Untapped Innovation Potential of University Research

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Abstract

Scientific and technological advances based in universities have sparked key marketplace innovations, fueling progress in economic prosperity and human health. Yet frictions may inhibit transfer of university research into application, leaving substantial innovation potential unrealized. This paper presents an integrated framework to measure, locate, and activate untapped innovation potential in university research. Using novel data that combines 15 universities' confidential faculty rosters, invention disclosures, patents, and licenses, we observe both the faculty and research ideas that begin pathways to commercialization and the faculty and research that do not. We find that most faculty engage in no commercialization activity, with large observable disparities by gender and career stage. We then develop AI models to predict commercialization potential from university research. These models successfully predict commercialization, reveal a large reservoir of faculty with high but unrealized innovation potential, and pinpoint specific research streams with promising commercialization opportunities. We then conduct a pre-registered randomized field experiment, partnering with the Technology Transfer Office (TTO) at a major research university. The field experiment leverages the AI tool to direct low-cost outreach from the TTO to faculty with high but latent innovation potential, comparing the treated faculty's ensuing commercialization activity against a control sample of faculty with equivalent potential. The outreach serves as an information treatment designed to raise faculty awareness of the innovation potential of their own research. Treated faculty were more likely than control faculty to file a new invention disclosure, with the difference largest and statistically detectable in the first several months following targeted outreach. Overall, this study reframes university innovation activities to consider not only realized inventions but also unrealized opportunities. Together, the results reveal a large reservoir of untapped innovation potential within universities, demonstrate that it can be systematically located among specific faculty and specific research streams, and present a mechanism to expand and accelerate the societal impact of scientific research.

Introduction

Universities are vital sources of research breakthroughs that propel standards of living and improve human health[1]. Whether transformative leaps like CRISPR and artificial intelligence (AI), broad interfaces between university science and marketplace invention[2,3], or direct commercialization activities embodied in university patenting and spin-outs, the work of university researchers underpins wide-ranging forms of progress. These benefits help motivate investment in university research, both to expand the frontiers of scientific knowledge and to spark tangible applications that yield substantial social and economic returns[1,4–8].

Yet amidst the successful applications of university research, a fundamental question persists: how much innovation potential remains untapped across the vast landscape of scientific advances at universities, and can it be unlocked? While decades of studies have examined conditions that enable or inhibit technology transfer, most studies focus on realized outputs[9–11], such as patents or startups, leaving the scale and nature of unrealized opportunities less clear.

Translating university research into innovation is inherently difficult[12]. The road from scientific insight to effective application often requires substantial investment, with uncertain prospects for success[12]. Further, individual researchers are highly specialized,[13,14] constrained by increasingly narrower expertise as the overall scale and depth of scientific knowledge has increased[15]. This narrowness of expertise creates potentially deep information gaps between researchers and market participants, making it difficult to perceive how new research insights might translate into tangible or valuable applications. Further, these knowledge gaps appear compounded by structural frictions[16,17]. Academic incentives prioritize publications and grants, crowding out attention to translational work[18–20]. The competitive pressures of publication and funding may then discourage the risky, boundary-spanning exploration that innovation often demands[21], and scientists may face substantial challenges when pursuing new directions[14,16]. As a result, universities and individual researchers that stand at the cutting edge of scientific discovery may struggle to recognize and support the application of their own breakthroughs. Together, these difficulties suggest potentially consequential limitations on technology transfer, where a system optimized toward producing knowledge may not be optimized to realize its broader potential[22].

Yet, despite these difficulties, there are wide-ranging and potentially increasing opportunities to translate science into application. Public uses of science are manifold[7]. Moreover, a growing share of modern inventions draw directly on prior scientific advances, and the technological relevance of university research continues to rise[2,3,23,24]. Analyses of the science-technology interface suggest that the structure of knowledge itself contains predictive signals of future invention, while machine learning models can detect latent patterns in research that anticipate downstream applications[23,25,26]. Indeed, whereas individual researchers are limited by specialized expertise, artificial intelligence can read and potentially see connections across the landscape of codified knowledge, directing attention to specific opportunities that human experts can further evaluate and pursue.

Whether such opportunities are realized depends on individual faculty, for whom commercialization typically begins with an invention disclosure, a report to the university's technology transfer office (TTO) describing a potentially commercializable invention. The considerations above suggest that the path to such a disclosure involves two distinct steps. The first is awareness, whereby a faculty member recognizes that their own research holds innovation potential. The second is conversion, whereby an aware faculty member acts on that recognition and submits a disclosure, a step that can be hindered by many other frictions, such as practical hurdles in engaging with the technology transfer process or competing demands on faculty time. Awareness is a precondition for conversion,

as these later frictions become relevant only once faculty perceive the potential of their own work. AI offers a direct means of addressing the first step, by identifying papers with high innovation potential and bringing them to the attention of the faculty who wrote them, whereas frictions at the conversion step are of a different nature and are unlikely to yield to information alone. This perspective also motivates the randomized field experiment we report later in the paper, which tests whether an information treatment aimed at awareness can activate faculty with high untapped innovation potential. Such a treatment can activate faculty for whom awareness is the binding constraint, but not those held back by frictions at the conversion step.

Here we construct a new database linking university faculty and their scientific research to downstream commercialization outcomes, enabling high-scale analysis of untapped innovation opportunities at US universities (Fig. 1). Critically, we obtain confidential, record-level data from the TTOs of 15 US universities [D1-D15], representing diverse institutional types and regions, and accounting for approximately 15% of R&D expenditures among US academic institutions in fiscal year 2024. These data were assembled through the Bridge initiative, a network of research universities seeking to unlock data opportunities, interpret outcomes, exchange insights, and enhance the university innovation process. This novel partnership provides unusual visibility into the commercialization lifecycle—from the moment an invention disclosure is submitted to subsequent patenting and licensing activity, allowing us to study commercialization activity from faculty intent (invention disclosure) to measures of market use (licensing outcomes). We further incorporate census-level faculty rosters for these universities, combining data from internal HR records [D16-D17] and the Academic Analytics Research Center (AARC) [D18]. With these data, we observe not only those faculty members who engage in commercialization activities, but also, crucially, every faculty member who does not, thereby capturing the broader population of potential innovators.

Our primary analysis follows tenure-line faculty over a decade of employment (2011-2020). We focus on faculty spanning life sciences & medicine (LSM) and physical sciences & engineering (PSE), yielding a panel of 12k individuals. We do not include faculty in the social sciences and humanities, where invention disclosures are rare and less relevant. Finally, we link these datasets [D1-D18] with large-scale datasets tracing publications, patents, and their interconnections, including Dimensions [D19], PatentsView [D20], and Reliance on Science[27–29] [D21], yielding a unified resource that connects people, ideas, and inventions across the academic research system.

Invention disclosures, patenting, and licensing among university faculty

We first examine faculty engagement across the commercialization lifecycle, following the steps of disclosure, patenting, and licensing. Among the 12k faculty in the 15 Bridge universities, 13.1-14.7% submit at least one invention disclosure in a given year (Fig. 2a). This share declines as we move down the pipeline: 9.1-10.6% of faculty in a given year submit a disclosure that is subsequently filed as a patent application, including both provisional and non-provisional filings (Fig. 2b), while only 2.5-3.1% submit a disclosure that is licensed within four years (Fig. 2c). All three rates remain relatively stable over the 2011-2020 period.

These aggregate rates mask substantial heterogeneity across faculty. Disaggregating by gender reveals a persistent gap at every stage of the pipeline throughout 2011-2020. In a typical year, 15.1-16.5% of male faculty file at least one disclosure, compared with 8.2-9.9% of female faculty (Fig. 2d), exhibiting a persistent gap of six to eight percentage points over the decade. The gap extends downstream: male faculty are roughly twice as likely as female faculty to have a patent application (10.6-12.1% versus 5.4-6.6%; Fig. 2e), and the difference remains visible, though smaller in absolute terms, for licensing (2.9-3.7% versus 1.2-1.6%; Fig. 2f). Disaggregating the sample by

career stage, we observe another gap over the same period. Senior faculty (associate and full professors) disclose at higher rates than junior faculty (assistant professors), 14.0-15.1% versus 10.0-13.3% across years (Fig. 2g), and this gap carries through to patenting (9.6-11.2% versus 7.3-8.7%; Fig. 2h) and licensing (about 2.8-3.4% versus 1.4-2.2%; Fig. 2i).

These patterns show that while commercialization activities differ across demographics and career stages, a substantial share of faculty does not engage in commercialization activity, even at the initial stage of invention disclosure. This raises a natural follow-up question: are there faculty doing commercially relevant work who do not engage in commercialization themselves, i.e., those with untapped innovation potential? Studying this question requires a scalable method to quantify latent innovation potential based on faculty's recent research, which we turn to next.

Measuring innovation potential with AI

To quantify a faculty member's innovation potential, we first estimate the patentability of individual papers and then aggregate these estimates at the faculty level using recent publications. We use patentability as a proxy for innovation potential: patenting is a key channel through which university research reaches application, and it is observable at scale. Our approach builds on recent work predicting papers' patenting potential from patent-paper citations[23,26] and leverages the largest existing patent-paper pair (PPP) dataset from Reliance on Science[27–29]. A PPP refers to patents and papers based on the same scientific idea, going beyond patent-paper citation relationships to provide a more precise identification of research ideas with high patentability.

For each focal year t between 2001 and 2022, we construct a supervised learning task. We treat papers that appear in PPPs during a preceding time window ([t-5, t-2]) as positive examples. We then draw an equal number of negative examples by randomly sampling papers from the same period, matched on publication year and field. We further use PPPs and matched non-PPPs from year t-1 as a validation set for hyperparameter tuning of the model. We then use focal year t as a test set for evaluating model performance.

The modeling approach uses high-dimensional SPECTER2[30] embeddings of each paper's abstract. Importantly, the model takes only the abstract text as input, deliberately excluding metadata such as author identities, institutional affiliations, and journal names. This design choice means that predictions reflect the content of the research itself rather than who produced it or where it appeared, mitigating the risk that the measure inherits biases associated with gender, career stage, or institutional prestige. Using these embeddings, we train a separate XGBoost[31] binary classifier for each focal year's training set. Figure 3a illustrates the architecture of the prediction pipeline. The average AUC (Area Under the Curve) across focal years is 0.86, indicating that the model has high predictive performance in the test sets in distinguishing papers with and without patenting potential.

We then apply each focal year's trained model to all papers by faculty members in that year. This assigns to each paper a patentability score between 0 and 1, where a higher score indicates greater patentability. Using this measure, we can map a given faculty member's research across papers and time, as in Fig. 3b, where each point represents a paper and its height reflects the AI-predicted patentability. We classify a paper as high-patentability if its score is at least 0.7.

Engagement gaps persist among faculty with high innovation potential

With this measure of innovation potential, we can now address the question raised earlier: are there faculty who appear to be conducting commercially-relevant research but are not engaging in commercialization themselves? The AI tool identifies research with potential commercial relevance, while the Bridge data allow us to observe commercialization activity across the broader faculty population—including faculty who never submit an invention disclosure. Combining these sources therefore allows us to identify where commercially promising research exists without corresponding faculty commercialization activity, and to begin to address the scale and location of untapped technology-transfer opportunities.

For each roster year between 2011 and 2020, we group faculty by the number of high-patentability papers they publish in that year (0, 1, or 2+) and compare invention engagement rates across groups, pooling faculty-years across roster years. Innovation potential strongly predicts engagement: faculty-years with two or more high-patentability papers are roughly six times more likely to include a disclosure than faculty-years with none (35.4% versus 6.0%; Fig. 4a), with similar patterns for patenting (27.7% versus 3.3%; Fig. 4b) and licensing (8.1% versus 0.9%; Fig. 4c). This pattern further validates the patentability score as a meaningful signal of commercial relevance. At the same time, even among faculty-years with the highest innovation potential, roughly two-thirds (64.6%) include no disclosure, suggesting potentially substantial untapped potential, which we examine in the next section. In addition, among faculty-years with 2+ high-patentability papers, male faculty disclose at markedly higher rates than female faculty (37.6% versus 26.8%; Fig. 4d), with parallel gaps in patenting (29.7% versus 19.6%; Fig. 4e) and licensing (9.0% versus 4.5%; Fig. 4f), and senior faculty similarly outpace junior faculty at each stage (36.8% versus 29.5% for disclosure; Fig. 4g-i). These results reveal a substantial share of high-potential faculty-years with no disclosures, patents, or licenses, and this gap is further shaped by gender and career stage: faculty producing comparably patentable work engage with the commercialization pipeline at systematically different rates.

While the raw comparisons above account for innovation potential, they do not adjust for differences in research productivity or the fields and universities where faculty work. To address this, we estimate OLS regressions on a panel with one row per faculty member, field, and roster year (faculty listed in several fields appear once per field), where the outcome is a binary indicator for whether a faculty member files a disclosure, has a disclosure advance to a patent application, or has a disclosure licensed within four years in a given year. We regress each outcome on innovation potential, gender, and career stage, including field, university, and year fixed effects (*SI Appendix* Tables S1-S3, Models 1-4); Models 2-4 further control for researcher productivity (log number of papers in year t). Innovation potential remains a strong predictor of all three outcomes: relative to faculty with no high-patentability papers, those with 2+ such papers are 22.6 percentage points more likely to disclose, 18.8 percentage points more likely to patent, and 5.7 percentage points more likely to license, conditional on productivity (*SI Appendix* Tables S1-S3, Model 2). The gender gap documented above also remains, with male faculty 2.6, 1.8, and 1.0 percentage points more likely than female faculty to disclose, patent, and license, respectively, whereas the senior-junior gap narrows to 0.7, 0.2, and 0.6 percentage points in the same regressions. Moreover, interaction models reveal that these gaps are concentrated precisely among faculty with the greatest potential. The gender gap among faculty with zero high-patentability papers is small and statistically insignificant, but widens by 9.3, 9.5, and 4.0 percentage points for disclosure, patenting, and licensing among faculty with 2+ high-patentability papers (*SI Appendix* Tables S1-S3, Model 3); the senior-junior gap likewise widens, by 6.9, 5.9, and 2.4 percentage points, among faculty with 2+ high-patentability papers (*SI Appendix* Tables S1-S3, Model 4). In other words, untapped

potential is not evenly distributed: it is most pronounced where research is most commercially promising, and the more so among female and junior faculty.

Individual faculty may differ in unobserved and time-invariant ways. To account for such time-invariant heterogeneity, we add faculty fixed effects to the regressions (*SI Appendix* Tables S1-S3, Models 5-6). Even within the same faculty member, years with 2+ high-patentability papers see significantly higher disclosure (2.8 percentage points) and patenting (1.7 percentage points) rates than years with no high-patentability papers, conditional on productivity (*SI Appendix* Tables S1-S3, Model 6), indicating that the link between innovation potential and engagement cannot simply be explained by individual differences. For licensing, the within-faculty estimate is positive but loses statistical significance after controlling for productivity, consistent with licensing being the rarest and noisiest outcome. The gender gap cannot be estimated in these models because gender is absorbed by the faculty fixed effects, while the senior-junior gap, identified among faculty promoted during the sample period, remains positive and significant across all three outcomes (2.6, 1.6, and 1.0 percentage points; *SI Appendix* Tables S1-S3, Model 6). Note that this analysis exploits within-faculty variation in innovation potential and career stage, reporting conditional correlations within faculty members, not causal estimates.

High-potential faculty outside the commercialization pipeline

The analyses above reveal large engagement gaps even among faculty producing highly patentable research in a given year. We now sharpen the focus from annual engagement to non-engagement over an extended period, centering on faculty who have filed no invention disclosures yet have produced high-potential research—a natural reservoir of untapped innovation potential. We ask two main questions about this group. First, do high-potential non-disclosers subsequently disclose at higher rates than their low-potential counterparts—previously non-disclosing faculty without such work? This provides an additional viewpoint on whether the AI tool prospectively locates research streams with higher commercial potential. Second, how does their disclosure rate compare with that of high-potential faculty who have already engaged with the commercialization pipeline? The latter group offers a behavioral benchmark: if high-potential non-disclosers subsequently disclose at rates far below high-potential prior disclosers, the shortfall is unlikely to be explained by the commercial relevance of their research alone, and instead points to frictions specific to initial engagement.

Prior literature suggests several candidate frictions that may keep high-potential faculty from disclosing. Following the two-step view introduced above, these frictions fall into two groups, namely those that limit awareness of one's own innovation potential and those that impede conversion once that potential is recognized. Faculty may not recognize the commercial relevance of their own work, as deepening specialization narrows the lens through which researchers evaluate applications. Even when relevance is perceived, faculty face search and transaction costs in engaging with technology transfer processes, while academic incentives centered on publications and grants raise the opportunity cost of translational effort, and pivots toward application can carry impact penalties. Others may hold preferences or professional norms that disfavor commercialization; disclosure propensities also appear socially transmitted through peers, mentors, and local environments, with additional gender-specific barriers operating through networks and industry ties. These channels differ in their implications for institutional action: whereas preferences and incentive structures are difficult to shift in the short run, information and search frictions are, in principle, addressable through low-cost, targeted outreach—the premise of the experimental intervention we describe in the next section.

To characterize this population and its subsequent disclosure behavior, for each roster year t between 2011 and 2019, we classify faculty along two dimensions: whether they filed any invention disclosure during the preceding five years [t-4, t], and whether they published at least one high-patentability lead-author paper in that window (high-potential versus low-potential). This yields four groups: high-potential non-disclosers, high-potential prior disclosers, low-potential non-disclosers, and low-potential prior disclosers (Fig. 5a). Because our disclosure records are drawn from the Bridge universities, a faculty member who recently moved from a non-Bridge institution may appear to have no disclosures while having disclosed elsewhere; we therefore exclude faculty whose primary (modal) university affiliation listed on their own papers during [t-4, t-1] is not a Bridge university, reducing the likelihood that zero disclosures reflect unobserved activity elsewhere. For the same reason, we require faculty to remain at the Bridge universities in year t+1, so that their subsequent disclosure behavior can be observed; this restricts the focal years to 2011-2019. Figure 5a shows the composition of the resulting faculty panel, pooled across roster years, so that each faculty member contributes one faculty-year for every roster year in the sample. High-potential non-disclosers—the population of interest—constitute 23% of faculty-years, nearly as large a group as high-potential prior disclosers (27%); the remainder comprises low-potential non-disclosers (43%) and low-potential prior disclosers (7%).

We then track the fraction of faculty-years in each group with a new disclosure in the year after the roster year (Fig. 5b). Two patterns stand out. First, among previously non-disclosing faculty, innovation potential strongly predicts entry: by the end of the year, a new disclosure follows in 7.1% of the faculty-years of high-potential non-disclosers, compared with 2.2% for low-potential non-disclosers, a more than threefold difference; high-potential non-disclosers enter at a higher rate than low-potential non-disclosers in every roster year, by a factor of 2.3 to 4.4. The AI tool thus prospectively identifies likely entrants before any recent commercialization behavior is observed. Second, this 7.1% entry rate remains far below the 41.1% rate at which high-potential prior disclosers file new disclosures over the same horizon (Fig. 5b). High-potential faculty thus diverge sharply by engagement history: high-potential non-disclosers realize roughly one-sixth the disclosure activity of high-potential prior disclosers, a gap consistent with persistent frictions to initial engagement rather than with an absence of commercially relevant ideas.

The remaining panels (Fig. 5c,d) focus on high-potential non-disclosers and examine how their entry rate varies across subgroups. By gender (Fig. 5c), male faculty enter at a higher rate than female faculty (7.5% versus 6.0% of faculty-years), directionally consistent with the population-wide results. By career stage (Fig. 5d), the pattern reverses relative to the population-wide results: junior faculty enter at a higher rate than senior faculty (9.8% versus 6.5%). This reversal is consistent with a revealed-preference interpretation: senior faculty who have gone years without disclosing have, in effect, demonstrated a lower propensity to commercialize, whereas junior faculty without disclosures are often early in their careers, with their commercialization behavior not yet revealed. The gender and career-stage patterns hold in regression analyses of all previously non-disclosing faculty, high- and low-potential alike, which include an indicator for high potential along with field, university, and year fixed effects, with and without a control for research productivity (*SI Appendix* Table S4, Models 1-4); the association between innovation potential and subsequent disclosure persists with faculty fixed effects (*SI Appendix* Table S4, Models 5-6). With faculty fixed effects, the career-stage coefficient changes sign, as years after promotion to associate or full professor carry a probability of a new disclosure that is 1.5-1.7 percentage points higher for the same faculty member (*SI Appendix* Table S4, Models 5-6), an estimate identified from faculty promoted during the sample period. The junior advantage among non-disclosers therefore reflects differences between faculty rather than changes within faculty.

Together, these results answer both questions posed above, as high-potential non-disclosers "self-tap" at markedly higher rates than low-potential non-disclosers, yet at rates far below the benchmark set by high-potential prior disclosers. Whether the frictions behind this shortfall can be addressed is the question taken up next: we test whether a simple information treatment, built from the AI tool, can draw these faculty into commercialization activity, and thus whether awareness constitutes a binding constraint on their engagement.

A randomized field experiment to activate untapped potential

To examine whether the untapped innovation potential identified in our measurement framework can be activated in practice, we conducted a pre-registered randomized field experiment at a large US R1 university. Drawing on the university's 2024 HR faculty roster, we identified 150 tenure-line faculty in the life sciences & medicine and in physical sciences & engineering who met two criteria: (i) no invention disclosures since 2020, and no more than three disclosures before 2020; and (ii) at least one AI-predicted high-potential lead-author paper published between January 2020 and February 2025. These faculty were randomly assigned to treatment (76 faculty) or control (74 faculty), with stratification by gender, career stage, and field; baseline characteristics, including predicted innovation potential and prior disclosure outcomes, did not differ significantly across groups. Faculty in the treatment group received a personalized email (see *SI Appendix* S1.1) in May 2025 from the TTO highlighting their recent high-potential papers (as identified by the AI model above) and inviting them to discuss possible commercialization opportunities. Between the finalization of the randomization list and the TTO's outreach email, one faculty member in the treatment group and one in the control group submitted invention disclosures; both were excluded from subsequent analyses. The analysis therefore covers 75 treated and 73 control faculty. Importantly, the intervention was designed to combine AI identification of promising research with TTO staff expertise in assessing commercialization fit, and to foster a structured human-AI collaboration intended to reduce search friction and informational barriers. Within the two-step view, the email serves as an information treatment aimed at awareness, showing each faculty member which of their recent papers carry high innovation potential. By inviting faculty to meet with the TTO, the outreach may also ease some conversion frictions, such as uncertainty about the disclosure process or a lack of practical support, while leaving many others unaddressed, such as the absence of new work ready for disclosure or competing demands on faculty time. The control group received no outreach. The pre-registered primary outcome was invention disclosures.

The outreach led to substantial engagement, with more than 70% of treated faculty responding and meeting with the TTO. According to the head of the TTO and the invention managers involved, many of these faculty were individuals with whom the office had previously had little or no interaction, indicating that the intervention surfaced researchers who otherwise would not have come into contact with the TTO. The TTO also noted that they valued these conversations, which provided opportunities to get to know faculty, learn about ongoing research directions, and collaboratively explore potential applications. Moreover, they observed that faculty appreciated the outreach, as it signaled that the university recognized and valued the potential real-world impact of their research.

For each month, we track the cumulative fraction of faculty who have filed at least one new invention disclosure since the outreach. Over the following 12 months, treated faculty disclosed at higher rates than control faculty, with the gap concentrated in the first few months. By month 4, 14.7% of treated faculty had filed a new disclosure, compared with 5.5% of control faculty, and by month 12 the shares were 20.0% and 16.4% (Fig. 6a). Estimating the treatment-control difference in this cumulative outcome at 3, 6, 9, and 12 months with OLS regressions, we

find a treatment effect of 8.3 percentage points at month 3 (significant at the 10% level; Fig. 6b). In later months, point estimates remain positive at 4.6-8.5 percentage points but are no longer statistically distinguishable from zero as the control group partially catches up; the month-12 treatment-control difference should therefore be read as directional, with the clearest evidence of a treatment effect lying in the acceleration of disclosures during the initial months after outreach. At the same time, 80.0% of treated faculty had not filed a new disclosure by month 12. Given that more than 70% of treated faculty met with the TTO, at least half of the treatment group did so yet had not disclosed by month 12, suggesting that conversion frictions not addressed by the outreach, such as the absence of new work ready for disclosure, continued to bind for many of these faculty.

Disaggregating the treatment effect reveals that the response is concentrated in specific groups (Figs. 6c-f). Among female faculty, treatment effects are small and statistically indistinguishable from zero (Fig. 6c), whereas among male faculty, the treatment effect is 10.2 percentage points at month 3 and 14.4 percentage points at month 9, significant at the 10% level at months 3 and 6 and at the 5% level at month 9 (Fig. 6d). By career stage, the effect is strongest among junior faculty, for whom treatment raises disclosure by 24.0 percentage points at month 6, significant at the 5% level (Fig. 6e), while effects for senior faculty are small and insignificant throughout (Fig. 6f). These patterns suggest that using AI models and low-cost, human outreach may unlock untapped potential, and that the approach is most effective among male and junior faculty. Notably, the most responsive groups are also those that engage at comparatively higher rates absent any intervention (Fig. 5c,d), suggesting that a single informational contact most readily activates faculty already near the margin of engagement, for whom awareness may have been the last remaining constraint; we examine the implications of this asymmetry in the Discussion.

Discussion

Taken together, our analysis reveals substantial and persistent untapped innovation potential among tenure-line faculty at US universities. In a typical year, only a small fraction of faculty files an invention disclosure, and fewer still see that work patented or licensed. This low engagement rate does not simply reflect an absence of ideas with innovation potential. Even among faculty whose research has high innovation potential, most do not disclose inventions. Indeed, faculty producing high-potential research without recent disclosures constitute nearly a quarter of the faculty-years in our panel—comparable in size to the actively engaged high-potential group—and their subsequent disclosure rate is roughly one-sixth that of high-potential prior disclosers.

By combining large-scale faculty rosters, confidential records of invention disclosures, patents, and licensing, and AI predictions of research patentability, we introduce a measurement framework that identifies this unrealized potential at scale. Unlike traditional approaches that rely solely on realized outcomes, our methods surface latent connections between scientific work and downstream technologies, capturing the technological relevance of research before it yields disclosures, patents, or licenses. The approach also targets a key friction at its source. Deepening specialization narrows what any individual researcher can perceive about the applications of their own work, whereas AI models trained on the science-technology interface can read across the boundaries of specialization, with human experts supplying the contextual judgment the models lack. This shift is conceptual as well as methodological, suggesting that the innovation performance of research institutions can be assessed not only by realized outputs but also by the latent potential of their research portfolios, and that the gap between the two is itself a measurable and actionable quantity. Notably, the framework is forward-looking in a testable sense. Among faculty with no recent disclosures, those identified as high-potential subsequently disclose at more than three times the rate of low-potential

non-disclosers, even in the absence of any intervention. The framework thus provides universities with actionable signals about where latent opportunities are located.

Whereas work on "missing Einsteins" and "lost Marie Curies" documents talent lost before entry into innovation careers[32,33], the phenomenon we document is different in kind. The untapped potential here arises among tenure-line faculty whose research already demonstrates technological relevance but who have not engaged with technology transfer processes. What keeps such faculty from disclosing? Our descriptive evidence speaks to the candidate frictions identified earlier. The concentration of subsequent entry among junior faculty is consistent with persistent non-disclosure among senior faculty partly reflecting revealed preferences, whereas non-disclosure among junior faculty more plausibly reflects information and search frictions not yet overcome—precisely the frictions that modest institutional actions can, in principle, address. Correspondingly, where frictions rather than preferences bind, mobilization may not require the long-time horizons of interventions that shape exposure to innovation early in life, nor large structural reforms. Viewed through the two-step lens of awareness and conversion, the appropriate remedy depends on where a friction arises, as information can relieve frictions at the awareness step, whereas frictions at the conversion step call for other forms of institutional support. The framework identifies candidates for engagement rather than certifying that engagement is optimal in every case—some faculty may reasonably maximize impact through open science—and pairing AI identification with the judgment of technology transfer professionals, as in the intervention we test, provides that filter.

Our randomized field experiment tests the information and search channel directly, providing initial evidence that a fraction of this untapped innovation potential can be activated through AI identification paired with low-cost human outreach. The intervention raised new invention disclosures among previously unengaged faculty within months, with treated faculty maintaining a higher disclosure rate over the one-year observation window. The outreach engaged faculty members who had historically had little or no contact with the TTO, and the large majority of treated faculty responded and met with the TTO. Because the treatment targets awareness while leaving many conversion frictions in place, faculty who remain non-disclosers after treatment point to frictions that information alone does not remove, and the measured effect likely understates what interventions addressing both steps could achieve. We note that the control group partially converges toward the treatment group over the observation window, so the measured effect may combine genuine activation with acceleration of disclosures that would eventually have occurred. These two interpretations carry distinct implications and merit unpacking. Under the activation interpretation, outreach expands the extensive margin of commercialization—drawing into the pipeline faculty who would otherwise never have engaged—the outcome most directly responsive to the untapped potential we document. Under the acceleration interpretation, outreach shifts forward the timing of disclosures that would have occurred regardless, leaving the eventual number of disclosing faculty unchanged. Our data cannot yet adjudicate between the two. The treatment-control difference in cumulative disclosure remains positive at month 12 but is not statistically significant, a pattern consistent with partial convergence. Yet with 148 faculty across the two arms, the experiment is powered to detect only large effects and cannot rule out a persistent gap of meaningful size. Importantly, acceleration alone would still be consequential. In a first-to-file patent system, earlier disclosure can be decisive for establishing priority; earlier engagement also compresses the lag between discovery and application, and the social value of innovations arriving sooner compounds over time. Moreover, the two mechanisms may interact dynamically. If a first disclosure builds relationships with the TTO and lowers the cost of subsequent engagement, accelerated entry today may generate genuine activation tomorrow, a possibility our one-year window cannot capture. Distinguishing these accounts therefore requires evidence over longer horizons, including whether the treatment-control gap persists or closes,

whether treatment-induced disclosures advance to patents and licenses at rates comparable to organic disclosures, and whether treated faculty go on to disclose repeatedly.

Furthermore, we find that the treatment response is concentrated among male and junior faculty, with effects for female and senior faculty statistically indistinguishable from zero. The strong response among junior faculty is consistent with the frictions interpretation, while the null effects for senior faculty accord with the revealed-preference account above. The gender pattern is similarly informative. Our observational analyses locate especially large unrealized potential among high-potential female faculty, yet the gender gap persists in the selected non-discloser sample and does not respond to the information treatment. This asymmetry deserves emphasis. The intervention proves most effective precisely where baseline engagement is already highest—among male and junior faculty (Fig. 5c,d)—and least effective where our measurement framework locates the largest unrealized potential. In this sense, light-touch informational outreach appears to activate faculty closest to the margin of engagement rather than those facing the deepest barriers, delimiting what such interventions can accomplish on their own. Together, these patterns suggest that the barriers facing female faculty are not simply informational but arise at least partly at the conversion step, that a single outreach email appears insufficient to close gender gaps in commercialization on its own, and that engaging underrepresented groups may require differently designed or complementary interventions—for example, peer- or mentor-based designs that leverage the social transmission of disclosure behavior, or outreach framed around societal impact rather than commercial opportunity, an important direction for future experimentation.

Beyond individual TTOs, these findings bear on national efforts to strengthen research translation. Given the negligible marginal cost of the intervention relative to typical innovation-policy instruments, even modest activation rates imply a highly favorable return on institutional effort. US national initiatives, such as NSF's Innovation Corps (I-Corps) and newer efforts under the Directorate for Technology, Innovation, and Partnerships, including Accelerating Research Translation (ART) and Assessing and Predicting Technology Outcomes (APTO), reflect growing federal interest in strengthening the pathways from discovery to societal impact. Our results suggest that scalable, data-driven approaches, when paired with human expertise, can help institutions engage more broadly and strategically with these initiatives—and our framework offers a concrete, tested template for the predictive approaches such programs envision.

Several limitations of our analysis warrant note and point to directions for future work. The field randomized experiment was conducted at one large R1 university, which cannot capture the full diversity of US research settings. Broadening institutional experiments remains an important direction for future work. At the same time, it is, to our knowledge, among the first randomized field experiments among US tenure-line faculty members to examine innovation outcomes. Such experiments are rare because they require deep institutional partnership in a high-stakes environment, and because key outcomes, such as invention disclosures, are unobservable in public data; our TTO partnership made it possible to test the intervention and observe early outcomes directly from confidential records. Moreover, our primary outcome, invention disclosure, captures entry into the commercialization pipeline rather than ultimate market impact, and downstream outcomes such as licensing will take time to accumulate. Finally, the intervention addresses mainly the awareness step; identifying which conversion frictions continue to bind for faculty who remain non-disclosers, and designing interventions that address them, is a natural extension of this work. While our empirical focus is on US research universities and on fields with close pathways to commercial application, the conceptual framework is general. For disciplines where societal impact manifests through policy influence, cultural transmission, or public engagement, similar methods can help identify unrealized opportunities

for impact.

Overall, most prior work on academic innovation has been organized around realized outcomes. Our results suggest that these outcomes capture only part of the relevant phenomenon. Systematic measurement of unrealized potential, combined with targeted, low-cost interventions, can expand and accelerate the societal impact of scientific research.

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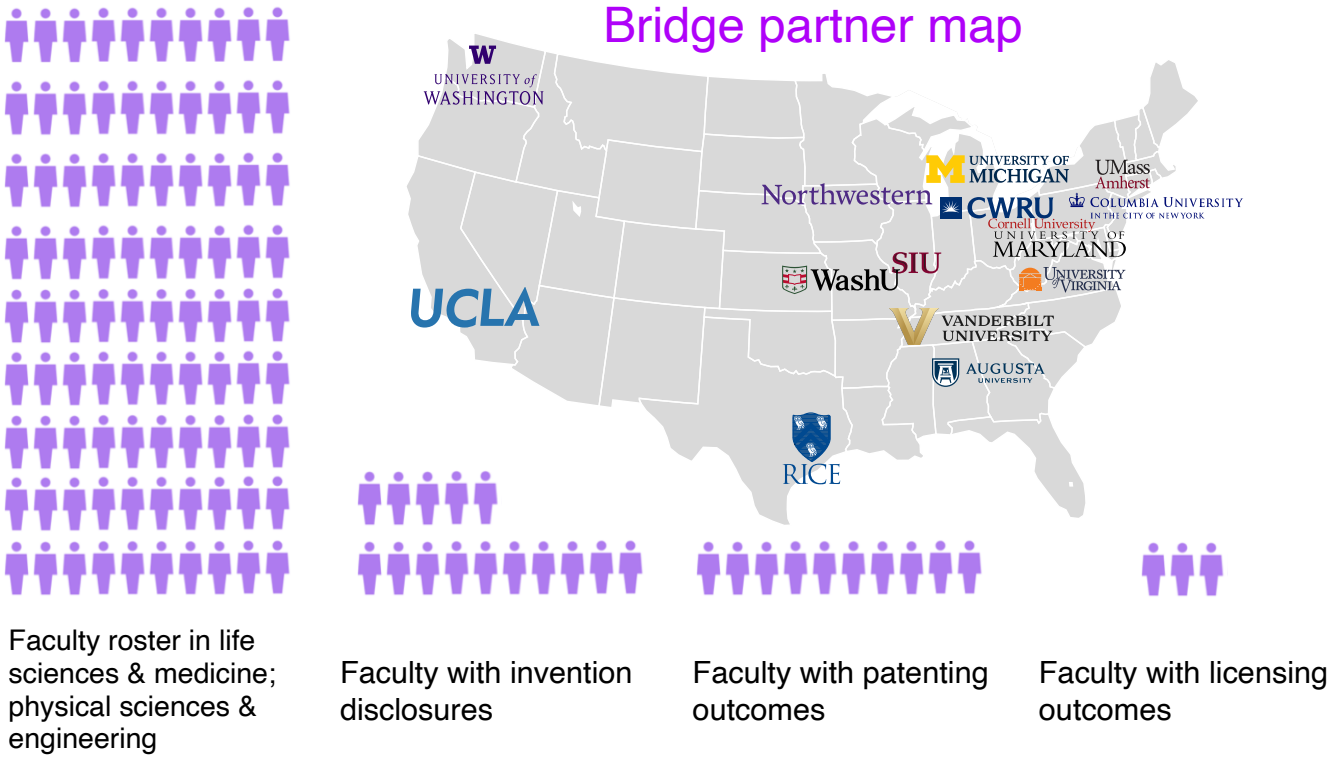


Fig. 1: **Overview of universities and data infrastructure.** The map shows the US research universities contributing confidential TTO and human resources data to this study, spanning diverse institutional types and regions. The lower panel provides an overview of the Bridge initiative data pipeline, linking complete faculty rosters in life sciences, medicine, physical sciences, and engineering to successive stages of commercialization, including invention disclosures, patenting, and licensing outcomes. This data structure allows us to study faculty and research streams that do and do not enter pathways to commercialization.

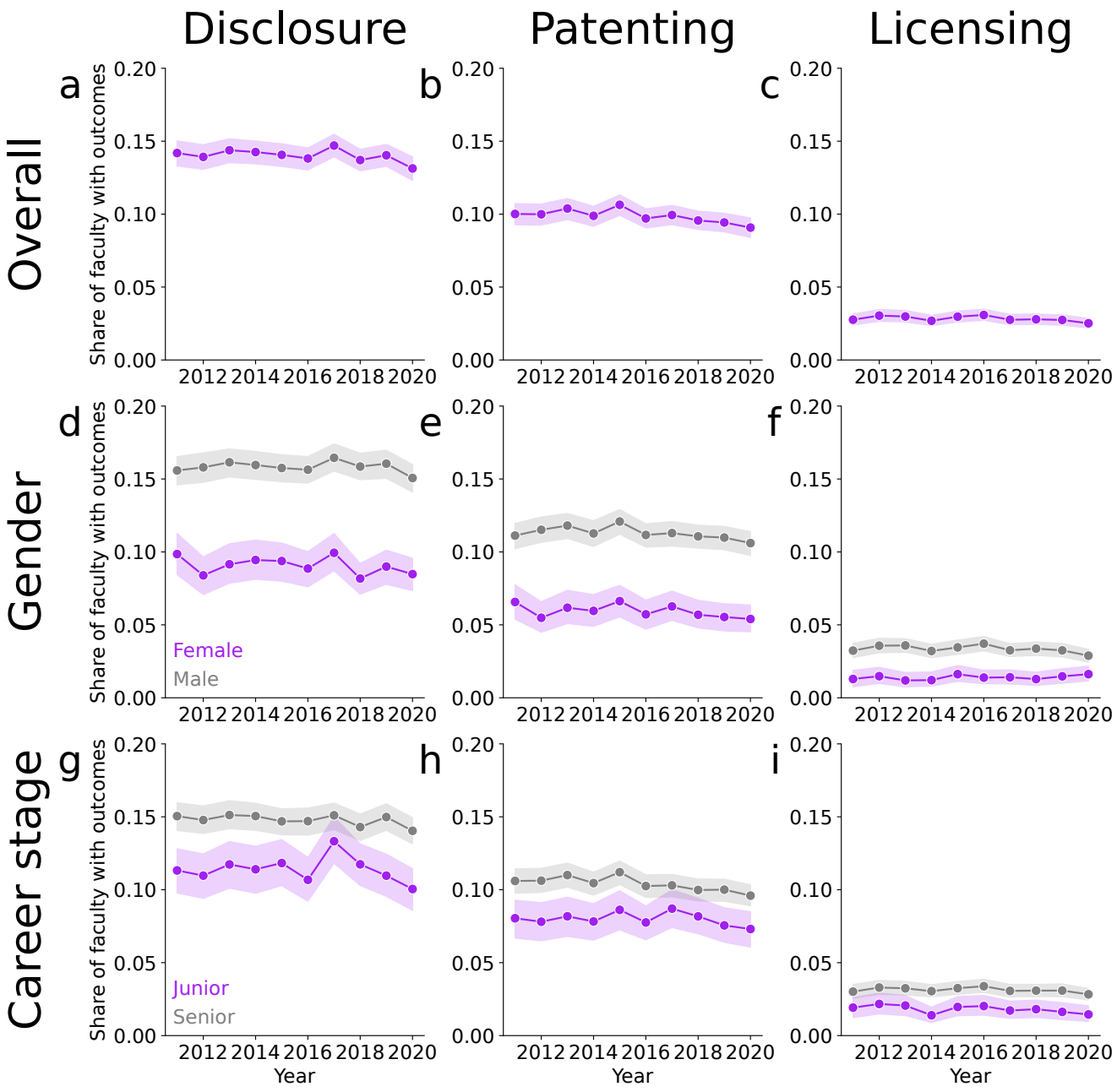


Fig. 2: **Faculty engagement across the commercialization lifecycle, 2011-2020.** For each year between 2011 and 2020, lines show the share of faculty in the Bridge universities with at least one invention disclosure in that year (**a**, **d**, **g**), at least one disclosure that subsequently advances to a patent application, including both provisional and non-provisional filings (**b**, **e**, **h**), or at least one disclosure that is licensed within four years (**c**, **f**, **i**). Shaded bands show 95% confidence intervals. (**a**-**c**) All faculty. (**d**-**f**) Female (purple) and male (grey) faculty. (**g**-**i**) Junior (purple; assistant professors) and senior (grey; associate and full professors) faculty.

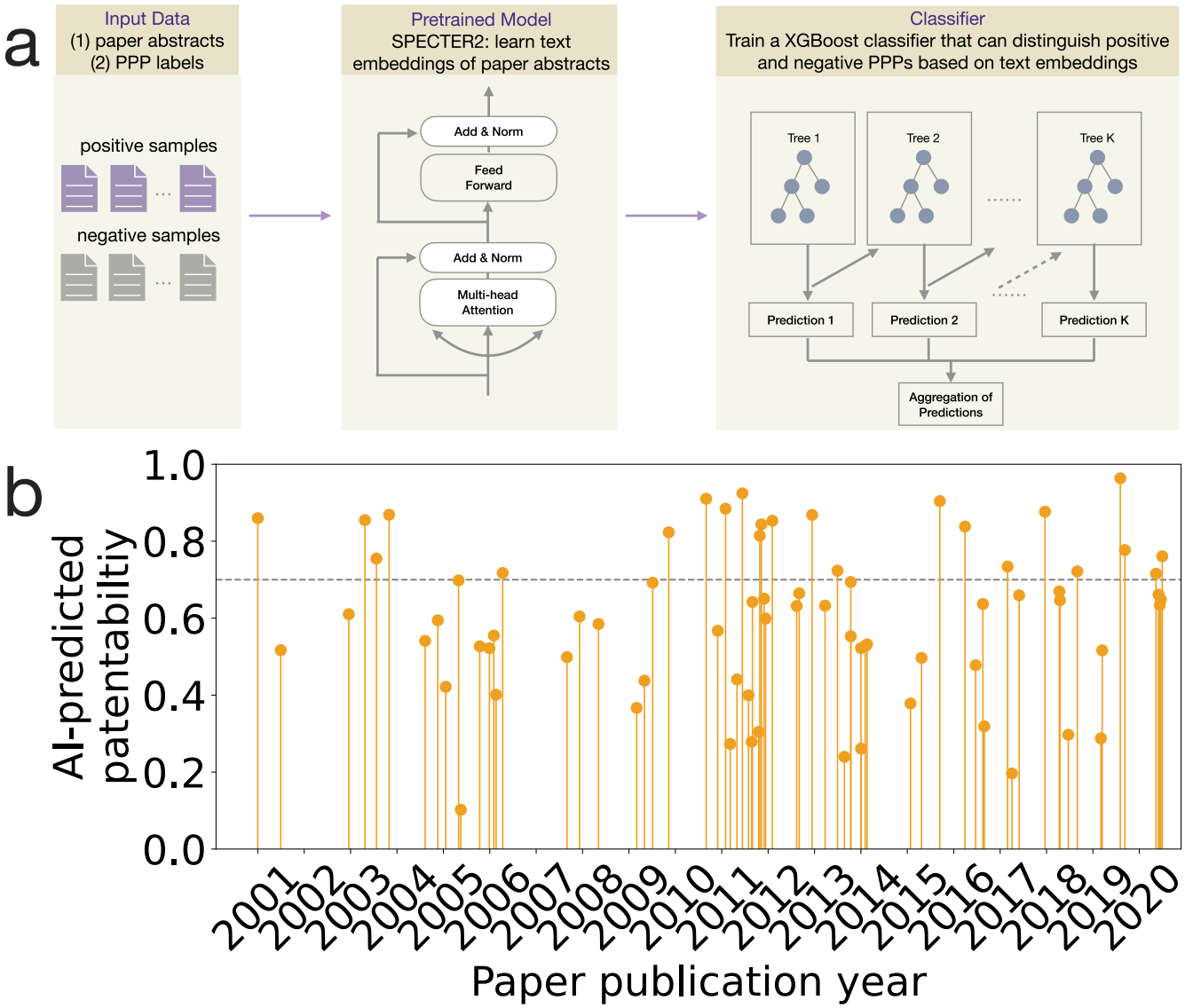


Fig. 3: **Measuring the innovation potential of faculty research.** (**a**) Architecture of the prediction pipeline. For each focal year between 2001 and 2022, papers appearing in patent-paper pairs (PPPs) during the preceding window serve as positive examples, matched with an equal number of negative examples sampled from the same period on publication year and field. Paper abstracts are embedded using SPECTER2, a pretrained transformer-based language model for scientific documents, and an XGBoost classifier is trained on these embeddings to distinguish positive from negative examples, with predictions aggregated across trees. (**b**) Example application: papers by one faculty member across their career, with each point showing a paper's AI-predicted patentability score (0-1) by publication year. The dashed line indicates the threshold for classifying a paper as high-patentability.

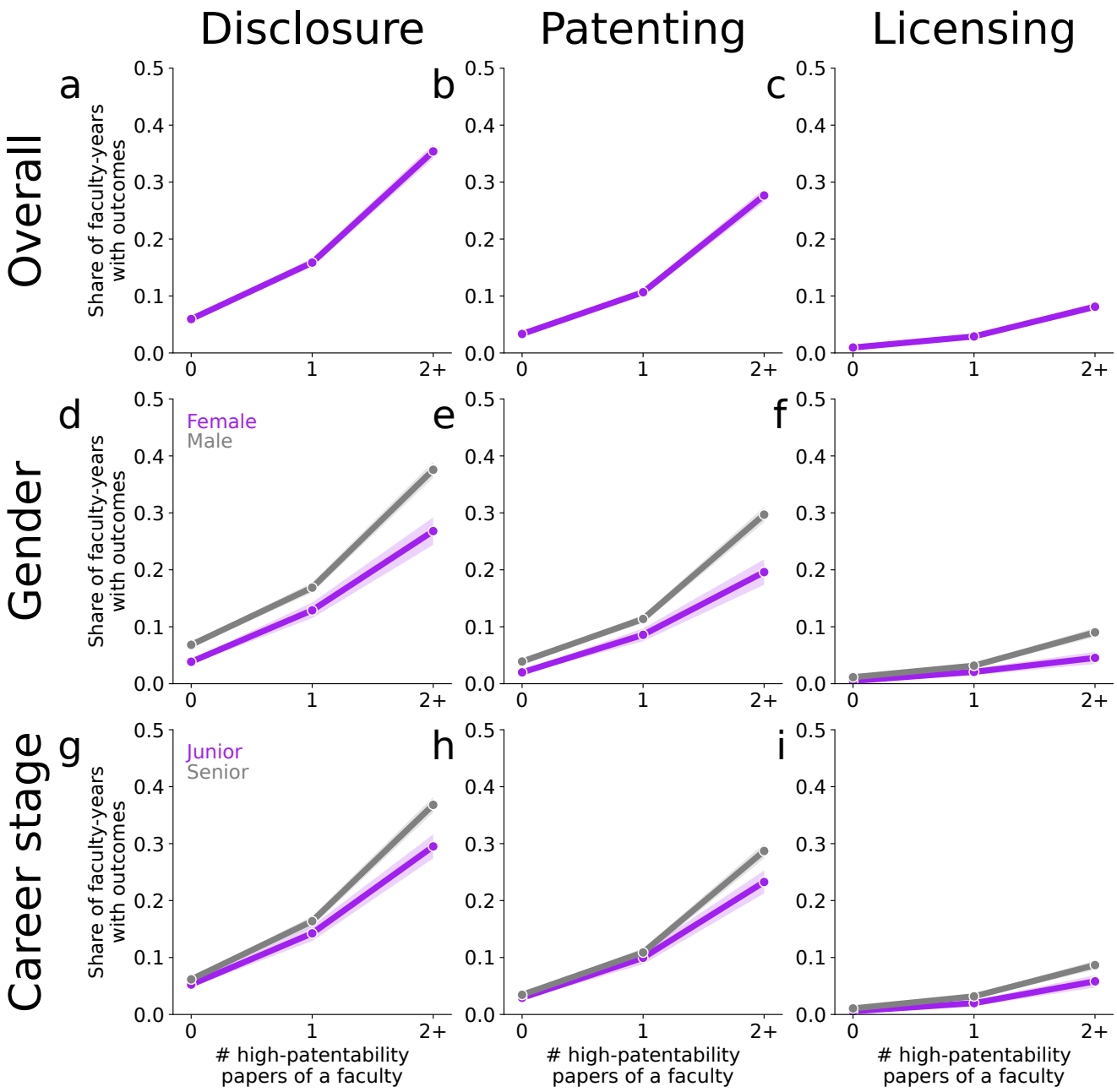


Fig. 4: **Faculty engagement across the commercialization lifecycle, by innovation potential.** For each roster year between 2011 and 2020, faculty are grouped by the number of high-patentability papers they publish in that year (0, 1, or 2+). Lines show the share of faculty-years in each group, pooled across roster years, with at least one invention disclosure in that year (**a**, **d**, **g**), at least one disclosure that subsequently advances to a patent application, including both provisional and non-provisional filings (**b**, **e**, **h**), or at least one disclosure that is licensed within four years (**c**, **f**, **i**); shaded bands show 95% confidence intervals. (**a**-**c**) All faculty. (**d**-**f**) Female (purple) and male (grey) faculty. (**g**-**i**) Junior (purple; assistant professors) and senior (grey; associate and full professors) faculty.

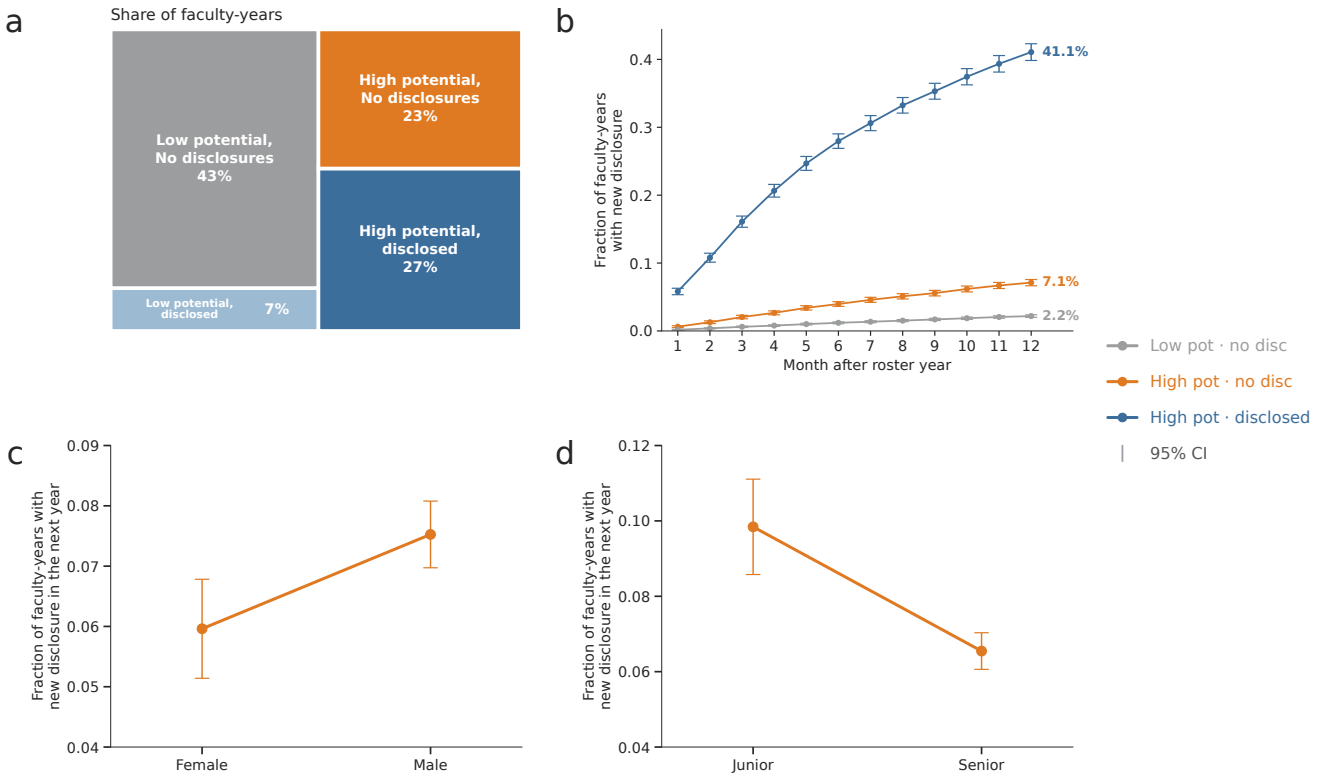


Fig. 5: **Subsequent disclosure rates by innovation potential and prior disclosure history.** For each roster year t between 2011 and 2019, faculty are classified along two dimensions: whether they filed at least one invention disclosure during the preceding five years [t-4, t], and whether they published at least one high-patentability lead-author paper during that window (high-potential versus low-potential), yielding four groups. (**a**) Share of faculty-years in each of the four groups, pooled across roster years; the area of each block is proportional to its share. (**b**) Cumulative fraction of faculty-years with a new disclosure by each month of the year after the roster year, for high-potential non-disclosers (orange), high-potential prior disclosers (blue), and low-potential non-disclosers (grey), with end-of-year values labeled. (**c**, **d**) High-potential non-disclosers only (orange in **a** and **b**), defined as faculty-years with no invention disclosure in [t-4, t] and at least one high-patentability lead-author paper in that window. Fraction of these faculty-years with a new disclosure in the year after the roster year, by gender (**c**) and career stage (**d**; junior: assistant professors; senior: associate and full professors); each panel has its own y-axis range. All points pool faculty-years across roster years; error bars show 95% confidence intervals.

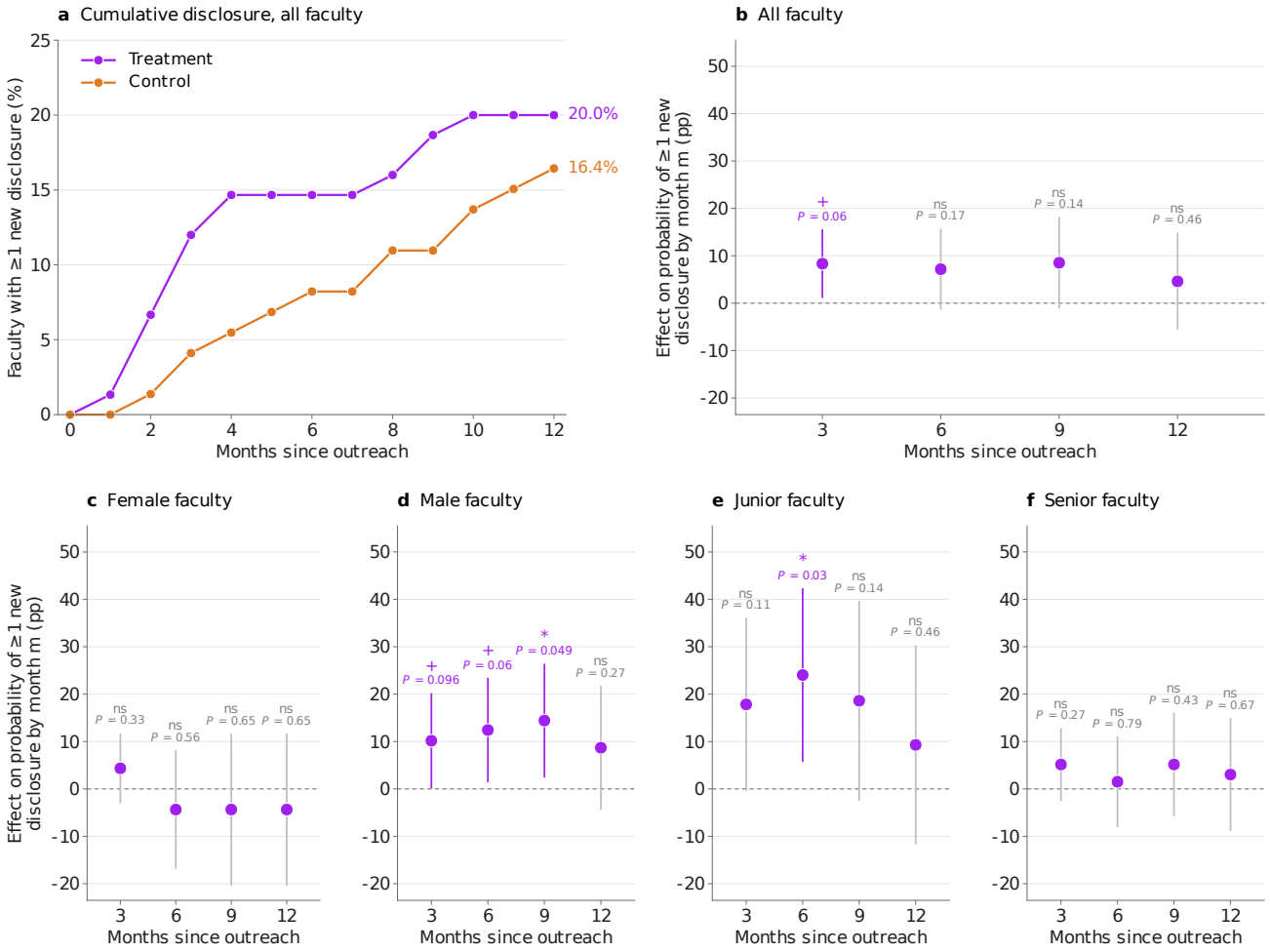


Fig. 6: **A randomized field experiment activating untapped innovation potential.** In May 2025, tenure-line faculty at a large US R1 university with no invention disclosures since 2020 and at least one AI-predicted high-potential lead-author paper published between January 2020 and February 2025 were randomly assigned to receive a personalized TTO outreach email highlighting their high-potential papers (treatment) or no outreach (control), with randomization stratified by gender, career stage, and field. (**a**) Cumulative fraction of faculty filing a new invention disclosure in each month after the outreach, for treatment and control groups. (**b**) OLS estimates of the treatment-control difference in the probability of having filed at least one new invention disclosure by 3, 6, 9, and 12 months after the outreach, with randomization-stratum (gender × career stage × field) fixed effects; dots show point estimates and bars show 90% confidence intervals, with purple bars indicating significance at the 10% level (+ $p < 0.1$) and grey bars indicating non-significance (ns); exact P values are shown above each bar. (**c**-**d**) Same specification estimated separately for female and male faculty, with randomization-stratum fixed effects. (**e**-**f**) Same specification estimated separately for junior and senior faculty, with randomization-stratum fixed effects. Heteroskedasticity-robust standard errors; * $p < 0.05$, + $p < 0.1$; ns, $p \geq 0.1$.

Supporting Information for
Untapped Innovation Potential of University Research

S1 Randomized field experiment

S1.1 Outreach email

In May 2025, the technology transfer office (TTO) of the university in which we conducted the field experiment sent the following email to each faculty member in the treatment group. The text below reproduces the email sent to one treated faculty member, with identifying details replaced as described beneath the box.

Email title:

Exploring the translational potential of your research

Email content:

Dear XXX,

The [technology transfer office] ([acronym of the technology transfer office]) is continually exploring ways to support the impact of our research in the world. We have been working to review recent publications to find signals for translational potential and have identified a number of your papers:

Publication 1: [Title of paper 1] ([year], [journal])

Publication 2: [Title of paper 2] ([year], [journal])

Publication 3: [Title of paper 3] ([year], [journal])

Publication 4: [Title of paper 4] ([year], [journal])

Publication 5: [Title of paper 5] ([year], [journal])

In addition, your prior work has been directly cited in patents, indicating how your research serves as a foundation for marketplace applications. *[This sentence was included only for faculty with at least one paper cited by a patent; it was omitted for all other faculty.]*

We would love to learn more about your work and explore opportunities with you. Do you have time to schedule a call or in-person meeting?

(XXX (copied here) can help find a time that is convenient for you.)

Thank you and look forward to connecting

XXX

XXX

XXX replaces the names of people, in the order they appear: the first name of the faculty member receiving the email; the name of the TTO staff member copied on the email, who scheduled the meetings; and the first name and the full name of the TTO staff member who sent the email. Bracketed text replaces the name and the acronym of the technology transfer office, which would identify the university. Each email listed the recipient's own papers identified by the AI model as having high innovation potential (five in the email shown); their titles, years and journals are replaced with bracketed placeholders to protect the recipient's identity. The sentence on patent citations

appeared only in emails to faculty with at least one paper cited by a patent.

S2 Supplementary tables

Table S1: Invention disclosure by innovation potential, gender, and career stage

	Invention disclosure					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Male	0.0274***	0.0260***	0.0059	0.0266***		
	(0.0045)	(0.0045)	(0.0036)	(0.0045)		
Senior	0.0114**	0.0069+	0.0077+	−0.0081*	0.0273***	0.0255***
	(0.0041)	(0.0041)	(0.0041)	(0.0036)	(0.0071)	(0.0071)
1 high-patentability paper	0.0802***	0.0636***	0.0538***	0.0595***	0.0096*	0.0036
	(0.0041)	(0.0044)	(0.0077)	(0.0078)	(0.0040)	(0.0041)
2+ high-patentability papers	0.2628***	0.2260***	0.1536***	0.1708***	0.0396***	0.0276***
	(0.0068)	(0.0067)	(0.0124)	(0.0115)	(0.0056)	(0.0059)
Log(1 + papers in year t)		0.0315***	0.0307***	0.0306***		0.0157***
		(0.0029)	(0.0028)	(0.0028)		(0.0027)
Male × 1 paper			0.0142			
			(0.0090)			
Male × 2+ papers			0.0926***			
			(0.0144)			
Senior × 1 paper				0.0059		
				(0.0089)		
Senior × 2+ papers				0.0694***		
				(0.0130)		
Field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
University fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Roster-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Faculty fixed effects	No	No	No	No	Yes	Yes
Observations	115,381	115,381	115,381	115,381	115,381	115,381
R^2	0.16026	0.16375	0.16558	0.16473	0.47530	0.47562

OLS (linear probability) estimates. The dependent variable equals 1 if the faculty member filed at least one invention disclosure in roster year t. High-patentability papers are papers the faculty member published in year t with a predicted patentability score of at least 0.7. The reference categories are female, junior, and no high-patentability papers. One observation per faculty member, field, and roster year, 2011-2020. Standard errors clustered by faculty member in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table S2: Patenting by innovation potential, gender, and career stage

	Patenting					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Male	0.0195***	0.0184***	−0.0021	0.0188***		
	(0.0038)	(0.0038)	(0.0027)	(0.0038)		
Senior	0.0052	0.0017	0.0026	−0.0102***	0.0174**	0.0160**
	(0.0036)	(0.0035)	(0.0035)	(0.0028)	(0.0061)	(0.0061)
1 high-patentability paper	0.0596***	0.0468***	0.0377***	0.0466***	0.0086*	0.0040
	(0.0035)	(0.0038)	(0.0064)	(0.0069)	(0.0034)	(0.0035)
2+ high-patentability papers	0.2167***	0.1884***	0.1139***	0.1418***	0.0265***	0.0174***
	(0.0063)	(0.0061)	(0.0114)	(0.0107)	(0.0050)	(0.0052)
Log(1 + papers in year t)		0.0242***	0.0234***	0.0235***		0.0120***
		(0.0026)	(0.0026)	(0.0026)		(0.0024)
Male × 1 paper			0.0132+			
			(0.0075)			
Male × 2+ papers			0.0952***			
			(0.0134)			
Senior × 1 paper				0.0006		
				(0.0079)		
Senior × 2+ papers				0.0587***		
				(0.0122)		
Field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
University fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Roster-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Faculty fixed effects	No	No	No	No	Yes	Yes
Observations	115,381	115,381	115,381	115,381	115,381	115,381
R^2	0.15197	0.15472	0.15731	0.15568	0.46610	0.46634

OLS (linear probability) estimates. The dependent variable equals 1 if the faculty member filed at least one invention disclosure in roster year t that advanced to a patent application (provisional or non-provisional). High-patentability papers are papers the faculty member published in year t with a predicted patentability score of at least 0.7. The reference categories are female, junior, and no high-patentability papers. One observation per faculty member, field, and roster year, 2011-2020. Standard errors clustered by faculty member in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table S3: Licensing by innovation potential, gender, and career stage

	Licensing					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Male	0.0107***	0.0103***	0.0018	0.0105***		
	(0.0021)	(0.0021)	(0.0013)	(0.0021)		
Senior	0.0073***	0.0060**	0.0064***	0.0005	0.0104**	0.0098*
	(0.0020)	(0.0019)	(0.0019)	(0.0013)	(0.0040)	(0.0040)
1 high-patentability paper	0.0141***	0.0093***	0.0060+	0.0066+	0.0014	−0.0005
	(0.0018)	(0.0021)	(0.0031)	(0.0034)	(0.0019)	(0.0020)
2+ high-patentability papers	0.0673***	0.0567***	0.0256***	0.0375***	0.0078**	0.0038
	(0.0039)	(0.0036)	(0.0067)	(0.0067)	(0.0030)	(0.0030)
Log(1 + papers in year t)		0.0090***	0.0087***	0.0087***		0.0052***
		(0.0018)	(0.0018)	(0.0018)		(0.0014)
Male × 1 paper			0.0050			
			(0.0037)			
Male × 2+ papers			0.0398***			
			(0.0082)			
Senior × 1 paper				0.0038		
				(0.0038)		
Senior × 2+ papers				0.0242**		
				(0.0077)		
Field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
University fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Roster-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Faculty fixed effects	No	No	No	No	Yes	Yes
Observations	115,381	115,381	115,381	115,381	115,381	115,381
R^2	0.04620	0.04741	0.04884	0.04790	0.37830	0.37844

OLS (linear probability) estimates. The dependent variable equals 1 if the faculty member filed at least one invention disclosure in roster year t that was licensed within four years. High-patentability papers are papers the faculty member published in year t with a predicted patentability score of at least 0.7. The reference categories are female, junior, and no high-patentability papers. One observation per faculty member, field, and roster year, 2011-2020. Standard errors clustered by faculty member in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table S4: Subsequent invention disclosure among previous non-disclosers

	New disclosure in the next year					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
High potential	0.0440***	0.0382***	0.0350***	0.0647***	0.0113*	0.0097+
	(0.0030)	(0.0031)	(0.0051)	(0.0081)	(0.0049)	(0.0050)
Male	0.0099***	0.0092***	0.0076**	0.0088***		
	(0.0026)	(0.0026)	(0.0024)	(0.0026)		
Senior	−0.0224***	−0.0248***	−0.0247***	−0.0138***	0.0169**	0.0151*
	(0.0036)	(0.0036)	(0.0036)	(0.0034)	(0.0060)	(0.0060)
Log(1 + papers in [t-4, t])		0.0092***	0.0092***	0.0095***		0.0063+
		(0.0013)	(0.0013)	(0.0013)		(0.0033)
Male × high potential			0.0043			
			(0.0061)			
Senior × high potential				−0.0319***		
				(0.0086)		
Field fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
University fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Roster-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Faculty fixed effects	No	No	No	No	Yes	Yes
Observations	54,118	54,118	54,118	54,118	54,118	54,118
R^2	0.02662	0.02810	0.02812	0.02890	0.47405	0.47414

OLS (linear probability) estimates for faculty with no invention disclosure in [t-4, t]. The dependent variable equals 1 if the faculty member filed at least one new invention disclosure in the year after roster year t. High potential is defined as at least one high-patentability lead-author paper in [t-4, t]. The reference categories are low potential, female, and junior. Faculty whose modal affiliation in [t-4, t-1] is not a Bridge university, or who are not on a Bridge roster in t+1, are excluded. One observation per faculty member, field, and roster year, 2011-2019. Standard errors clustered by faculty member in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.