The Returns to Recognition:
Patent Grants and Inventors' Life Trajectories

Colleen V. Chien* Joan Farre-Mensa† Jillian Grennan‡

Abstract

Patents are typically viewed as generating private value for firms and public value through knowledge spillovers but less attention has been paid to the question, what's in it for the inventor? We study this question using examiner leniency as exogenous variation, and find evidence that suggests receiving a patent grant reshapes an inventor's life trajectory. Patent receipt significantly increases entry into high-growth entrepreneurship, including founding and working at VC-backed startups, while others advance internally at firms through higher retention and promotion. Mechanism tests support the development of complementary leadership, networking, and social skills that expand opportunities rather than merely boosting confidence. Such recognition also induces technological specialization, superstar collaborations, and breakthrough inventions. Overall, the evidence suggests that patents bolster recognition of a person's underappreciated innovativeness, exposing a new channel through which innovation policy shapes life meaning.

JEL: J1, O3, O34
Keywords: Patents, Intellectual Property, Research and Development, Innovator-Inventor Gap, Innovation, Labor Economics

We thank Amy Lim for excellent research assistance, and Jun Chen for sharing his linkage file. We thank David Schwartz (discussant) and participants at the Workshop on Empirical Intellectual Property for helpful comments on an earlier version. All remaining errors are our own.

*Berkeley Law, cchien@berkeley.edu
†University of Illinois Chicago, Finance Department, jfarre@uic.edu
‡Emory University, Economics Department, jillian.grennan@emory.edu

What did becoming an inventor mean to you?

> *"Being recognized as an inventor validates one's creativity, empowering one to do more."*
>
> — Sujesha S., *became an inventor at age 38*

> *"As an engineer you are usually stuck in an endless cycle of building the next billion-dollar product and in the world of ever-evolving and ever-updating software, most of our work is never permanent. But when you become an inventor and build something, which no one ever thought of, you make a permanent mark of your existence in the tech industry. I still remember how happy I was when I filed my first patent, which was a moment of great joy and pride. And as time went by, I filed multiple patents and I felt more confident and more accomplished."*
>
> — Kshitij I., *became an inventor at age 27*

1 Introduction

Innovation is a cornerstone of economic growth, yet our understanding of the people who generate new ideas remains surprisingly limited. Innovation policy is written largely around firms, emerging technologies, and intellectual property (IP) rights, rather than workers. As a result, we know little about how the institutions governing invention shape inventors' careers and life trajectories.[1] This omission matters because innovation is not only a process of creative destruction but also a labor-market process. The incentives and constraints that inventors face influence where they work, the risks they take, and whether they ultimately found new firms that contribute to economic growth. Understanding how patent recognition may influence these choices is central to designing policies that foster shared economic prosperity.

In this paper, we study how receiving a patent alters the life trajectories of first-time patent applicants.[2] A patent grant is a distinctive labor-market event. It confers legal sta-

[1]A large literature documents who becomes an inventor and the early-life determinants of inventive activity, including family background, exposure, education, and geography (e.g., Bell et al. (2019); Akcigit et al. (2017); Kahn and MacGarvie (2016); Toole et al. (2020); Chien and Grennan (2024). By contrast, there is far less evidence on how institutions supporting invention, and patent grants in particular, shape inventors' subsequent career paths, entrepreneurial decisions, and long-run professional outcomes.

[2]We are careful to distinguish between being an innovator with an inventive idea and being a named inventor, recognizing the "innovator-inventor" gap faced by historically underrepresented groups (URGs) in achieving named inventor status on a patent grant (Chien, 2024; Chien and Ouellette, 2023; Chien and Grennan, 2024).

tus on the person - they are now an "inventor"[3] while also serving as a public and durable signal of inventive ability. By certifying that an idea is novel and non-obvious, patent recognition can bolster an inventor's confidence and/or expand their opportunity set (Chien and Grennan, 2025). The patent has the potential to raise visibility to employers, collaborators, and investors, strengthen bargaining power within firms, and alter the feasibility of entrepreneurial risk-taking. If other frictions and pre-existing constraints, such as potential investor or employer behavioral biases, also influence the extent to which named inventors on a patent grant can convert their newly acquired status into opportunities, the importance of patents as a labor-market signal may be underappreciated. Therefore, we also carefully explore heterogeneity in how first-time inventors convert these expanded opportunities, based on education, gender, ethnicity, and other predetermined constraints, such as prior networks and prestige.

Despite the centrality of patents to innovation policy, empirical evidence on how patent grants influence inventors' life trajectories remains limited. Existing work emphasizes two competing forces. On one hand, patenting may raise inventors' earnings and career prospects, with benefits concentrated among high-skilled and "star-inventor" workers (Toivanen and Väänänen, 2012; Addario and Depalo, 2014; Kline et al., 2019; Aghion et al., 2019). On the other hand, patents may restrict mobility by tying inventors to firm-owned IP, in effect transforming the inventor's ideas into a firm's intangible asset, one that they have no rights to practice outside of their employer,[4] and functioning as an implicit mobility constraint (Melero et al., 2020). While these studies provide important insights, they focus on narrower labor-market margins, whereas we examine a broader range of outcomes. For example, we test whether the same recognition shock can lead one inventor to entrepreneurship, another to internal advancement, and a third to deeper specialization within a firm.

[3] In most cases, patent rights accrue to the organization of the inventor, rather than the inventor themselves, either by direct assignment or under the hired to invent doctrine. In Germany and Japan, inventors also retain remuneration rights, but generally speaking, the extent to which the firm shares direct benefits with the inventor is discretionary (Chien, 2022).

[4] Because the employer wholly retains the rights to the invention, making it technically illegal for the inventor to practice without permission if they move to another employer.

To provide detailed analyses of how patent recognition reshapes inventors' life trajectories, we draw upon a vast online bank of actual resumes from LinkedIn. We match resume data to the universe of first-time patent applicants at the United States Patent and Trademark Office (USPTO). In addition, we match resume position details to PitchBook data on entrepreneurial firms, Glassdoor data on employees' perceptions of firms, Revelio wage estimates and rankings of firm, geographic, and educational prestige, and detailed subsequent-invention and inventor-network data. Ultimately, our sample covers 1.5 million first-time inventors over more than two decades. Our identification strategy leverages the quasi-random assignment of applications to patent examiners within art units. These examiners have differing historical grant rates or leniency rates (Lemley and Sampat, 2012; Righi and Simcoe, 2019), which serve as a well-established source of plausibly exogenous variation (Sampat and Williams, 2019; Farre-Mensa et al., 2020; Goldsmith-Pinkham et al., 2025).

Consistent with the perspective of patents being labor-market signals that reshape inventors' life trajectories, survey evidence from engineers drawn from a larger survey[5] indicate that becoming a named inventor is widely perceived as having a positive life impact (mean of 1.23 on a scale of -2 [negative impact] to +2 [positive impact]). In this study, we also summarize the hundreds of responses we received to the open-ended question asking the engineers to describe the life impact of becoming a named inventor. The responses suggest that patent recognition is perceived as a pivotal career milestone that brings notoriety both within the firm and in the broader community, shaping confidence, professional identity, and perceived access to collaborators and leadership opportunities. This qualitative evidence supports our motivation to broadly explore how patents influence life meaning.

Our empirical analyses yield four main findings. First, patent recognition substantially increases entry into high-growth entrepreneurship. Inventors who receive a patent grant are about 1.0 percentage point (p.p.) more likely to found a VC-backed startup, relative to

[5] Chien and Grennan (2024) surveyed thousands of engineers about the invention process and how it is influenced by firm policies, and analyses of the survey data show that it is reliable, internally consistent, and externally valid.

a baseline founding rate of 2.8 percent, implying a 36% increase. While baseline rates of VC-backed entrepreneurship are low, the estimated gains to entry from patent recognition are large. Patent grants also increase employment at VC-backed startups more broadly, with a 4.7 p.p. increase relative to a baseline mean of 19.8 percent, a 24% increase. Over time, estimates indicate that employees move to startups within the first three years after the grant, whereas founding a high-growth venture takes closer to five years to materialize. The entrepreneurial estimates are driven largely by White and Asian men, suggesting that early recognition lowers barriers to external risk-taking for inventors already positioned to access entrepreneurial networks and capital markets.

Importantly, heterogeneity in entrepreneurial entry reveals the role of credentialing and access. Inventors with only bachelor's degrees and those working in IT/software rather than BioTech/pharma experience larger gains from patent receipt, consistent with patents serving as substitutes for other credentials such as advanced scientific degrees or research grants. While women and underrepresented minorities (URMs)[6] also benefit from patent recognition and move to startups, they do not convert recognition into founding a firm. Mechanism tests indicate that patent recognition translates into entrepreneurship primarily when inventors have sufficient network depth and organizational scale to act on new opportunities. Founding effects are strongest for team-based inventors and those at larger firms, highlighting that patents operate as credentials most easily converted into entrepreneurship when inventors have access to dense networks, complementary collaborators, and scalable organizational environments. These results are robust to alternative standard error constructions, alternative IV estimators, richer sets of predetermined controls and fixed effects, and sample restrictions by art unit size and data completeness.

Second, patent grants reshape careers within firms. Awardees are 3.7 p.p. more likely to remain with their employer or a 21% increase, consistent with the creation of firm-specific human capital or implicit mobility constraints. When inventors do move, they are significantly

[6] We define URM as non-white and non-Asian.

more likely to transition to higher-prestige firms, and they experience faster promotion and increased leadership responsibilities. These internal career gains are accompanied by measurable changes in social skills. Following patent receipt, inventors are significantly more likely to report gains in leadership skills, hold concurrent roles such as board or advisory positions, and expand their professional networks. These patterns suggest that patent recognition enhances not only technical standing but also the social capital required to operate in senior and coordinating roles within firms, providing a mechanism through which recognition translates into internal advancement rather than external exit.

In contrast to findings that external opportunities accrue to white and Asian males, we find that women and URM inventors are more likely to be promoted internally following patent receipt. Geographic mobility also rises, but primarily through exits from innovation hubs rather than entry, a pattern again driven disproportionately by URM inventors and potentially consistent with a desire to return home. These findings suggest that patent recognition improves opportunities within firms even when other frictions may constrain external mobility.

Third, patent recognition alters the trajectory of subsequent innovation. Awardees are more likely to file again and more likely to receive future grants, and their later patents exhibit substantially higher quality, with elevated forward citations, higher valuations, and a greater likelihood of being classified as breakthrough inventions. These gains are largest for inventors with a bachelor's degree or less, a group that faces tighter baseline constraints. At the same time, inventors do not broaden their technological scope. Instead, they specialize, deepening existing relationships and continuing to innovate within their initial domain. They also do not appear to broaden their collaborator network more than their counterfactuals in terms of number of co-inventors, but they are more likely to work with superstar inventors (those in the top decile of patenting or citations for a technology).

Finally, we present suggestive evidence that internal advancement does not fully absorb the gains from recognition. Using Glassdoor data, we find that inventors who remain at their firms report declining assessments of career advancement opportunities and overall rating, with the strength of the relation growing over time. Wage growth is also lower among retained inventors. While these measures can be criticized as noisier, the pattern is consistent with positive lock-in, whereby patent recognition expands outside options, but organizational constraints and the allocation of IP rights limit inventors' ability to realize those options internally, helping to explain why some ultimately seek opportunities elsewhere.

Looking across the various tests, we find evidence for a unified mechanism. Patent grants act as a highly visible shock to inventors' outside option value. For inventors with access to dense networks and scalable organizational environments, this shock is converted into entrepreneurship and external mobility. For others, it strengthens bargaining power within firms, leading to promotion, leadership, and deeper specialization. Thus, patent recognition does not generate a single career pathway. Rather, it widens the set of feasible trajectories, with differences in networks, institutional context, and constraints determining how recognition is ultimately translated into career outcomes. Importantly, for many first-time inventors, these opportunities may not otherwise be available.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the institutional setting and identification strategy. Section 4 presents the data and outcome construction. Section 5 reports the main findings. Section 6 discusses robustness and implications for access to innovation and entrepreneurship. Section 7 concludes.

2 Related Literature

This paper builds on three strands of research: entrepreneurial finance, innovation economics, and personnel and organizational economics. Across these literatures, prior work has examined some aspects of how innovative activity shapes labor outcomes and inventive productivity, but we are the first, to our knowledge, to focus on whether patent recognition is connected to entrepreneurial opportunities and to accumulating the leadership and soft skills that complement technical expertise and have become increasingly valuable in team-based and entrepreneurial settings Deming (2017). Related work shows that performance-based credentials can convey economically meaningful information even outside traditional degree programs, particularly in settings where ability and job readiness are otherwise difficult to observe (Deming et al., 2016; Athey and Palikot, 2025). Our analysis extends this insight to innovation-driven labor markets, where patent grants may serve as analogous performance-based signals.

First, the literature in entrepreneurial finance examines who becomes an entrepreneur and how external circumstances shape the supply of high-growth startups. Financial constraints (Kerr and Nanda, 2009; Hall and Lerner, 2010; Ewens et al., 2018; Ewens and Farre-Mensa, 2020; Bernstein et al., 2022; Babina et al., 2023), government programs (Lerner, 2012; Chatterji et al., 2014; Howell, 2017; Azoulay et al., 2018; Denes et al., 2023), entrepreneurial and VC ecosystems (Guzman and Stern, 2015, 2020; Eldar and Grennan, 2023; Chen and Ewens, 2025), incubators (Gonzalez-Uribe and Leatherbee, 2017; González-Uribe and Reyes, 2021), and immigration policies (Glennon, 2024; Gupta, 2025; Gupta et al., 2025) all play a role. Founders' networks, prior experience, reputation, and optimism all matter when determining which startups receive venture funding and scale (Hochberg et al., 2007; Gompers et al., 2010; Hochberg et al., 2010; Puri and Robinson, 2013; Bernstein et al., 2017; Howell and Nanda, 2024). These papers examine external interventions or financing shocks. Instead, we study an internal recognition event: the receipt of a patent grant, and we use it to show that such recognition substantially increases the probability that an inventor forms a VC-backed startup. Thus, our paper provides new evidence on how signals of inventive capability translate into high-growth entrepreneurship.

A second literature examines unequal access to innovation careers, inventor mobility, and the diffusion of knowledge. A large body of work shows that labor mobility is a central channel through which ideas spread across firms and regions (Fallick et al., 2006; Singh and Agrawal, 2011; Akcigit et al., 2017; Matray, 2021). At the same time, who becomes an inventor and who ultimately captures the returns to invention is highly unequal across gender, race, and background (Bell et al., 2019; Toole et al., 2020; Pairolero et al., 2022; Chien et al., 2025; Koffi and Marx, 2025), with important implications for the direction and composition of technological change (Koning et al., 2020, 2021). Closely related work by Melero et al. (2020) shows that patent grants reduce inventor mobility and interprets this effect as an increase in firm-specific human capital. We corroborate this retention component but extend the analysis along several new dimensions. In particular, we show that patent recognition reshapes inventors' broader opportunity sets, influencing entry into entrepreneurship, geographic mobility, professional networks, and the nature of subsequent inventive activity. Importantly, these responses are highly heterogeneous. Differences by gender, race, education, and industry indicate that recognition alone is often insufficient to overcome external constraints.

A third literature connects recognition, human capital, and career advancement within firms. Research in personnel and organizational economics emphasizes how signals of ability, network referrals, evaluation processes, and internal promotion systems shape incentives, retention, and long-run career trajectories (Kahn and Lange, 2014; Burks et al., 2015; Hoffman et al., 2017; Benson et al., 2019; Gallus and Heikensten, 2020). Recent work further emphasizes the growing importance of general-purpose and social skills—such as coordination, judgment, and leadership—in team-based production and innovation-driven settings (Deming, 2017; Deming and Kahn, 2018). Our results contribute to this literature by showing that patent grants operate as a salient recognition shock that accelerates promotions, expands leadership roles, and alters retention decisions. Importantly, these gains are heterogeneous: men are more likely to translate recognition into entrepreneurial entry, while women and underrepresented inventors disproportionately convert recognition into internal advancement. The finding that organizational satisfaction declines following recognition points to a novel mechanism through which patent protection may interact with internal labor-market frictions and authority structures within firms (Lazear et al., 2015; Hoffman and Tadelis, 2021;

Cullen and Perez-Truglia, 2023).

A fourth literature connects these strands by examining how firm-level shocks affect labor-market outcomes both internally, through bargaining power and retention, and externally, through mobility and entrepreneurship (Babina, 2019; Berger et al., 2022; Babina and Howell, 2024). A closely related work by Kline et al. (2019) studies patent allowances at the firm level and shows that managers and shareholders capture most of the surplus generated by valuable patents, with limited pass-through to individual inventors. Our findings extend this rent-sharing perspective. Rather than focusing on wages or firm-level outcomes, we show that patent recognition affects harder-to-measure traits that shape long-run careers, including entrepreneurial entry, leadership roles, professional networks, and perceived opportunity. These margins have no analog in firm-level rent-sharing models and highlight new channels through which patent recognition can reshape workers' outside options and bargaining positions even when firms retain formal control over the IP. Moreover, our evidence of increased retention alongside declining organizational satisfaction suggests a novel interaction between patent recognition and implicit mobility constraints, echoing recent work on non-compete enforcement and labor-market frictions (Starr et al., 2021; Jeffers, 2023). In this sense, patent grants reshape workers' bargaining power not primarily through wages, but through changes in opportunity sets, identity, and career trajectories.

Across these literatures, our contribution is to provide the first comprehensive causal evidence on how patent recognition restructures the long-run career and innovation life cycle of inventors, linking entrepreneurial entry, mobility, internal advancement, network formation, and subsequent invention within a unified framework.

3 Empirical Design

Identifying the effect of early patent grants on innovators' career (and life) outcomes is challenging because inventor talent is likely to be correlated with both the likelihood of patent approval and with innovator's career outcomes, thus raising endogeneity concerns. For instance, a more talented innovator is both more likely to have her patent application approved and to experience positive career outcomes, such as earning a promotion or founding a successful startup.

To identify the effects of early patent grants on innovator's careers, our identification strategy builds upon Sampat and Williams (2019) and Farre-Mensa et al. (2020) by exploiting exogenous variation in patent examiners' approval rates to instrument for the probability that a patent application is approved. The validity of our IV rests on two institutional features of the USPTO patent review process. First, throughout our period of analysis, the USPTO assigned applications to examiners in each technology field (or "art unit") randomly with respect to the quality of the underlying application (Lemley and Sampat, 2012; Sampat and Williams, 2019). Second, patent examiners vary in their propensity to approve applications. Some are more lenient while others are stricter (Cockburn et al., 2003). Together, these two features result in the quasi-random assignment of similar applications to examiners who differ in their propensity to approve patents, creating exogenous variation in the likelihood that applications of comparable quality are approved.

To illustrate, consider the outcome Yn, defined as an indicator equal to one if the innovator founds a VC-funded startup within n years of the decision on her first patent application, and zero otherwise. To identify the effect of patent approval on this outcome, we can estimate the following equation:

$$Y^n_{iajt} = \beta FirstApplicationApproved_{iajt} + \phi X_{iajt} + \upsilon_{at} + \epsilon_{iajt} \tag{1}$$

where i indexes innovators, a indexes the art unit where the innovator's first patent application (p) is assigned, j indexes the patent examiner assigned to review application p, and t is the year when patent application p is filed. $FirstApplicationApproved_{iajt}$ is an indicator variable for whether the examiner's final decision approves the application. As Aneja et al. (2024) documents, most applications are rejected initially, but many more are approved thereafter. The vector X_{iajt} includes a variety of control variables (e.g., the innovator's state of residence, her highest academic degree, and an indicator for whether she graduated from an Ivy Plus institution). We include art-unit-by-application-year fixed effects, υ_{at}. Examiner assignment within art units is effectively random. Assuming this set changes slowly over time, including art unit-by-year fixed effects is necessary to help us account for the fact that the assignment of patent applications to examiners is only quasi-random within art units, which, as explained above, is key to our identification strategy. Standard errors are clustered at the art unit level.

As argued above, the variable $FirstApplicationApproved_{aijt}$ is likely endogenous, because it is likely to be correlated with the error term ϵ_{iajt} due to our inability to observe and include in X all innovator characteristics that are likely to impact both Y and the likelihood of an innovator's first patent being approved. To address this endogeneity, we follow Farre-Mensa et al. (2020), and we use examiner j's past approval rate as an instrument for whether an innovator's first application is approved and estimate equation Equation 1 using two-stage least squares (2SLS).

Specifically, we calculate the approval rate of examiner j belonging to art unit a assigned to review innovator i's first patent application submitted at time t as follows:

$$ExaminerApprovalRate_{iajt} = n_{granted_{ajt}}/n_{reviewed_{ajt}} \tag{2}$$

where $n_{reviewed_{ajt}}$ and $n_{granted_{ajt}}$ are the numbers of patents examiner j has reviewed and granted, respectively, prior to date t. The first stage of our 2SLS model then consists of regressing patent approval on the instrument by estimating the following linear probability model:

$$FirstApplicationAppvoed_{iajt} = \theta ExaminerApprovalRate_{iajt} + X_{iajt} + u_{iajt} \tag{3}$$

Next, we discuss several implications and limitations of our empirical strategy.

3.1 Discussion of Empirical Strategy

3.1.1 Focus on First Patent Application

Our empirical strategy focuses on identifying the effect of an inventor's first patent application approval on her subsequent professional and personal trajectory. This focus is motivated by several practical, institutional, and econometric considerations:

First, we expect the outcome of an inventor's first patent application to be especially consequential for her career. It marks the initial formal recognition of inventive activity and may shape future opportunities in a path-dependent way. As such, it is a natural focal point for our study—though we remain cautious not to extrapolate our findings to later applications.

Second, restricting attention to first applications allows us to define the sample as all inventors who submit at least one patent application. Requiring multiple applications would introduce additional selection bias, as it would condition on unobserved persistence or success in the inventive process.

Third, our IV is particularly well-suited to identifying the causal effect of a single patent application's approval, regardless of whether it is an innovator's first or tenth application. If, instead, we aimed to instrument the outcome of multiple applications (e.g., the first ten), we would need to average the leniency of the ten examiners assigned to those applications to construct our instrument. However, by the law of large numbers, this average would exhibit less cross-sectional variation than the leniency of any single examiner, thereby weakening the instrument's first-stage relationship and increasing the risk of a weak instrument problem.

3.1.2 LATE and External Validity

As with any instrument, our estimator identifies a local average treatment effect (LATE). Specifically, the effect of an innovator having her first patent application approved on subsequent career outcomes for the subpopulation of compliers. Put another way, for innovators whose first application outcome is influenced by the leniency of their assigned examiner.

These are likely to be inventors whose first application is of moderate quality: Not so strong that nearly any examiner would approve it ("always takers"), and not so weak that nearly all would reject it ("never takers").

We expect a substantial share of applications to fall into this intermediate quality range. First, it is costly to apply for a parent, so "never takers" are likely not to engage in the process in the first place. Indeed, historically, patent application approval rates have hovered near 70%. While "always takers" do not face cost constraints, focusing on first-time innovators does imply they are more likely to be in the intermediary range. This occurs because there is a hidden curriculum in the patenting process that makes becoming a named inventor particularly challenging for those who have not previously done it. Either way, LATE is ultimately an empirical question, which we can test using the methods discussed in (Angrist and Pischke, 2009).

Should we expect the LATE estimated from our IV to generalize to always-takers or never-takers? Likely not. The signaling value of having a first patent application approved is probably highest for compliers. A top-tier innovator submitting an obviously strong application may not need a patent to signal her quality credibly. Conversely, a very low-quality innovator is unlikely to benefit much from approval, as the market may still infer her low quality even if her first application were approved. By contrast, the future careers of mid-quality innovators (i.e., those whose first application outcomes are more likely to be influenced by examiner leniency) may be most affected by whether their first application is approved.

3.1.3 Examiner specialization

Righi and Simcoe (2019) document evidence of examiner specialization within certain USPTO art units, casting doubt on the notion that patent applications are quasi-randomly assigned to examiners across all units. While we adopt the term "quasi-random matching" for brevity and consistency with much of the prior literature, it is important to emphasize that our instrumental variable does not rely on strict quasi-random assignment. Rather, the key requirement for our identification strategy is that the examiner leniency instrument satisfies the exclusion restriction. Namely, it must affect the outcome variable Y in Eq. 1 only through its effect on the likelihood that an inventor's first patent application is approved. In particular, this means that it must be uncorrelated with the error term ϵ.

Importantly, Righi and Simcoe (2019) find little evidence that certain examiners within a given art unit are assigned to the applications with the largest families or broadest claims, which are both common proxies for patent application importance and scope. This suggests that examiner specialization is unlikely to involve selection on unobservable dimensions of application quality, mitigating concerns about violations of the exclusion restriction. Be that as it may, we will follow this approach to ensure that our findings are robust to (1) including fine-grained technology fixed effects (e.g., subclass fixed effects), and (2) restricting the sample to those art units where the assignment of patent applications to examiners is most consistent with random assignment, as identified by Feng and Jaravel (2020).

3.1.4 Timing considerations

We measure career outcomes Y in Eq. 1 relative to the first-action decision date of an inventor's first patent application. This choice parallels Farre-Mensa et al. (2020), who measure startup outcomes from the first-action decision on a startup's first patent application, and it is motivated by similar concerns. In particular, the timing of the final decision is largely influenced by applicant behavior, such as delays in responding to examiner communications, and is therefore potentially endogenous.

3.1.5 Leniency Designs

Leniency designs rest on the assumption that many cases are close calls, in which lenient decision-makers approve, whereas stricter ones deny. For the IV regression to produce unbiased estimates, the exclusion restriction must hold. In this case, it seems plausible that the exclusion restriction is satisfied. For example, patent examiners are not permitted to consult with firms on how to obtain patent approval, and they are unlikely to interact with applicants outside their decision-making capacity. The second required assumption is the relevance condition. Here, one potential concern is the many weak-instrument biases arising in 2SLS (Bound et al., 1995), which is explicitly highlighted in the recent econometric literature on leniency design Goldsmith-Pinkham et al. (2025).

The idea is that we do not know the true population-level leniency of the examiners; instead, we have estimates of their leniency relative to others who could have received the application. The 2SLS bias arises because one's own treatment status affects others' relative leniency. While we intentionally exclude innovator i's application and any subsequent applications to reduce this mechanical bias, it may nevertheless remain. Therefore, we follow best practices recommended by Goldsmith-Pinkham et al. (2025) to recover a bias-free alternative. Specifically, we avoid a mechanical correlation with ϵ by using the unbiased jackknife instrumental variable estimator (UJIVE) proposed by Kolesár (2013). We also test monotonicity to assess the plausibility of a LATE interpretation.

Finally, we verify the balance on other observables as a test of the as-good-as-random assumption. Specifically, we examine whether predetermined characteristics are equal across types of decision-makers, conditional on the necessary controls (i.e., art-unit-by-year fixed effects). Appendix **??** presents balance tests. Each row reports a UJIVE coefficient from regressing a predetermined covariate on patent approval, instrumenting with examiner indicators, and controlling for art unit-by-year fixed effects. Consistent with the assumption of quasi-randomness, the estimates show no meaningful difference across groups.

4 Data

Survey responses from inventors provide direct evidence that patent recognition is experienced as a broad and consequential career shock rather than a narrow legal event. As shown in Table 1, respondents consistently describe patent grants as conferring external validation and industry-wide credibility, increasing confidence and innovative identity, and expanding visibility within firms and professional networks. These qualitative responses point to multiple channels through which recognition may translate into observable economic outcomes, including entrepreneurship, startup employment, internal promotion, leadership and mentoring roles, geographic mobility, and subsequent innovation choices. Guided by these qualitative insights, we design our empirical analysis to measure the career and innovation margins most frequently cited by inventors as consequential responses to patent recognition. To do so, we assemble a novel inventor-level dataset that links detailed patent records to comprehensive career histories, enabling us to trace how recognition translates into observable changes in employment, entrepreneurship, leadership, mobility, and subsequent innovation.

Central to this empirical strategy is the integration of detailed USPTO patent records—drawing on PatEx and PatentsView—with inventor-level data from Revelio Labs, a third-party platform that aggregates employee information primarily from LinkedIn, as well as related professional and job-posting sources. These data allow us to observe inventors' educational and career backgrounds prior to patenting and a rich set of post–first-application outcomes, including employment mobility, promotions, wage changes, human capital investments, and entry into entrepreneurship.

Matching patent applicants and inventors in the USPTO records to Revelio Labs individual profiles poses a formidable challenge. We implement a conservative, multi-stage matching procedure that prioritizes precision over coverage, yielding a final analysis sample of 1,798,909 first-time applicants between 1976 and 2023, approximately 10 percent of all first-time applicants in the USPTO data. The matched sample reflects known coverage limitations of online professional profiles and is tilted toward corporate inventors in technology-intensive sectors. Within this sample, 76% of first applications are granted, closely mirroring USPTO grant rates for comparable corporate applicants.

Appendix C provides a detailed description of the matching process, including the five-stage linkage strategy, match-quality thresholds, validation exercises, and sample composition by match type, technology, entity, and filing cohort. It also documents how the final treatment and control groups are constructed and assesses balance and representativeness across matching methods.

To measure entrepreneurial activity and participation in high-growth startups, we match individual employment histories from Revelio Labs to firm-level data from PitchBook. This linkage allows us to identify inventors who become founders or hold entrepreneurial roles at venture-capital-backed startups, as well as those who transition to startup employment more broadly. We distinguish between founding a VC-backed firm, working at a VC-backed startup, and working at a startup regardless of financing status, using PitchBook's venture funding classifications, firm age, accelerator participation, and job-title information. These measures capture entry into the segment of entrepreneurship most closely associated with innovation-driven growth and form the paper's primary external-career outcomes.

Beyond entrepreneurship, we construct a rich set of outcomes capturing inventors' internal career progression, mobility, human capital development, and subsequent innovation. Using Revelio data, we observe retention, promotions within and across firms, transitions to prestigious employers, and geographic mobility, including moves into and out of major innovation hubs. We also measure leadership and external engagement through changes in reported leadership skills, concurrent positions such as board or volunteer roles, and growth in professional networks. Finally, we track subsequent patenting activity using USPTO data, including measures of patent success and quality—such as grants, citations, scope, originality, generality, and breakthrough status—to assess whether recognition leads inventors to broaden their technological focus or deepen specialization within existing domains. Appendix A provides detailed definitions and construction procedures for all variables.

By examining a comprehensive set of outcomes, our study sheds light on how innovation incentives shape inventors' lives beyond the workplace, potentially generating spillover effects that contribute to broader social welfare. For example, Bell et al. (2019) show that exposure to innovation in childhood significantly increases the likelihood of becoming an inventor, with large disparities by socioeconomic background. By analyzing how patent grants affect both economic security and social engagement, our study complements this work, exploring whether recognition through the patent system creates feedback loops that either reinforce or mitigate early-life disparities in access to innovation careers.

4.1 Summary Statistics

Table 2 reports demographic characteristics of our matched sample of first-time patent applicants. The sample is predominantly male (82.0 percent), with women comprising 15.5 percent of inventors. In terms of race and ethnicity, 62.2 percent of inventors are White and 32.4 percent are Asian or Asian/Pacific Islander, consistent with the concentration of patenting activity in technology-intensive fields. Educational attainment is high but incompletely observed: among inventors with reported education, 16.5 percent hold a bachelor's degree, 16.0 percent a master's degree, and 14.5 percent a PhD, though education is missing for 46.9 percent of the sample. Inventors are affiliated with relatively prestigious institutions on average, with a mean standardized prestige score of 0.353, and report an average of 249 LinkedIn connections.

Patent-level characteristics are summarized in Table 3. The sample is dominated by utility patents (97.7 percent), with the remainder consisting primarily of design patents. Most applications originate from large entities (76.2 percent), with smaller shares from small (22.7 percent) and micro (1.2 percent) entities. Grant rates vary sharply by entity size: 80.2 percent for large entities, compared to 61.2 percent for small entities and 49.1 percent for micro entities. Applications span a broad range of technological fields—the five most common technology classes together account for only 15.0 percent of the sample—highlighting the diversity of inventive activity represented in the data. The mean filing year is 2008, with granted applications filed slightly earlier on average than rejected applications.

Appendix Table C.3 compares pre-patent characteristics across treatment and control groups. Inventors whose first applications are granted differ systematically from those whose applications are rejected on observable dimensions. The largest differences arise in educational attainment and institutional prestige: the treatment group contains a higher share of inventors with graduate degrees and higher average prestige scores. Treated inventors also report more extensive professional networks prior to patenting. These patterns indicate strong positive selection into patent grants, implying that simple comparisons between granted and rejected applicants would conflate the effects of patent recognition with underlying differences in inventor quality, resources, and institutional support.

Gender and education patterns reinforce this concern. Women constitute a larger share of rejected applications (17.6 percent) than granted applications (14.8 percent), a statistically significant gap that mirrors prior evidence of differential attrition during patent examination (Aneja et al., 2024). Similarly, inventors with advanced degrees are substantially more likely to receive patent grants: 32.9 percent of granted applications come from inventors with graduate degrees, compared to 24.4 percent among rejected applications. These differences persist even after conditioning on observable credentials and institutional prestige, suggesting that unobserved factors correlated with both patent approval and career outcomes remain important.

In conclusion, the summary statistics indicate an imbalance between the treatment and control groups with respect to key predetermined characteristics. These differences underscore the need for an empirical strategy that isolates exogenous variation in patent grants. Our empirical approach, which exploits quasi-random assignment of applications to examiners with differing approval propensities, is designed to address these selection concerns.

Appendix Tables C.4 and C.5 provide additional balance tests, and Appendix C.6 explores examiner traits. Finally, in Appendix Tables C.7 and C.10 we evaluate the strength of the examiner leniency instrument, with first-stage F-statistics exceeding 8600 in our main specification, well above conventional thresholds for a strong instrument. We provide visual evidence that the monotonicity assumption holds in C.1.

5 Results

5.1 External Recognition

We now turn to the results, focusing first on how patent recognition reshapes inventors' external opportunity sets through entrepreneurship and startup employment.

5.1.1 Entrepreneurial Outcomes

Table 4 reports the results from our 2SLS regressions examining whether receiving a patent grant influences innovators' subsequent entrepreneurial activity and employment at startups. We find that receiving a patent grant substantially increases the likelihood that an inventor becomes an entrepreneur at a VC-backed startup. Column (1) shows that a patent grant raises the probability of founding a VC-backed firm by approximately 1 percentage point. Given that the low baseline probability of ever founding a VC-backed startup is about 2.8 percent, this is an economically meaningful effect. Thus, this estimate implies an increase of roughly 36 percent relative to the mean, underscoring the importance of patent recognition for ultimately developing the confidence and connections to pursue high-growth entrepreneurship.

Columns (2) and (3) broaden the scope to startup employment more generally. Patent grants also increase the likelihood that inventors move to VC-backed and non-VC-backed startups, indicating that the effects extend beyond founding to participation in startup ecosystems more broadly. The magnitudes are comparable across VC-backed and non-VC-backed firms, suggesting that patent recognition expands inventors' access to entrepreneurial environments rather than merely reallocating them across firm types. These results show that formal recognition of inventive achievement does not simply enable firms and managers to accrue rents but meaningfully reshapes inventors' external opportunity sets, allowing them to transition into entrepreneurial activity.

The LATE that we document for all inventors masks substantial heterogeneity in who converts patent recognition into entrepreneurial activity. Table 5 explores this heterogeneity by estimating the relation between patent grant and entry into high-growth entrepreneurship separately across gender, race, education, and technology sectors.

Two patterns stand out. First, the increase in entrepreneurial founding at VC-backed startups is driven almost entirely by men. Panel A shows that receiving a patent grant significantly increases the probability that male inventors found a VC-backed firm, while the corresponding estimate for women is small and statistically indistinguishable from zero. Similarly, when breaking down the increase in entrepreneurial founding at VC-backed startups by ethnicity, we see is driven almost entirely by men.

Second, the entrepreneurship response varies systematically across other dimensions of background and field. Founding one's own firm is concentrated among inventors with a bachelor's degree or less and among those working in the software and IT sectors. Of course, these are sectors where other forms of external recognition, such as being a doctor at a prominent university, may be less common. In contrast, inventors in biotech and pharmaceuticals exhibit little response in founding.

Panel B shows a broader set of responses when considering moves to VC-backed startups, regardless of founding status. Here, patent grants increase transitions to VC-backed firms across nearly all demographic and educational groups, including women and URMs. While the coefficient estimate for URMs is only significant at the 90th percentile, the economic magnitude is meaningful. This pattern indicates that while patent recognition expands access to entrepreneurial environments for a wide range of inventors, only a subset is able to convert that access into firm creation. The contrast between founding and employment responses foreshadows the mechanism analyses that follow, which examine how networks, team structure, firm environment, and timing shape the translation of patent recognition into entrepreneurial entry.

5.1.2 Mechanism Tests for Entrepreneurial Outcomes

Table 6 examines the mechanisms underlying entrepreneurial entry by asking when patent recognition translates into founding a VC-backed firm. Panel A focuses on network capacity and organizational scale. The effects of patent grants on entrepreneurship are substantially stronger when inventors operate in environments that provide sufficient team depth and institutional resources. Founding responses are concentrated among inventors embedded in team-based innovation rather than solo inventors, among those working in larger teams rather than small ones, and among inventors originating from larger firms. These patterns indicate that recognition alone is not sufficient to induce entrepreneurship; rather, patent grants are most effective when inventors have access to a critical mass of collaborators and complementary skills that can be mobilized to form a new venture.

Panel B examines credentialing more directly by comparing inventors working in technology domains where external validation is particularly salient. Patent grants are statistically significantly associated with VC-backed entrepreneurship among inventors in IT and software, where patents plausibly serve as visible credentials in external capital markets, but the point estimate is close to zero in biotech and pharmaceuticals, where alternative credentials—such as advanced degrees, institutional affiliations, and regulatory milestones—are already well established. These findings reinforce the interpretation of patents as credentialing devices that expand access to entrepreneurial opportunities by improving inventors' visibility and credibility, but only when paired with sufficiently dense networks and scalable organizational contexts. This mechanism helps reconcile why patent recognition leads immediately to startup employment yet translates into firm creation only for a subset of inventors positioned to leverage those opportunities.

Figure 1 illustrates a sharp distinction between access to entrepreneurial environments and entry into entrepreneurship itself. Transitions into VC-backed startup employment occur almost immediately following patent recognition, with effects concentrated in the first three years after the patent decision. By contrast, entry into VC-backed entrepreneurship emerges later, peaking in the four-to-six-year window and remaining elevated thereafter. This temporal pattern is inconsistent with a purely confidence- or liquidity-based explanation and instead points to the gradual accumulation of complementary skills and resources.

Thus, we interpret patent grants as serving additional purposes beyond purely private or public value in the traditional sense. Patents also act as a credentialing device that initially expands inventors' access to startup ecosystems, where they build professional networks, leadership experience, and social capital. Only after acquiring these complementary capabilities do a subset of inventors convert recognition into firm creation. The timing evidence thus supports a mechanism in which patent recognition reshapes opportunity sets immediately, while entrepreneurial founding reflects a slower process of capability formation.

5.2 Internal Recognition

We now turn to the results for how patent recognition reshapes inventors' internal opportunity sets through career advancement, skill development, and technological specialization.

5.2.1 Career Advancement

Next, we examine how patent grants reshape inventors' careers inside the firm. While earlier tables show that patent recognition expands inventors' external options and increases transitions into entrepreneurial environments, we want to understand whether patent grants simultaneously generate substantial internal career advancement.

Table 7 examines how patent grants reshape inventors' careers inside the firm. Panel A shows that receiving a patent grant increases the probability that an inventor remains with her current employer by 3.7 p.p., relative to a baseline retention rate of 17.7 percent. At the same time, patent grants significantly increase promotion rates. The probability of being promoted by the same firm rises by 4.2 p.p., and the probability of promotion by another firm increases by 4.6 p.p., both economically large effects relative to baseline promotion rates. In addition, patent recipients are 4.2 p.p. more likely to move to a more prestigious firm. These patterns suggest that recognition via patent grants helps inventors advance their career trajectory. Current employers respond by retaining and promoting inventors, while external firms compete for recognized talent.

Panel B reveals substantial heterogeneity in these internal responses. The coefficient estimates on promotion are particularly pronounced for women and URM inventors. For women, a patent grant increases the probability of promotion by the same firm by 5.4 p.p., compared with 3.8 p.p. for men. Given that women are less likely to get promoted, this is an economically meaningful effect and an important catalyst for internal recognition. Similarly, URM inventors also experience promotion gains (6.2 p.p. increase). These magnitudes imply that patent recognition plays a disproportionately important role in advancing the careers of groups that may face greater informational frictions or weaker bargaining positions in internal labor markets.

The contrast between these internal career gains and the entrepreneurship results in earlier tables is informative about mechanism. Patent grants expand the opportunity set for all inventors, but the way those opportunities are realized differs across groups. For women and URMs, recognition is more likely to be translated into internal advancement and leadership, consistent with improved bargaining power within firms. For men, recognition is more likely to be converted into external transitions and entrepreneurial entry. This divergence suggests that patent grants do not merely reward inventive output; they interact with pre-existing constraints and institutional environments to shape how inventors allocate talent across internal advancement, external mobility, and entrepreneurship. While these gains for women and URMs are promising, this could simultaneously create forces that limit external mobility through firm-specific human capital lock-in.

Next, Table 8 examines how patent grants affect inventors' geographic mobility and their relationship to innovation hubs. Receiving a patent grant significantly increases the likelihood that an inventor changes location, raising geographic mobility by 4.4 percentage points relative to a baseline mobility rate of 19.6 percent. Thus, patent recognition expands inventors' willingness or ability to relocate.

Strikingly, this increased mobility does not reflect greater entry into innovation hubs. Column (2) shows no increase in moves to innovation hubs following a patent grant. Instead, Column (3) shows that patent grants increase the probability that inventors leave innovation hubs by 1.2 percentage points, relative to a baseline exit rate of 3.5 percent. This pattern contrasts with standard narratives in which innovation success pulls talent toward major clusters, and instead suggests that patent recognition may relax geographic constraints or reduce the need to remain in dense innovation ecosystems.

Panel B reveals that this exit from innovation hubs is driven by specific groups. The effect is concentrated among women and URM inventors and among those working in information technology and software. For these inventors, patent grants significantly increase the probability of leaving an innovation hub, whereas effects are small for white and asian inventors and statistically insignificant for men. Furthermore, for capital-intensive industries that may only be in a limited number of cities like biotech and pharmaceutical sectors, we see no movement. These patterns suggest that patent recognition may enable some inventors, particularly those facing greater frictions or lower attachment to hubs, to relocate toward alternative labor markets or communities once recognition secures their professional standing. That patent recognition appears to facilitate diaspora away from established hubs is an interesting finding and an underexplored aspect of innovation policy.

5.2.2 Leadership and Soft Skills

Table 9 examines how patent grants affect inventors' leadership skills, external engagement, and professional networks—key mechanisms through which recognition may translate into career advancement and entrepreneurship. Panel A shows that patent grants significantly increase leadership capacity and external engagement. Receiving a patent grant raises measured leadership skills by 3.0 percentage points relative to a baseline of 32.7 percent, and increases the likelihood that inventors hold concurrent positions—such as board seats or volunteer leadership roles—by 1.1 percentage points. These effects indicate that patent recognition elevates inventors into roles with greater responsibility, visibility, and influence beyond their core technical positions. Patent grants also substantially expand professional networks. Column (3) shows that patent recipients add approximately 15 additional LinkedIn connections, a nontrivial increase relative to a baseline of 276 connections. This network expansion provides a plausible channel linking patent recognition to subsequent entrepreneurship and external mobility.

Panel B highlights heterogeneity in network expansion. The increase in LinkedIn connections is driven disproportionately by women and by inventors working in information technology and software. Female inventors experience especially large network gains, consistent with patent recognition alleviating informational or access frictions in professional networks. By contrast, network expansion is more modest for men and statistically insignificant for inventors in biotech and pharmaceutical sectors, where career progression may rely more heavily on formal organizational pathways.

In addition, Table 9 provides direct evidence that patent recognition operates through a networking and credentialing channel. Beyond increases in self-reported leadership skills and concurrent positions, we find that patent grants significantly expand inventors' professional networks and, importantly, their access to elite collaborators. Column (4) of Panel A shows that receiving a patent increases the likelihood of collaborating with "superstar" inventors, who we define as being in the top decile of lifetime patent counts or forward citations, suggesting that recognition alters how inventors are perceived and with whom they are able to work. Panels C further reinforce this mechanism: elite collaborations are present across groups. Taken together, these results indicate that patents function as widely recognized credentials that unlock higher-quality professional relationships. This expansion of social capital and exposure to elite collaborators provides a natural bridge with the entrepreneurial timing results (see Figure 1) and serves as a mechanism that explains both internal and external patterns, as working with more experienced and visible innovators facilitates the accumulation of leadership, coordination, and market-facing skills necessary for founding a firm.

In untabulated results, we also examine heterogeneity in leadership gains. In contrast to network connections, leadership gains are broadly shared across gender, indicating that patent recognition raises leadership roles for both men and women. However, leadership effects by ethnicity are concentrated among White and Asian inventors, suggesting heterogeneity in how recognition translates into formal leadership opportunities across groups. These results confirm that patent recognition increases leadership responsibilities and external engagement while expanding professional networks, with strong network effects for women. These patterns help explain how patent grants generate downstream effects on entrepreneurship and career mobility, while also revealing group-specific pathways through which recognition is converted into opportunity.

5.2.3 Technological Specialization

Table 10 examines how patent grants affect inventors' subsequent inventive activity and whether recognition induces broader exploration or deeper specialization. The evidence points decisively toward specialization. The results show a clear shift toward specialization. Panel A shows that receiving a patent grant increases the likelihood that an inventor files again and that subsequent applications are granted. Patent recipients are 1.8 p.p. more likely to have a subsequent patent application approved. Relative to a baseline probability of 47 percent, this indicates a meaningful economic magnitude. By contrast, the total number of subsequent patent applications does not increase, and the point estimate is statistically indistinguishable from 0. Thus, patent recognition appears to raise patent approval rates conditional on patenting, rather than increase the volume of inventive effort. Intuitively, this makes sense as the quasi-random patent grant does not convey knowledge about the patent process, nor does it alter a person's creative capacity or inventive efficiency.

Panel B provides direct evidence on the structure of inventive activity. Patent grants reduce inventor network expansion: recipients experience a decline in overall network growth and a substantial reduction in the share of new co-inventors. At the same time, inventors do not expand into new USPTO technology classes. These patterns indicate that patent recognition does not encourage inventors to broaden their collaborative or technological scope. Instead, inventors appear to deepen existing relationships and remain within familiar technological domains.

Panel C shows that this specialization is associated with higher-quality innovation. Subsequent patents filed by grant recipients receive significantly more forward citations, exhibit higher estimated patent value, and are more likely to qualify as breakthrough patents. For example, forward citations increase by approximately five citations relative to a baseline of 7.8, and the probability of producing a breakthrough patent rises by 1.4 percentage points, nearly a 40 percent increase relative to the mean. These gains indicate that specialization following recognition is productive, because inventors are building on prior knowledge to generate more impactful innovations.

This suggests that patent recognition induces inventors to further leverage their comparative advantage. Rather than expanding into new technologies or forming new teams, inventors consolidate their existing networks and domains, producing fewer but more successful and higher-quality innovations. This pattern complements earlier findings on career advancement and entrepreneurship, highlighting specialization as a central channel through which patent grants shape long-run inventive outcomes.

5.2.4 Workplace perceptions

Table 11 presents complementary evidence on workplace perceptions and compensation following patent recognition. Using data from crowd-sourced employee reviews on Glassdoor, a career intelligence website that attempts to provide transparency about jobs, salaries, and companies, we examine the relation between the mentorship program and employees' perceptions of their workplace environment.[7] It is worth noting that these outcomes are based on self-disclosed Glassdoor reviews and resume-based wage measures estimated by Revelio, so they are noisier than our main career and mobility measures and should be interpreted cautiously. With that caveat, the results point to a consistent pattern. After receiving a patent grant, engineers at the applicant's current firm report lower assessments of the firm along several dimensions, including overall ratings, culture, career advancement, and the strength of cultural norms surrounding innovation.

These declines persist even as the same inventors experience higher probabilities of retention and promotion, suggesting that internal advancement does not necessarily translate into sustained positive perceptions of their employer, growth opportunities, or career advancement. In addition, we observe modestly lower subsequent wage growth, consistent with the view that firms capture much of the surplus from patented innovations (Kline et al., 2019). Taken together, these patterns provide suggestive evidence of a divergence in career paths. While patent recognition initially facilitates technical specialization and advancement within firms, it may also contribute to perceived career ceilings and organizational frictions, helping to explain why some inventors ultimately seek opportunities outside the firm despite early success.

5.3 A Unified Mechanism: Patent Recognition and Outside Options

The results across Sections 5.1 and 5.2 can be understood through a common mechanism. Namely, patent recognition operates as a highly visible shock to an inventor's outside options. A granted patent publicly certifies inventive ability, raises visibility, and improves perceived credibility with employers, collaborators, and investors. This expansion of outside options reshapes inventors' opportunity sets, but the manner in which those opportunities are realized varies systematically with constraints, networks, and organizational context.

[7] Previous studies have used the Glassdoor database to evaluate non-pecuniary benefits and in the process have shown that the crowd-sourced data is reliable and consistent with internal firm surveys (Tambe et al., 2020; Graham et al., 2022; Grennan, 2023; Liu et al., 2023; Martellini et al., 2024; Gornall et al., 2025).

Inventors with access to dense professional networks and scalable organizational environments, particularly men in software and IT, are more likely to leverage these outside options to move externally. In particular, we find that these inventors move quickly into startup employment and, with time, convert accumulated networks and leadership experience into firm creation. By contrast, inventors facing greater external frictions/bias or higher fixed costs of entrepreneurship (e.g., women and URMs) are more likely to translate the same recognition shock into internal advancement. For these inventors, patent grants increase retention, promotions, leadership roles, and access to elite collaborators, consistent with improved bargaining power within firms.

This framework also reconciles seemingly divergent findings. Increased retention and specialization reflect the strengthening of firm-specific human capital following recognition, even as external opportunities expand. Declining workplace satisfaction among retained inventors is consistent with "positive lock-in," in which outside options rise faster than internal organizational capacity to accommodate advancement. Similarly, our timing evidence, which shows immediate transitions into startup employment but delayed entry into entrepreneurship, reflects the gradual accumulation of complementary skills required to exercise high-fixed-cost outside options.

This nuance highlights an important but largely overlooked role of the patent system. Patents are typically viewed as instruments that allocate private value to firms and generate public value through knowledge spillovers. Our results show that they also play a central role in shaping the life trajectories of inventors themselves. Patent recognition does not generate a single career pathway. Instead, it widens the set of feasible trajectories by expanding outside options, with differences in networks, institutional context, and constraints determining whether recognition is converted into entrepreneurship, internal leadership, geographic mobility, or deeper inventive specialization. This perspective reframes patents as labor-market institutions as much as legal ones. Recognizing the human consequences of patent grants has important implications for innovation policy, suggesting that decisions made at the patent office influence not only which ideas are commercialized, but also who becomes an entrepreneur, who advances within organizations, and how innovative talent is allocated across firms, regions, and careers.

6 Robustness

First, Appendix Table D.1 compare our entrepreneurship heterogeneity results under two standard error specifications: (1) the main specification with standard errors clustered at the art unit level, and (2) heteroskedasticity-robust standard errors following the recommendations in Goldsmith-Pinkham et al. (2025).

Second, Appendix Table D.2 presents UJIVE estimates of the effect of patent application approval on entrepreneurship. Rather than using the 2SLS estimation procedure, we estimate our coefficients with UJIVE by instrumenting with examiner indicators.

Third, Appendix Table D.3 presents alternative 2SLS estimates of the effect of patent grant on entrepreneurship. Specifically, we restrict to inventors with complete demographic data to include a richer set of predetermined controls. Second, we limit to large art units. Third, we replace the art unit *times* year fixed effects with finer USPC subclass $\times$ year fixed effects.

Fourth, we could not present all the heterogeneity results in the main body. Appendix Tables D.4, D.5, provide additional heterogeneity checks, highlighting how the opportunities enabled by patent recognition differ by gender, ethnicity, education, and job seniority.

7 Conclusion

This paper studies how formal recognition through the patent system shapes the life trajectories of inventors. Using quasi-random variation in patent grant decisions, we show that receiving a first patent has large and persistent effects on careers. Patent recognition expands inventors' opportunity sets, increasing entry into high-growth entrepreneurship and startup employment, accelerating internal career advancement, fostering leadership and network formation, and raising the quality of subsequent innovation. At the same time, these effects are heterogeneous. Some inventors convert recognition into external opportunities such as entrepreneurship and mobility across firms and regions, while others translate recognition into retention, promotion, and leadership within organizations.

A central insight of our findings is that patent recognition operates less as a narrow legal event and more as a broad social and economic signal. Recognition affects confidence, visibility, and credibility, shaping how inventors are perceived by firms, investors, peers, and themselves. These mechanisms help explain why recognition leads to deeper specialization and higher-impact innovation rather than broader experimentation, and why increased geographic mobility manifests as exits from innovation hubs rather than increased entry into them.

The heterogeneity we document highlights important distributional considerations. Women and URM inventors are more likely to translate recognition into internal advancement and leadership, whereas white and Asian men are more likely to pursue entrepreneurial pathways. These patterns suggest that the same recognition shock can generate different economic outcomes depending on prior constraints, access to networks, and institutional context. As a result, policies that expand access to inventorship and recognition may affect not only aggregate innovation, but also who benefits from innovation and how innovative talent is allocated across firms, careers, and places. These changes in opportunity have important implications for shared prosperity.

More broadly, our results show that innovation policy shapes economic growth not only through the ideas it protects, but through the people it recognizes. Patent grants influence who becomes an entrepreneur, who advances within firms, where inventors choose to live and work, and how inventive effort evolves over the life cycle. Rather than generating a single pathway, patent recognition expands the set of feasible career trajectories, with differences in networks, organizational context, and constraints determining whether recognition is converted into entrepreneurship, internal leadership, geographic mobility, or deeper technological specialization. In this sense, patents operate as labor-market institutions as much as legal ones, reallocating innovative talent across careers, organizations, and places.

For policymakers, this perspective has direct implications. Patent examination decisions and institutional practices affect not only patent quality, but also the careers and opportunities of inventors themselves. Transparency, consistency, and training in the examination process, therefore, matter not only for allocative efficiency in IP, but for who gains access to entrepreneurship, leadership, and high-impact innovation.

Looking ahead, these findings open new directions for research at the intersection of education, organizational economics, and innovation. Future work could examine how early recognition shapes skill accumulation and authority over the life cycle, how organizational responses to recognition influence the emergence of entrepreneurial talent, and whether complementary institutions can broaden access to the networks and support needed to translate inventive achievement into widely shared economic opportunity.

References

Addario, Sabrina Di, Domenico Depalo. 2014. Shedding light on inventors' returns to patents .

Aghion, Philippe, Ufuk Akcigit, Antonin Bergeaud, Richard Blundell, David Hémous. 2019. Innovation and top income inequality. *Review of Economic Studies* **86**(1) 1–45.

Akcigit, Ufuk, John Grigsby, Tom Nicholas. 2017. Immigration and the rise of american ingenuity. *American Economic Review* **107**(5) 327—-331.

Aneja, Abhay, Oren Reshef, Gauri Subramani. 2024. Attrition and the gender patenting gap. *The Review of Economics and Statistics* .

Angrist, Joshua D., Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics*. Princeton University Press.

Athey, Susan, Emil Palikot. 2025. The value of non-traditional credentials in the labor market.

Azoulay, Pierre, Joshua S Graff Zivin, Danielle Li, Bhaven N Sampat. 2018. Public r&d investments and private-sector patenting: Evidence from nih funding rules. *The Review of Economic Studies* **86**(1) 117–152.

Babina, Tania. 2019. Destructive creation at work: How financial distress spurs entrepreneurship. *Review of Financial Studies* **33**(9) 4061–4101.

Babina, Tania, Asaf Bernstein, Filippo Mezzanotti. 2023. Financial disruptions and the organization of innovation: Evidence from the great depression. *Review of Financial Studies* **36**(11) 4271–4317.

Babina, Tania, Sabrina T. Howell. 2024. Entrepreneurial spillovers from corporate r&d. *Journal of Labor Economics* **42**(2) 469–509.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, John Van Reenen. 2019. Who becomes an inventor in america? the importance of exposure to innovation. *Quarterly Journal of Economics* **134**(2) 647–713.

Benson, Alan, Danielle Li, Kelly Shue. 2019. Promotions and the peter principle. *Quarterly Journal of Economics* **134**(4) 2085–2134.

Berger, David, Kyle Herkenhoff, Simon Mongey. 2022. Labor market power. *American Economic Review* **112**(4) 1147—-1193.

Bernstein, Shai, Emanuele Colonnelli, Davide Malacrino, Tim McQuade. 2022. Who creates new firms when local opportunities arise? *Journal of Financial Economics* **143**(1) 107–130.

Bernstein, Shai, Arthur Korteweg, Kevin Laws. 2017. Attracting early-stage investors: Evidence from a randomized field experiment. *Journal of Finance* **72**(2) 509–538.

Bound, John, David A. Jaeger, Regina M. Baker. 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogeneous explanatory variable is weak. *Journal of the American Statistical Association* **90**(430) 443–450.

Burks, Stephen V., Bo Cowgill, Mitchell Hoffman, Michael Housman. 2015. The value of hiring through employee referrals. *Quarterly Journal of Economics* **130**(2) 805–839.

Chatterji, Aaron, Edward Glaeser, William Kerr. 2014. Clusters of entrepreneurship and innovation. *Innovation Policy and the Economy* **14** 129–166.

Chen, Jun, Michael Ewens. 2025. Venture capital and startup agglomeration. *Journal of Finance* **80**(4) 2153–2198.

Chien, Colleen. 2024. Redefining progress and the case for diversity in innovation and inventing. *UCLA Law Review* .

Chien, Colleen V. 2022. The inequalities of innovation.

Chien, Colleen V., Jillian Grennan. 2024. Unpacking the innovator-inventor gap: Evidence from engineers. Working Paper.

Chien, Colleen V., Jillian Grennan. 2025. The inventor diary survey: What it means to become an inventor. Working Paper.

Chien, Colleen V., Jillian Grennan, Jason Sandvik. 2025. Small-scale mentoring, large-scale innovation: Evidence from a superstar firm. Working Paper.

Chien, Colleen V., Lisa Larrimore Ouellette. 2023. Improving equity in patent inventorship. *Science* **382**(6675) 1128–1129.

Cockburn, Iain M., Samuel Kortum, Scott Stern. 2003. Are all patent examiners equal? examiners, patent characteristics, and litigation outcomes. Wesley M. Cohen, Stephen A. Merrill, eds., *Patents in the Knowledge-Based Economy*. National Academies Press.

Cullen, Zoë, Ricardo Perez-Truglia. 2023. The old boys' club: Schmoozing and the gender gap. *American Economic Review* **113**(7) 1703—1740.

Deming, David, Lisa B. Kahn. 2018. Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics* **36**(S1) S337–S369.

Deming, David J. 2017. The growing importance of social skills in the labor market. *Quarterly Journal of Economics* **132**(4) 1593–1640.

Deming, David J., Noam Yuchtman, Amira Abulafi, Claudia Goldin, Lawrence F. Katz. 2016. The value of postsecondary credentials in the labor market: An experimental study. *American Economic Review* **106**(3) 778—-806.

Denes, Matthew, Sabrina Howell, Filippo Mezzanotti, XinXin Wang, Ting Xu. 2023. Investor tax credits and entrepreneurship: Evidence from u.s. states. *Journal of Finance* **78**(5) 2621–2671.

Eldar, Ofer, Jillian Grennan. 2023. Common venture capital investors and startup growth. *Review of Financial Studies* **37**(2) 549–590.

Ewens, Michael, Joan Farre-Mensa. 2020. The deregulation of the private equity markets and the decline in ipos. *Review of Financial Studies* **33**(12) 5463–5509.

Ewens, Michael, Ramana Nanda, Matthew Rhodes-Kropf. 2018. Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics* **128**(3) 422–442.

Fallick, Bruce, Charles A. Fleischman, James B. Rebitzer. 2006. Job-hopping in silicon valley: Some evidence concerning the microfoundations of a high-technology cluster. *The Review of Economics and Statistics* **88**(3) 472–481.

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

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

Gallus, Jana, Emma Heikensten. 2020. Awards and the gender gap in knowledge contributions in stem. *AEA Papers and Proceedings* **110** 241—244.

Glennon, Britta. 2024. Skilled immigrants, firms, and the global geography of innovation. *Journal of Economic Perspectives* **38**(1) 3—-26.

Goldsmith-Pinkham, Paul, Peter Hull, Michael Kolesar. 2025. Leniency designs: An operator's manual. NBER Working Paper 34473.

Gompers, Paul A., Anna Kovner, Josh Lerner, David Scharfstein. 2010. Venture capital investment cycles: The role of experience and networks. *Journal of Financial Economics* **96**(1) 18–32.

Gonzalez-Uribe, Juanita, Michael Leatherbee. 2017. The effects of business accelerators on venture performance: Evidence from start-up chile. *Review of Financial Studies* **31**(4) 1566–1603.

González-Uribe, Juanita, Santiago Reyes. 2021. Identifying and boosting "gazelles": Evidence from business accelerators. *Journal of Financial Economics* **139**(1) 260–287.

Gornall, Will, Oleg R. Gredil, Sabrina T. Howell, Xing Liu, Jason Sockin. 2025. Do employees cheer for private equity? the heterogeneous effects of buyouts on job quality. *Management Science* **0**(0) null.

Graham, John R., Jillian Grennan, Campbell R. Harvey, Shivaram Rajgopal. 2022. Corporate culture: Evidence from the field. *Journal of Financial Economics* **146**(2) 552–593.

Grennan, Jillian. 2023. A corporate culture channel: How increased shareholder governance reduces firm value. *Working paper* .

Gupta, Abhinav. 2025. Labor mobility, entrepreneurship, and firm monopsony: Evidence from immigration wait-lines. *UNC Working Paper* .

Gupta, Abhinav, Franklin Qian, Yifan Sun. 2025. Entrepreneur experience and success: Causal evidence from immigration wait lines. *UNC Working Paper* .

Guzman, Jorge, Scott Stern. 2015. Where is silicon valley? *Science* **347**(6222) 606–609. doi:10.1126/science.aaa0185.

Guzman, Jorge, Scott Stern. 2020. The state of american entrepreneurship: New estimates of entrepreneurial quality. *American Economic Review* **110**(4) 1134–1183.

Hall, Bronwyn H., Josh Lerner. 2010. Chapter 14 - the financing of r&d and innovation. Bronwyn H. Hall, Nathan Rosenberg, eds., *Handbook of The Economics of Innovation, Vol. 1*, *Handbook of the Economics of Innovation*, vol. 1. North-Holland, 609–639.

Hochberg, Yael V., Alexander Ljungqvist, Yang Lu. 2007. Whom you know matters: Venture capital networks and investment performance. *Journal of Financial Economics* **84**(3) 590–618.

Hochberg, Yael V., Alexander Ljungqvist, Yang Lu. 2010. Networking as a barrier to entry and the competitive supply of venture capital. *Journal of Finance* **65**(3) 829–859.

Hoffman, Mitchell, Lisa B Kahn, Danielle Li. 2017. Discretion in hiring. *Quarterly Journal of Economics* **133**(2) 765–800.

Hoffman, Mitchell, Steven Tadelis. 2021. People management skills, employee attrition, and manager rewards: An empirical analysis. *Journal of Political Economy* **129**(1) 000–000.

Howell, Sabrina T. 2017. Financing innovation: Evidence from r&d grants. *American Economic Review* **107**(4) 1136—1164.

Howell, Sabrina T., Ramana Nanda. 2024. Networking frictions in venture capital, and the gender gap in entrepreneurship. *Journal of Financial and Quantitative Analysis* **59**(6) 2733—-2761.

Jeffers, Jessica S. 2023. The impact of restricting labor mobility on corporate investment and entrepreneurship. *Review of Financial Studies* **37**(1) 1–44.

Kahn, Lisa B., Fabian Lange. 2014. Employer learning, productivity, and the earnings distribution: Evidence from performance measures. *The Review of Economic Studies* **81**(4) 1575–1613.

Kahn, Shulamit, Megan J. MacGarvie. 2016. How important is u.s. location for research in science? *Review of Economics and Statistics* **98**(2) 397–414.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, Matt Taddy. 2021. Measuring technological innovation over the long run. *American Economic Review: Insights* **3**(3) 303—-320.

Kerr, William R. 2010. Breakthrough inventions and migrating clusters of innovation. *Journal of Urban Economics* **67**(1) 46 – 60. doi:https://doi.org/10.1016/j.jue.2009.09.006. Special Issue: Cities and Entrepreneurship.

Kerr, William R., Ramana Nanda. 2009. Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship. *Journal of Financial Economics* **94**(1) 124–149.

Kline, Patrick, Neviana Petkova, Heidi Williams, Owen Zidar. 2019. Who profits from patents? rent sharing at innovative firms. *Quarterly Journal of Economics* **134**(3) 1343–1404.

Koffi, Marlene, Matthew Marx. 2025. Cassatts in the attic. *American Economic Journal: Applied Economics* .

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, Noah Stoffman. 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* **132**(2) 665–712.

Kolesár, Michal. 2013. Estimation in an instrumental variables model with treatment effect heterogeneity. Working paper, Princeton University.

Koning, Rembrand, Sampsa Samila, John-Paul Ferguson. 2020. Inventor gender and the direction of invention. *AEA Papers and Proceedings* **110** 250–254.

Koning, Rembrand, Sampsa Samila, John-Paul Ferguson. 2021. Who do we invent for? patents by women focus more on women's health, but few women get to invent. *Science* **372**(6548) 1345–1348.

Kuhn, Jeffrey, Neil Thompson. 2019. How to measure and draw causal inferences with patent scope. *International Journal of the Economics of Business* **26** 5–38.

Lazear, Edward P., Kathryn L. Shaw, Christopher T. Stanton. 2015. The value of bosses. *Journal of Labor Economics* **33**(4) 823–861. doi:10.1086/681097.

Lemley, Mark, Bhaven Sampat. 2012. Examiner characteristics and patent office outcomes. *Review of Economics and Statistics* **94**(3) 817–827.

Lerner, Josh. 2012. *Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed—and What to Do About It*. Princeton University Press, Princeton, NJ.

Liu, Tim, Christos A Makridis, Paige Ouimet, Elena Simintzi. 2023. The distribution of nonwage benefits: maternity benefits and gender diversity. *Review of Financial Studies* **36**(1) 194–234.

Martellini, Paolo, Todd Schoellman, Jason Sockin. 2024. The global distribution of college graduate quality. *Journal of Political Economy* **132**(2) 434–483.

Matray, Adrien. 2021. The local innovation spillovers of listed firms. *Journal of Financial Economics* **141**(2) 395–412.

Melero, Eduardo, Neus Palomeras, David Wehrheim. 2020. The effect of patent protection on inventor mobility. *Management Science* **66**(12) 5485–5504.

O'Reilly, Charles A., Jennifer Chatman, David F. Caldwell. 1991. People and organizational culture: A profile comparison approach to assessing person-organization fit. *The Academy of Management Journal* **34**(3) 487–516.

Pairolero, Nicholas A., Andrew A. Toole, Peter-Anthony Pappas, Charles A. deGrazia, Mike H. Teodorescu. 2022. Closing the gender gap in patenting: Evidence from a randomized control trial at the uspto. *USPTO White Paper* .

Puri, Manju, David T. Robinson. 2013. The economic psychology of entrepreneurship and family business. *Journal of Economics & Management Strategy* **22**(2) 423–444.

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

Sampat, Bhaven, Heidi L. Williams. 2019. How do patents affect follow-on innovation? evidence from the human genome. *American Economic Review* **109**(1) 203–236.

Singh, Jasjit, Ajay Agrawal. 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science* **57**(1) 129–150.

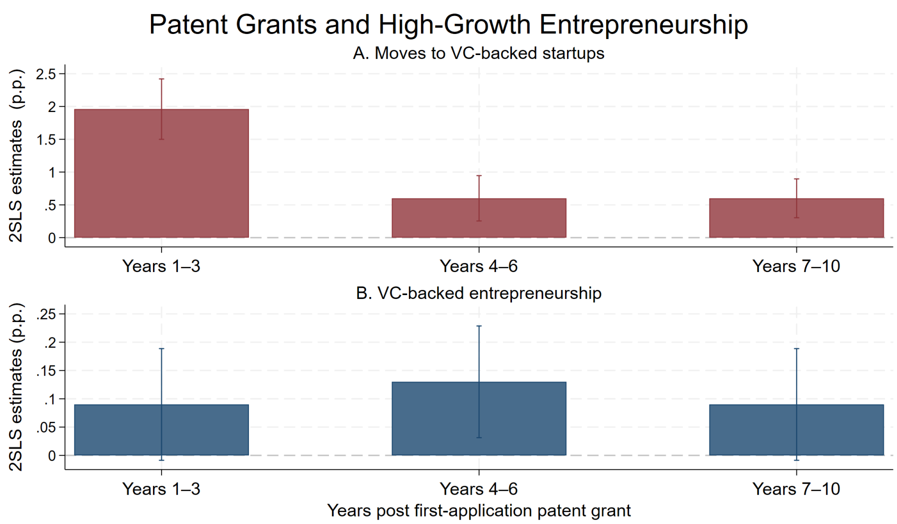
Starr, Evan P., J.J. Prescott, Norman D. Bishara. 2021. Noncompete agreements in the us labor force. *Journal of Law and Economics* **64**(1) 53–84.

Tambe, Prasanna, Xuan Ye, Peter Cappelli. 2020. Paying to program? engineering brand and high-tech wages. *Management Science* **66**(7) 3010–3028.

Toivanen, Otto, Lotta Väänänen. 2012. Returns to inventors. *Review of Economics and Statistics* **94**(4) 1173–1190.

Toole, Andrew, Michelle Saksena, Charles deGrazia, Katherine Black, Francesco Lissoni, Ernest Miguelez, Gianluca Tarasconi. 2020. Progress and potential: 2020 update on u.s. women invetor-patentees. *U.S. Patent and Trademark Office, Office of the Chief Economist* .

Figure 1: **Timing of Patent Grant Effects on VC-Backed Startup Employment and Entrepreneurship**



Notes. This figure plots 2SLS estimates of the effect of receiving a first patent grant on subsequent transitions into VC-backed startup employment (Panel A) and VC-backed entrepreneurship (Panel B) over mutually exclusive post-decision windows. Bars show point estimates; vertical lines denote 95 percent confidence intervals. Estimates are obtained using examiner leniency as an instrument for patent grant status and include art-unit-by-application-year fixed effects and baseline controls. Outcomes indicate the first transition occurring within each window. Standard errors are clustered at the art-unit level.

Table 1: Survey Evidence on Perceived Effects of Patent Recognition

Theme	Representative responses	Pct.
Panel A: External Recognition		
Esteem of one's peers	"It becomes a badge or credential that is respected industry-wide. It also has been a component of discussions around promotions." "A patent is like a college degree. It is universally recognized, and something that never goes away or gets stale. It brings credibility to oneself." "Helped create industry visibility and build reputation capital." "The recognition of being awarded a patent has provided external validation that the ideas I have are innovative, consequential, and valuable."	38%
Notoriety within the firm	"Inventing helped me collaborate with other domain influencers on the projects... the team is always stronger than the individual." "My innovator journey has connected me with a wide network of like-minded individuals." "Doors were opened, and I worked with engineers I never would have met otherwise. It helped me to expand my professional circle."	33%
Esteem of friends and family	"I was able to show my family a glimpse of my work and achievements." "While I don't mention it to friends outside of work, they somehow find out and bring it up in conversation. It makes me feel good."	7%
Community impact	"This helped me put down more permanent roots in my community... I have applied my engineering mind to help solve problems in my condo community and church, and have seen some benefit there."	5%
Panel B: Behavioral Traits		
Increased confidence and self-esteem	"I started trusting myself that I can solve problems and think of solutions that others may not have thought of." "The impact of becoming an inventor is it fills one with confidence on one's own innovative and creative thinking ability." "It helped me gain confidence in sharing my thoughts in huge forums."	68%
Innovator mindset and creative identity	"For me, it helped greatly learn to elevate my thought process beyond implementation limitations and also keep me engaged in the technology area I like." "It is always good to stretch one's abilities to be at the forefront of new ideas." "This improved my problem-solving skills, and I started appreciating all the ideas."	47%

Notes: This table reports qualitative responses from an open-ended question on a survey of inventors about the perceived life impact after becoming a named inventor on a patent. Percentages indicate the share of respondents mentioning each theme. Responses are lightly edited for clarity. This question was included in a broader survey of engineers on the innovation process (Chien and Grennan, 2024).

Table 2: Innovator Summary Statistics

Panel A. Gender	Obs. (1)	Pct. (2)
Female	279,518	15.54
Male	1,475,286	82.01
Missing	44,105	2.45
Panel B. Gender Race/Ethnicity		
White	1,118,824	62.20
Asian/API	583,051	32.41
Black	44,991	2.50
Hispanic	47,547	2.64
Multiple	3,493	0.19
Native American	730	0.04
Panel C. Education		
High School	10,765	0.60
Associate	19,947	1.11
Bachelor's	296,816	16.50
Master's	287,696	15.99
PhD/Doctorate	260,766	14.50
MBA	85,038	4.73
Missing	843,504	46.88
Panel D. Professional Characteristics	Mean	Median
Prestige score	0.353	NA
(range: -0.855 to 2.343, higher = more prestigious)		
LinkedIn connections	249	191
Job tenure	NA	NA
Positions held	NA	NA
Total Observations	**1,798,909**	

Notes: This table presents demographic and professional characteristics for the sample of first-time patent applicants matched to resume data. Gender and ethnicity are predicted algorithmically using names and other profile information. Education is the highest degree listed on LinkedIn profiles. Prestige score is based on undergraduate institution attended. LinkedIn connections are as reported on user profiles at the time of data collection (June 2024). Job tenure and positions held are based on LinkedIn profiles. For additional sample construction and variable details, see Appendix A.

Table 3: Patent Application Characteristics

	Full Sample		By Outcome	
	Obs.	Pct.	Granted	Rejected
Panel A. Application Type	(1)	(2)	(3)	(4)
Utility	1,752,359	97.72	97.00%	99.94%
Design	39,561	2.21	2.91%	0.04%
Plant	898	0.05	0.06%	0.02%
Re-Issue	449	0.03	0.03%	0.01%
Panel B. Entity Status				
Micro	21,161	1.18%	0.77%	2.46%
Small	406,277	22.66%	18.36%	35.91%
Large (undiscounted)	1,365,846	76.16%	80.87%	61.63%
Panel C. Top 5 Technology Classes (USPC)				
705 (Data processing)	62,941	3.51%		
424 (Drug/bio-affecting)	54,481	3.04%		
514 (Drug/bio-affecting)	53,821	3.00%		
435 (Chemistry)	52,311	2.92%		
709 (Electrical computers)	45,010	2.51%		
Panel D. Filing Characteristics				
Filing year (mean)	2008		2008	2009
AIA filing	503,395	28.07%		

Notes: This table presents patent application characteristics. Panel A shows application types. Panel B shows entity status (micro/small entities receive fee discounts). Panel C shows the top 5 technology classes by USPC classification. Panel D shows filing characteristics. For additional sample construction and variable details, see Appendix A.

Table 4: Effect of Patent Grant on Entrepreneurship and Startup Employment

	Dep. Var. =		
	Entrepreneur at VC-backed startup	Moved to at VC-backed startup	Moved to non-VC startup
Pane A: Overall movement	(1)	(2)	(3)
Patent Grant	0.010***	0.047***	0.016***
	(0.002)	(0.006)	(0.004)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.028	0.198	0.066
Observations	1,566,604	1,363,394	1,363,394
First-stage F-stat	7,701	6,655	6,655

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit $\times$ year fixed effects and control for demographics, education, and network size. Standard errors clustered by art unit in parentheses. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 5: Who Moves to Entrepreneurial Firms?

Panel A: Entrepreneur at VC-backed startup	Female (1)	Male (2)	White+ Asian (3)	URM (4)	Adv. Deg. (5)	Bach. or Less (6)	IT/ Software (7)	Biotech/ Pharma (8)
Patent Grant	0.006	0.010***	0.009***	0.013	0.009**	0.018***	0.028***	−0.000
	(0.004)	(0.002)	(0.002)	(0.010)	(0.004)	(0.005)	(0.005)	(0.003)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.020	0.029	0.027	0.035	0.042	0.037	0.044	0.018
Observations	239,853	1,287,808	1,480,469	83,433	577,279	292,249	416,286	381,119
First-stage F-stat	3,972	7,221	7,730	1,367	4,798	3,273	2,075	3,223
Panel B: Moves to VC-backed startup	**Female (1)**	**Male (2)**	**White+ Asian (3)**	**URM (4)**	**Adv. Deg. (5)**	**Bach. or Less (6)**	**IT/ Software (7)**	**Biotech/ Pharma (8)**
Patent Grant	0.058***	0.045***	0.048***	0.045*	0.059***	0.052***	0.094***	0.027***
	(0.011)	(0.007)	(0.006)	(0.023)	(0.010)	(0.012)	(0.012)	(0.009)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.183	0.202	0.195	0.221	0.252	0.157	0.303	0.156
Observations	208,366	1,125,273	1,286,189	74,402	571,213	288,213	378,624	318,663
First-stage F-stat	3,683	6,158	6,768	1,164	4,747	3,151	1,732	3,003

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit $\times$ year fixed effects and control for demographics, education, and network size. Gender and race/ethnicity are predicted using Revelio Labs' proprietary algorithm, which is based on LinkedIn profile information. Education is determined from credentials listed in the inventor's LinkedIn profile; advanced degree includes master's, PhD, MBA, or professional degrees. URM = Black, Hispanic, Native American, or Multiple races. VC-backed status uses universe classification from PitchBook. Software/IT patents are defined as USPC classes 700–726; Biotech/Pharma patents are defined as USPC classes 424, 435, 514, 530, and 800. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 6: Mechanism Underlying Move to Entrepreneurial Firms

	Dep var. = Entrepreneur at VC-backed startup					
	Network Density		Team size		Initial firm size	
	Solo	Team	Small	Large	Small	Large
Panel A: Enhanced opportunities	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	0.017***	0.011***	0.011***	0.013**	0.008**	0.010***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.028	0.027	0.025	0.030	0.194	0.012
Observations	590,030	1,022,172	727,376	294,238	130,233	1,480,930
First-stage F-stat	3,177	7,915	7,245	2,948	1,531	7,970

	Dep var. = Entrepreneur at VC-backed startup			
	IT / Software		BioTech / Pharma	
	Adv.	No.Adv.	Adv.	No.Adv.
Panel B: Credentialing	(1)	(2)	(3)	(4)
Patent Grant	0.023**	0.043***	0.016	0.001
	(0.009)	(0.006)	(0.013)	(0.004)
Art-unit-by-time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Dep. Var. Mean	0.039	0.035	0.033	0.009
Observations	125,687	196,021	74,283	86,292
First-stage F-stat	1,028	1,524	567	789

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × year fixed effects and control for demographics, education, and network size. Gender and race/ethnicity are predicted using Revelio Labs' proprietary algorithm, which is based on LinkedIn profile information. Education is determined from credentials listed in the inventor's LinkedIn profile; advanced degree includes master's, PhD, MBA, or professional degrees. URM = Black, Hispanic, Native American, or Multiple races. VC-backed status uses universe classification from PitchBook. Software/IT patents are defined as USPC classes 700–726; Biotech/Pharma patents are defined as USPC classes 424, 435, 514, 530, and 800. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 7: Career Advancement

	Dep. Var. =			
	Stayed with the same firm	Promoted by the same firm	Promoted by another firm	Moved to a more prestigious firm
Pane A: Overall	(1)	(2)	(3)	(4)
Patent Grant	0.037***	0.042***	0.046***	0.040***
	(0.005)	(0.006)	(0.006)	(0.006)
Art-unit-by-time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Dep. Var. Mean	0.177	0.496	0.618	0.283
Observations	1,361,695	1,361,695	1,361,695	1,361,695
First-stage F-stat	6,577	6,577	6,577	6,577

	Dep. Var. = Promoted by the same firm			
	By gender		By ethnicity	
	Female	Male	White + Asian	URM
Panel B: Heterogeneity	(1)	(2)	(3)	(4)
Patent Grant	0.054***	0.038***	0.042***	0.062***
	(0.014)	(0.006)	(0.006)	(0.028)
Art-unit-by-time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Dep. Var. Mean	0.490	0.496	0.491	0.519
Observations	208,169	1,123,813	1,284,591	74,302
First-stage F-stat	3,495	6,132	6,653	1,094

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × year fixed effects and control for demographics, education, and network size. Gender and race/ethnicity are predicted using Revelio Labs' proprietary algorithm, which is based on LinkedIn profile information. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 8: Geographic Mobility and Innovation Hubs

Panel A: Overall movement	Changed location (1)	Dep. Var. = Moved to innov. hub (2)	Left innov. hub (3)
Patent Grant	0.044***	0.004	0.012***
	(0.005)	(0.003)	(0.002)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.196	0.075	0.035
Observations	1,361,695	1,361,695	1,361,695
First-stage F-stat	6,577	6,577	6,577

	Dep. Var. = Left innovation hub					
	By gender		By ethnicity		By industry	
Panel B: Heterogeneity	Female (1)	Male (2)	White+ Asian (3)	URM (4)	IT/ Software (5)	Biotech/ Pharma (6)
Patent Grant	0.044***	0.004	0.011***	0.029***	0.023***	0.011
	(0.005)	(0.003)	(0.002)	(0.013)	(0.005)	(0.008)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.034	0.035	0.033	0.048	0.045	0.039
Observations	208,169	1,123,813	1,284,591	74,302	289,701	131,067
First-stage F-stat	3,495	6,132	6,653	1,094	1,418	738

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × year fixed effects and control for demographics, education, and network size. Gender and race/ethnicity are predicted using Revelio Labs' proprietary algorithm based on LinkedIn profile information. URM = Black, Hispanic, Native American, or Multiple races. Software/IT patents are defined as USPC classes 700–726; Biotech/Pharma patents are defined as USPC classes 424, 435, 514, 530, and 800. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 9: Leadership and Networking

Panel A: Overall	Leadership skills (1)	Dep. Var. = Concurrent positions (2)	LinkedIn connections (3)	Superstar collaboration (4)
Patent Grant	0.030***	0.011***	15.315***	0.110***
	(0.006)	(0.006)	(9.116)	(0.008)
Art-unit-by-time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Dep. Var. Mean	0.327	0.326	275.670	0.266
Observations	1,361,195	1,361,195	1,361,195	771,133
First-stage F-stat	6,577	6,577	6,577	6,717

	Dep. Var. = LinkedIn Connections					
	By gender		By ethnicity		By industry	
Panel B: Heterogeneity	Female (1)	Male (2)	White+ Asian (3)	URM (4)	IT/ Software (5)	Biotech/ Pharma (6)
Patent Grant	63.6***	2.6	15.8*	41.4	58.9***	2.7
	(22.2)	(10.7)	(9.4)	(31.2)	(16.9)	(25.1)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	276.2	277.7	274.0	303.8	327.3	274.1
Observations	208,169	1,123,813	1,284,591	74,302	289,701	131,067
First-stage F-stat	3,495	6,132	6,653	1,094	1,418	738

	Dep. Var. = Superstar collaboration					
	By gender		By ethnicity		By industry	
Panel C: Heterogeneity	Female (1)	Male (2)	White+ Asian (3)	URM (4)	IT/ Software (5)	Biotech/ Pharma (6)
Patent Grant	0.115***	0.109***	0.108***	0.080**	0.118***	0.130**
	(0.016)	(0.009)	(0.009)	(0.035)	(0.018)	(0.023)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.260	0.270	0.264	0.282	0.266	0.263
Observations	113,586	635,751	702,744	37,719	143,897	80,209
First-stage F-stat	2,442	6,212	6,150	627	1,175	660

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × year fixed effects and control for demographics, education, and network size. Superstar collaboration is defined as working with an inventor ranked in the top decile for either granted patents or forward citations within a particular USPC. Gender and race/ethnicity are predicted using Revelio Labs' proprietary algorithm based on LinkedIn profile information. URM = Black, Hispanic, Native American, or Multiple races. Software/IT patents are defined as USPC classes 700–726; Biotech/Pharma patents are defined as USPC classes 424, 435, 514, 530, and 800. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 10: Patenting and Subsequent Specialization

	Dep. Var. =		
Panel A: Subsequent patenting	Has subsequent patent app. (1)	Total subsequent patent app. (2)	Patent Number approved (3)
Patent Grant	0.018***	0.023	0.172***
	(0.007)	(0.025)	(0.020)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.473	1.325	0.916
Observations	1,644,539	1,644,539	1,644,539
First-stage F-stat	6,836	6,836	6,836
Panel B: Inventor network growth	Network growth (1)	Pct. new co-inventors (2)	USPC expansion (3)
Patent Grant	-0.023***	-4.539***	-0.050***
	(0.008)	(0.793)	(0.010)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.412	71.321	0.597
Observations	780,687	646,363	780,687
First-stage F-stat	6,836	6,836	6,836
Panel C: Patent quality	Forward citations (1)	Patent value (2)	Breakthrough patent (3)
Patent Grant	3.948***	0.041*	0.014***
	(0.640)	(0.022)	(0.002)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	7.848	0.603	0.037
Observations	1,644,539	163,339	1,644,539
First-stage F-stat	6,836	1,958	6,836

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × year fixed effects and control for demographics, education, and network size. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table 11: Patenting and Workplace Satisfaction and Wages

	Dep. Var. =				
	Overall rating	Culture rating	Career rating	Innov. culture	Wage growth
Panel A: Workplace Glassdoor perceptions	(1)	(2)	(3)	(4)	(5)
Patent Grant	-0.031***	-0.044***	-0.049***	-0.009***	-0.30**
	(0.009)	(0.011)	(0.010)	(0.001)	(0.130)
Art-unit-by-time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Sample restrictions	✓	✓	✓	✓	
Dep. Var. Mean	1.079	1.064	1.075	1.046	1.384
Observations	106,925	88,881	106,932	107,027	752,909
First-stage F-stat	967	797	965	968	6,717

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, and connections. For the Glassdoor regressions in Columns (1) through (4), the sample is restricted to firms with more than 10 reviews in a year by current employees with a job title associated with being an engineer or scientist. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

A Variable Definitions

A.1 Variable Definitions

Entrepreneurship outcomes: By matching Revelio employment histories to PitchBook company data, we obtain detailed measures of startup and venture-backed employment:

- **Entrepreneur at VC-Backed:** Indicator equal to one if the inventor holds an entrepreneurial title at a VC-backed company, capturing founders of venture-funded startups specifically. Keywords for entrepreneurial title include "founder," "co-founder," "entrepreneur," "founding team," "founding member," "founding engineer," "owner," and "co-owner." Executive titles (CEO, CTO, President) are included only when the position is at a verified startup firm.
- **Moved to Startup:** Indicator equal to one if the inventor works at a startup firm, identified through: (1) keyword matching in PitchBook company descriptions ("startup," "stealth," "pre-launch," "spinout," "spinoff"); (2) participation in major accelerator programs (Y Combinator, Techstars, 500 Startups, MassChallenge, Sequoia Arc, Plug and Play, among others); or (3) company age of five years or less at the time of the position.
- **Moved to VC-Backed Startup:** Indicator equal to one if the inventor holds any position at a venture capital-backed company. VC-backed status is identified from PitchBook's "universe" classification, which directly flags companies that have received venture capital financing.

Enhanced opportunities: One mechanism we examine is whether patent recognition expands entrepreneurial opportunities by increasing inventors' access to sufficiently large and dense professional networks. If entrepreneurial ideas, cofounders, and early employees are drawn from existing social and professional connections, then the ability to found a firm may depend not only on individual skill or recognition, but also on whether an inventor is embedded in a network with enough collaborators to mobilize a venture. We proxy for this channel using characteristics of the inventor's initial collaborative and organizational environment, capturing variation in the scale of potential connections available to leverage following patent recognition.

- **Network density:** Solo is an individual who applied for a patent as a solo inventor (either as an individual inventor or through her employer), and team is the individuals who first applied for a patent in teams.
- **Team size:** A small team size is two inventors, a large team size is three or more inventors.
- **Initial firm size:** We define firm size based on the number of employees rather than total assets, as we want to understand the potential for social connections. Less than 1000 employees is small. More than 1000 is large.

Career advancement and mobility outcomes: These are Revelio-specific measures, including geographic location.

- **Stayed with the same firm:** Indicator equal to one if the inventor remains with the same firm following the patent decision, capturing internal retention effects.
- **Promoted by the same firm:** Indicator equal to one if the inventor's recorded job rank or seniority level increases relative to their position at the time of patent filing.
- **Promoted by another firm:** This variable serves as the inclusive measure of upward career mobility. It is a broad indicator capturing promotion by another firm through any channel, including:
  - Rank or seniority upgrade,
  - Wage growth exceeding 10% relative to prior position,
  - Title-based upgrade (e.g., "Engineer" → "Senior Engineer"),
- **Moved to prestigious firm:** Indicator equal to one if the inventor transitions to an employer ranked in the top decile of Revelio's firm prestige index.
- **Changed location:** Indicator for geographic mobility, equal to one if the inventor's subsequent position is located in a different city or region.
- **Moved to Innovation Hub:** Indicator equal to one if the inventor's new employer is headquartered in a major innovation region (e.g., Bay Area, Boston, Seattle, Austin).
- **Moved from Innovation Hub:** Indicator equal to one if the inventor leaves an innovation region for employment elsewhere.

Human capital development outcomes: These are based on LinkedIn skills sections as well as details filled in on the "About Me," or "Job Description" sections.

- **Gained leadership skills:** Indicator equal to one if new leadership-related keywords (e.g., "management," "strategy," "team leadership") appear in the inventor's LinkedIn skill set after the patent decision.
- **Concurrent positions:** Indicator equal to one if the inventor holds overlapping employment spells during the same period, suggesting secondary work as a board member or consulting activity.
- **Networking:** Continuous measure of professional network size from LinkedIn, log-transformed to reduce skewness.
- **Superstar collaborator**: We define superstar inventors based on their cumulative track record within each technology class and year (USPC). Specifically, for each UPSC class $\times$ year cell, we calculate each inventor's cumulative patent count and cumulative forward citations as of the prior year. An inventor is classified as a superstar if the rank is in the top decile (p90) in either category. For robustness, we also examine

the top quartile (p75) and the counts of superstar inventors with whom they worked. This within-field, time-varying definition ensures that superstars are identified relative to their peers in the same technology domain and at the same point in time. This analysis is limited to inventors who filed at least one subsequent patent after their first application, thereby restricting the sample to 771,133 inventors (approximately half of the full sample).

Patenting and technological specialization outcomes:

- **Claims:** The count of the number of dependent and independent claims. The data source is Patent Views.

- **Scope**: Kuhn and Thompson (2019) provide evidence consistent with the number of words in the first claim serving as a good proxy for patent scope (i.e., the extent of the legal coverage that a patent provides). Broad patents typically offer more protection against infringers than a narrow patent, because they can be more difficult to design around. Thus, a patent's scope can be measured by counting the number of words in its first claim, with more words corresponding to less scope.

- **Forward citations**: Citations made to U.S. granted patents by U.S. patents over the lifetime of the patent.

- **Originality**: is a summary statistic on the backward citations of patents, capturing their dispersion across different technology classes. We measure the originality of patent i using the distribution of technology classes of the *cited* prior art on which the patent builds. Let s_{ij} denote the share of backward citations made by patent i that reference prior patents in technology class j, where $\sum_j s_{ij} = 1$. Our originality index is defined as
$$\text{Originality}_i \;=\; 1 - \sum_j s_{ij}^2,$$
so that patents whose prior art draws heavily from a narrow set of classes have low originality, while those that combine knowledge from many distinct classes have high originality.

- **Generality**: is a summary statistic on the forward citations of patents, capturing their dispersion across different technology classes. For each focal patent i, we measure the generality of its impact across technology fields at the USPC subcategory level using the distribution of technology classes of its *citing* patents. Let s_{ij} denote the share of forward citations to patent i that come from citing patents in technology class j, where $\sum_j s_{ij} = 1$. Our generality index is defined as
$$\text{Generality}_i \;=\; 1 - \sum_j s_{ij}^2,$$
so that patents whose follow-on citations are concentrated in a narrow set of classes have low generality, while those whose follow-on citations are spread across many classes have high generality.

- **Radical patent**: Following Kerr (2010), we define a radical patent as being in the 95th percentile or higher for lifetime forward citations in a given application year and USPC category.

- **Breakthrough patent**: Kelly et al. (2021) analyze the text of patents and define breakthrough patents as those in the 90th percentile or above of the unconditional distribution of the ratio of 10-year forward textual similarity to 5-year backward textual similarity. This ratio captures textual dissimilarity with the existing patent stock at the time it was filed. Specifically, we use their variable with the pneumonic $break\_p90\_rrfsim05$.

- **Patent value**: This is the nominal patent value measure described in Kogan et al. (2017) that is available for public firms. We use the real version (pneumonic xi_real. We note that restricting the sample to first-time applicants with subsequent patents granted while at public firms reduces the combined control and treatment group to 163,339 observations (approximately 10% of the sample). Data source: `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`

Workplace perception outcomes:

- **Star ratings:** Glassdoor provides 1-5 star ratings for overall satisfaction, culture, and career opportunities. We standardize these variables for comparison.

- **Innovative culture:** Glassdoor also provides open-ended text boxes where employees can write the pros, cons, and advice to management about the firm. We use a BERT-based algorithm at the sentence level to predict whether a sentence demonstrates cultural norms consistent with valuing innovation (+1), the opposite of valuing innovation (-1), or neutrality (i.e., no mention). We then aggregate to the review level and then again to the firm-year level. For additional details, please see Appendix B.

- Wage growth: Continuous measure of the percent change in wage between consecutive positions, winsorized at the 1st and 99th percentiles ot limit the effect of outliers.

Treat, instrument, and control variables: These are the main variables used throughout the analyses.

- **Treatment = Patent granted:** Binary indicator equal to one if the inventor's first patent application was approved by the USPTO. Serves as the endogenous treatment variable in all IV regressions.

- **Instrument = Examiner leniency:** Continuous instrument equal to the examiner's historical grant rate prior to the focal inventor's first application, computed within the same art unit. Provides exogenous variation in the likelihood of receiving a patent.

- **Gender:** Indicator equal to one if the inventor is identified as female, inferred from first-name–gender probabilities.

- **Ethnicity:** Mutually exclusive indicators for Asian, Black, Hispanic, Native American, and Multiple-race categories, derived from name-based and geographic inference.
- **Education:** Indicators for highest completed degree—*High School, Bachelor's, Master's, MBA, PhD*—based on education records from professional profiles.
- **Prestige score:** Continuous measure of institutional prestige, based on the ranking of the inventor's undergraduate or most recent institution, standardized to mean zero and unit variance.

B Culture Variable Construction

This appendix provides definitions of cultural values and norms and discusses the procedure for generating the text-based measures of corporate culture. The seven cultural values represent the principal components of culture derived by O'Reilly et al. (1991), and they are supplemented to include community-oriented, which was added to reflect changes in cultural values in the last thirty years. The seven cultural values are adaptability, collaboration, community-oriented, customer-oriented, detail-oriented, integrity, and results-oriented. The same cultural values used in Graham et al. (2022) were benchmarked to executives' descriptions of their culture and website-based values. The terms pillars and cultural values are used interchangeably. Each cultural value or pillar has norms or sub-pillars described below. These norms are elements of the culture that are subcomponents of the main cultural values. Note this is a shortened word list meant to help familiarize the reader. Our approach did not use a word list or dictionary-based method. Instead, we used a Bidirectional Encoder Representations from Transformers (BERT)-based model.

The dataset consists of Glassdoor reviews for a given organization. The reviews have been parsed into multiple, non-overlapping sentences. Each sentence is associated with one of the four open text areas where they could have been entered. The four open text areas include title, pros, cons, and advice. We use a semi-supervised machine learning (ML) approach, which means for a subsample of the sentences, they have been annotated by three reviewers with their actual cultural values and norms. Specifically, each sentence in this training data is annotated for three classes +1, 0, and -1, for 7 different pillars and 34 different sub-pillars.

Glassdoor review sentences tend to be highly imbalanced, with most of the data belonging to the 0 class and more data belonging to the +1 class than to the -1 class. Therefore, we artificially increased the number of samples in the minority classes through oversampling to balance the dataset. The value for each pillar is directly related to the subpillars, as such we only run our classifier models on the subpillars and aggregate to the pillar level using the predicted subpillars. The model used for sentence classification is a hierarchical BERT-based model that includes sentence type information with oversampling and a trained separate multiclassifier (-1, 0, +1) for each subpillar. A weighted cross-entropy loss function was applied, further addressing class imbalance by giving higher weights to minority classes.

We experimented with other variations, and selected the model that performed the best across the 34 subpillars. Our experiments with sentence type showed that incorporating this information improved the model performance. We also experimented with different transformer-based language models, including RoBERTa and Sentence Transformers, which are optimized for generating sentence embeddings. The other transformer models did not yield meaningful performance improvements in precision, recall, or F-1 scores, so we stuck with the BERT model. Finally, we also considered a k-shot classifier based on exemplary sentences and two-stage predictions where presence (+1/-1) vs. absence (0) and positive (+1) vs. negative (-1) sentiment were classified. While an individual subpillar may outperform using these alternatives, we found that the average F-1 score across all 34 subpillars was better with the multiclassifier model.

To aggregate from the predicted subpillars to the pillars, we sum the total predicted scores across all subpillars. We then aggregate the sentence-level scores to review-level scores by weighting sentences according to their word count. This makes the implicit assumption that more detailed explanations are more valuable. For our analysis, we focus on adaptability as it contains the subpillar of innovation. Below we describe the adaptability subpillar. Then, we show the matching process and the resulting sample restrictions.

Cultural Value 1 (i.e., Pillar 1) Adaptability

- Subpillar 1 Adaptability
  - Words: adaptable, turnaround, change, dynamic, upcoming, flexible, spin-off
  - Phrases: changing environment, constantly trying to improve, weathered downturn, plan for shifting, willing to change, constant evaluation of advancement, follow latest trends
- Subpillar 2 Fast Moving
  - Words: fast, rapid, quick, new
  - Phrases: fast-paced, constantly changing, always something new, growth mindset
- Subpillar 3 Takes initiative
  - Words: initiative, entrepreneurial, proactive, independent, self-motivated, self-starter,

  - Phrases: new projects, forward-thinking, seizes opportunities, takes the lead, makes hard decisions, takes charge, takes a stance, drives action, goes the extra mile

- Subpillar 4 Autonomy vs. Bureaucracy
  - Words: autonomy, independence, empowerment, access
  - Phrases: individual contributions, no micromanagement, opportunity to contribute, value ideas, removing bureaucracies, ability to interact with leaders,

- Subpillar 5 Innovative
  - Words: technology, innovative, inventive, creative
  - Phrases: new solutions, technology leader, deep technology, exposed to lots of technology

Table B.1: Sample Construction and Glassdoor Coverage

	Glassdoor Samples	
	All Employees	Current engineers & scientists
Panel A: Data Linking	(1)	(2)
Starting: First-time patent applicants	1,458,214	1,458,214
With examiner data	1,391,366	1,391,366
Panel B: Glassdoor Coverage		
Person-year observations (2008–2024)	24,289,865	24,289,865
Unique users w/ Glassdoor data	231,181	195,971
Coverage rate	(16.6%)	(14.1%)
Panel C: Analysis Samples		
Unrestricted (with outcome t=1)	188,786	157,422
Main: Reviews $\geq$ 10	**162,905**	**107,879**
Robustness: Reviews $\geq$ 25	145,260	81,180

Notes. This table describes the construction of the Glassdoor-linked samples used to analyze workplace perceptions following patent recognition. Panel A reports the number of first-time patent applicants that can be linked to examiner assignment data. Panel B documents Glassdoor coverage over 2008–2024, defined as the presence of at least one employee review at the inventor's employing firm in a given year. Panel C reports the final analysis samples used in the main and robustness specifications, imposing minimum review-count thresholds to ensure reliable firm–year measures. Workplace perception measures are constructed using both star ratings and BERT-based text embeddings applied to Glassdoor reviews. The sample of engineers and scientists is based on self-reported job titles. Current removes former employees' reviews.

C Sample Construction and First-stage Results

C.1 Matching Process

This appendix describes the construction of our final analysis sample of 1,798,909 first-time patent applicants, detailing the multi-stage matching process used to link USPTO patent application data to Revelio Labs employment profiles.

We began with 17,932,860 first-time patent applicants in the USPTO database spanning 1976-2023. Through a multi-stage matching process, we successfully linked 1,798,909 inventors (10.0% match rate) to Revelio Labs career data. Our 10% match rate reflects four factors:

(1) **LinkedIn coverage limitations**: LinkedIn was founded in 2003, meaning pre-2000 cohorts are systematically under-represented;

(2) **Demographic selection**: patent inventors with LinkedIn profiles are disproportionately corporate employees in technology sectors rather than independent inventors or non-technology fields;

(3) **Data quality requirements**: we require sufficient information (name, location, employer, temporal alignment) for confident matching; and

(4) **Conservative matching thresholds**: we prioritize match precision over coverage to minimize false positives (80% company similarity, Levenshtein distance $\leq$2).

Our matching process leveraged five complementary strategies to maximize coverage while maintaining quality, which include:

(1) **Stage 1 (Exact Matching)**: matched 285,444 inventors (15.9% of final sample) on standardized first name, last name, company (patent assignee to employer), location (state-level), and application number.

(2) **Stage 2 (Fuzzy Matching)**: matched 7,681 inventors (0.4%) by relaxing name requirements to allow Levenshtein distance $\leq$2 for first names while requiring exact last names and token-based company similarity ($\geq$80% overlap).

(3) **Stage 3 (PatentsView-Assisted)**: matched 733,969 inventors (40.8%) by leveraging PatentsView's disambiguation algorithm, which links inventors across patents using name, location, employer, and co-inventor networks.

(4) **Stage 4 (User-Level Fuzzy)**: matched 84,401 inventors (4.7%) in edge cases, including name changes, company acquisitions, and multiple LinkedIn profiles, with manual validation of a 500-case subsample.

(5) **Stage 5 (Direct Revelio)**: incorporated 687,414 inventors (38.2%) through Revelio Labs' proprietary linkages between patent records and LinkedIn profiles.

Table C.1 explains in detail how we go from 17.9 million observations to 1.80 million matched innovators. Our main analysis focuses on first applications only to examine the impact of initial patent success on career trajectories. The final analysis sample contains 1,798,909 first-time applicants, with 1,359,316 in the treatment group (first application granted) and 439,593 in the control group (first application rejected). The control group's smaller size reflects the USPTO's high overall grant rate (approximately 76% in our matched sample, slightly higher than the aggregate USPTO rate of 70%, reflecting selection toward higher-quality corporate applicants who maintain LinkedIn profiles).

Table C.2 shows sample composition by patent characteristics. The control group is smaller (24.4% of sample) due to the USPTO's high overall grant rate (∼76% in our matched sample, slightly higher than the aggregate USPTO rate of 70%, reflecting selection toward higher-quality corporate applicants). Treatment rates vary substantially by entity type and filing decade.

Table C.3 shows the final sample by matching method. The distribution is fairly consistent across treatment and control groups. Direct Revelio matches have a modestly higher treatment rate (76.6%) compared to other match types (74.9-75.0%), likely because Revelio's proprietary matching emphasizes corporate employees at large firms with higher grant rates.

C.2 Balance Tests

Table C.4 compares treatment and control groups on pre-patent characteristics. As expected in an observational study, the groups differ significantly on most observable dimensions. The most striking imbalances occur in education: the treatment group has 3.60 percentage points more PhD holders (normalized difference = 0.105) and 4.90 percentage points more Master's degree holders (normalized difference = 0.137). The treatment group also has higher prestige scores (0.368 vs. 0.306, normalized difference = 0.134) and more LinkedIn connections (259 vs. 219, normalized difference = 0.037). These substantial differences demonstrate that simply comparing granted vs. rejected inventors would conflate the effect of patent approval with underlying differences in inventor quality—and likely on unobservables such as talent, persistence, and institutional support. Our instrumental variable strategy addresses this selection problem by exploiting quasi-random variation in examiner leniency.

When we weight by application year × technology class (Table C.5), balance improves substantially for key professional characteristics. Prestige scores become nearly identical (0.333 vs. 0.331, normalized difference = 0.005), and LinkedIn connections show minimal difference (228 vs. 213, normalized difference = 0.019). However, gender and ethnicity imbalances increase under this weighting, suggesting these characteristics vary systematically across technology fields and time periods in ways that correlate with approval rates. While weighting helps with professional characteristics, it cannot fully address selection, motivating our instrumental variable approach.

These imbalances do not invalidate our identification strategy, provided that: (1) examiner assignment is quasi-random within art units and filing years, and (2) examiner leniency affects career outcomes only through its effect on patent grants (the exclusion restriction). Next, we address these identification assumptions with first-stage diagnostics showing that examiner leniency is uncorrelated with inventor characteristics conditional on art unit $\times$ year fixed effects.

C.3 Examiner Characteristics and First Stage Analysis

This appendix presents descriptive statistics on patent examiners and documents the strength of our instrumental variable. Following Sampat and Williams (2019) and Farre-Mensa et al. (2020), we exploit quasi-random variation in examiner leniency—defined as an examiner's historical approval rate—to instrument for whether an inventor's patent application is granted.

Table C.6 presents descriptive statistics on the patent examiners in our sample. We observe 15,288 unique examiners across 1,029 art units (technology classification groups). Examiner leniency—measured as each examiner's approval rate on all applications examined prior to the current application—exhibits substantial variation, with a mean of 0.71-0.73 and standard deviation of 0.19-0.22. The 10th percentile examiner approves 41-44% of applications, while the 90th percentile examiner approves 92-99%, demonstrating considerable heterogeneity in examiner stringency. Examiner experience also varies substantially: in our first-applications sample, examiners have reviewed a median of 90 prior applications (mean: 132), while in the full staggered sample, the median examiner has 486 prior applications (mean: 654), ranging from zero (the examiner's first case) to over 1,300-6,800 applications.

Table C.7 presents our first-stage results, demonstrating that examiner leniency is a strong predictor of whether a patent application is granted. We estimate five specifications with progressively stricter controls, culminating in our main specification (Column 5) which includes art unit $\times$ year fixed effects and inventor demographic controls. Across all specifications, examiner leniency is a highly significant predictor of patent grants, with F-statistics far exceeding the conventional threshold of 10 for a strong instrument. In our main specification for first applications (Column 5, Panel A), a one-standard-deviation increase in examiner leniency (0.222) increases the probability of patent grant by 11.9 percentage points, with an F-statistic of 8,618. The staggered design using all applications (Panel B) yields even stronger first-stage relationships, with F-statistics exceeding 290,000, reflecting both the larger sample size and the inclusion of repeat applicants. The first-stage relationship remains strong across specifications with varying levels of fixed effects—moving from no fixed effects to art unit fixed effects slightly attenuates the coefficient (as expected when controlling for systematic differences in approval rates across technology fields), and adding year fixed effects and inventor controls further attenuates the coefficient modestly, but the instrument remains highly significant throughout.

Table C.8 examines whether the first stage varies across inventor characteristics. We find that examiner leniency predicts patent grants strongly for all subgroups, though with some heterogeneity in magnitude. The first stage is strong for both female (F = 4,157) and male inventors (F = 8,290), though the coefficient is slightly larger for female inventors (0.579 vs. 0.532), suggesting examiner leniency affects approval rates similarly across genders and validating the use of our IV approach for analyzing gender disparities in career outcomes. PhD holders exhibit a somewhat smaller first-stage coefficient (0.494) than non-PhD inventors (0.549), though both F-statistics remain well above conventional thresholds, likely reflecting that PhD holders file higher-quality applications on average. Nevertheless, the strong F-statistic (2,660) indicates examiner assignment generates substantial variation in approval even among highly educated inventors. The coefficient is similar across first (0.707) and later applications (0.775), suggesting examiner leniency operates similarly throughout inventors' careers and validating our staggered design as a robustness check.

A unique advantage of our staggered design is the ability to estimate the first stage using within-inventor variation. Table C.9 presents results adding inventor fixed effects, which identify the effect of examiner leniency solely from variation across multiple applications filed by the same inventor. The first stage remains exceptionally strong even when restricting to within-inventor variation (F = 298,007), with a coefficient (0.808) nearly identical to the main specification (0.762). This demonstrates that the same inventor, filing multiple applications over time, experiences quasi-random variation in approval rates depending on which examiner reviews each application. The high R-squared (0.412) reflects that inventor fixed effects absorb substantial variation in approval propensity, yet examiner leniency remains highly predictive even after controlling for all time-invariant inventor characteristics.

For our IV strategy to identify causal effects, examiner leniency must satisfy the exclusion restriction: it must affect inventor career outcomes only through its effect on patent grants. A key implication is that conditional on art unit $\times$ year fixed effects, examiner leniency should not predict inventor characteristics, as examiner assignment is quasi-random within these groups.

Table C.10 tests this by regressing inventor characteristics on examiner leniency, controlling for art unit × year fixed effects. We find that several characteristics—education, prestige, and LinkedIn connections—are statistically significantly related to examiner leniency, suggesting potential violations of strict random assignment. However, the magnitudes are economically small: a one-standard-deviation increase in examiner leniency (0.222) predicts only a 2.1 percentage point increase in PhD share and a 2.9 percentage point increase in prestige score. These correlations likely reflect mild deviations from pure random assignment—for instance, if supervisors assign certain types of applications to more experienced examiners, and those applications happen to come from more credentialed inventors. Importantly, our IV estimator remains consistent even with imperfect randomization, provided examiner leniency is uncorrelated with unobserved determinants of career outcomes conditional on observables and fixed effects (Angrist and Pischke, 2009). The small magnitudes in Table C.10 suggest that any residual sorting on observables is modest, and we control for these characteristics in our main IV specifications.

In summary, our first-stage analysis demonstrates that examiner leniency is an exceptionally strong instrument for patent grants, with F-statistics ranging from 8,618 (first applications) to 298,000 (staggered design). The first stage is robust to stringent controls, including art unit × year fixed effects and inventor characteristics, and remains strong across all inventor subgroups and application sequences. Within-inventor estimates confirm that the same inventor experiences quasi-random variation in approval depending on examiner assignment, validating our identification strategy. While we detect statistically significant (but economically small) correlations between examiner leniency and inventor characteristics, these do not invalidate our IV approach provided we control for observables, which we do throughout our main analysis.

Table C.1: Sample Construction: From USPTO Applicants to Final Analysis Sample

Starting Universe	Obs. (1)	Pct. (2)	Notes (3)
USPTO first-time applicants	17,932,860	100.0%	All first-time applicants, 1976-2023
Match to Revelio Process			
Exact matches	285,444	1.6%	Name, company, location, app number
Fuzzy matches	7,681	0.04%	Relaxed name/company matching
PatentsView-assisted	733,969	4.1%	Leveraging PatentsView disambiguation
User-level fuzzy	84,401	0.5%	Edge cases
Direct Revelio linkages	687,414	3.8%	Revelio's proprietary matches
Successfully matched to Revelio	**1,798,909**	**10.0%**	Sum of all matching methods
For Matched Inventors: All Applications			
All applications	9,038,379	50.4%	Matched Inventors and all possible applications
First applications	1,869,531	10.4%	
Subsequent applications	7,168,848	40.0%	
Restrict to First Applications Only			
First applications (matched sample)	1,869,531	10.4%	
Drop: Still Pending/Other	70,622	0.4%	
Final Analysis Sample	**1,798,909**	**10.0%**	
Treatment (granted)	1,359,316	7.6%	First application was granted
Control (rejected)	439,593	2.5%	First application was rejected

Notes: This table documents the complete sample construction process. All percentages are calculated relative to the starting universe of 17.9M first-time USPTO applicants. We successfully match 1.80M inventors (10.0%) to Revelio Labs using five complementary methods. The 90% unmatched primarily reflects LinkedIn coverage limitations—particularly for pre-2003 cohorts, independent inventors, and non-technology sectors. For the 1.80M matched inventors, we observe all their patent applications over time (9.04M total, or 5.0 applications per inventor on average), but our main analysis focuses on first applications only (1.80M) to examine the impact of initial patent success. Match types are assigned hierarchically (exact takes precedence over fuzzy, etc.). The 70,622 observations dropped reflect pending applications and matching errors discovered during data validation.

Table C.2: First Application Sample Composition by Patent Characteristics

Overall	Total (1)	Treatment (2)	Control (3)	% Treatment (4)
Total Sample	1,798,909	1,359,316	439,593	75.6%
By Entity Type				
Large Entity	1,370,564	1,098,881	271,683	80.2%
Small Entity	407,153	249,050	158,103	61.2%
Micro Entity	21,190	11,383	9,807	53.7%
By Filing Decade				
1970s	2,486	2,478	8	99.7%
1980s	38,603	36,420	2,183	94.3%
1990s	146,424	142,575	3,849	97.4%
2000s	765,137	510,067	255,070	66.7%
2010s	773,842	606,453	167,389	78.4%
2020s	72,316	61,272	11,044	84.7%
By Application Type				
Utility	1,757,950	1,319,084	438,866	75.0%
Design	39,594	39,434	160	99.6%
Other	1,365	798	567	58.5%

Notes: Sample composition by key patent characteristics. Treatment rates are substantially higher for design patents (99.6%), large entities (80.2%), and pre-2000 cohorts (94-100%). The 2000s decline to 66.7% likely reflects increased examination stringency following the 2007 USPTO quality initiatives and the 2011 America Invents Act. The 2010s-2020s rebound (78-85%) may reflect both relaxed standards and selection—inventors with LinkedIn profiles (our sample) may file higher-quality applications than the broader population.

Table C.3: Distribution of Final Sample by Matching Method

Match Type	Control (1)	Treatment (2)	Total (3)	% Treatment (4)
Exact	71,611 (16.3%)	213,833 (15.7%)	285,444	74.9%
Fuzzy	1,925 (0.4%)	5,756 (0.4%)	7,681	74.9%
Fuzzy-PatentsView	183,992 (41.9%)	549,977 (40.5%)	733,969	74.9%
Fuzzy-User-Level	21,100 (4.8%)	63,301 (4.7%)	84,401	75.0%
Direct Revelio	160,965 (36.6%)	526,449 (38.7%)	687,414	76.6%
Total	**439,593**	**1,359,316**	**1,798,909**	**75.6%**

*N*otes: Column percentages in parentheses indicate share of each match type within treatment and control groups. Each inventor is assigned to exactly one match type based on a hierarchical rule: exact matches take precedence, followed by fuzzy, PatentsView-assisted, user-level fuzzy, and finally direct Revelio matches. Direct Revelio matches represent inventors linked through Revelio's proprietary systems. Treatment rates are remarkably consistent across match types (74.9-76.6%), suggesting match quality does not substantially affect treatment assignment.

Table C.4: Covariate Balance: Treatment vs Control (Unweighted)

Variable	Treatment	Control	Difference	P-value	Norm. Diff
Gender					
Female	0.1485	0.1715	−0.0230	0.000***	−0.076
Male	0.8294	0.7912	0.0382	0.000***	0.098
Ethnicity					
White	0.6216	0.6216	0.0000	0.000***	−0.007
Asian/API	0.3244	0.3182	0.0062	0.000***	0.013
Black	0.0250	0.0250	0.0000	0.000***	−0.006
Hispanic	0.0264	0.0264	0.0000	0.000***	−0.014
Multiple	0.0020	0.0017	0.0003	0.000***	0.006
Native American	0.0004	0.0004	0.0000	0.096	0.003
Education					
High School	0.0060	0.0060	0.0000	0.005***	−0.005
Associate	0.0114	0.0105	0.0009	0.000***	0.008
Bachelor’s	0.1736	0.1465	0.0271	0.000***	0.074
Master’s	0.1752	0.1262	0.0490	0.000***	0.137
PhD/Doctor	0.1541	0.1182	0.0360	0.000***	0.105
MBA	0.0508	0.0385	0.0122	0.000***	0.059
Professional Characteristics					
Prestige	0.368	0.306	0.062	0.000***	0.134
LinkedIn connections	258.6	218.9	39.6	0.000***	0.037
Filing year	2008.3	2008.7	−0.4	0.000***	−0.050

*N*otes: *** p<0.01, ** p<0.05, * p<0.10. Treatment group: N=1,359,316. Control group: N=439,593. P-values from two-sample t-tests with equal variances. Normalized difference = (Treatment mean − Control mean) / Pooled standard deviation. Values above 0.1 in absolute value indicate meaningful imbalance. The substantial imbalances (particularly for Master’s: 0.137, Prestige: 0.134, PhD: 0.105) motivate our instrumental variable approach using examiner leniency.

Table C.5: Covariate Balance: Treatment vs Control (Weighted by App Year × Tech Class)

Panel A. Gender	Treatment (1)	Control (2)	Difference (3)	P-value (4)	Norm. Diff (5)
Female	0.121	0.195	−0.074	0.000***	−0.162
Male	0.865	0.793	0.072	0.000***	0.192
Panel B. Ethnicity					
White	0.736	0.652	0.084	0.000***	0.183
Asian/API	0.188	0.287	−0.098	0.000***	−0.212
Black	0.049	0.040	0.009	0.380	0.042
Hispanic	0.025	0.029	−0.004	0.264	−0.024
Panel C. Education					
High School	0.008	0.006	0.001	0.342	0.015
Associate	0.019	0.013	0.006	0.044**	0.048
Bachelor's	0.200	0.164	0.036	0.011**	0.093
Master's	0.141	0.122	0.019	0.116	0.056
PhD/Doctor	0.168	0.154	0.015	0.362	0.041
MBA	0.054	0.033	0.021	0.000***	0.101
Panel D. Professional Characteristics					
Prestige	0.333	0.331	0.002	0.917	0.005
LinkedIn connections	228.0	212.7	15.3	0.096*	0.019
Filing year	1993.9	2010.1	−16.2	0.000***	−0.622

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at art unit level. Weighting by application year × technology class (first digit of USPC) cells accounts for the fact that patent characteristics vary substantially across fields and time. Most covariates show improved balance compared to unweighted comparison, with key professional characteristics (prestige, connections) now balanced. The large filing year imbalance reflects that the weighting adjusts for systematic differences in approval rates over time.

Table C.6: Examiner Characteristics

Panel A. Sample composition	First Apps Only (1)	All Apps (Staggered) (2)
Total observations	1,758,769	8,489,918
Unique examiners	15,288	15,288
Unique inventors	1,772,602	1,798,038
Unique art units	989	1,029
Applications per inventor (median)	1.0	15.0
Panel B. Examiner Leniency (Approval Rate)		
Mean	0.731	0.710
Standard deviation	0.222	0.190
10th percentile	0.409	0.439
25th percentile	0.600	0.599
Median	0.783	0.750
75th percentile	0.915	0.855
90th percentile	0.987	0.917
Range	[0.000, 1.000]	[0.000, 1.000]
Panel C. Examiner Experience (Prior Applications)		
Mean	132	654
25th percentile	38	209
Median	90	486
75th percentile	179	907
Range	[0, 1,386]	[0, 6,831]

Notes: This table presents characteristics of USPTO patent examiners in our sample. "First Apps Only" restricts to inventors' first patent applications (N=1.76M). "All Apps (Staggered)" includes all applications by matched inventors (N=8.49M). Examiner leniency is measured as the examiner's approval rate on all applications examined prior to the current application. Examiner experience is the number of applications the examiner has reviewed before the current application. Art units are USPTO technology classification groups to which examiners are assigned.

Table C.7: First Stage: Examiner Leniency Predicts Patent Grant

	Dep. var. = Patent Grant				
Panel A. First Applications Only	(1)	(2)	(3)	(4)	(5)
Examiner leniency	0.693***	0.673***	0.684***	0.533***	0.536***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
F-statistic	10,349	9,527	10,098	8,541	8,618
R-squared	0.088	0.093	0.151	0.179	0.178
Panel B. All Applications Staggered)					
Examiner leniency	0.843***	0.769***	0.791***	0.789***	0.762***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
F-statistic	364,962	327,560	—	—	290,992
R-squared	0.125	0.131	0.194	0.195	0.211
Art unit FE		✓	✓	✓	
Year FE			✓	✓	
Inventor controls				✓	✓
Art unit×year FE					✓

*N*otes: This table presents first-stage regressions of patent grant indicator on examiner leniency. Panel A restricts to first applications only; Panel B includes all applications (staggered design). Examiner leniency is the examiner's approval rate on all applications examined prior to the current application. Inventor controls include gender, race/ethnicity, education, prestige score, and LinkedIn connections. Standard errors clustered at art unit level (Panel A) or inventor level (Panel B) in parentheses. All F-statistics far exceed the threshold of 10 for a strong instrument. ***p<0.01.

Table C.8: First Stage Heterogeneity by Inventor Characteristics

	Dep. Var. = Patent Grant			
	First Apps Only		All Apps (Staggered)	
	Coefficient	F-statistic	Coefficient	F-statistic
Panel A. By Gender	(1)	(2)	(3)	(4)
Female inventors	0.579***	4,157	—	—
	(0.009)			
Male inventors	0.532***	8,290	—	—
	(0.006)			
Panel B. By Education				
No PhD	0.549***	8,466	—	—
	(0.006)			
PhD holders	0.494***	2,660	—	—
	(0.010)			
Panel C. By Application Sequence				
First application	0.707***	11,259	0.707***	11,259
	(0.007)		(0.007)	
2nd-5th applications	—	—	0.775***	234,336
			(0.002)	
All applications	—	—	0.764***	302,594
			(0.001)	

Notes: This table presents first-stage regressions by inventor subgroups. All specifications include art unit×year fixed effects. Standard errors clustered at art unit level (first apps) or inventor level (staggered). All F-statistics exceed 10, indicating strong instruments across all subgroups. ***p<0.01.

Table C.9: First Stage with Inventor Fixed Effects (Within-Inventor Variation)

	Dep. Var. = Patent Grant	
	Art Unit×Year FE [Between Variation]	+ Inventor FE [Within Variation]
	(1)	(2)
Examiner leniency	0.762***	0.808***
	(0.001)	(0.001)
F-statistic	290,992	298,007
R-squared	0.211	0.412
Observations	8,489,918	8,489,788

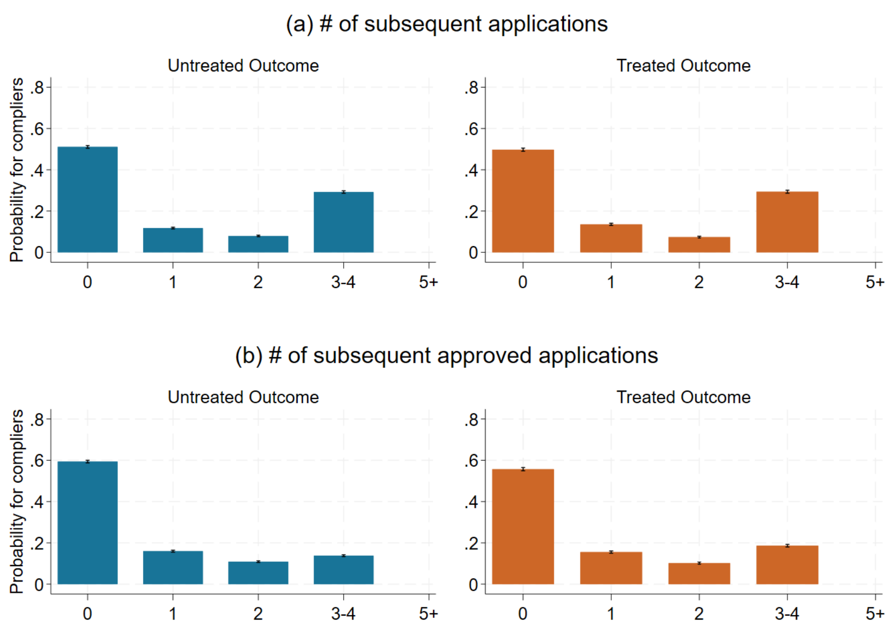
Notes: This table examines the first stage using within-inventor variation in the staggered design. Column 1 repeats the main specification from Appendix Table C.7. Column 2 adds inventor fixed effects, identifying solely from variation in examiner leniency across multiple applications by the same inventor. The strong first stage persists, demonstrating that examiner assignment continues to generate quasi-random variation in approval even for repeat applicants. Standard errors clustered at the inventor level. ***p<0.01.

Table C.10: Exclusion Restriction Test: Examiner Leniency vs. Inventor Characteristics

Dep. var. = Inventor characteristic	
Panel A. Demographics	(1)
Female	−0.015***
	(0.003)
White	0.014***
	(0.004)
Asian/API	−0.012***
	(0.004)
Black	−0.001
	(0.001)
Hispanic	−0.002**
	(0.001)
Panel B. Education	
Bachelor's degree	0.006***
	(0.002)
Master's degree	0.016***
	(0.002)
PhD	0.021***
	(0.003)
MBA	0.006***
	(0.001)
Panel C. Professional Characteristics	
Prestige score	0.029***
	(0.003)
LinkedIn connections	10.5
	(8.3)

Notes: This table tests whether examiner leniency predicts inventor characteristics conditional on art unit×year fixed effects. Each row is a separate regression of the inventor characteristic on examiner leniency with art unit×year FE. Standard errors clustered at art unit level in parentheses. All coefficients are economically small: a one-standard-deviation increase in examiner leniency (0.222) predicts changes of less than 0.05 SD in most characteristics. ***p<0.01, **p<0.05, *p<0.10.

Figure C.1: Monotonicity Checks



Notes. This figure shows the distributions of treated and control outcomes for the number of subsequent patent applications. The outcomes for treated and control compliers are estimated separately with UJIVE Kolesár (2013). Vertical bars indicate 95% confidence intervals that are robust to heteroskedasticity and treatment effect heterogeneity.

Table C.11: Covariate Balance Test

Panel A: Demographics	Coefficient (1)	Std. Error (2)	p-value (3)
Female	-0.014^{***}	(0.002)	0.000
Asian	-0.005^{**}	(0.002)	0.041
Black	-0.001	(0.001)	0.183
Hispanic	-0.001	(0.001)	0.274
Panel B: Education			
Bachelor's	0.005^{**}	(0.002)	0.019
Master's	0.013^{***}	(0.002)	0.000
PhD	0.019^{***}	(0.002)	0.000
MBA	0.005^{***}	(0.001)	0.000
Panel C: Professional Characteristics			
Prestige	0.024^{***}	(0.002)	0.000
Num. Connections	12.309	(7.698)	0.110
Art-unit-by-time FE		✓	

Notes. This table reports balance tests following Goldsmith-Pinkham et al. (2025). Each row presents the coefficient from a regression of the covariate on examiner leniency, controlling for art-unit-by-year fixed effects with heteroskedasticity-robust standard errors. While some covariates show statistically significant correlations with examiner leniency, the magnitudes are economically small. For example, a one-standard-deviation increase in examiner leniency is associated with only a 1.4 percentage point decrease in the probability of being female and a 1.9 percentage point increase in the probability of having a PhD. These small imbalances are typical in large samples and do not substantively threaten identification. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

D Robustness and Heterogeneity Tests

Table D.1: Robustness: Standard Errors

	Dep. Var. = Entrepreneur at VC-backed startup		
	Cluster by art unit	Robust	Cluster by examiner
Pane A: Overall movement	(1)	(2)	(3)
Patent Grant	0.010***	0.010***	0.011***
	(0.002)	(0.001)	(0.003)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.028	0.028	0.028
Observations	1,566,604	1,566,604	1,566,604
First-stage F-stat	7,701	7,701	7,701

Notes. This table presents robustness checks of our main entrepreneurship findings using alternative standard errors. Column (1) reports our main specification with robust standard errors clustered at the art unit level. Column (2) reports the heteroskedasticity-robust standard errors following recommendations in Goldsmith-Pinkham et al. (2025). Column (3) reports with robust standard errors clustered at the examiner level. All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, prestige, and connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.2: Robustness: Unbiased Jack-knife Instrumental Variable Estimator (UJIVE)

	Dep. Var. = Entrepreneur at VC-backed startup		
	2SLS	UJIVE	OLS
Pane A: Overall movement	(1)	(2)	(3)
Patent Grant	0.010***	0.008***	0.015***
	(0.002)	(0.002)	(0.003)
Art-unit-by-time FE	✓	✓	✓
Controls	✓	✓	✓
Dep. Var. Mean	0.028	0.028	0.028
Observations	1,566,604	1,566,604	1,566,604
First-stage F-stat	7,701	NA	NA

Notes. This table presents robustness checks of our main entrepreneurship findings using alternative standard errors. Column (1) reports our main 2SLS specification with examiner leniency as an instrument for patent grant. Column (2) reports the UJIVE estimate Goldsmith-Pinkham et al. (2025). Column (3) reports the OLS estimate. All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, prestige, and connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.3: Robustness: Alternative Specifications

	Dep. Var. = Entrepreneur at VC-backed startup		
	Complete demographics	Large art units	USPC Fixed effects
	(1)	(2)	(3)
Patent Grant	0.010***	0.010***	-0.006**
	(0.002)	(0.002)	(0.003)
Observations	1,566,612	1,553,577	1,317,966
Art-unit-by-time FE	✓	✓	
USPC-by-time FE			✓
Controls	✓	✓	✓
Dep. Var. Mean	0.028	0.027	0.027
First-stage F-stat	7,698	7,754	6,034

Notes. This table presents alternative specifications of our main entrepreneurship findings. Column (1) restricts the sample to innovators with complete demographic data to include a richer set of predetermined controls. Column (2) restricts to large art units. Column (3) replaces the art unit × year fixed effects with finer USPC subclass × year fixed effects. Controls for gender, ethnicity, education, prestige, and connections are included in all specifications. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.4: Career Advancement: Additional Heterogeneity

	Dep. Var. = Stayed with the same firm					
	By gender		By ethnicity		By rank	
	Female	Male	White + Asian	URM	High rank	Low rank
Panel A: Heterogeneity	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	0.038***	0.038***	0.038***	0.029	0.037***	0.027***
	(0.010)	(0.005)	(0.005)	(0.021)	(0.008)	(0.009)
Art-unit-by-time FE	✓	✓	✓	✓✓	✓	
Controls	✓	✓	✓	✓✓	✓	
Dep. Var. Mean	0.184	0.177	0.176	0.181	0.215	0.235
Observations	208,169	1,123,813	1,284,591	74,302	506,352	560,015

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. Low rank refers to inventors in junior positions at the time of patent application, whereas high rank refers to senior positions. All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, prestige, and connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.5: Geographic Mobility: Additional Robustness

	Dep. Var. = Changed location					
	By gender		By ethnicity		By rank	
	Female	Male	White + Asian	URM	High rank	Low rank
Panel A: Heterogeneity	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	0.047***	0.042***	0.043***	0.070***	0.042***	0.027***
	(0.011)	(0.006)	(0.005)	(0.022)	(0.005)	(0.008)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.185	0.197	0.193	0.215	0.241	0.257
Observations	208,169	1,123,813	1,284,591	74,302	506,352	560,015

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. Low rank refers to inventors in junior positions at the time of patent application, whereas high rank refers to senior positions. All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, prestige, and connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.6: Patenting and Subsequent Specialization: Heterogeneity

	Dep. Var. =					
	Has subsequent patent app.		Total subsequent patent app.		Patent number approved	
	Female	Male	Female	Male	Female	Male
Panel A: Subsequent patenting	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	0.026*	0.013*	0.064	0.006	0.133***	0.111***
	(0.014)	(0.008)	(0.047)	(0.027)	(0.015)	(0.007)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.458	0.476	1.209	1.347	0.639	0.682
Observations	253,931	1,349,387	253,931	1,349,387	115,439	643,879
	Network growth		Pct. new co-inventors		USPC expansion	
	Female	Male	Female	Male	Female	Male
Panel B: Inventor network growth	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	0.011	-0.025***	-6.835***	-4.249***	-0.083***	-0.045***
	(0.089)	(0.046)	(1.640)	(0.894)	(0.021)	(0.010)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.408	0.403	64.427	72.559	0.536	0.606
Observations	253,931	1,349,387	253,931	1,349,387	115,439	643,879
	Forward citations		Patent value		Breakthrough patent	
	Female	Male	Female	Male	Female	Male
Panel C: Patent quality	(1)	(2)	(3)	(4)	(5)	(6)
Patent Grant	3.907***	3.985***	0.040***	0.030***	0.016***	0.013***
	(1.003)	(0.738)	(0.004)	(0.003)	(0.007)	(0.004)
Art-unit-by-time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	4.979	8.512	0.076	0.104	0.027	0.040
Observations	253,931	1,349,387	253,931	1,349,387	253,931	1,349,387

Notes. This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit $\times$ year fixed effects and control for demographics, education, and network size. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.