation title fixed effects. The coefficient shrinks to -0.17 percentage points (SE $= 0.05$). The 64% reduction in magnitude (from -0.47 to -0.17) indicates that occupational sorting explains the majority of the raw gap: Black employees are concentrated in occupations with lower patenting rates.

Column (3) adds company fixed effects, comparing Black and non-Black employees in the same occupation at the same firm. The coefficient falls to -0.12 percentage points (SE $= 0.05$), representing 6% of the mean. The additional 29% reduction suggests that Black employees are somewhat concentrated at firms with lower patenting rates. Column (4) restricts to observations with high-confidence race classifications and yields -0.11 percentage points (SE $= 0.06$). Stability across columns (3) and (4) indicates that race classification noise does not drive the result.

The persistent 6% within-firm, within-occupation gap could reflect several mechanisms: differential project assignment, mentorship, or encouragement to file; Black employees working on less patentable projects; or different inclinations to pursue patents. Distinguishing these mechanisms is beyond the scope of our data, but all represent pre-filing factors rather than discrimination during the examination process.

A.2. Patenting Gap vs. Founding Gap

Panel B estimates the same specification with founding as the outcome, where the dependent variable is an indicator for founding any startup (identified from LinkedIn job titles containing "founder" or "co-founder"), multiplied by 100. The unconditional mean is 2.25%. In contrast to patenting, the coefficient on I(Black) is positive and grows with controls: +0.29 (column 1), +0.77 (column 2), +0.86 (column 3), and +0.88 (column 4). The column (3) estimate represents 38% of the mean founding rate.

This result is striking: Black employees are *more* likely to found startups after joining innovative firms, even as they are *less* likely to patent. The patenting gap does not translate into a founding gap. This disconnect suggests that whatever mechanisms suppress Black patenting do not similarly suppress entrepreneurship, but may widen funding gaps given how heavily VCs weight patents.

B. Testing for Discrimination in Examination

The preceding analysis establishes that Black employees patent at lower rates, but the cross-sectional comparison cannot distinguish between two fundamentally different explanations. The gap could reflect *supply-side* factors: differential project assignment, mentorship, or inclination to file within firms. Alternatively, it could reflect *demand-side* discrimination: if Black inventors anticipate lower approval rates or reduced returns to patents, they may rationally choose not to file. We now test this demand-side channel directly.

B.1. Approval Rates by Race

Table IV restricts attention to first-time inventors at large firms: inventors whose first patent application was filed while employed at a research-active assignee (50+ patents) between 2002 and 2019. The sample includes 43,908 patent applications (N = 588 by Black inventors). The unit of observation is an inventor's first patent application. To test for approval disparities, we estimate:

$$\text{Granted}_{i,au,a,t} \times 100 = \beta \cdot \text{Black}_i + \gamma' X_i + \delta_t + \theta_a + \phi_{au} + \varepsilon_{i,au,a,t}, \tag{2}$$

where i indexes inventors, au indexes USPTO art units (approximately 400 technology departments), a indexes assignees (innovative firms), and t indexes filing year. The dependent variable is an indicator for whether the application was ultimately granted, multiplied by 100. The unconditional mean is 75%. δ_t are filing year fixed effects, θ_a are assignee fixed effects, and ϕ_{au} are art unit fixed effects. The covariate vector X_i includes: tenure at the firm before filing, PhD/JD/MD degree, top school attendance, CS/Engineering major, senior role experience, brand-name employer experience, and an indicator for prior patent applications. Standard errors are clustered by examiner throughout.

[INSERT TABLE IV ABOUT HERE.]

Conditional on filing year and assignee, Black inventors face no approval penalty. Column (1) yields a coefficient of −0.31 percentage points (SE = 1.59), less than 0.5% of the 75%

mean grant rate. Column (2) adds art unit fixed effects: the coefficient is -0.37 (SE = 1.51). Column (3) adds inventor covariates: the coefficient is -0.34 (SE = 1.51). Column (4) replaces separate year and art unit fixed effects with interacted year $\times$ art unit fixed effects ($\phi_{au,t}$), absorbing technology-specific time trends. The coefficient is -0.58 (SE = 1.65).

Across all specifications, the coefficient on I(Black) is economically small and statistically insignificant. Figure 1 plots point estimates and 95% confidence intervals for the four specifications in Table IV. The shaded bands mark effect sizes of 5%, 10%, and 15% of the mean grant rate. All confidence intervals fall within the 5% band, ruling out approval gaps exceeding 3.7 percentage points on a base of 75%.

[INSERT FIGURE 1 ABOUT HERE.]

B.2. Examiner Leniency as an Instrument

The null result above is consistent with no discrimination, but a potential concern remains: patent approval depends on the examiner assigned to evaluate the application, and examiner assignment might not be independent of inventor race. For instance, if more experienced examiners were systematically assigned to evaluate applications by Black inventors, we might observe similar approval rates despite underlying discrimination.

We address this concern using an instrumental variables approach that exploits quasi-random assignment of applications to examiners within art units (Williams, 2013; Lemley and Sampat, 2012). The key insight is that within a given technology area and time period, applications are assigned to available examiners based on capacity and timing rather than application characteristics.

Our instrument is examiner leniency, defined as the examiner's leave-one-out grant rate minus the art unit average. Figure 2 displays the distribution; the interquartile range spans approximately 10 percentage points, indicating substantial variation in examiner stringency.

[INSERT FIGURE 2 ABOUT HERE.]

For the instrument to be valid, examiner leniency must predict patent approval (relevance) and must be uncorrelated with inventor characteristics (exogeneity). Table V validates both conditions. Columns 1–3 report the first stage. To test instrument strength, we estimate:

$$\text{Granted}_{i,au,t} \times 100 = \gamma \cdot \text{Leniency}_e + \phi_{au} + \delta_t + \nu_{i,au,t}, \tag{3}$$

where e indexes examiners and Leniency_e is the leave-one-out grant rate for examiner e. ϕ_{au} are art unit fixed effects and δ_t are year fixed effects. Standard errors are clustered by examiner.

[INSERT TABLE V ABOUT HERE.]

Column (1) uses all inventors: the coefficient on leniency is 0.70 (SE = 0.015), with an F-statistic of 2,180. This exceeds the Stock-Yogo threshold of 16.4 for 10% maximal IV size by a factor of 133. Column (2) restricts to Black inventors (N = 588): the coefficient is 0.70 (SE = 0.15), with an F-statistic of 20.5, still exceeding the threshold. Column (3) restricts to non-Black inventors: the coefficient is 0.70 (SE = 0.015), with an F-statistic of 2,150. The first stage is equally strong for Black and non-Black inventors. A lenient examiner is equally lenient regardless of inventor race.

Columns 4–6 provide a falsification check for the exogeneity assumption. While we cannot directly test exogeneity, we can examine whether examiner leniency correlates with inventor characteristics determined before filing. Such correlation would raise concerns about the identifying assumption. We estimate:

$$\text{Leniency}_e \times 100 = \beta' Z_i + \phi_{au} + \delta_t + \eta_{i,au,t}, \tag{4}$$

where Z_i includes demographics (column 4: Black, Female), education (column 5: PhD/JD/MD, top school, CS/Engineering), and experience (column 6: senior roles, brand-name employer, tenure). All coefficients are small and statistically insignificant. The coefficient on I(Black) is 0.32 (SE = 0.57). Examiner leniency is uncorrelated with observable inventor characteristics, supporting the identifying assumption of quasi-random assignment.

B.3. Outcome Test: Marginal Patent Quality

The null OLS and IV results establish that Black inventors receive patents at the same rate as observationally similar non-Black inventors. We push further with an outcome test: if examiners discriminated against Black inventors, marginally approved Black patents would need to be of *higher quality* to overcome the discrimination. Following Becker (1993) and Subramani, Aneja, Reshef and Louis (2021), we implement this outcome test.

Table VI reports the results. The dependent variable is the inverse hyperbolic sine of forward citations, which accommodates zero values while approximating log transformations for positive values. To test whether marginally approved Black patents differ in quality, we estimate:

$$\text{asinh}(\text{Citations}_i) = \beta \cdot \text{Black}_i + \gamma' X_i + \phi_{au,t} + \theta_a + \varepsilon_i \quad \text{if } \text{Granted}_i = 1, \tag{5}$$

for OLS (column 1, restricted to the 32,712 granted patents). $\phi_{au,t}$ are art unit $\times$ year fixed effects and θ_a are assignee fixed effects. Standard errors are clustered by examiner. The mean of asinh(citations) among granted patents is 2.856.

[INSERT TABLE VI ABOUT HERE.]

Column (1) OLS shows a coefficient on I(Black) of 0.02 (SE = 0.07), indicating no cross-sectional difference in citation quality between Black and non-Black granted patents. Columns (2) and (3) use the full sample and instrument patent approval with examiner leniency to isolate the *marginal* patents, those whose approval status was determined by examiner leniency rather than unambiguous quality. To estimate the effect of marginal patent approval on citations, we estimate:

$$\text{asinh}(\text{Citations}_i) = \beta_1 \cdot \widehat{\text{Granted}}_i + \beta_2 \cdot \text{Black}_i + \gamma' X_i + \phi_{au,t} + \theta_a + \varepsilon_i, \tag{6}$$

$$\text{First stage:} \quad \text{Granted}_i = \pi \cdot \text{Leniency}_e + \phi_{au,t} + \theta_a + \nu_i.$$

The IV coefficient on I(Patent Granted) is 0.52 (SE = 0.07), with a first-stage F-statistic of 1,996. Marginally approved patents receive more citations than marginally rejected patents.

Column (3) interacts I(Black) with I(Granted), instrumenting both endogenous terms:

$$\text{asinh}(\text{Citations}_i) = \beta_1 \cdot \widehat{\text{Granted}}_i + \beta_2 \cdot (\text{Black}_i \times \widehat{\text{Granted}}_i) + \beta_3 \cdot \text{Black}_i + \gamma' X_i + \phi_{au,t} + \theta_a + \varepsilon_i, \tag{7}$$

Instruments: Leniency_e, $\text{Black}_i \times \text{Leniency}_e$.

The first-stage F-statistic for the joint instruments is 27. The IV coefficient on I(Black) × I(Granted) is 0.36 (SE = 0.44), positive but statistically insignificant. The sign of this coefficient is informative: if taste-based discrimination existed, we would expect this coefficient to be *positive* (marginally approved Black patents would be of higher quality to overcome discrimination). The positive point estimate, while noisy, is inconsistent with discrimination.

C. Differential Returns to Patents

Having found no evidence of discrimination in patent examination, we return to the original puzzle: why do Black employees patent at lower rates? One remaining possibility is that patents are less *valuable* to Black inventors. If labor market or entrepreneurship returns to patents are lower for Black inventors, they may rationally invest less in patenting. We test this hypothesis by examining whether patent grants differentially affect entrepreneurship outcomes by race.

C.1. Perceived Value: Patent Posting Behavior

We begin with a behavioral measure: whether inventors post their patents on LinkedIn. Posting a patent signals that the inventor perceives value in the credential. Approximately 22% of inventors with granted patents post them on LinkedIn. Table VII tests whether Black inventors are less likely to post their patents. The sample consists of the first-time inventors at innovative firms. To test for differences in patent posting, we estimate:

$$\text{Posted}_{i,au,a,t} \times 100 = \beta \cdot \text{Black}_i + \gamma' X_i + \delta_t + \theta_a + \phi_{au} + \varepsilon_{i,au,a,t} \quad \text{if Granted}_i = 1, \tag{8}$$

where the dependent variable is an indicator for posting the patent on LinkedIn, multiplied by 100. The unconditional mean is 22.4%. Standard errors are clustered by examiner.

[INSERT TABLE VII ABOUT HERE.]

Column (1) includes year and assignee fixed effects. The coefficient on I(Black) is +1.09 (SE = 1.77), representing 5% of the mean posting rate. Column (2) adds art unit fixed effects: +1.12 (SE = 1.79). Column (3) adds inventor covariates: +1.07 (SE = 1.79). Column (4) uses interacted art unit × year fixed effects: +0.74 (SE = 2.04). Across all specifications, Black inventors are, if anything, slightly *more* likely to post their patents. This finding suggests that Black inventors do not perceive their patents as less valuable.

C.2. Entrepreneurship Outcomes

We now test whether patent approval affects subsequent entrepreneurship using the examiner leniency instrument. Table VIII returns to the full first-time inventor applications. The outcomes are founding a PitchBook-tracked startup within 5 years of patent filing (mean = 0.95%) and founding a VC-backed startup within 5 years (mean = 0.88%). These outcomes connect directly to the funding gap documented by Cook, Marx and Yimfor (2022): if patents are less effective at propelling Black inventors toward VC-backed entrepreneurship, this could explain why Black founders raise less capital even conditional on founding. To test whether patent grants have differential effects on entrepreneurship by race, we estimate:

$$\text{Founded}_i \times 100 = \beta_1 \cdot \text{Granted}_i + \beta_2 \cdot (\text{Black}_i \times \text{Granted}_i) + \beta_3 \cdot \text{Black}_i + \gamma' X_i + \phi_{au,t} + \theta_a + \varepsilon_i, \quad (9)$$

for OLS (columns 1 and 3). All specifications include art unit × year and assignee fixed effects, plus inventor covariates. Standard errors are clustered by examiner. The OLS coefficients on I(Black) × I(Granted) are 0.25 (column 1) and 0.29 (column 3), positive but imprecisely estimated.

[INSERT TABLE VIII ABOUT HERE.]

Columns (2) and (4) instrument both I(Granted) and I(Black) × I(Granted):

$$\text{Founded}_i \times 100 = \beta_1 \cdot \widehat{\text{Granted}}_i + \beta_2 \cdot (\text{Black}_i \times \widehat{\text{Granted}}_i) + \beta_3 \cdot \text{Black}_i + \gamma' X_i + \phi_{au,t} + \theta_a + \varepsilon_i, \tag{10}$$

$$\text{Instruments: Leniency}_e, \quad \text{Black}_i \times \text{Leniency}_e.$$

The first-stage F-statistic for the joint instruments is 27. The IV coefficient on I(Black) × I(Granted) is 0.04 (column 2) and 0.34 (column 4), both statistically insignificant. The column (2) estimate represents less than 5% of the 0.95% mean founding rate.

The main effect of patent approval on entrepreneurship is also imprecisely estimated: the coefficient on I(Patent Granted) is 0.47 (SE = 0.48) in column (2) and 0.32 (SE = 0.47) in column (4). The lack of a strong main effect may also reflect the low baseline founding rate (under 1%) and the noisiness of the IV approach with rare outcomes. We fail to find evidence that patent grants are less effectual in propelling Black inventors toward entrepreneurship. Whatever barriers Black employees face in patenting do not appear to extend to the translation of patents into entrepreneurship.

In sum, we find a persistent patenting gap but no evidence of discrimination during examination or differential returns afterward. The gap forms upstream.

IV. Discussion

Our findings point to a supply-side explanation for racial disparities in patenting and, by extension, high-growth entrepreneurship. We systematically tested and ruled out demand-side discrimination at multiple stages: patent examination (approval rates differ by less than 0.5% of mean), patent quality assessment (no citation differential for marginally-approved patents), signaling behavior (Black inventors post patents at equal or higher rates), and entrepreneurial returns (patent grants are equally effective in catalyzing founding). The gap forms upstream, at the patent filing stage.

Several mechanisms could explain why Black employees at innovative firms patent at lower rates, even controlling for job title, company, and start year. First, Black employees may be assigned to less patentable projects within the same job category. Lightcast title fixed effects control for occupation (e.g., "Software Engineer"), but not for the specific team, project, or manager. If Black engineers are disproportionately assigned to maintenance rather than R&D, this would manifest as a patenting gap within title. Second, workplace climate may discourage patent filing. Employees who feel undervalued may be less inclined to propose inventions or navigate the internal patent disclosure process, even if they work on patentable projects. Third, mentorship and network effects may differ by race. Senior inventors often encourage junior colleagues to file patents; if such mentorship networks are racially homophilous, Black employees may receive less encouragement.

Inventor characteristics provide additional evidence for upstream barriers. The credential patterns in Table II show that among first-time inventors, Black inventors have *higher* rates of PhD/JD/MD degrees (12.5% vs. 11.6%), CS/Engineering majors (38.7% vs. 35.6%), and top-school attendance (18.3% vs. 16.8%) than White inventors. These differences suggest that Black employees may face higher bars for becoming inventors, not that they lack qualifications.

These interpretations, while consistent with the data, remain speculative. Our analysis has several limitations. First, we observe employees at firms with 50+ patents. These are large, research-intensive organizations that may not be representative of the broader economy. Second, race classification succeeded for 44% of our stratified sample. Employees with classified photos are positively selected: more educated, more experienced, and more likely to patent (Table A.1). The credential patterns among Black inventors suggest our gap estimates are conservative. Third, the examiner leniency instrument, while strong (F $>$ 2,000), applies only to the margin of patent approval. The local average treatment effect may not generalize to inframarginal patents.

V. Conclusion

Black employees at innovative firms patent at one-fifth the rate of colleagues in the same role and company. We tested whether this gap reflects demand-side discrimination and found no evidence. Approval rates are virtually identical. Marginally-approved Black patents receive equal citations. Black inventors post patents on LinkedIn at equal rates. Patent grants are equally effective in catalyzing entrepreneurship. The gap forms upstream, at the filing stage.

Two additional findings reinforce this conclusion. Black inventors who do file have stronger credentials than their peers: higher rates of advanced degrees and elite schooling. And Black employees are more likely to found startups, even as they patent less. Whatever suppresses Black patenting does not reflect lower qualifications or entrepreneurial drive.

Among 211,742 employees at 1,798 firms, only 0.34% of Black employees patent compared to 1.89% of others. This disparity shrinks with controls for job title and company but remains significant. Within-firm factors such as project assignment, mentorship, and workplace climate likely play a role.

Policy interventions should focus upstream. Expanding access to patentable projects, strengthening mentorship networks, and fostering inclusive innovation cultures may be more effective than targeting patent examination. Closing the patenting gap at innovative firms would likely reduce the funding gap in high-growth entrepreneurship.

REFERENCES

Aneja, Abhay, Oren Reshef, and Gauri Subramani. 2024. “Attrition and the Gender Patenting Gap.” *The Review of Economics and Statistics*.

Babina, Tania, and Sabrina T. Howell. 2024. “Entrepreneurial Spillovers from Corporate R&D.” *Journal of Labor Economics*, 42(2): 469–509.

Becker, Gary S. 1993. “Nobel lecture: The economic way of looking at behavior.” *Journal of Political Economy*, 101(3): 385–409.

Conti, Annamaria, Marie Thursby, and Frank T Rothaermel. 2013. “Show me the right stuff: Signals for high-tech startups.” *Journal of Economics & Management Strategy*, 22(2): 341–364.

Cook, Lisa D, Matt Marx, and Emmanuel Yimfor. 2022. “Funding Black High-Growth Startups.” National Bureau of Economic Research.

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.

Feng, Josh, and Xavier Jaravel. 2020. “Crafting intellectual property rights: Implications for patent assertion entities, litigation, and innovation.” *American Economic Journal: Applied Economics*, 12(1): 140–181.

Gao, Janet, Wenting Ma, and Qiping Xu. 2022. “Access to Financing and Racial Pay Gap Inside Firms.”

Greenwald, Daniel L, Sabrina T Howell, Cangyuan Li, and Emmanuel Yimfor. 2024. “Regulatory arbitrage or random errors? Implications of race prediction algorithms in fair lending analysis.” *Journal of Financial Economics*, 157: 103857.

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): 212–243.

Hampole, Menaka, Dimitris Papanikolaou, Lawrence D.W. Schmidt, and Bryan Seegmiller. 2025. “Artificial Intelligence and the Labor Market.” National Bureau of Economic Research Working Paper 33509.

Hoenig, Daniel, and Joachim Henkel. 2015. “Quality signals? The role of patents, alliances, and team experience in venture capital financing.” *Research Policy*, 44(5): 1049–1064.

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.

Lemley, Mark A, and Bhaven Sampat. 2012. "Examiner characteristics and patent office outcomes." *Review of economics and statistics*, 94(3): 817–827.

Lerner, Josh, Markus Lithell, and Gordon M. Phillips. 2025. "Impact Investing and Worker Outcomes." Harvard Business School Working Paper 25-040.

Righi, Cesare, and Timothy Simcoe. 2019. "Patent examiner specialization." *Research Policy*, 48(1): 137–148.

Subramani, Gauri, Abhay Aneja, Oren Reshef, and WS Louis. 2021. "Persistence and the gender innovation gap." Technical report, Working Paper.

Tsvetkova, Alexandra, Elettra D'Amico, Alexander Lembcke, Polina Knutsson, and Wessel Vermeulen. 2024. "How well do online job postings match national sources in large English speaking countries? Benchmarking Lightcast data against statistical sources across regions, sectors and occupations." *OECD Local Economic and Employment Development (LEED) Working Papers*, , (1): I–65.

Williams, Heidi L. 2013. "Intellectual property rights and innovation: Evidence from the human genome." *Journal of Political Economy*, 121(1): 1–27.

Xie, Fangzhou. 2022. "rethnicity: An R package for predicting ethnicity from names." *SoftwareX*, 17: 100965.

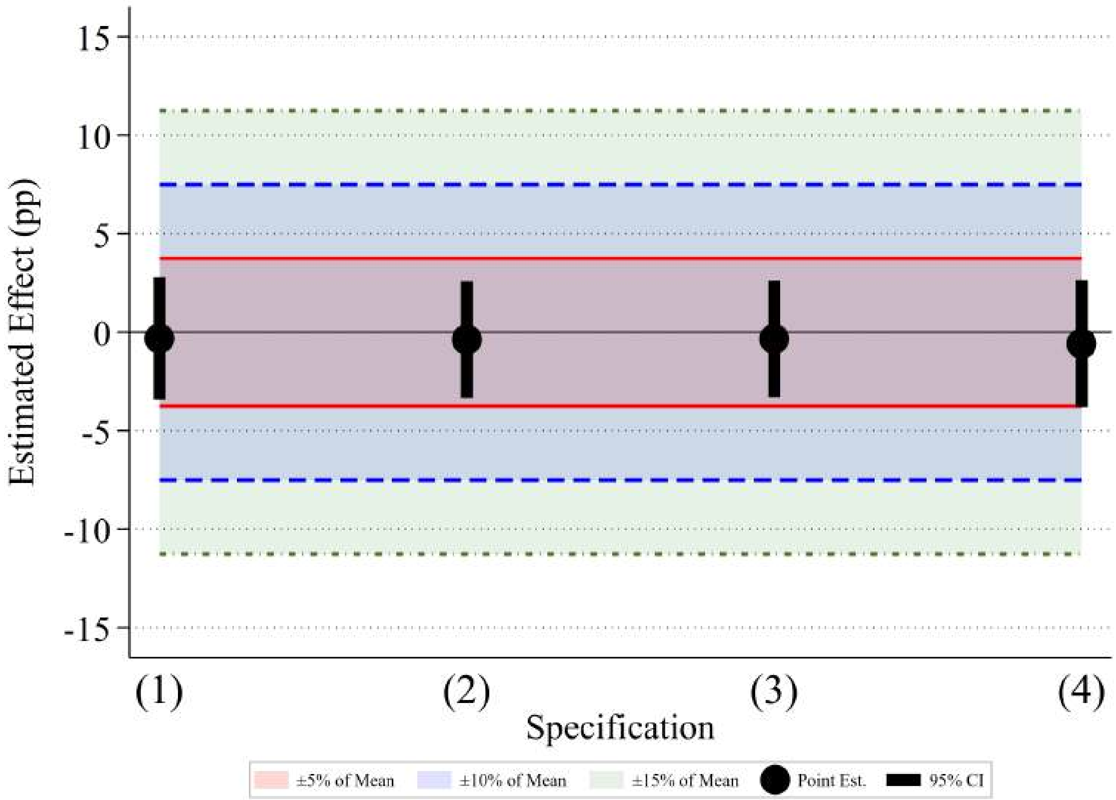

Figure 1: Power Analysis: Estimated Effects with Effect Size Benchmarks

This figure displays estimated effects of Black inventor status on patent approval probability alongside economically meaningful effect size benchmarks based on the results in Table IV. Point estimates and 95% confidence intervals are shown for each of the four specifications. Three reference line pairs show effect sizes equal to ±5% (red dashed), ±10% (blue dash-dot), and ±15% (green dotted) of the unconditional mean patent grant rate (75%). The confidence intervals for all specifications include zero and exclude effects larger than approximately 4 percentage points, suggesting we can rule out economically meaningful racial disparities in patent approval.

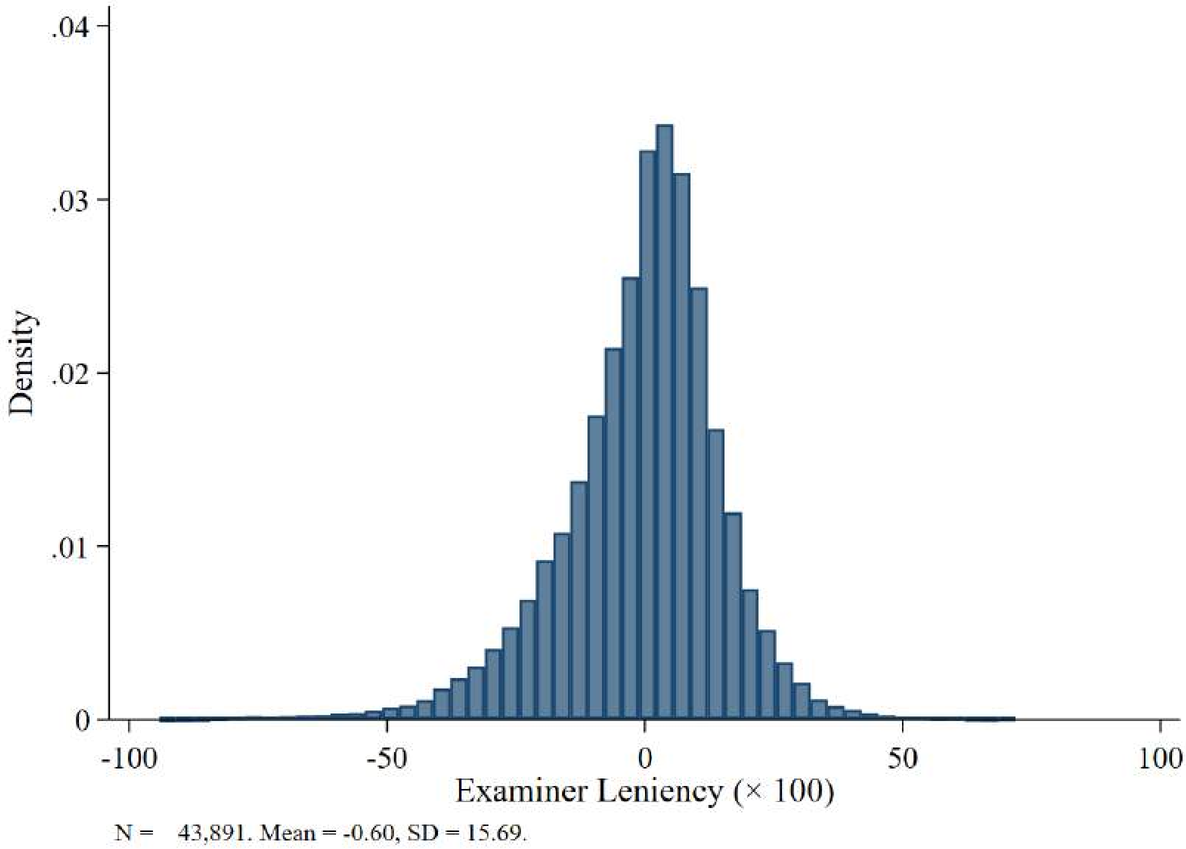

Figure 2: Distribution of Examiner Leniency

This figure plots the distribution of examiner leniency in the sample of first-time inventors at large firms. Leniency is defined as the examiner's leave-one-out grant rate minus the art unit average grant rate, scaled by 100. A value of 5 means the examiner grants patents at a rate 5 percentage points above the art unit average.

Table I: VC-Backed Founders and the Tech Firm Pipeline

This table examines the pipeline from large technology firms to venture-backed entrepreneurship. Panel A presents statistics for all PitchBook VC-backed founders of startups formed between 2010 and 2025 who were successfully matched to CoreSignal LinkedIn profiles. "Research-active firms" are defined as companies with 50 or more unique inventors in the USPTO patent data. "Were inventors" indicates founders who held patents, identified either through name-matching to USPTO inventor records or through self-reported patents on LinkedIn profiles. Panel B restricts the sample to founders with race classifications from Cook, Marx and Yimfor (2022). Dollar-weighted columns ($-wtd) weight each founder by their share of VC funding raised, calculated as total company VC funding divided by the number of co-founders. For founders of multiple startups, weights are summed across companies. All dollar amounts are inflation-adjusted to 2025 dollars.

Panel A: All VC-Backed Founders (2010–2025)

	N	%	%($-wtd)
Founders matched to CoreSignal	107,664	100.0	100.0
Worked at research-active firm	39,509	36.7	40.5
Were inventors	9,251	23.4	32.7

Panel B: By Race

	Black	White	Black($-wtd) / White($-wtd)
N founders	2,058	46,273	–
% worked at research-active firm	39.5 / 47.6	34.2 / 41.1	1.16×
% were inventors | research-active	14.1 / 20.2	24.9 / 31.6	0.64×

Table II: Summary Statistics

This table presents summary statistics for the main samples and key outcomes. Research-active firms have 50+ unique inventors in USPTO data. Panel A reports race distributions from image classification following Cook, Marx and Yimfor (2022). Panel B reports LinkedIn covariate means for employees in the regression sample (Table III) and first-time inventors in the regression sample (Tables V–VIII); missing indicator variables are imputed as zero, while years of experience reports non-missing means. Panel C reports key outcomes: patenting rates among employees, patent approval rates and forward citations among first-time inventors, and startup founding rates. *Top School* indicates attendance at a top-20 university for producing VC-backed founders. *Brand-Name Firm* indicates prior employment at Google, Apple, Microsoft, Amazon, or Meta.

	All Employees			**First-Time Inventors**		
Sample Construction						
N	211,742			43,908		
Panel A: Race Distribution (%)						
White	62.7			61.4		
Black	8.2			1.7		
Asian	17.7			32.8		
Hispanic	9.1			4.2		
	All	Black	White	All	Black	White
Panel B: LinkedIn Covariates						
Years of Prior Experience	8.5	6.5	9.4			
Master's Degree (%)	15.3	10.2	12.4			
MBA (%)	5.6	4.5	5.8			
PhD/JD/MD (%)	5.5	2.4	4.9	14.4	12.5	11.6
CS or Engineering (%)	30.4	21.5	26.7	40.2	38.7	35.6
Top School (%)	16.5	13.1	16.7	17.6	18.3	16.8
Senior Role Experience (%)	43.6	33.9	46.9	32.2	32.1	31.9
Brand-Name Firm (%)	4.5	2.9	4.2	10.5	9.0	9.3
Panel C: Key Outcomes						
Patented after joining firm (%)	2.00	0.34	1.89			
Founded startup after joining (LinkedIn, %)	2.25	2.18	2.16			
Patent application granted (%)				75.0	74.0	74.4
Forward citations (if granted)				30.9	32.2	32.7
Founded startup after filing (PitchBook, %)				0.95	1.06	0.96
Founded VC-backed startup (PitchBook, %)				0.88	1.06	0.92

Table III: Racial Disparities in Patenting and Founding After Joining Research-Active Firms

This table examines whether Black employees are less likely to patent or found startups after joining a research-active firm (defined as having 50+ inventors). The sample consists of employees at these firms between 2010–2019 whose race was classified from LinkedIn profile images. In Panel A, the dependent variable is an indicator equal to one if the employee has any granted patent after their start date at the firm, multiplied by 100. In Panel B, the dependent variable is an indicator for founding any startup after joining, identified from LinkedIn job titles containing or multiplied by 100. The unit of observation is an employee's first job at a research-active firm. Column (1) includes start year fixed effects and employee covariates. Column (2) adds Lightcast standardized occupation title fixed effects. Column (3) adds company fixed effects. Column (4) restricts to observations with high-confidence race classifications. Employee covariates include: indicator for inventor before start, graduate degree indicators, CS/engineering major, top school attendance, years of prior experience, senior role experience, brand-name employer experience, founder experience, and female indicator. Standard errors are clustered by company in columns (3)–(4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
Panel A: Patenting After Start (Dep. Var. Mean = 2%)				
I(Black)	-0.473***	-0.171***	-0.121**	-0.107*
	(0.039)	(0.047)	(0.054)	(0.056)
Observations	211,742	195,777	195,777	180,616
Adjusted R^2	0.42	0.41	0.42	0.42
Start Year FE	Yes	Yes	Yes	Yes
Title FE	No	Yes	Yes	Yes
Company FE	No	No	Yes	Yes
Panel B: Founding After Joining (Dep. Var. Mean = 2.25%)				
I(Black)	0.289**	0.770***	0.856***	0.882***
	(0.115)	(0.128)	(0.136)	(0.142)
Observations	211,742	195,777	195,777	180,616
Adjusted R^2	0.02	0.05	0.06	0.06
Start Year FE	Yes	Yes	Yes	Yes
Title FE	No	Yes	Yes	Yes
Company FE	No	No	Yes	Yes

Table IV: Patent Approval Disparities by Race

This table tests whether Black inventors face lower patent approval rates. The dependent variable is an indicator equal to one if the patent application was granted, multiplied by 100 (unconditional mean = 75%). The sample consists of first-time inventors at large firms—inventors whose first patent application was filed while employed at a research-active assignee (50+ inventors), between 2002–2019. This is the same sample used in Table V. Column (1) includes year and assignee fixed effects. Column (2) adds art unit fixed effects. Column (3) adds inventor covariates (tenure at firm, education, prior experience). Column (4) replaces separate year and art unit fixed effects with interacted year × art unit fixed effects. Tenure measures years at the large firm before filing the first patent. Standard errors clustered by examiner. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
Dependent Variable:	I(Patent Granted) × 100			
I(Black)	-0.314	-0.371	-0.338	-0.576
	(1.587)	(1.514)	(1.513)	(1.649)
Observations	43,678	43,661	43,661	42,169
Adjusted R^2	0.072	0.155	0.155	0.197
Covariates	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	
Art Unit FE	No	Yes	Yes	
Year × Art Unit FE	No	No	No	Yes
Assignee FE	Yes	Yes	Yes	Yes

Table V: Examiner Leniency Instrument Validation

This table validates the examiner leniency instrument. Columns 1–3 report the first stage, regressing patent granted (×100) on examiner leniency. Columns 4–6 test exogeneity by regressing examiner leniency (×100) on inventor characteristics determined before patent filing: demographics (column 4), education (column 5), and prior work experience (column 6). The sample consists of first-time inventors at large firms—inventors whose first patent application was filed while employed at a research-active assignee (50+ inventors), between 2002–2019. Leniency is the examiner's leave-one-out grant rate minus the art unit average. Standard errors clustered by examiner. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	First Stage: Granted (×100)			Exogeneity: Leniency (×100)		
	All	Black	Non-Black	Demog.	Educ.	Exper.
	(1)	(2)	(3)	(4)	(5)	(6)
Examiner leniency	0.698***	0.695***	0.698***			
	(0.015)	(0.154)	(0.015)			
Black				0.321		
				(0.574)		
Female				-0.071		
				(0.213)		
PhD/JD/MD					0.075	
					(0.221)	
Top school					-0.058	
					(0.202)	
CS/Engineering					0.161	
					(0.191)	
Senior roles						-0.181
						(0.188)
Brand-name employer						0.136
						(0.297)
Tenure (years)						0.027
						(0.028)
Observations	43,891	588	43,135	43,891	43,891	43,891
Adjusted R^2	0.189	0.200	0.189	0.008	0.008	0.008
First-stage F	2180.1	20.5	2150.2			
Dep. var. mean	75.0	72.6	75.0			
Art Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table VI: Marginal Patent Quality: Forward Citations

This table examines whether marginally approved patents have lower citation quality. The dependent variable is the inverse hyperbolic sine of forward citations (mean among granted = 2.856). The sample consists of first-time inventors at large firms. Column (1) presents OLS estimates restricted to granted patents only. Columns (2)–(3) use the full sample and instrument patent approval with examiner leniency. Column (3) interacts I(Black) with I(Granted), instrumenting both endogenous terms with leniency and I(Black) × leniency. All specifications include art unit, year, and assignee fixed effects, plus inventor covariates. Standard errors clustered by examiner. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)
Dependent Variable:	asinh(Forward Citations)		
Specification:	OLS	IV	IV
Sample:	Granted only	Full	Full
I(Patent Granted)		0.524***	0.517***
		(0.070)	(0.070)
I(Black) × I(Granted)			0.363
			(0.435)
I(Black)	0.022	0.032	-0.237
	(0.065)	(0.054)	(0.328)
Adjusted R^2	0.391	-0.213	-0.214
Observations	30,852	42,169	42,169
First-stage F		1996.2	27.0
Covariates	Yes	Yes	Yes
Art Unit × Year FE	Yes	Yes	Yes
Assignee FE	Yes	Yes	Yes

Table VII: Propensity to Post Patents on LinkedIn

This table examines whether Black inventors are more or less likely to post (announce) their patents on LinkedIn. The dependent variable is I(Posted Patent) $\times$ 100 (mean = 22.4%). A patent is "posted" if it appears on the inventor's LinkedIn profile. The sample consists of first-time inventors at large firms with *granted* patents, the same sample restriction as Column (1) of Table VI. Columns (1)–(2) progressively add fixed effects. Columns (3)–(4) add inventor covariates. Column (4) uses interacted art unit $\times$ year fixed effects. Standard errors clustered by examiner. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
Dependent Variable:	I(Posted Patent) $\times$ 100			
I(Black)	1.090	1.119	1.070	0.735
	(1.767)	(1.792)	(1.787)	(2.036)
Adjusted R^2	0.081	0.084	0.087	0.093
Observations	32,670	32,653	32,653	30,852
Covariates	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	–
Art Unit FE	No	Yes	Yes	–
Art Unit $\times$ Year FE	No	No	No	Yes
Assignee FE	Yes	Yes	Yes	Yes

Table VIII: Patent Approval and Entrepreneurship: IV Estimates

This table examines whether patent approval affects entrepreneurship using examiner leniency as an instrument. Columns (1)–(2) use founding a PitchBook-tracked startup within 5 years of patent filing as the outcome (mean = 0.95%). Columns (3)–(4) restrict to VC-backed startups in PitchBook (mean = 0.88%). The sample consists of first-time inventors at large firms. Columns (1) and (3) present OLS estimates with I(Black) × I(Granted) included. Columns (2) and (4) instrument both I(Granted) and I(Black) × I(Granted) with examiner leniency and I(Black) × leniency. All specifications include art unit × year and assignee fixed effects, plus inventor covariates. Standard errors clustered by examiner. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
Dep. Var.:	I(Founded) × 100		I(VC-backed) × 100	
Data Source:	PitchBook (5-year window)			
Specification:	OLS	IV	OLS	IV
I(Patent Granted)	0.100	0.469	0.163	0.319
	(0.139)	(0.478)	(0.134)	(0.467)
I(Black) × I(Granted)	0.248	0.042	0.293	0.339
	(1.106)	(4.118)	(1.103)	(4.110)
I(Black)	0.262	0.417	0.280	0.247
	(0.943)	(3.054)	(0.943)	(3.049)
Adjusted R^2	0.006	-0.254	0.003	-0.254
Observations	42,169	42,169	42,169	42,169
First-stage F		27.0		27.0
Covariates	Yes	Yes	Yes	Yes
Art Unit × Year FE	Yes	Yes	Yes	Yes
Assignee FE	Yes	Yes	Yes	Yes

Supply-Side Barriers in Black Patenting: Evidence from Innovative Firms

Internet Appendix

Table A.1: Selection into LinkedIn Photo Availability

This table tests for selection bias in LinkedIn photo availability. The sample consists of 527,820 employees who joined research-active firms (50+ inventors) between 2010–2023. *With Photo* includes 230,262 employees whose race was classified from their LinkedIn profile image. *Without Photo* includes 297,558 employees lacking profile photos. All covariates are measured as of the employee's start date. Indicator variables (I(·)) are reported as proportions. *Top School* indicates attendance at a top-20 university for producing VC-backed founders. *Brand-Name Firm* indicates prior employment at Google, Apple, Microsoft, Amazon, or Meta. *Filed Patent After Joining* and *Granted Patent After Joining* are based on USPTO patent applications filed after the employee's start date at the firm. t-statistics test the null hypothesis of equal means. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	With Photo		**Without Photo**		
	N = 230,262		N = 297,558		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
Years of Prior Experience	9.25	8.43	7.39	7.47	40.73***
I(Bachelor's Degree)	0.642	0.479	0.574	0.494	16.10***
I(Master's Degree)	0.170	0.375	0.138	0.345	13.81***
I(MBA)	0.059	0.235	0.051	0.220	6.24***
I(PhD/JD/MD)	0.061	0.240	0.043	0.203	15.48***
I(CS or Engineering)	0.331	0.470	0.255	0.436	22.69***
I(Top School)	0.176	0.381	0.157	0.364	10.68***
Number of Prior Employers	3.42	3.08	3.14	3.06	11.45***
I(Senior Role Experience)	0.475	0.499	0.417	0.493	18.15***
I(Brand-Name Firm)	0.053	0.224	0.041	0.199	8.26***
I(Filed Patent After Joining)	0.022	0.146	0.013	0.112	13.40***
I(Granted Patent After Joining)	0.018	0.134	0.010	0.102	12.48***