# The Returns to Recognition: Patent Grants and the Allocation of Innovative Talent

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**Abstract**

We study whether patent grants facilitate personal and professional recognition, leading to the reallocation of inventive talent across startups and incumbent firms. Using examiner leniency as exogenous variation in first patent grants, we find that becoming an inventor increases entry into high-growth entrepreneurship: successful applicants are more likely to found VC-backed startups and to join VC-backed startups as employees. Receipt of a first patent also increases retention, promotion, and transitions to higher-prestige employers. While their employers generally retain the property rights, inventors gain recognition and benefit from expanded professional networks, collaborations with superstar inventors, and greater leadership skills. Becoming an inventor also induces technological specialization and higher-quality subsequent innovation. In these ways, inventorship appears to reshape outside options and talent allocation.

**JEL**: G24, J24, J62, L26, O31, O34
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***What did becoming an inventor mean to you?***

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

# 1 Introduction

High-growth entrepreneurship depends on the allocation of scarce innovative talent. Startup investors, co-founders, and early employees must assess the quality of first-time innovators under severe information frictions. These frictions are central to entrepreneurial finance: Investors provide capital and support to young firms when founder quality, technical ability, and commercial potential are difficult to observe ex ante. They are also central to the allocation of human capital between startups and incumbents. Talented innovators may have ideas that could form the basis of high-growth ventures, but without credible signals of ability they may remain inside established firms, fail to attract collaborators or capital, or be unable to move into entrepreneurial ecosystems.

Patent grants may help resolve these frictions. While patents confer property rights over inventions, they can also serve as public signals of the ability of the inventors named on them, much as they have been recognized as providing insights into firm-level knowledge capital, activity, and strategy Long (2002). A first patent grant verifies that an inventor produced an idea deemed novel, useful, and non-obvious by the United States Patent and Trademark Office (USPTO). As theorized by Rantanen and Jack (2019), this certification may therefore function as a portable signal of inventive ability, increasing an inventor's credibility with investors, co-founders, employers, and collaborators. Importantly, this signal can be valuable even when the inventor does not personally own the underlying intellectual property (IP). In most cases, patent rights accrue to the inventor's employer rather than to the inventor herself.[1] Thus, a patent grant can simultaneously increase an inventor's outside-option value and strengthen the incumbent firm's control over the underlying innovation.

This dual role creates a central tradeoff. On one hand, patent recognition may certify otherwise hard-to-observe talent and expand inventors' access to VC-backed entrepreneurship, startup

[1] Patent rights are typically assigned to the inventor's organization either explicitly through contract (35 USC 261) or implicitly under the hired-to invent doctrine (Teets v. Chromalloy, 83 F. 3d 403).

employment, higher-prestige firms, and high-quality collaborators. On the other hand, because the employer typically owns the patent, the grant may increase firm-specific human capital, strengthen incumbent attachment, or restrict the inventor's ability to commercialize related ideas elsewhere (Melero et al., 2020). Whether patent grants primarily facilitate the reallocation of innovative talent toward startups or instead bind inventors more closely to incumbent firms is therefore an empirical question.

In this paper, we study how receiving a first patent grant affects inventors' subsequent career trajectories. We focus on first-time patent applicants because first approval is the initial public certification of inventive ability. Our main question is whether this certification reallocates innovative human capital across startup ecosystems and incumbent firms. Specifically, we examine whether patent recognition affects VC-backed founding, startup employment, moves to higher-prestige employers, retention and promotion within the incumbent firm, professional networks, collaborations with superstar inventors, and subsequent innovation.

Identifying the causal effect of patent recognition is challenging. More talented inventors are more likely to receive patents and also more likely to become entrepreneurs, move to better firms, attract collaborators, and produce future innovations. Simple comparisons between successful and unsuccessful patent applicants therefore confound the effect of recognition with underlying inventor quality. Ideally, one would randomly assign patent recognition among otherwise similar first-time applicants and then track their subsequent careers. In practice, we approximate this ideal experiment by exploiting quasi-random variation in patent examiners' propensity to grant applications.

Our empirical strategy builds on the examiner-leniency design used by Sampat and Williams (2019) and Farre-Mensa et al. (2020). We instrument for whether an inventor's first observable patent application is granted using the historical grant rate of the examiner assigned to review the application. The validity of this approach rests on two institutional features of the USPTO review process. First, applications are assigned to examiners within narrow technology fields, or art units, quasi-randomly with respect to the quality of the underlying invention (Lemley and Sampat, 2012; Sampat and Williams, 2019). Second, examiners within the same art unit vary substantially in their propensity to approve applications (Cockburn et al., 2003). Our specifications therefore

compare applicants within art-unit-by-application-year cells and control for predetermined inventor characteristics, including demographics, education, employer prestige, and professional networks. The resulting estimates identify the effect of receiving a first patent grant for applicants whose grant outcome is shifted by examiner leniency.

As with any instrumental-variables design, our estimates should be interpreted as local average treatment effects. Specifically, they capture the effect of receiving a first patent grant for applicants whose approval outcome is affected by examiner leniency. These applicants are likely to be closer to the patentability margin, so the estimates need not generalize to inventors whose applications would be granted or rejected regardless of examiner assignment. This limitation is important. At the same time, if patent grants serve as certification, this is precisely the margin where one would expect certification to matter most—for first-time applicants whose inventive ability is plausible but not yet well established.

We assemble a large inventor-level dataset linking USPTO patent records to detailed career histories from Revelio Labs, which aggregates professional profiles primarily from LinkedIn. This linkage allows us to observe first-time patent applicants' education, employers, job titles, skills, locations, promotions, and professional networks. We then link these career histories to PitchBook to identify startup employment and VC-backed entrepreneurship; to Glassdoor to measure workplace perceptions; to Revelio wage and employer-prestige measures; and to subsequent patent records to measure later innovation, inventor networks, superstar collaborations, and patent quality. Our analysis sample includes roughly 1.4 million first-time patent applicants whose first applications were filed between January 1, 2001 and September 30, 2020.

Our first main finding is that patent recognition increases entry into high-growth entrepreneurship. Receiving a first patent grant increases the probability of becoming an entrepreneur at a VC-backed startup by 0.9 percentage points, relative to a baseline rate of 2.5 percent. This implies a 36 percent increase. Patent grants also increase the probability of moving to a VC-backed startup in a non-founder role by 4.7 percentage points, relative to a baseline rate of 19 percent. The effect is therefore not limited to founding; patent recognition increases inventors' broader entry into startup ecosystems.

The timing of these effects helps distinguish between startup access and startup founding.

Moves into VC-backed startups rise quickly after patent recognition, while VC-backed founding emerges more gradually. This pattern suggests that certification first opens access to startup networks and only later translates into firm creation. Consistent with this interpretation, patent grants increase professional network size, collaborations with superstar inventors, and self-reported leadership skills. These results point to a mechanism in which patent recognition makes inventor quality more credible, allowing inventors to accumulate the collaborators, networks, and market-facing skills needed to found a high-growth venture.

The entrepreneurship response is heterogeneous in ways that further support a certification interpretation. The effect on VC-backed founding is especially strong in IT and software, where patents can serve as visible signals of technical ability and where entrepreneurial entry may depend less on formal scientific credentials. By contrast, the founding response is weaker in biotech and pharmaceuticals, where alternative credentials such as advanced degrees, university affiliations, scientific publications, and regulatory milestones may already help certify quality. Moves to VC-backed startups increase across demographic groups, but the conversion of startup access into founding is more selective. These patterns suggest that patent recognition relaxes information frictions, but that founding a VC-backed startup also requires complementary access to capital, collaborators, and entrepreneurial networks.

Our second main finding is that patent recognition also affects careers within established firms. Receiving a first patent grant increases the probability that an inventor remains with the same employer by 4.1 percentage points, a 22 percent increase relative to the baseline retention rate. It also increases the probability of promotion by the current employer. These patterns are consistent with patent grants increasing firm-specific human capital or improving inventors' internal bargaining power. Yet this internal response does not come at the expense of external opportunities: Recognized inventors are also more likely to move to higher-prestige employers and, as shown above, to startup ecosystems. Thus, patent recognition appears to raise inventors' value both within their current firms and in the external labor market.

Our third main finding is that internal advancement does not fully absorb the recognition shock. Using Glassdoor data, we find that patent grants are followed by lower assessments of overall workplace satisfaction and career opportunities at inventors' firms. We also find suggestive evidence

of lower wage growth. These outcomes are noisier than our main mobility and career measures, but they point in a consistent direction: Patent recognition appears to raise inventors' outside-option value faster than incumbent firms adjust compensation, authority, or career opportunities. This helps reconcile the simultaneous increase in retention, promotion, higher-prestige moves, startup entry, and entrepreneurship. Patent recognition creates value for inventors, but employer ownership of IP and organizational constraints may limit how much of that value is realized internally.

Finally, patent recognition affects subsequent innovation. Inventors whose first application is granted are more likely to file again and more likely to receive future grants. Their later patents receive more forward citations, have higher estimated private value, and are more likely to be classified as breakthrough inventions. At the same time, recognized inventors do not broaden their technological scope. Instead, they specialize: They deepen work within their initial technological domain, rely less on new co-inventors, and are more likely to collaborate with superstar inventors. Thus, patent recognition appears to help inventors build on their comparative advantage and connect to higher-quality collaborators, rather than simply inducing broader experimentation.

Taken together, our findings show that patent grants operate as certification shocks that reallocate innovative human capital. A first patent grant makes inventive ability more credible and visible. This expanded credibility increases access to startup ecosystems and VC-backed entrepreneurship, but it also increases the inventor's value inside the incumbent firm. The same recognition shock can therefore generate different career responses depending on complementary resources, networks, and constraints. Some inventors convert recognition into startup employment or VC-backed founding. Others convert it into retention, promotion, moves to more prestigious firms, or deeper innovative specialization. Patent recognition therefore affects not only which ideas receive legal protection, but also which inventors become visible, mobile, and able to access high-growth opportunities.

Our paper contributes to four literatures. First, we contribute to entrepreneurial finance by showing that certification operates not only at the firm level, but also at the individual inventor level. Prior work emphasizes that young firms face severe information asymmetries when seeking external finance and that certification can help startups access capital (Howell, 2017; Farre-Mensa et al., 2020). We show that a public signal of individual innovative ability increases entry into VC-backed entrepreneurship and startup employment. This evidence highlights a labor-market

channel through which information frictions shape the supply of high-growth entrepreneurs.

Second, we contribute to the literature on talent allocation between startups and incumbent firms. A large literature shows that incumbent firms are important sources of entrepreneurial talent and new venture creation. Gompers et al. (2005) show that public corporations spawn venture-backed startups, while Babina and Howell (2024) show that corporate R&D increases employee departures to startup founding teams. We complement this work by identifying a specific certification shock that helps determine which inventors move from incumbent firms into startup ecosystems. In this sense, our paper studies not only whether incumbent firms generate entrepreneurial spillovers, but also how individual-level signals affect the allocation of innovative human capital between incumbents and startups.

Third, we contribute to work on information frictions and worker-level signals in labor markets. Gupta et al. (2026) show that public disclosure of worker productivity reallocates high-quality workers toward larger firms. We study a different signal in a different market: Patent recognition publicly certifies inventive ability and reallocates innovative talent toward startup ecosystems, VC-backed entrepreneurship, higher-prestige employers, and internal advancement. Taken together, these findings suggest that public signals of worker quality can meaningfully alter the allocation of human capital, but that the destination of this reallocation depends on the nature of the signal and the frictions it relaxes.

Finally, we contribute to the literature on patents, inventor mobility, and the private returns to innovation. Prior work shows that patents affect inventor earnings, rent sharing, and mobility (Toivanen and Väänänen, 2012; Addario and Depalo, 2014; Kline et al., 2019; Aghion et al., 2019; Melero et al., 2020). We complement this work by studying a broader set of career and entrepreneurial outcomes, including VC-backed founding, startup employment, internal advancement, employer prestige, professional networks, superstar collaborations, and subsequent innovation quality. This distinction is important because patent recognition may affect inventors through margins that are not captured by immediate job-to-job mobility. In particular, while Melero et al. (2020) emphasize that patent grants can reduce inventor mobility by increasing firm-specific human capital, we show that patent grants also expand inventors' external opportunity sets, increasing movement into startup ecosystems, VC-backed entrepreneurship, and higher-prestige employers. In doing so,

we, like Long (2002) highlight a role for patents that is distinct from their traditional role as property rights over ideas: Patents also function as labor-market credentials that shape the allocation of innovative human capital.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting, the examiner-leniency research design, and the interpretation of the resulting IV estimates. Section 3 presents the linked patent-career data and defines the main outcome variables. Section 4 reports the main results on startup entry, internal careers, subsequent innovation, and workplace perceptions, and then synthesizes the evidence around the outside-options mechanism. Section 5 presents robustness tests and additional heterogeneity analyses. Section 6 concludes.

## 2 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 innovators' 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 innovators' 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:

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

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. $First\ Application\ Approved_{iajt}$ 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, $\upsilon_{at}$, to 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 $First\ Application\ Approved_{aijt}$ is potentially endogenous, because it is likely to be correlated with the error term $\epsilon_{iajt}$ due to our inability to observe and include in $X$ all innovator characteristics that may impact both $Y$ and the likelihood of an innovator's first patent being approved. To address this endogeneity concern, we estimate Equation 1 by two-stage least squares (2SLS), instrumenting approval of the innovator's first application with examiner $j$'s historical approval rate, following Farre-Mensa et al. (2020).

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:

$$Examiner\ Approval\ Rate_{iajt} = n_{granted_{ajt}}/n_{reviewed_{ajt}} \tag{2}$$

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:

$$First\ Application\ Approved_{iajt} = \theta Examiner\ Approval\ Rate_{iajt} + X_{iajt} + u_{iajt} \tag{3}$$

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

## 2.1 Discussion of Empirical Strategy

### 2.1.1 Focus on First Patent Application

Our empirical strategy focuses on identifying the effect of an inventor's first observable patent application approval on her subsequent professional and personal outcomes. We acknowledge the limitation in our study that some applicants in our sample that appear to be applying for the first-time, may have, in fact, previously applied for a patent that was never published. While our decision to limit our dataset to after 2001, when patent applications started to be published 18 months after filing, meaningfully reduces this risk, even after 2001, there remain a small subset of applications that are not visible. We therefore interpret "first application" as the inventor's first observable application and note that any resulting misclassification does not threaten identification because prior unpublished filings are not systematically related to examiner assignment. We focus on first application grants for economic and econometric reasons.

First, we expect the outcome of an inventor's initial patent application to be particularly consequential for her career because approval may provide the first formal recognition of her inventive activity and shape subsequent opportunities in path-dependent ways. Accordingly, the initial application provides a natural focal point for our analysis, without implying similar effects for later applications.

Second, focusing on first applications avoids conditioning on subsequent filing behavior. Approval of an inventor's initial application may affect both the likelihood and characteristics of later applications. Including subsequent filings in the estimation would incorporate post-initial-outcome behavior that may itself respond to the treatment, thereby blurring the interpretation of the causal effect of first approval.

Third, our instrument is defined at the application level and is therefore well suited to identifying

the causal effect of a single application's approval. If we instead attempted to instrument the outcomes of multiple applications (e.g., an inventor's first ten applications), we would need to aggregate the leniency of the examiners assigned to those filings. Averaging examiner leniency across applications would mechanically compress cross-sectional variation in the resulting inventor-level instrument relative to application-level variation, weakening the first stage and increasing weak-instrument concerns.

### 2.1.2 LATE and External Validity

As with any instrument, our estimator identifies a local average treatment effect (LATE). More precisely, it identifies the effect of obtaining a patent grant on subsequent career outcomes for the subpopulation of innovators whose application outcomes are influenced by the leniency of their assigned examiner. Conventionally known as "compliers," these applications would be granted if assigned to a sufficiently lenient examiner but rejected if assigned to a sufficiently strict one.

This population excludes applications that are so strong that nearly any examiner would approve it ("always takers"), and 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 be submitted to the Patent Office in the first place. Indeed, historically, patent application approval rates have hovered near 70%. [2]

## 3 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 to the question, what did becoming an inventor mean to you, 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 1,493,514 first-time applicants between January 1, 2001 and September 30, 2020, prior to the automated routing of applications, approximately 8 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, 73% 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.

### 3.1 Summary Statistics

Table 2 reports demographic characteristics of our matched sample of first-time patent applicants. The sample is predominantly male (81.1 percent), with women comprising 16.2 percent of inventors. In terms of race and ethnicity, 60.4 percent of inventors are White and 34.4 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, 17.0 percent hold a bachelor's degree, 16.4 percent a master's degree, and 14.8 percent a PhD, though education is missing for 46.7 percent of the sample. Inventors are affiliated with relatively prestigious institutions on average, with a mean standardized prestige score of 0.356, and report an average of 248 LinkedIn connections.

Patent-level characteristics are summarized in Table 3. Most applications originate from large entities (75.1 percent), with smaller shares from small (23.7 percent) and micro (1.2 percent) entities. Grant rates vary sharply by entity size: 80.1 percent for large entities, compared to 19.0 percent for small entities and 1.2 percent for micro entities. Applications span a broad range of technological fields—the five most common technology classes together account for only 15.7 percent of the sample—highlighting the diversity of inventive activity represented in the data. The mean filing year is 2010, with granted applications filed slightly earlier on average than rejected applications.

Appendix Table C.4 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 (17.7 percent) than granted applications (15.4 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: 43.5 percent of granted applications come from inventors with graduate degrees, compared to 36.7 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.5 provide additional balance tests, and Appendix C.6 explores examiner traits. Finally, in Appendix Tables C.7 through C.10, we evaluate the strength of the examiner leniency instrument, with first-stage $F$-statistics exceeding 690 in our main specification, well above conventional thresholds for a strong instrument. We provide visual evidence that the monotonicity assumption holds in C.1.

# 4 Results

## 4.1 External Recognition

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

### 4.1.1 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 2.5 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, indi-

cating 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, and the corresponding estimate for women is also positive and statistically significant, though smaller. Similarly, when breaking down the increase in entrepreneurial founding at VC-backed startups by ethnicity, we see a clear and statistically significant increase for White and Asian inventors, while the estimate for URMs is positive but not statistically distinguishable from zero.

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.

### 4.1.2 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 solo innovation rather than team-based innovation, 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 estimates are statistically indistinguishable from zero in biotech and pharmaceuticals, where alternative credentials—such as advanced degrees, institutional affiliations, and regulatory milestones—are already well established. These findings, which are consistent with Farre-Mensa et al. (2020), 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 liquidity-based explanation and instead points to the gradual accumulation of complementary skills and resources, set in motion by inventorship recognition.

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.

## 4.2 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.

### 4.2.1 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 4.1 p.p., relative to a baseline retention rate of 18.3 percent, consistent with Melero et al. (2020) and Kline et al. (2019) . At the same time, patent grants significantly increase promotion rates. The probability of being promoted by the same firm rises by 3.6 p.p., and the probability of promotion by another firm increases by 4.5 p.p., both economically large effects relative to the baseline. In addition, patent recipients are 4.6 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 3.5 p.p., compared with 3.4 p.p. for men. Given that baseline promotion rates are similar for women and men in this sample, this is an economically meaningful effect and an important catalyst for internal recognition. Similarly, URM inventors also experience promotion gains (5.0 p.p. increase), though this estimate is less precisely estimated. 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 suggest a mechanism by which recognition reshapes an innovator's trajectories. 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 the rate of relocation by 4.3 percentage points relative to a baseline rate of 19.5 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 meaningful 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 3.3 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, often expensive, innovation ecosystems.

### 4.2.2 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 2.9 percentage points relative to a baseline of 43.3 percent, and increases the likelihood that inventors hold concurrent positions—such as board seats or volunteer leadership roles—by 0.9 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 17 additional LinkedIn connections, a nontrivial increase relative to a baseline of 277 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 female inventors 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.

### 4.2.3 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 1.5 p.p. more likely to have a subsequent patent application, relative to a baseline probability of 48 percent. By contrast, the total number of subsequent patent applications does not increase, and the point estimate is statistically indistin-

guishable from 0. Thus, patent recognition appears to shift outcomes on the extensive margin of 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 about 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 5.2 citations relative to a baseline of 6.0, and the probability of producing a breakthrough patent rises by 1.6 percentage points, nearly a 50 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.

### 4.2.4 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 initial filing success and employees' perceptions of their workplace

environment.[3] 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.

### 4.3 A Unified Mechanism: Patent Recognition and Outside Options

The results across Sections 4.1 and 4.2 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 based on inventors' constraints, networks, and organizational context.

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, are more likely to convert accumulated networks and leadership experience into firm creation.

[3]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).

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.

Taken together, our results 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 an important role in shaping the career trajectories of inventors themselves. Patent recognition does not generate a single career pathway. Instead, it widens the set of feasible trajectories by internal and external 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.

## 5 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 implements the scrambled-examiner placebo test following Chudik et al. (2025). Under this placebo assignment, the first stage collapses, consistent with examiner leniency being the source of identifying variation in the baseline design.

Fourth, Appendix Table D.4 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.

Fifth, Appendix Table D.5 examines heterogeneity by senior co-inventor status. The estimated association between a first patent grant and subsequent VC-backed entrepreneurship is large and statistically significant for inventors without a senior co-inventor, but smaller and statistically insignificant when a senior co-inventor is present. This pattern is consistent with patent grants being more informative when inventors lack alternative sources of reputation or credibility.

Sixth, Appendix Table D.6 examines heterogeneity by assignee type. The estimated association is small and statistically insignificant for university-assigned patents but large and statistically significant for patents assigned to publicly traded firms. Because university affiliation already provides strong credentialing, while inventors at public firms are more anonymous, these results further support a credentialing interpretation of the main findings.

Seventh, we could not present all the heterogeneity results in the main body. Appendix Tables D.7, D.8, D.9 provide additional heterogeneity checks, highlighting how the opportunities enabled by patent recognition differ by gender, ethnicity, education, and job seniority.

## 6 Conclusion

This paper studies the impact of first-time patent grants and the role of recognition in reallocating scarce inventive talent across startup ecosystems and incumbent firms. Using quasi-random variation in first patent grants induced by examiner leniency, we show that patent recognition has economically large effects on subsequent careers. Successful patent applicants are more likely to

enter high-growth entrepreneurship, both by founding VC-backed startups and by moving into VC-backed startup employment. Patent recognition also affects careers inside established firms, increasing retention and promotion, while also raising transitions to higher-prestige employers. These findings suggest that patent grants increase both internal value and external labor-market opportunities.

The evidence points to the presence of a certification mechanism. A first patent grant is not merely a legal event that assigns property rights over an invention; it is also a public signal of the ability of the individual named on the patent. Consistent with this interpretation, patent recognition expands professional networks, increases collaborations with superstar inventors, and strengthens leadership skills. The timing of the entrepreneurship results further supports this view: Successful applicants experience a boost in the likelihood of moving into startup ecosystems relatively quickly, while VC-backed founding emerges more gradually, consistent with a process in which certification first expands access to entrepreneurial networks and only later translates into firm creation.

Patent recognition also shapes subsequent innovation. Successful applicants are more likely to continue patenting, and their later patents receive more citations, have higher estimated private value, and are more likely to be classified as breakthrough inventions. At the same time, patent success does not appear to broaden their technological scope. Instead, they specialize, deepen work within their existing technological domains, and connect to higher-quality collaborators. These results suggest that recognition helps inventors build on their comparative advantage rather than simply inducing increased innovative activity.

The effects of patent recognition are heterogeneous. Some inventors convert recognition into startup employment and VC-backed entrepreneurship; others convert it into retention, promotion, higher-prestige moves, or deeper innovative specialization. These differences are consistent with the idea that certification expands opportunity sets, but that the way those opportunities are realized depends on complementary resources, networks, and constraints. Patent recognition therefore does not generate a single career path. It changes the feasible set of career and innovation choices available to first-time applicants.

More broadly, our results show that patents operate not only as property rights over inventions,

but also as labor-market credentials for the people who produce them. This perspective has implications for both entrepreneurial finance and innovation policy. If patent grants certify otherwise hard-to-observe inventive ability, then patent examination decisions can affect who becomes visible to investors, co-founders, employers, and collaborators; who enters startup ecosystems; who gains access to leadership roles and high-quality collaborators; and how innovative talent is ultimately allocated between young firms and incumbents.

Patent policy therefore shapes economic growth not only by protecting inventions and improving allocative efficiency in IP, but also by influencing the allocation of the human capital that produces innovation. Viewed through this lens, transparency, consistency, and examiner training in the patent-review process matter not only for patent quality, but also for the career opportunities created by patent recognition.

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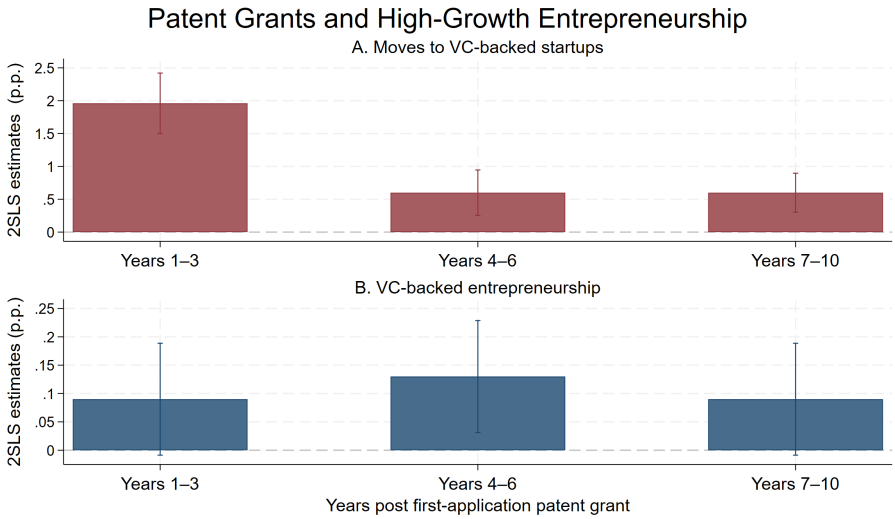
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Figure 1: **Timing of Patent Grant Effects on VC-Backed Startup Employment and Entrepreneurship**




*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." | 38% |
| | "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." | |
| Notoriety within the firm | "Inventing helped me collaborate with other domain influencers on the projects... the team is always stronger than the individual." | 33% |
| | "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." | |
| Esteem of friends and family | "I was able to show my family a glimpse of my work and achievements." | 7% |
| | "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." | |
| 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." | 68% |
| | "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." | |
| 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." | 47% |
| | "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." | |

*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 | 229,070 | 16.17 |
| Male | 1,148,855 | 81.11 |
| Missing | 38,511 | 2.72 |
| **Panel B. Race/Ethnicity** | | |
| White | 855,423 | 60.39 |
| Asian/API | 486,675 | 34.36 |
| Black | 32,954 | 2.33 |
| Hispanic | 37,751 | 2.67 |
| Multiple | 2,846 | 0.20 |
| Native American | 600 | 0.04 |
| **Panel C. Education** | | |
| High School | 8,068 | 0.57 |
| Associate | 14,285 | 1.01 |
| Bachelor's | 240,626 | 16.99 |
| Master's | 231,911 | 16.37 |
| PhD/Doctorate | 209,091 | 14.76 |
| MBA | 64,553 | 4.56 |
| Missing | 662,187 | 46.75 |
| **Panel D. Professional Characteristics** | **Mean** | **Median** |
| Prestige score (range: -0.855 to 2.343, higher = more prestigious) | 0.356 | NA |
| LinkedIn connections | 248 | 190 |
| **Total Observations** | **1,416,436** | |

*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. Entity Status | (1) | (2) | (3) | (4) |
| Micro | 17,564 | 1.24% | 0.90% | 2.14% |
| Small | 335,246 | 23.67% | 18.98% | 35.80% |
| Large (undiscounted) | 1,063,624 | 75.09% | 80.11% | 62.06% |
| Panel B. Top 5 Technology Classes (USPC) | | | | |
| 705 (Data processing) | 51,376 | 3.63% | | |
| 424 (Drug/bio-affecting) | 46,830 | 3.31% | | |
| 514 (Drug/bio-affecting) | 45,020 | 3.18% | | |
| 435 (Chemistry) | 42,814 | 3.02% | | |
| 709 (Electrical computers) | 35,788 | 2.53% | | |
| Panel C. Filing Characteristics | | | | |
| Filing year (mean) | 2010 | | 2010 | 2009 |
| AIA filing | 516,877 | 36.49% | | |

*Notes:* This table presents patent application characteristics. Panel A shows entity status (micro/small entities receive fee discounts). Panel B shows the top 5 technology classes by USPC classification. Panel C 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 VC-backed startup | Moved to non-VC startup |
| Panel A: Overall movement | (1) | (2) | (3) |
| Patent Grant | 0.009*** | 0.047*** | 0.015*** |
| | (0.002) | (0.006) | (0.003) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.025 | 0.190 | 0.063 |
| Observations | 1,335,998 | 1,150,972 | 1,150,972 |
| F-statistic | 8,686 | 7,222 | 7,222 |

*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. 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 | 0.007** | 0.010*** | 0.009*** | 0.014 | 0.016*** | 0.011*** | 0.033*** | 0.004 |
| | (0.003) | (0.002) | (0.002) | (0.009) | (0.005) | (0.004) | (0.006) | (0.006) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.019 | 0.026 | 0.024 | 0.034 | 0.036 | 0.039 | 0.055 | 0.029 |
| Observations | 213,986 | 1,086,852 | 1,265,347 | 69,193 | 287,176 | 442,828 | 265,736 | 113,762 |
| F-statistic | 4,920 | 8,084 | 8,642 | 1,633 | 4,443 | 4,687 | 1,557 | 1,032 |
| **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 | 0.057*** | 0.044*** | 0.047*** | 0.042** | 0.062*** | 0.055*** | 0.110*** | 0.070*** |
| | (0.010) | (0.006) | (0.006) | (0.021) | (0.011) | (0.010) | (0.012) | (0.013) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.178 | 0.196 | 0.188 | 0.220 | 0.246 | 0.244 | 0.321 | 0.174 |
| Observations | 184,539 | 940,245 | 1,087,986 | 61,458 | 284,306 | 437,286 | 265,736 | 113,762 |
| F-statistic | 4,385 | 6,637 | 7,222 | 1,386 | 4,380 | 4,516 | 1,557 | 1,032 |

*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 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 | 0.014*** | 0.008*** | 0.008*** | 0.010** | −0.007 | 0.006*** |
| | (0.003) | (0.002) | (0.002) | (0.004) | (0.017) | (0.001) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.024 | 0.025 | 0.025 | 0.026 | 0.185 | 0.011 |
| Observations | 421,933 | 913,467 | 639,936 | 273,103 | 108,594 | 1,226,428 |
| F-statistic | 3,579 | 8,394 | 7,616 | 3,403 | 1,662 | 8,764 |

| | 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 | 0.025** | 0.041*** | 0.020 | 0.006 |
| | (0.011) | (0.010) | (0.015) | (0.011) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.064 | 0.065 | 0.021 | 0.044 |
| Observations | 79,864 | 101,669 | 17,945 | 58,655 |
| F-statistic | 1,065 | 917 | 643 | 600 |

*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 |
| Panel A: Overall | (1) | (2) | (3) | (4) |
| Patent Grant | 0.041*** | 0.036*** | 0.045*** | 0.046*** |
| | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.006) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.183 | 0.414 | 0.598 | 0.283 |
| Observations | 1,149,440 | 1,149,440 | 1,149,440 | 1,149,440 |
| F-statistic | 7,190 | 7,190 | 7,190 | 7,190 |

| | 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 | 0.035*** | 0.034*** | 0.035*** | 0.050* |
| | ( 0.013) | ( 0.006) | ( 0.005) | ( 0.026) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.419 | 0.416 | 0.412 | 0.453 |
| Observations | 184,356 | 938,938 | 1,086,535 | 61,375 |
| F-statistic | 4,020 | 6,626 | 7,151 | 1,361 |

*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) | Moved to innov. hub (2) | Left innov. hub (3) |
|---|---|---|---|
| | | Dep. Var. = | |
| Patent Grant | 0.043*** | 0.003 | 0.012*** |
| | ( 0.005) | ( 0.003) | ( 0.002) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.195 | 0.061 | 0.033 |
| Observations | 1,149,440 | 1,149,440 | 1,149,440 |
| F-statistic | 7,190 | 7,190 | 7,190 |

| Panel B: Heterogeneity | By gender: Female (1) | By gender: Male (2) | By ethnicity: White+ Asian (3) | By ethnicity: URM (4) | By industry: IT/ Software (5) | By industry: Biotech/ Pharma (6) |
|---|---|---|---|---|---|---|
| | | | Dep. Var. = Left innovation hub | | | |
| | By gender | | By ethnicity | | By industry | |
| Patent Grant | 0.011** | 0.012*** | 0.011*** | 0.028** | 0.020*** | 0.018*** |
| | ( 0.005) | ( 0.002) | ( 0.002) | ( 0.012) | ( 0.005) | ( 0.007) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.033 | 0.033 | 0.032 | 0.049 | 0.044 | 0.036 |
| Observations | 184,356 | 938,938 | 1,086,535 | 61,375 | 265,481 | 113,647 |
| F-statistic | 4,020 | 6,626 | 7,151 | 1,361 | 1,561 | 994 |

*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 | Dep. Var. = Leadership skills (1) | Concurrent positions (2) | LinkedIn connections (3) | Superstar collaboration (4) |
|---|---|---|---|---|
| Patent Grant | 0.029*** | 0.009* | 17.412** | 0.110*** |
| | ( 0.004) | ( 0.005) | ( 8.795) | ( 0.009) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.433 | 0.316 | 277.316 | 0.255 |
| Observations | 1,149,440 | 1,149,440 | 1,149,440 | 567,513 |
| F-statistic | 7,190 | 7,190 | 7,189 | 6,041 |

| | 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 | 57.7*** | 6.5 | 17.9** | 38.6 | 65.2*** | 7.8 |
| | ( 21.0) | ( 10.4) | ( 9.1) | ( 29.4) | ( 16.3) | ( 24.3) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 276.8 | 279.9 | 275.3 | 312.2 | 326.6 | 272.4 |
| Observations | 184,356 | 938,938 | 1,086,535 | 61,375 | 265,481 | 113,647 |
| F-statistic | 4,025 | 6,625 | 7,151 | 1,362 | 1,560 | 994 |

| | 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 | 0.118*** | 0.110*** | 0.109*** | 0.124*** | 0.104*** | 0.124*** |
| | ( 0.018) | ( 0.010) | ( 0.009) | ( 0.034) | ( 0.017) | ( 0.021) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.254 | 0.257 | 0.254 | 0.270 | 0.262 | 0.254 |
| Observations | 88,172 | 465,603 | 535,332 | 29,913 | 126,368 | 60,367 |
| F-statistic | 2,291 | 5,534 | 5,979 | 679 | 1,387 | 798 |

*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. = | |
|---|---|---|---|
| | Has subsequent patent app. | Total subsequent patent app. | Patent Number approved |
| Panel A: Subsequent patenting | (1) | (2) | (3) |
| Patent Grant | 0.015** | 0.018 | 0.175*** |
| | ( 0.007) | ( 0.024) | ( 0.020) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.481 | 1.336 | 0.924 |
| Observations | 1,407,964 | 1,407,964 | 1,407,964 |
| F-statistic | 7,661 | 7,661 | 7,661 |
| | Network growth | Pct. new co-inventors | USPC expansion |
| Panel B: Inventor network growth | (1) | (2) | (3) |
| Patent Grant | -0.020*** | -4.020*** | -0.051*** |
| | ( 0.008) | ( 0.727) | ( 0.009) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.409 | 68.723 | 0.582 |
| Observations | 678,681 | 570,159 | 678,681 |
| F-statistic | 6,640 | 6,446 | 6,640 |
| | Forward citations | Patent value | Breakthrough patent |
| Panel C: Patent quality | (1) | (2) | (3) |
| Patent Grant | 5.182*** | 0.051*** | 0.016*** |
| | ( 0.750) | ( 0.005) | ( 0.002) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 5.950 | 0.144 | 0.033 |
| Observations | 1,407,964 | 1,407,964 | 1,407,964 |
| F-statistic | 7,661 | 7,661 | 7,661 |

*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. = | | | | |
|---|---|---|---|---|---|
| Panel A: Workplace Glassdoor perceptions | Overall rating (1) | Culture rating (2) | Career rating (3) | Innov. culture (4) | Wage growth (5) |
| Patent Grant | -0.047*** | -0.046*** | -0.049*** | -0.008*** | -0.02** |
| | ( 0.009) | ( 0.012) | ( 0.010) | ( 0.002) | ( 0.011) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample restrictions | ✓ | ✓ | ✓ | ✓ | |
| Dep. Var. Mean | 1.084 | 1.070 | 1.090 | 1.009 | 1.341 |
| Observations | 101,099 | 82,972 | 101,001 | 101,090 | 640,766 |
| F-statistic | 941 | 771 | 940 | 943 | 4,945 |

*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.

# INTERNET APPENDIX

## The Returns to Recognition: Patent Grants and the Allocation of Innovative Talent

## (NOT INTENDED FOR PUBLICATION)

# 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" $\rightarrow$ "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 1,493,514 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 18,809,358 first-time patent applicants in the USPTO database spanning 2001–2020. Through a multi-stage matching process, we successfully linked 1,493,514 inventors (7.9% match rate) to Revelio Labs career data. Our 7.9% 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 529,645 inventors (35.5% 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 4,447 inventors (0.3%) 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 526,469 inventors (35.3%) 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 27,564 inventors (1.8%) 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 405,389 inventors (27.1%) through Revelio Labs' proprietary linkages between patent records and LinkedIn profiles.

Table C.1 explains in detail how we go from 18.8 million observations to 1.49 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 1,469,160 first-time applicants, with 1,065,236 in the treatment group (first application granted) and 403,924 in the control group (first application rejected). The control group's smaller size reflects the USPTO's high overall grant rate (approximately 73% 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 due to the USPTO's high overall grant rate (∼73% 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 than other match types, 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 2.16 percentage points more PhD holders (normalized difference = 0.058) and 4.00 percentage points more Master's degree holders (normalized difference = 0.104). The treatment group also has higher prestige scores (0.386 vs. 0.344, normalized difference = 0.091) and more LinkedIn connections (285 vs. 254, normalized difference = 0.036). 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 (0.411 vs. 0.362, normalized difference = 0.103), and LinkedIn connections show minimal difference (280 vs. 242, normalized difference = 0.050). 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 × 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 11,813 unique examiners across 742 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 0.683–0.696 and standard deviation of 0.189–0.218. The 10th percentile examiner approves 37.5–42.5% of applications, while the 90th percentile examiner approves 90.5–93.0%, demonstrating considerable heterogeneity in examiner stringency. Examiner experience also varies substantially: in our first-applications sample, examiners have reviewed a median of 81 prior applications (mean: 111), while in the full staggered sample, the median examiner has 435 prior applications (mean: 588), ranging from zero (the examiner's first case) to over 875–6,237 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 × 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 (0.218) increases the probability of patent grant by 12.2 percentage points, with an $F$-statistic of 690. The staggered design using all applications (Panel B) yields even stronger

first-stage relationships, with an $F$-statistic of 27,385 in the main specification, 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 = 4,395) and male inventors (F = 6,610), though the coefficient is slightly larger for female inventors (0.608 vs. 0.550), 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 (0.526) than non-PhD inventors (0.567), 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 (2,247) indicates examiner assignment generates substantial variation in approval even among highly educated inventors. The coefficient is similar across first (0.735) and later applications (0.780), 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. Column 1 reports the baseline first-stage relationship in the full staggered sample with art unit $\times$ year fixed effects, where examiner leniency strongly predicts patent grants (coefficient 0.774; $F = 395{,}633$). Column 2 adds inventor fixed effects and restricts to inventors with two or more applications. In this specification, inventor fixed effects absorb nearly all variation in the outcome (R-squared = 1.000), and the coefficient is mechanically near zero. This reflects the fact that, once inventor fixed effects fully absorb grant propensities in a saturated specification, there is limited remaining variation to attribute to examiner leniency. Importantly, Column 1 still demonstrates that examiner leniency generates substantial quasi-random variation in patent grant probabilities in the staggered sample under art unit $\times$ year fixed effects.

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 (0.218) predicts only a 1.7 percentage point increase in PhD share and a 0.005 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 690 (first applications) to 27,385 (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

| | Obs. | Pct. | Notes |
|---|---|---|---|
| | (1) | (2) | (3) |
| **USPTO first-time applications** | **18,809,358** | **100.0%** | Utility patents, 2001–2020, with examiner |
| Match to Revelio Labs | | | |
| From PatEx | 333,783 | 1.8% | Matched via PatEx linkage |
| Exact matches | 172,305 | 0.9% | Name, company, location, app number |
| Fuzzy matches | 4,270 | 0.02% | Relaxed name/company matching |
| PatentsView-assisted | 499,348 | 2.7% | Leveraging PatentsView disambiguation |
| User-level fuzzy | 26,586 | 0.1% | Edge cases |
| Direct Revelio linkages | 380,144 | 2.0% | Revelio's proprietary matches |
| **Successfully matched to Revelio** | **1,416,436** | **7.5%** | Sum of all matching methods |
| For Matched Inventors: All Applications | | | |
| All applications | 7,871,481 | 41.8% | Matched inventors and all their applications |
| First applications | 1,416,436 | 7.5% | |
| Subsequent applications | 6,455,045 | 34.3% | |
| Restrict to First Applications Only | | | |
| First applications (matched) | 1,416,436 | 7.5% | |
| Drop: Still Pending/Other | 18,201 | 0.1% | Applications without final decision |
| **Final Analysis Sample** | **1,398,235** | **7.4%** | |
| Treatment (granted) | 1,015,491 | 5.4% | First application was granted |
| Control (rejected) | 382,744 | 2.0% | First application was rejected |

*N*otes: This table documents the sample construction process. Sample restricted to utility patent applications filed January 1, 2001 through September 30, 2020 with assigned examiners. Pre-2001 applications are excluded because they were only made public if approved, creating selection bias. Post-September 2020 applications are excluded due to automated examiner assignment issues. Among 18,809,358 first-time applicants in this period, we successfully match 1,416,436 (7.5%) to Revelio Labs employment records using six complementary methods. For matched inventors, we observe 7,871,481 total applications (5.6 per inventor on average). Our analysis focuses on first applications with final decisions, yielding 1,398,235 observations.

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

| | Total | Treatment | Control | % Treatment |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Total Sample | 1,398,235 | 1,015,491 | 382,744 | 72.6% |
| By Entity Type | | | | |
| Large Entity | 1,051,087 | 813,541 | 237,546 | 77.4% |
| Small Entity | 329,802 | 192,778 | 137,024 | 58.5% |
| Micro Entity | 17,344 | 9,170 | 8,174 | 52.9% |
| By Technology Type | | | | |
| Biotech/Pharma | 193,764 | 117,218 | 76,546 | 60.5% |
| Software/IT | 429,197 | 325,111 | 104,086 | 75.7% |
| Other Technology | 775,274 | 573,162 | 202,112 | 73.9% |

*N*otes: Sample composition by patent characteristics. Entity type based on USPTO fee status. Technology based on USPC codes: Biotech/Pharma (424, 435, 514, 600-607); Software/IT (700-726, 340-342, 370-398).

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

| Match Type | Control (1) | Treatment (2) | Total (3) | % Treatment (4) |
|---|---|---|---|---|
| Exact | 60 ( 0.0%) | 160,962 (15.8%) | 161,022 | 100.0% |
| Fuzzy | 0 ( 0.0%) | 4,270 ( 0.4%) | 4,270 | 100.0% |
| Fuzzy-PatentsView | 171,433 (44.8%) | 321,684 (31.7%) | 493,117 | 65.2% |
| Fuzzy-User-Level | 11,163 ( 2.9%) | 15,423 ( 1.5%) | 26,586 | 58.0% |
| Direct Revelio | 1,123 ( 0.3%) | 379,021 (37.3%) | 380,144 | 99.7% |
| From PatEx | 198,965 (52.0%) | 134,131 (13.2%) | 333,096 | 40.3% |
| **Total** | **382,744** | **1,015,491** | **1,398,235** | **72.6%** |

*N*otes: Column percentages show share within treatment/control. Treatment rate is the percentage of applications granted within each match type.

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

| Variable | Treatment | Control | Difference | P-value | Norm. Diff |
|---|---|---|---|---|---|
| **Gender** | | | | | |
| Female | 0.1554 | 0.1772 | −0.0218 | 0.000*** | −0.059 |
| Male | 0.8235 | 0.7964 | 0.0271 | 0.000*** | 0.069 |
| **Ethnicity** | | | | | |
| White | 0.6121 | 0.6456 | −0.0335 | 0.000*** | −0.069 |
| Asian/API | 0.3337 | 0.2991 | 0.0346 | 0.000*** | 0.074 |
| Black | 0.0239 | 0.0252 | −0.0014 | 0.000*** | −0.009 |
| Hispanic | 0.0274 | 0.0277 | −0.0003 | 0.425 | −0.002 |
| Multiple | 0.0022 | 0.0018 | 0.0004 | 0.000*** | 0.010 |
| Native American | 0.0004 | 0.0004 | 0.0000 | 0.449 | 0.002 |
| **Education** | | | | | |
| High School | 0.0063 | 0.0078 | −0.0015 | 0.000*** | −0.018 |
| Bachelor's | 0.2003 | 0.1936 | 0.0067 | 0.000*** | 0.017 |
| Master's | 0.2020 | 0.1620 | 0.0400 | 0.000*** | 0.104 |
| PhD/Doctor | 0.1776 | 0.1561 | 0.0216 | 0.000*** | 0.058 |
| MBA | 0.0552 | 0.0492 | 0.0060 | 0.000*** | 0.027 |
| **Professional Characteristics** | | | | | |
| Prestige | 0.386 | 0.344 | 0.042 | 0.000*** | 0.091 |
| LinkedIn connections | 285.0 | 254.2 | 30.8 | 0.000*** | 0.036 |
| Filing year | 2010.4 | 2008.5 | 1.8 | 0.000*** | 0.345 |

*N*otes: *** p<0.01, ** p<0.05, * p<0.10. Treatment N=1,015,491; Control N=382,744. Normalized difference = (Treatment - Control) / Pooled SD. Values >0.1 indicate meaningful imbalance.

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

| | Treatment | Control | Difference | P-value | Norm. Diff |
|---|---|---|---|---|---|
| Panel A. Gender | (1) | (2) | (3) | (4) | (5) |
| Female | 0.181 | 0.196 | −0.015 | 0.088* | −0.038 |
| Male | 0.796 | 0.778 | 0.019 | 0.032** | 0.045 |
| Panel B. Ethnicity | | | | | |
| White | 0.645 | 0.664 | −0.019 | 0.028** | −0.040 |
| Asian/API | 0.300 | 0.281 | 0.019 | 0.069* | 0.041 |
| Black | 0.025 | 0.025 | −0.000 | 0.867 | −0.002 |
| Hispanic | 0.028 | 0.028 | 0.000 | 0.964 | 0.001 |
| Panel C. Education | | | | | |
| High School | 0.006 | 0.008 | −0.002 | 0.156 | −0.021 |
| Bachelor's | 0.191 | 0.197 | −0.006 | 0.707 | −0.015 |
| Master's | 0.187 | 0.147 | 0.040 | 0.000*** | 0.108 |
| PhD/Doctor | 0.225 | 0.181 | 0.044 | 0.000*** | 0.111 |
| MBA | 0.048 | 0.045 | 0.004 | 0.046** | 0.017 |
| Panel D. Professional Characteristics | | | | | |
| Prestige | 0.411 | 0.362 | 0.048 | 0.000*** | 0.103 |
| LinkedIn connections | 279.9 | 242.0 | 37.9 | 0.000*** | 0.050 |
| Filing year | 2011.2 | 2008.7 | 2.5 | 0.000*** | 0.463 |

*N*otes: *** p<0.01, ** p<0.05, * p<0.10. SEs clustered at art unit. Weighting by year × tech class cells.

Table C.6: Examiner Characteristics

| Panel A. Sample Composition | First Apps Only (1) | All Apps (Staggered) (2) |
|---|---|---|
| Total observations | 1,398,235 | 7,290,457 |
| Unique examiners | 11,813 | 12,229 |
| Unique inventors | 1,398,235 | 7,290,457 |
| Unique art units | 742 | 767 |
| Applications per inventor (median) | 1.0 | 1.0 |
| **Panel B. Examiner Leniency (Approval Rate)** | | |
| Mean | 0.683 | 0.696 |
| Standard deviation | 0.218 | 0.189 |
| 10th percentile | 0.375 | 0.425 |
| 25th percentile | 0.550 | 0.584 |
| Median | 0.722 | 0.735 |
| 75th percentile | 0.850 | 0.841 |
| 90th percentile | 0.930 | 0.905 |
| Range | [0.000, 1.000] | [0.000, 1.000] |
| **Panel C. Examiner Experience (Prior Applications)** | | |
| Mean | 111 | 588 |
| 25th percentile | 35 | 191 |
| Median | 81 | 435 |
| 75th percentile | 155 | 812 |
| Range | [0, 875] | [0, 6,237] |

*N*otes: Examiner leniency calculated separately for each sample. First Apps: leniency from first apps only. All Apps: leniency from all applications.

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 | 0.753*** | 0.647*** | 0.613*** | 0.593*** | 0.559*** |
| | (0.008) | (0.006) | (0.006) | (0.007) | (0.007) |
| F-statistic | 8,828 | 12,004 | 9,657 | 751 | 690 |
| R-squared | 0.135 | 0.152 | 0.173 | 0.168 | 0.189 |
| Panel B. All Applications (Staggered) | | | | | |
| Examiner leniency | 0.874*** | 0.826*** | 0.800*** | 0.791*** | 0.766*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| F-statistic | 1,185,943 | 561,285 | — | — | 27,385 |
| R-squared | 0.145 | 0.151 | 0.160 | 0.158 | 0.169 |
| Art unit FE | | ✓ | ✓ | ✓ | |
| Year FE | | | ✓ | ✓ | |
| Inventor controls | | | | ✓ | ✓ |
| Art unit×year FE | | | | | ✓ |

*N*otes: Examiner leniency calculated separately: Panel A uses only first apps; Panel B uses all apps. SEs clustered at art unit (Panel A) or inventor (Panel B). ***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 | 0.608*** | 4395 | — | — |
| | (0.009) | | | |
| Male inventors | 0.550*** | 6610 | — | — |
| | (0.007) | | | |
| Panel B. By Education | | | | |
| No PhD | 0.567*** | 7070 | — | — |
| | (0.007) | | | |
| PhD holders | 0.526*** | 2247 | — | — |
| | (0.011) | | | |
| Panel C. By Application Sequence | | | | |
| First application | 0.735*** | 13371 | 0.735*** | 13371 |
| | (0.006) | | (0.006) | |
| 2nd-5th applications | — | — | 0.780*** | 319191 |
| | | | (0.001) | |
| All applications | — | — | 0.774*** | 395646 |
| | | | (0.001) | |

*N*otes: All specifications include art unit×year FE. All F-statistics exceed 10. ***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 | 0.774*** | 0.000*** |
| | (0.001) | (0.000) |
| $F$-statistic | 395,633 | – |
| R-squared | 0.170 | 1.000 |
| Observations | 7,290,158 | 7,290,158 |

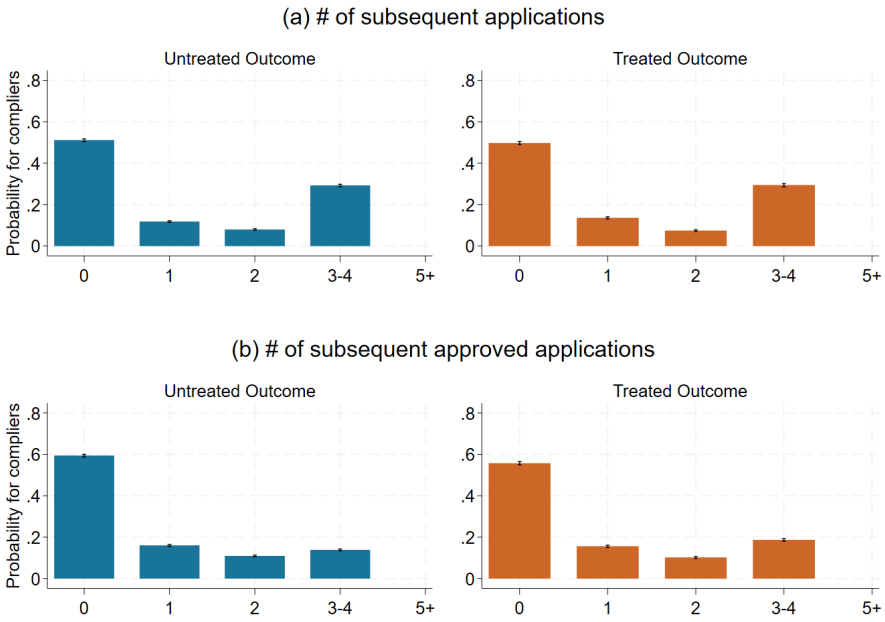
*N*otes: Column 1 uses all applications. Column 2 adds inventor FE and restricts to inventors with 2+ applications to identify from within-inventor variation. SEs clustered at inventor level. ***p<0.01.

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

| Dep. var. = Inventor characteristic | |
|---|---|
| Panel A. Demographics | (1) |
| Female | −0.014*** |
| | (0.003) |
| White | 0.004 |
| | (0.004) |
| Asian/API | −0.002 |
| | (0.004) |
| Black | −0.001 |
| | (0.001) |
| Hispanic | −0.001 |
| | (0.001) |
| Panel B. Education | |
| Bachelor's degree | -0.002 |
| | (0.003) |
| Master's degree | 0.011*** |
| | (0.002) |
| PhD | 0.017*** |
| | (0.003) |
| MBA | 0.006*** |
| | (0.002) |
| Panel C. Professional Characteristics | |
| Prestige score | 0.022*** |
| | (0.003) |
| LinkedIn connections | 8.4* |
| | ( 5.0) |

*N*otes: Each row is a separate regression with art unit×year FE. SEs clustered at art unit. ***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 | 0.009*** | 0.009*** | 0.009*** |
| | (0.002) | (0.002) | (0.002) |
| Observations | 1,335,987 | 1,335,987 | 1,335,987 |
| Dep. Var. Mean | 0.025 | 0.025 | 0.025 |
| F-Statistic | 8,670 | 5,1535 | 17,555 |

*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 |
| | (1) | (2) | (3) |
| *Panel A: Art-unit-by-year Fixed Effects* | | | |
| Patent Grant | 0.0094*** | 0.0061*** | 0.0065*** |
| | ( 0.0016) | ( .) | ( 0.0003) |
| Dep. Var. Mean | 0.025 | 0.025 | 0.025 |
| Observations | 1,335,996 | 1,347,034 | 1,347,460 |
| F-statistic | 51,564 | 9.6 | – |
| *Panel B: Year Fixed Effects Only* | | | |
| Patent Grant | -0.0090*** | -0.0102*** | 0.0039*** |
| | ( 0.0010) | ( .) | ( 0.0003) |
| Dep. Var. Mean | 0.025 | 0.025 | 0.025 |
| Observations | 1,336,374 | 1,347,431 | 1,347,856 |
| F-statistic | 164,188 | 20.0 | – |

*Notes.* This table presents robustness checks of our main entrepreneurship findings using alternative estimators. Column (1) reports our main 2SLS specification with leave-out examiner leniency as an instrument for patent grant. Column (2) reports the UJIVE estimate following Goldsmith-Pinkham et al. (2025), which uses examiner fixed effects as many instruments and corrects for many-instrument bias. Column (3) reports the OLS estimate. Panel A includes art-unit-by-year fixed effects, which control for time-varying differences across technology fields. Panel B includes only year fixed effects (no art unit fixed effects). The sign reversal in Panel B suggests that the art-unit fixed effects are essential for identification, as they account for systematic differences in approval rates and entrepreneurship propensities across technology fields. All regressions include controls for gender, ethnicity, education, prestige, and connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.3: Robustness: Scrambled Examiner Placebo Test

| | Dep. Var. = Patent Grant (First Stage) | |
|---|---|---|
| | Real Examiners | Scrambled Examiners |
| | (1) | (2) |
| Examiner Leniency | 0.5756*** | 0.0016 |
| | (0.0025) | (0.0025) |
| Art-unit-by-year FE | ✓ | ✓ |
| Controls | ✓ | ✓ |
| Observations | 1,336,002 | 1,325,366 |
| F-Statistic | 51,544 | 0.42 |

*Notes.* This table presents the Chudik et al. (2025) scrambled examiner placebo test for instrument validity. Column (1) reports the first-stage relationship between examiner leniency and patent grant using real examiner assignments. Column (2) randomly reassigns examiner IDs within art-unit-year cells, breaking the true examiner-application link while preserving the distribution of leniency within each cell. If the instrument reflects genuine examiner effects, the F-statistic should collapse toward zero under scrambling. The F-statistic drops from 51,544 to 0.42, confirming that our instrument captures true examiner leniency rather than mechanical bias. Across 20 scrambled iterations, the mean F-statistic is 0.93 (std. dev. = 1.11, max = 3.68). All regressions include art-unit-by-year fixed effects and controls for gender, ethnicity, education, prestige, and connections. Standard errors are heteroskedasticity-robust. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.4: Robustness: Alternative Specifications

| | Dep. Var. = Entrepreneur at VC-backed startup | | |
|---|---|---|---|
| | Complete demographics | Large art units | USPC Fixed effects |
| | (1) | (2) | (3) |
| Patent Grant | 0.009*** | 0.009*** | 0.006** |
| | (0.002) | (0.002) | (0.003) |
| Observations | 1,336,005 | 1,334,669 | 1,151,112 |
| Art-unit-by-time FE | ✓ | ✓ | |
| USPC-by-time FE | | | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.025 | 0.025 | 0.029 |
| F-Statistic | 8,680 | 8,686 | 5,242 |

*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.5: Heterogeneous Effects by Senior Co-inventor Status: VC-Backed Entrepreneurship

| | Dep. Var. = Entrepreneur at VC-Backed | |
|---|---|---|
| | No Senior Co-inventor | Has Senior Co-inventor |
| | (1) | (2) |
| Patent Grant | 0.060*** | 0.028 |
| | ( 0.007) | ( 0.027) |
| Art-unit-by-time FE | ✓ | ✓ |
| Controls | ✓ | ✓ |
| Dep. Var. Mean | 0.222 | 0.277 |
| F-statistic | 7,726 | 1,065 |
| Observations | 1,342,191 | 61,129 |

*Notes.* This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant, split by whether any co-inventor on the focal inventor's first patent application had at least 2 prior patent grants. Senior co-inventor indicates the presence of an experienced co-inventor. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × application year fixed effects. Controls include gender, race/ethnicity, education, employer prestige, and network connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.6: Heterogeneous Effects by Assignee Type: VC-Backed Entrepreneurship

| | Dep. Var. = Entrepreneur at VC-Backed | | | | | |
|---|---|---|---|---|---|---|
| | All Firms | US Public | US Private | Foreign Firms | Univ. | Indiv. Inv. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Patent Grant | 0.061*** | 0.048*** | 0.072*** | 0.009 | 0.016 | -0.152 |
| | ( 0.006) | ( 0.015) | ( 0.026) | ( 0.006) | ( 0.022) | ( 0.246) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.224 | 0.352 | 0.344 | 0.089 | 0.172 | 0.120 |
| F-statistic | 8,689 | 2,381 | 1,214 | 4,410 | 624 | 8 |
| Observations | 1,335,997 | 173,808 | 67,000 | 309,622 | 40,929 | 1,221 |

*Notes.* This table presents 2SLS estimates using examiner leniency as an instrument for the first patent grant, split by assignee type. Column (1) includes all firms. Columns (2)-(6) restrict to applications where the assignee is: US Public (US Company with KPSS match), US Private (US Company without KPSS match), Foreign Company, University (keyword match), or Individual Inventor. Government assignees are excluded due to insufficient observations. Robust standard errors clustered at the art unit level are reported in parentheses. All specifications include art unit × application year fixed effects. Controls include gender, race/ethnicity, education, employer prestige, and network connections. Statistical significance of 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Table D.7: 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 | 0.041*** | 0.040*** | 0.041*** | 0.034* | 0.037*** | 0.028*** |
| | (0.010) | (0.005) | (0.005) | (0.020) | (0.007) | (0.010) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.189 | 0.185 | 0.183 | 0.196 | 0.206 | 0.258 |
| Observations | 184,345 | 938,947 | 1,086,517 | 61,386 | 492,484 | 428,219 |
| F-Statistic | 4,114 | 6,618 | 7,148 | 1,346 | 5,500 | 4,229 |

*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.8: 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 | 0.053*** | 0.039*** | 0.042*** | 0.076*** | 0.039*** | 0.027*** |
| | (0.010) | (0.006) | (0.005) | (0.021) | (0.008) | (0.009) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.186 | 0.198 | 0.193 | 0.224 | 0.241 | 0.249 |
| Observations | 184,345 | 938,947 | 1,086,517 | 61,386 | 492,484 | 428,219 |
| F-Statistic | 4,114 | 6,618 | 7,148 | 1,346 | 5,500 | 4,229 |

*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.9: 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 | 0.029** | 0.008 | 0.074* | -0.006 | 0.217*** | 0.162*** |
| | ( 0.013) | ( 0.007) | ( 0.043) | ( 0.026) | ( 0.033) | ( 0.022) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.467 | 0.483 | 1.230 | 1.357 | 0.811 | 0.947 |
| F-statistic | 4,220 | 7,243 | 4,220 | 7,243 | 4,220 | 7,243 |
| Observations | 226,948 | 1,143,694 | 226,948 | 1,143,694 | 226,948 | 1,143,694 |
| | 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 | -0.005 | -0.023*** | -5.877*** | -3.835*** | -0.083*** | -0.047*** |
| | ( 0.017) | ( 0.008) | ( 1.527) | ( 0.812) | ( 0.019) | ( 0.010) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 0.404 | 0.410 | 62.554 | 69.803 | 0.529 | 0.591 |
| F-statistic | 2,605 | 6,142 | 2,283 | 5,978 | 2,605 | 6,142 |
| Observations | 105,733 | 553,937 | 90,787 | 463,286 | 105,733 | 553,937 |
| | Forward citations | | Patent value | | Breakthrough patent | |
| | Female | Male | Female | Male | Female | Male |
| Panel C: Patent quality | (1) | (2) | (3) | (4) | (5) | (6) |
| Patent Grant | 4.295*** | 5.328*** | 0.061*** | 0.050*** | 0.021*** | 0.015*** |
| | ( 0.847) | ( 0.895) | ( 0.009) | ( 0.005) | ( 0.004) | ( 0.003) |
| Art-unit-by-time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Dep. Var. Mean | 4.053 | 6.407 | 0.112 | 0.151 | 0.024 | 0.035 |
| F-statistic | 4,220 | 7,243 | 4,220 | 7,243.8 | 4,220 | 7,243 |
| Observations | 226,948 | 1,143,694 | 226,948 | 1,143,694 | 226,948 | 1,143,694 |

*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.