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Dataset on Publication-Level Use of Scientific Equipment

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My submission introduces a new longitudinal dataset measuring the use of costly scientific equipment at scale. I construct a comprehensive price list of scientific equipment from federal research-grant records, and combine those records with an industry buyer's guide. I then link the resulting equipment price data to approximately 7.5 million U.S.-authored scientific publications' full text data spanning around four decades. The data make it possible to study a dimension of scientific production that is consequential but difficult to observe: the capital intensity of research.

The dataset will be useful to researchers studying the economics of science, innovation, research funding, university–industry interaction, and the diffusion of research technologies. It provides measures that can be used to examine which researchers and organizations gain access to costly instrument, and how new instruments diffuse across fields and institutions. As the publications data is linked to the OpenAlex publications dataset through Document Object Identifiers, researchers can integrate this dataset into their existing workflows. More broadly, the project demonstrates a replicable approach for recovering research inputs from administrative records and unstructured product information.

I will focus my presentation on the construction and potential uses of the dataset (that is, an extended version of Appendix B in the following paper). The presentation will open with the sourcing of the grant data and industry buyer's guide and then proceed through the machine-based (and human-assisted) extraction and harmonization of equipment names and prices. I will then explain how I link the equipment names to scientific publications, which produces the paper-level measures of equipment use and cost. Stylized facts about equipment use across time, sector, institution, and author type will be discussed. I will also discuss a variety of validation exercises that quantify false positive rates. Some coverage limitations will also be discussed. I will conclude with illustrative applications and solicit feedback from the I3 community. The attached paper represents one such application.

I plan to release a research-ready data product soon, with variable documentation, and replication code through a public repository such as Zenodo and/or Google BigQuery with a persistent identifier. Pending licensing restrictions from some of the base data I am using, the release will include the equipment dictionary and classification system, derived equipment-use and cost measures, relevant crosswalks, and code documenting the principal construction and matching procedures. I also plan to maintain versioned documentation so that researchers can evaluate coverage, reproduce the measures, and extend the data to additional grants, publications, fields, or time periods. Thank you for your consideration.

Instrumental Burden: Rising Capital Intensity in Science and Consequences for Innovation *

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Abstract

Why is academic science harder to commercialize than corporate science? I propose that the lower capital intensity of university research can help explain the university commercialization "discount." Commercially relevant research is equipment intensive, but universities lag corporations in their adoption of such equipment. I place the cause of this equipment gap in downstream value capture: Firms can appropriate the commercial returns of inventions through manufacturing, sales and distribution, while universities capture a smaller share of these returns. Consequently, academics should be less likely to adopt equipment compared to firms. To test the theory, I construct a new dataset of scientific capital by extracting equipment purchases from federal research grants and an industry buyer's guide, then match these equipment to around 7.5 million U.S.-authored scientific publications. Equipment use in science has roughly doubled over the past four decades. Papers using scientific equipment are more likely to be cited by patents and to form patent-paper pairs, including within simultaneous discoveries and in specifications using nearby federal equipment-funding shocks as instrumental variables. Yet universities are less likely than firms to use costly equipment, especially when their value capture is weaker, as proxied by use of own science in patents. Two further measures of appropriability are associated with greater capital intensity: i) firms that extract more stock-market value from a given unit of science and ii) university researchers who sell patents both show greater equipment use. To compensate for lower appropriability, academics in capital intensive fields skew toward scientifically novel but less invention-linked work, deepening a division of scientific labor between academia and industry. The findings suggest that the commercialization discount of university science reflects an institutional mismatch between the rising capital requirements of applied science and universities' limited downstream appropriability.

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1 Introduction

Why is academic science harder to commercialize than corporate science? This question has become more pressing as the decline of corporate science has placed greater responsibility on universities to supply the research that can be translated into new products and services (Arora, Belenzon, Patacconi, & Suh, 2020, 2025). University research suffers from a commercialization "discount" relative to corporate research: papers authored by university researchers are 2.8 times less likely than corporate papers to be cited by patents and four times less likely to have a patent pair, according to data calculated from (Marx & Fuegi, 2020).

While we now understand the extent of this discount reasonably well, much less is known about why it persists. One line of explanation holds that academic research is of systematically lower quality, because an emphasis on publication priority incentivizes a "race to the bottom" that trades off quality for speed (Hill & Stein, 2025; Tranchero, Fons-Rosen, & Fleming, 2025). Yet Bikard (2020), who holds quality fixed by comparing papers on simultaneous discoveries, still finds university research cited 23% less often by patents than corporate research. Differences in quality alone, then, cannot be the whole story.

Why would research of similar scientific merit commercialize at such divergent rates? I argue that the capital intensity of science is a critical but underexplored factor: commercially relevant research is capital intensive, but university research tends to be less capital intensive because academics capture less of the commercial value they create compared to their corporate counterparts. Capital in science consists of the physically embodied raw materials, instruments, and apparatus used in research—the means by which abstract knowledge is rendered into physical form and tested. In this paper, I focus on scientific equipment for the measurement (e.g., microscopes and spectrometers) and manipulation (e.g., automated liquid handling robots, epitaxial growth methods) of nature.[1]

These instruments of science have been critical not only to verifying scientific theories but improving the performance of new inventions and thereby clearing hurdles to commercialization (Rosenberg, 1994, Chapter 7). Finding a vaccine against COVID-19 required not only theories about manipulating messenger RNA but also identifying the shape of the viral spike

[1] I use the terms equipment and instrument interchangeably throughout the paper.

to be mimicked, a task that depended on cryo-electron microscopes. Producing modern semiconductor chips likewise depends on observing and manipulating phenomena at the atomic scale, tasks impossible without microscopes and molecular beam epitaxy machines whose setup costs run into the millions. These anecdotes show that commercially relevant research tends to be equipment intensive, but no systematic work has so far mapped scientific equipment use across fields and sectors or traced equipment effects on downstream innovation. I fill this gap by assembling new data to show that academic research lags industrial research in capital intensity, and that this gap accounts for a meaningful share of the commercialization discount: fields in the top decile of capital intensity show academic commercialization discounts that are around 30% greater than those in the bottom decile.

To identify the equipment used in science, I extract price information from roughly 84,000 federal grants for the purchase of scientific instruments and combine it with a vendor directory of research equipment. I match this to around 7.5 million scientific publications by U.S. authors, allowing me to track the capital intensity of research and its impact on commercialization by field and author affiliation across four decades.

Three patterns stand out. First, modern science has become markedly more capital intensive: measured by the share of papers using expensive equipment, capital intensity has roughly doubled over the past four decades in both the life and physical sciences. Second, scientific equipment facilitate the translation of knowledge into invention. Comparing papers on simultaneous discoveries—which holds the underlying discovery fixed—I find that papers using equipment are about 10.9% more likely to be cited by patents than those that do not. To address the concern that unobserved quality jointly raises capital intensity and inventive relevance, I instrument a researcher's capital intensity with nearby government equipment-funding windfalls and continue to find a positive effect on invention. Third, and despite this inventive payoff, universities are about 26% less likely to use equipment than firms. Lower capital intensity accounts for the university commercialization discount, and the gap is widest in the most capital-intensive fields.

Why does university research show lower capital intensity? I argue that while researchers care about both scientific discovery and commercial application (Sauermann & Cohen, 2010), the returns from commercial application depend on appropriability. Universities possess fewer

downstream value-capture devices—manufacturing, sales, distribution—than firms, which dampens their incentive to invest in capital equipment and redirects their attention to research projects that promise greater scientific recognition instead.

My empirical strategy measures variations in downstream value capture and tests whether they can explain adoption of equipment by researchers. Among firms, I measure appropriability by the excess stock-market value a firm-field captures from a given unit of science (Kogan, Papanikolaou, Seru, & Stoffman, 2017): a one-standard-deviation increase in this measure is associated with about 8% greater capital intensity. For university researchers, I measure appropriability by the share of a researcher's patents that are traded in markets for technology through reassignment; a one-standard-deviation increase is associated with roughly a 1% greater likelihood of using expensive instruments.

I make three contributions. First, I highlight the role of capital in determining the rate and direction of technical change (Barbosu & Teodoridis, 2025; Baruffaldi & Gaessler, 2026; Ganguli & Murciano-Goroff, 2025; McKeon & Boudou, 2024). Rosenberg (1992) reminds us that techniques such as nuclear magnetic resonance, now central to analytical chemistry and structural biology, originated as tools for physics experiments. Teodoridis (2018) took early steps toward studying how research tools shape discovery; I extend that effort to the whole of science. Because measuring capital intensity for scientific papers has been difficult, theories about the determinants of their use have remained speculative.[2] The dataset I assemble provides a consistent measure of capital intensity across fields, time, and author sector.

Second, I extend past work on the academic "taste" for pure science by foregrounding downstream appropriability as an overlooked source for it. Prior models of the science-industry interface typically assume the academic holds an idiosyncratic taste for science independent of downstream conditions (Aghion, Dewatripont, & Stein, 2008; Lacetera, 2009). But what appears as a personal preference may itself be shaped by appropriability. By showing that value-capture gaps can account for academics' apparent preference for Bohr's-quadrant work (curiosity-driven but use-agnostic) over Pasteur's-quadrant work (curiosity- and use-

[2] von Hippel (1976) and Riggs and von Hippel (1994) are notable exceptions. Yet, because their focus is on gauging the role of user innovation in inventing new scientific instruments, they fall short of measuring adoption or diffusion of said tools in the field. Fine-grained data collection at the government level also seems to have been sporadic: Stephan (1996, p.1223) cites equipment surveys from the National Science Foundation that now seem to have been discontinued.

driven), I relocate part of this “taste” from primitive preference to an equilibrium response.

Third, I highlight the role of "demand-side" determinants of tool adoption that have not received due attention in the literature. The fact that research tools advance science is well received.[3] Since the Scientific Revolution, instruments enabled experiments that rapidly updated our understanding of nature.[4] However, what is far less understood is the unevenness of tool adoption among researchers and the causes thereof. The majority of prior work has been focused on "supply-side" factors, finding variations in the availability of tools to study their impact on adoption behavior (Agrawal & Goldfarb, 2008; Ding, Levin, Stephan, & Winkler, 2010; Furman & Stern, 2011; Helmers & Overman, 2017; Jung & Lee, 2014; Murray, 2010; Murray & Stern, 2007). This parallels successive calls in the science policy community to shore up public resources to make equipment more accessible to academics (Committee on Advanced Research Instrumentation & Committee on Science, Engineering, and Public Policy, 2006; Klopsteg, 1957).

Explanations on the "demand-side" that studies user incentives, on the other hand, have not received due attention. My work takes a first step in this direction by showing that greater downstream returns can drive the capital intensity of upstream research. This finding has direct policy implications: if the academic capital gap is driven by value capture rather than by funding scarcity, then more supply side expansions of equipment grants will fail to close the gap to industry. Mechanisms that strengthen universities’ downstream appropriability (such as stronger TLOs) may do more. In a way, university-affiliated hospital systems offer one avenue through which academic life sciences can be captured by the researcher.

The rest of the paper proceeds as follows. Section 2 lays out the theoretical framework and empirical strategy; Section 3 presents the data on scientific instruments and their users; Section 4 presents the empirical results; Section 5 concludes.

[3] As Price (1986, p.247) aptly put it: "If you did not know about the technological opportunities that created the new science, you would understandably think it all happened by people putting on some sort of new thinking cap... revolutionary changes... more commonly seem due to the application of technology to science"

[4] Kepler and Galileo’s challenges to the Ptolemaic model of a geocentric solar system, for instance, would have been impossible without their telescopes. The field of microbiology similarly could only begin after Robert Hooke’s use of his microscope to discover the cell as the building block of living organisms in *Micrographia* (1665). The development of spectroscopy was indebted to Joseph von Fraunhofer, who started his career as an industrialist in the glass-making business and applied his expertise to replacing Newton’s prism with diffraction grating to create wavelength dispersion (1814).

2 Theory and Research Design

Why are universities worse than corporations at commercializing their research? There are two theories that can explain the university commercialization "discount": the first argues that university research quality is worse than corporate research of the same type. Hill and Stein (2025) show that academics, primarily motivated by rewards of priority, trade off speed for quality within the field of structural biology. Tranchero, Fons-Rosen, and Fleming (2025) show instances of scientific malpractice to be more common among academics than firms within the field of Alzheimer's research. On the other hand, however, academics of the same caliber may also produce different types of research from corporations. A key dimension in which this difference appears is in the capital intensity of science. Below, I first build the case that while equipments matter for commercialization, academic research is less likely to be capital intensive than corporates'. I show the innovative consequences this has had on the commercialization of advanced materials for electronic applications. The second half of this section then theorizes how differences in downstream appropriability can account for the capital intensity gap between academia and industry.

2.1 Capital intensity as an explanation for the university commercialization discount

A scientific discovery is a statement about the workings of nature: by itself, it is rarely commercially useful. For discoveries to be useful, they need to be manifested in a prototype, the prototype customized to human needs and then scaled to serve paying customers. Scientific equipment enable this follow-on, "translational" research that helps bridge discovery and production. LED bulbs illustrate how capital-intensive clearing technical hurdles toward a new innovation can be. A working LED prototype was built in 1962 at General Electric, but a competitive LED bulb to replace household incandescents took nearly fifty years to materialize, as the messy nature of LED fabrication frustrated attempts to improve the diode's brightness and longevity. Various forms of epitaxy (techniques to deposit thin films) were attempted, each requiring expensive, customized equipment: liquid phase epitaxy required furnaces to hold molten semiconductor, custom crucibles and sliding stages, and purified hydrogen gas (John-

stone, 2007), while chemical vapor deposition required custom-built reaction chambers costing millions in the 1980s. Shuji Nakamura, later a Nobel laureate for his work mass-producing blue LEDs, estimated his setup at Nichia Chemicals totaled $2 million in 1989 (Nakamura, 2014). New doping "tricks" had to be developed (RCA's metal-insulator-semiconductor construction, Nakamura's thermal annealing), and because these high-temperature, atomically exacting reactions yielded erratic results, checking for defects during epitaxy required advanced microscopes such as the Scanning Electron Microscope. Access to scientific equipment, in short, constitute a ticket of admission to applied problems with commercial implications: without them, fabricating and testing new artifacts is not possible.

Capital intensity of modern science has risen steadily thanks to scientist demand for instruments of greater precision, speed, and more diverse modalities. Take the advances made in microscopy, for instance: As early as the 1930s, Ernst Ruska and Max Knoll invented the transmission electron microscope (TEM) which could resolve 2-dimensional images at the nanometer level, overcoming limits posed by compound microscopes that operate in visible light.[5] RCA then followed up with the first commercial scanning electron microscope (the Model B) that allowed nanometer resolution in 3D in 1940. The 1980s saw the integration of charged coupled devices (CCDs) which allowed for digitized image collection. This was then followed by IBM's Scanning Tunneling Microscope (1981) and Atomic Force Microscope (1986) that could measure surface phenomena at the atomic level. In contrast to other consumer electronics products whose prices have dropped precipitously, the price of advanced microscopes have held relatively stable. The inflation-adjusted price of new models have ranged between $300,000 to $500,000 since the 1940s. Indeed, newer models, such as cryo-electron microscopes (a specialized TEM that is used by structural biologists), sell for more than $15 million.[6]

2.1.1 Academic science lags corporate science in capital intensity

Faced with rising capital intensity in the science, universities have lagged firms in their adoption of expensive instruments. While the share of U.S. firms publishing in the sciences has

[5] The first commercially available TEM would be built by Siemens in 1938.

[6] See "The must-have multimillion-dollar microscopy machine", *Nature Index* 31 August 2021 (https://www.nature.com/nature-index/news/must-have-multimillion-dollar-microscopy-machine-cryo-em)

dropped over the past four decades (Arora, Belenzon, Patacconi, & Suh, 2020), firms that have persisted in the sciences have updated their laboratories with the latest instruments. Many firms spearhead the invention of new tools for internal use. In the life sciences, one of the most cost intensive phases of drug development before clinical trials is the screening of drug candidates. To streamline this process, large pharmaceutical firms such as Merck and Pfizer pioneered High Throughput Screening (HTS) systems that integrated multi-well microplates (that housed more assays in tighter spaces) and automated pipetting robots (that improved on speed and accuracy compared to human lab assistants) in the 1990s (the tools these days retail for upwards of $1 million). Artificial Intelligence (AI) research is another field where firms not only invest heavily in specialized chips such as graphical processing units (GPUs) but also in vast troves of data infrastructure to help train superior neural network models (Hartmann & Henkel, 2019).

Universities, on the other hand, have not kept apace with this explosion in capital intensity. While the use of HTS systems in industry is commonplace, it is limited in academia. The NIH's Molecular Libraries Program (MLP) in the mid-2000s briefly funded academic HTS centers to democratize screening, but only a handful of universities (e.g., Scripps, Harvard's ICCB, Broad Institute) built real HTS facilities, with others relying on collaborations with industry. In AI research, Ahmed, Wahed, and Thompson (2023) show evidence that the number of parameters used in corporate papers outnumber university counterparts by three orders of magnitude, suggesting a scale advantage in compute and data at corporations.

2.1.2 The consequences of the academia-industry gap for innovation

A direct consequence of lower capital intensity at academia is that their research is less readily translated into market-ready inventions. The increasing capital intensity of silicon semiconductor research illustrates this point. Thanks to competition among leading chip manufacturers vying to pack more transistors in a smaller area, photolithography systems have rapidly grown in sophistication.[7] The price of the first lithography system (the GCA DSW 4800) was

[7] At first, mercury arc lamps were used as a light source until the 1990s for g-line (435nm) and i-line (365nm) stepper machines. The industry then switched to Krypton Fluoride and Argon Fluoride excimer lasers to introduce deep ultraviolet (UV) lithography (at around 200nm). More recent extreme UV lithography machines that use tin plasma are able to produce feature sizes as small as 10 nanometers.

around $300 thousand (Chip History Center, n.d.; Levinson, 2019); a Deep UV system using excimer lasers cost $80 million; the latest Extreme UV systems sell upwards of $300 million.[8] Though solid state electronics was the mainstay of electrical engineering and applied physics groups at universities when the transistor and integrated circuits were invented, academics largely exited research on or using advanced lithography systems.[9]

Instead, university researchers specialized in research related to chip design or in non-silicon materials. Carver Mead and Lynn Conway's landmark work on Very Large Scale Integration (VLSI) in 1980 is an example of the former. The standardization of chip design routines in VLSI work allowed for computer scientists to develop new algorithms such as SAT Solvers to optimize the layout of chips which were becoming increasingly dense (Nenni & McLellan, 2013). The majority of materials scientists, on the other hand, exited silicon transistor research and transitioned into compound semiconductors that promised optical applications. Indeed, III-V semiconductors such as Gallium Arsenide (GaAs) and Gallium Nitride (GaN) form the backbone of diode lasers and LEDs (Hecht, 2005; Sanderson & Simons, 2014). Others ventured farther into carbon-based 2-dimensional materials such as fullerenes and graphenes that did not have immediate downstream applications (Dresselhaus & Terrones, 2013). Andre Geim and Konstantin Novoselov isolated graphene by peeling scotch tape from a graphite crystal (later termed "mechanical exfoliation") and studied its electronic properties. While still requiring some investment in equipment (mostly in metrology), research away from silicon-based semiconductors were capital light, yet garnered much scientific recognition from peers: Geim and Novoselov won the 2010 Nobel Prize in Physics for spawning a new subfield of nanoscience. Still, innovations based on 2-d materials are still slow to reach the downstream market, owing to problems with scaling and reliability in mass production.

2.2 A simple model of researcher project choice

Why have universities lagged corporations in their capital intensity? Budget constraints may offer an explanation, but not a complete one: one reason is that public funding has been

[8] See https://www.reuters.com/technology/seeking-edge-over-rivals-intel-first-assemble-asmls-next-gen-chip-tool-2024-04-18/

[9] Though some national labs such as Lawrence Livermore and Brookhaven maintain EUV light sources, no university purchases complete stepper machines that may enable deeper process innovations.

plentiful. The flagship funding agencies each created their own core facility programs, with dedicated funding pools to support the procurement and maintenance of costly instruments. The earliest such program was the National Institutes of Health's S10 Instrumentation Grant Program which began in 1982 to assist principal investigators facing budget constraints with acquiring lab equipment. The National Science Foundation expanded a similar program in 1994 to begin the Major Research Instrumentation (MRI) program, while the Defense Department formalized its equipment purchase arrangements for universities through the Defense University Research Infrastructure Program (DURIP) in 1997.[10] It is universities, not firms, that gain priority access to core facilities funded by government. Academics also obtain access to instruments through partnerships with and donations from firms. A fuller understanding of the capital gap between academia and industry therefore requires theorizing demand side explanations for why universities may select out of capital intensive projects due to the different incentives they face.

I build on a long line of work establishing that scientists are motivated by both the non-pecuniary ("Glory") and pecuniary ("Gold") returns to research. Pecuniary returns refer to monetary payoffs realized when research yields a commercializable invention and either sales or licensing of intellectual property occur. Non-pecuniary motives include extrinsic factors such as recognition for priority of scientific discoveries, which is the key reward system that is used by the scientific community.[11] Intrinsic motivations matter too: scientists may have a "taste for science" and willing to take salary cuts to continue to engage with the open science community (Stern, 2004). Sauermann and Cohen (2010) found that a preference for intellectual challenge and independence among corporate researchers explains superior innovative performance independent of raw effort. Cohen, Sauermann, and Stephan (2020) add a desire for social impact as another motivation: figures such as Jonas Salk who made polio vaccines free for public use fit into this category. For tractability, I collapse these varied non-pecuniary researcher motivations into one term - "glory."

Use of scientific equipment can create economic value ("gold") by facilitating more inven-

[10] The doubling of the NIH budget in the late 1990s as well as the American Recovery and Reinvestment act after the global financial crisis in 2007 each saw substantial funds devoted to purchasing equipment.

[11] This is what Dasgupta and David have called the "collegiate role" of the scientific community (Dasgupta & David, 1994, p.505) that Karl Polanyi (1962) termed the "Republic of Science."

tions, but the capture of said value depends on downstream complementary assets such as manufacturing, sales, distribution, and IP infrastructure. Universities possess fewer of these assets (than firms) through which the returns to capital-intensive science can be captured. It follows that researchers with lower downstream appropriability (i.e., academics) will be less likely to select capital-intensive projects.[12]

Formally, consider a researcher choosing capital intensity (θ) to maximize her payoff. Researchers care about the "glory" as well "gold" that can come from choosing a project, net of costs.

$$\max_{\theta \in [0,1]} \quad \lambda q \phi(\theta) \; + \; \gamma q \psi(\theta) \; - \; \frac{\theta^2}{2q} \tag{1}$$

"Glory" (non-pecuniary payoffs) is captured by the first term ($\lambda q \phi(\theta)$) and represents extrinsic payoffs from peer recognition and intrinsic payoffs from a sense of autonomy and intellectual challenge that curiosity-driven work may provide. $\phi(\theta)$ represent the non-pecuniary rewards from using capital. $\lambda \sim F(0,1)$ refers to the weight researchers place on glory and could be determined by taste for peer recognition. "Gold" (pecuniary payoffs) is captured in the second term ($\gamma q \psi(\theta)$) and represents returns from downstream commercialization. $\psi(\theta)$ refers to inventions that result from the use of capital; γ refers to downstream value capture. Costs ($C(\theta, q) = \theta^2/2q$) are convex in capital intensity (θ) and decreasing in q: more talented scientists are better able to manage large-scale projects, giving them a comparative advantage in capital-intensive work. This drives sorting due to quality. I assume that capital-intensive projects create more academic value by yielding papers ($\phi'(\theta) > 0$), more commercial value by yielding inventions ($\psi'(\theta) > 0$), and that academics capture less of this commercial value ($\gamma_{univ} < \gamma_{corp}$) as they do not possess the manufacturing plants, sales organizations or IP infrastructure that incumbent firms maintain.

Two sets of predictions follow (Appendix A contains the detailed proofs). First, researchers with greater value capture should exhibit more capital intensity. Large scientific equipments raise the payoff from research, but firms with complementary assets can capture more economic value. This implies corporate research should be more capital intensive than research

[12] Note that I depart from Roach and Sauermann (2010) and Sauermann and Roach (2014) who show that scientist preferences can cause sorting into academia versus industry. My model, on the other hand, can account for greater capital intensity for corporate researchers even if ex ante scientist tastes in both sectors are distributed equally.

at universities, whose downstream value capture is dwarfed by firms'.

A corollary of this is that the academia-industry capital intensity gap will be greater in scientific fields where capital is especially useful for invention (that is, $\psi'(\theta)$ is greater). The value created by capital use will be greater for fields such as molecular biology, which are almost wholly reliant on equipment to produce inventions, compared to number theory, which is far less reliant. Since firms are better positioned to capture that value, their capital intensity gap to universities should be wider in fields where capital is more effective for invention.

The second prediction is that reaching a given θ^* requires university scientists to clear a higher threshold for λ (taste for non-pecuniary rewards), since their weaker value capture requires the marginal cost of capital intensity to be covered by payoffs through peer recognition (i.e., the glory channel) instead of proceeds from inventions (i.e., the gold channel). Greater capital intensity will be associated with deeper specialization between academics and industrial scientists.

2.3 Empirical Strategy

[TABLE 1 HERE]

Table 1 summarizes the empirical strategy which proceeds in three steps. First, I validate the key assumption that capital-intensive projects yield more invention ($\psi'(\theta) > 0$). I measure a paper's inventive relevance by Non-Patent Literature (both front page and in-text) citations from patents and patent-paper pairs and regress it on the capital intensity of the paper, which is proxied by the use and cost of expensive scientific equipment reported in the paper. Because both invention and capital intensity correlate with unobserved researcher quality, I control for paper quality, team size, and field, journal, year fixed effects. I further add comparisons within "paper twins" on the same subject and also instrument a scientist's capital intensity by federal equipment grants flowing to her geographic neighbors outside her focal field. I expect capital intensity to increase the inventive relevance of science independent of researcher quality.

Second, I test the central proposition that capital intensity rises with downstream value capture (γ). Downstream value capture is measured by three measures: first, for papers that are cited by patents, I measure whether the author's own organization shows up as a citing

patentee. The assumption is that an organization well positioned to capture downstream value will more likely use its own science. At the firm level, I estimate the average stock-market return a firm extracts per unit of science. Third, for university researchers, I proxy value capture by their propensity to trade patents in markets for technology.

Finally, I test whether universities sort into "glory" more under greater capital intensity. Measuring glory by the textual novelty of a paper's abstract relative to prior work, I predict that academic scientists pursue glory-yielding projects more than industry scientists as capital-intensity rises. The next section explains how the variables of these analyses are constructed.

3 Data

I combine information on scientific equipment, the papers that use these equipment, the authors of these papers, their inventions and downstream value appropriability.

3.1 Capital Equipment

Two challenges need to be overcome to construct a comprehensive dataset on costly scientific equipment. First, the range of equipment used by modern science is vast and is beyond the domain of any single subject matter expert. Second, equipment price data is often undisclosed. I attempt to overcome both challenges by collecting funding details of all federal grants awarded to principal investigators proposing to purchase specific models of equipment. I complement this data using an equipment vendor directory published by an industry publication.[13] This yields a comprehensive list of equipment and their price estimates.

Equipment Purchase Grants — I collect 1,353,220 grants that were awarded by U.S. government agencies from 1980 to 2022 using data from Dimensions.ai. I then narrow these grants down to those that are exclusively focused on procuring a new scientific equipment with the aid of OpenAI's Batch API and extensive human checks. There are two conditions that need to be met before a grant qualifies as being solely about an instrument: first, a single scientific equipment must be mentioned. If a grant has multiple equipment mentioned, it prohibits ascribing the grant amount to a single equipment. Second, the grant should not propose to

[13] Please see Appendix B for further details on data construction.

upgrade or maintain an existing equipment possessed by the principal investigator (PI). While the maintenance and renovation of existing equipment are important, the customized nature of these modifications makes it difficult to price them consistently across researchers.

After finding 83,809 grants that fit this description, I manually check whether the size of the grant realistically estimates the price of the identified equipment. A common issue arises when the name of an instrument is too generic, such as "microscope", "laser" and "camera". For this reason, I exclude purchase grants of data and compute infrastructure (e.g., Linux clusters, cloud computing environments, supercomputers, workstations) because their prices fluctuate widely (e.g., between a single personal computer and a full scale supercomputer used for meteorological simulations). For similar reasons, requests to buy materials such as boules of rare earth minerals or animal models (e.g., oncomice) are excluded as the lack of quantity data make it difficult to estimate prices. I also preclude areas where firms are prima facie unlikely to invest in, such as the oceanic sciences (unmanned submersibles) or astronomy (telescopes and observatories).

After the checks, 9,759 grants containing 4,679 instruments remain. The mean funding amount is $931,526, though the range between the 5th ($39,680) and 95th percentile ($2.6 million) grant is large, at over $2 million. The most common purchase type is a mass spectrometer (374 grants), followed by confocal microscopes (240) and flow cytometers (137). I then cluster these instruments into 47 subtypes classified under 24 types that fall under three broad categories (imaging, metrology and processing).[14]

There are two sources of bias on these equipment price estimates: first, grants often contain indirect costs such as overhead contributions to the university or the hiring of specialized personnel. The presence of these costs may overestimate the price of the equipment. Second, depending on the PI's circumstances, the grant may ask for only part of the funding (with the rest being contributed by private foundations or the researcher's startup package), which can result in an underestimate.

AZO Networks — I cross-check the coverage of the grants-based equipment price index by comparing it against a vendor directory from an instruments industry publication, AZO Networks. AZO collects comprehensive information of the latest equipment and their manufac-

[14]The summary graphs in Appendix B are aggregated at the subtype level.

turers. I manually scrape the instrument model and manufacturer information for AZO Nano (228 entries), Materials (1,289), Quantum (64) and Optics (228). I separate both the type of equipment (e.g., a raman microscope) and supplier names (e.g., Renishaw). 94 companies producing 354 types of equipment are found.[15]

3.2 Scientific Papers

General Index — I measure use of equipment by whether an author of a scientific paper mentions the focal equipment in the main text of the paper. This is standard practice within the natural sciences as precise information on the paper's experimental conditions are critical to replicating and verifying the claims of a paper. Such details, however, usually emerge within the full text of the paper, posing a challenge for innovation researchers whose access was usually limited to titles and abstracts. I overcome this limitation by leveraging a large scale repository, "General Index", which extracts 355 billion n-grams (from unigrams up to 5-grams) derived from 107 million journal articles.[16]

The names of the scientific instruments and their manufacturers from the federal grants and AZO networks are stemmed, with name variants and acronyms added to increase search fidelity.[17] The stemmed ngrams are then exact-matched against the General Index ngrams, yielding papers that mention scientific instruments.

Dimensions.ai, Web of Science, and OpenAlex — I limit the set of science and engineering papers in the Web of Science Science Citation Index to those published between 1980 and 2018 and by at least one U.S. author. Author countries are extracted by linking the bibliographic details (digital object identifier, publication year, authors, journal name) of each General Index paper to records in the Dimensions.ai publications dataset that standardizes author affiliations into GRID (Global Researcher Identifier Database) IDs. The GRID IDs also allow us to identify the types of authors - government, university or corporate. I use the SCImago Journal Rank (SJR) as well as field citation ratios (FCRs) provided by Dimensions to proxy for the scientific quality of papers.[18] I measure the commercialization of science by patent citations received

[15] Cross checks on the federal grants data using the AZO data is available in B.1.2.
[16] The data was downloaded via https://archive.org/details/GeneralIndex.
[17] For instance, SIMS (Secondary Ion Mass Spectroscopy) is a subtype of mass spectrometry for which we search for both the full name as well as the acronym.
[18] FCRs divide the number of forward citations received by a paper by the average forward citations received by

by papers within 5 years of publication, and an indicator for whether a paper has a patent pair, both provided by Marx and Fuegi (2020). The main paper sample consists of 7,462,076 papers, 470,143 (6%) of which are authored by corporations. Around 25% of all papers mention use of at least one scientific equipment.

3.3 Downstream Value Capture

Own Science Use — I identify whether a paper author's home institution is using the science in its patents by first identifying all Dimensions GRID ID(s) linked to the author(s) of a paper. I then find all patents citing the focal paper using Marx and Fuegi (2020) and identify the GRID ID(s) of the patent assignees. For each paper that is cited by a patent, I define a dummy that indicates whether there is at least one assignee that has the same GRID ID as one of the authors' GRID IDs ("Cited by Own Patent").

Patent Stock Market Returns — I collect all U.S. corporate patents citing scientific papers by merging the DISCERN dataset (Arora, Belenzon, Cioaca, Sheer, Shin, & Shvadron, 2024) with Marx and Fuegi (2020). I then add patent-level stock market value from Kogan, Papanikolaou, Seru, and Stoffman (2017). I then estimate the following specification on all U.S. public firm patents (p) citing scientific papers (s):

$$Stock\ Market\ Value_{sp} = \alpha_s + value_capture_{mf} + \omega_{sp} \tag{2}$$

By including the cited paper dummy (α_s), the firm dummy $\widehat{value_capture}_{mf}$ for citing firm m in paper field f estimates the added economic value from a firm's inventions (as assessed by the stock market) while controlling for the quality of the scientific base of the invention (Masclans, 2026).[19]

University Patent Reassignment — For university reassignments, I follow Arora, Belenzon, and Suh (2022) and Serrano and Ziedonis (2018) to measure whether a university scientist reassigns her patent to another firm. Using data from the USPTO Assignment Dataset (Graham, Marco, & Myers, 2018), I keep only reassignments that are transfers of ownership between independent entities, excluding name changes, security interests, or mergers and

all papers in the same field and year.

[19] Appendix presents the top firms in terms of $\widehat{value_capture}_{mf}$ by field

acquisitions. I also exclude reassignments from faculty to their home institution (which is typical policy at university technology licensing offices). I divide the number of patents traded by total patents issued in a year for a researcher ("Share of Patents Traded").[20]

3.4 Summary Statistics

Modern science has become more capital intensive. The share of papers that mention a capital equipment has more than doubled from 8.4% to 19.6% from 1980 to 2018, while average equipment cost for a scientific paper has increased 3.6 fold from around $76,000 to $280,000 from 1980 to 2018.[21] As modern science has become more capital intensive, corporations have stayed ahead of universities in the use of costly scientific instruments. The left panel of Figure 1 shows that this corporate-university "gap" is preserved throughout the sample period, rising somewhat during the 1990s before closing starting from the 2010s. Table 2 Panel A shows that corporate papers on average spend around $340,000 on equipment costs, while university papers spend around a third less, at $240,000.

[FIGURE 1 & TABLE 2 HERE]

The university commercialization "discount" is accentuated in areas where the intersectoral capital usage gap is greater. The right panel of Figure 1 plots the share of university and corporate papers cited by patents against the capital intensity of the paper's field (measured by average equipment cost stated in their papers). Compared to university research in fields at the bottom 10th percentile of capital intensity (around $43,000), university research in the top 10th percentile (around $540,000) experiences a 30% greater commercialization discount compared to corporate research (-8.2% vs -6.3%).

I theorized that academics use less capital because they lack the ability to capture economic value downstream. The first cut of the data shows patterns consistent with the conjecture: Table 2 Panel A, for instance, shows that universities are less likely to use their own science in invention: a university paper is around 11% less likely (75% vs 67%) to be cited by

[20] Appendix presents the top universities based on average researcher reassignment rates.

[21] Appendix Figure B2 breaks this rise down by scientific field. Fields that are inherently abstract such as Mathematics and Computer Science employ very few instruments throughout the period. On the other hand, fields such as Materials Science and Molecular Biology see a doubling of instrument intensity.

a patent by the same university as a corporate paper. The next section tests the theory more rigorously.

4 Empirical Results

I follow the empirical strategy laid out in Section 2 to guide the empirics. First, I test whether capital intensive research is closer to invention. I mitigate the role of researcher or project-specific quality confounding this relation by focusing on twin discoveries and finding government funding variations that affect researcher access to capital but are exogenous to invention. Second, I test whether researcher capital intensity increases in downstream value capture measured by i) own use of science in patents ii) firm-field level stock market returns per scientific paper and iii) patent reassignment rates among university researchers. Third, I test whether capital intensity deepens a division of scientific labor between researchers by sorting academics into scientifically ambitious projects that are not commercializable (gold) but promise scientific recognition (glory).

4.1 Capital hastens science-based invention

I run the following linear probability model at the paper level to validate a key model assumption that capital-intensive projects yield more inventions ($\psi'(\theta) > 0$).

$$INVENT_s = \beta K_s + X_s'\xi + \tau_t + \zeta_f + \epsilon_s \tag{3}$$

where inventive relevance ($INVENT_s$) is measured by whether the paper is cited by patents and whether the paper has a patent pair (PPP).[22] Capital intensity (K) is measured by a dummy indicating whether a paper uses an expensive scientific equipment, as well as a continuous measure of the cost of the equipment. Both invention and capital intensity are *potentially* positively correlated to researcher quality (q), upwardly biasing $\hat{\beta}$.[23] I mitigate concerns of this bias by controlling for field-normalized forward paper citations as well as author team size (X_s). I also add year (τ_t), field and journal dummies (ζ_f). Table 3 presents the results.

[22] For patent citations of papers, I include both front-page and in-text citations with a confidence level of 9 (out of 10) or higher available from (Marx & Fuegi, 2020).

[23] Appendix A Proposition 2 derives this formally.

Column 1 finds that papers which use instruments are associated with a 1.7% higher likelihood of being cited by a patent. Column 3 shows that using a standard deviation more expensive instrument is associated with a 12.4% greater likelihood of being cited by patents (relative to the sample mean). Columns 5 and 7 show directionally similar results when I measure invention by patent-paper pairs.

[TABLE 3 HERE]

To further mitigate concerns that papers using equipment (even within the same field, year, and journal) have unobserved differences in underlying quality, I limit the comparison to papers on simultaneous discoveries only in Columns 2, 4, 6, and 8.[24] Interestingly, paper twins tend to be close to five times more likely to be cited by patents in their unconditional means (23.7% vs 4.5%). This may be because areas where "twins" are more prevalent are areas where there is scientific competition. Accordingly, the marginal differences associated with using a costly instrument are smaller relative to the sample mean (the instrument "advantage" was around 35.5% relative to the sample mean in Column 1, but only around 10.9% in Column 2). However, the coefficients estimates are still positive and significant: even within paper twins, the use of instruments is associated with a higher likelihood of invention.

To further mitigate concerns that the positive association between invention and capital intensity is an artifact of quality sorting, I instrument a researcher's (i) capital intensity by federal equipment grants received by her neighbors (j) in year t in a two-stage least squares (2SLS) specification:

$$K_{it} = Z_{it} + X'_{it}\xi + \tau_t + \rho_i + \nu_{it}$$

$$INVENT_{it} = \widehat{K_{it}} + X'_{it}\xi + \tau_t + \rho_i + \eta_{it}$$

Where K_{it} measures the average capital intensity of a scientist's papers and $INVENT_{it}$ is a dummy equal to one if a paper is cited by a patent. The instrument Z_{it} is the stock of all equipment funding received by U.S. scientists outside of i's focal scientific field after distance-

[24] I source data on simultaneous discoveries from Marx and Hsu (2022) who replicate the method pioneered by Bikard (2020) and identify papers on the same scientific discoveries published in the same year. Such simultaneous discoveries are found by finding instances of "co-citation" where paper pairs published in the same year that are textually similar also appear together frequently within the same parentheses when being cited by future articles.

decaying them.[25] I control for funding in the scientist's focal field to mitigate field-specific shocks (e.g., a windfall for AI) from biasing the results.

[TABLE 4 HERE]

Table 4 presents the results. The first stage coefficients in Column 4 suggests that a standard deviation increase in local equipment funding leads to an around $1,480 increase in capital intensity (around .4% of the sample mean) measured by equipment cost.[26] The second stage coefficients in Column 5 suggests that a standard deviation increase in instrumented capital intensity leads to around 31% greater chance the researcher's paper being cited by a patent. The result is mostly driven by universities (Columns 6-7), whose subsample has a tenfold stronger first stage F-statistic (31.079 vs 1.621) compared to the corporate researcher subsample (Column 8-9). I interpret that corporations are already optimally bunched at higher levels of capital intensity. Therefore, a funding windfall does not meaningfully shift their project choice (i.e., there are fewer compliers to the treatment).

I also note that the 2nd stage least squares estimates are an order of magnitude greater than their OLS counterparts in Columns 1-3. While this is consistent with attenuation bias, it can also imply that compliers are higher-quality researchers for whom the marginal return to capital intensity is higher. They were not using instruments before because the economic ("Gold") returns did not justify the cost at prevailing prices, but once the (effective) price falls thanks to a nearby grant windfall, their project choice shifts and the resulting work delivers inventions. The IV therefore estimates the effect for a high-return slice of the population, and the Local Average Treatment Effect exceeds the Average Treatment Effect that the OLS approximates.[27]

[25] The distance decay constant is 10, which implies around two-thirds of the funding is lost by mile 10. I first calculate the flow of funding each year as $F_{it} := \sum_j funding_{jt} \cdot \exp(-\frac{distance_{ij}}{10})$ and calculate the stock of equipment funding by using a 15% perpetual inventory method: $Z_{it} = (1-\delta)Z_{i,t-1} + F_{it}$, $\delta = 0.15$

[26] I replicate the results by replacing equipment cost with equipment use dummy in Appendix Table C1 and find that the same increase in local equipment funding leads to an around .2% greater likelihood of using a capital equipment.

[27] Proposition 4 in the Appendix Model formally derives the result. The intuition is that the cross partial of capital choice with respect to price drops ($-p$) and quality (q) is positive ($-\frac{\partial^2 \theta^*}{\partial p \partial q} > 0$) such that a unit price drop has a greater effect for higher quality researchers.

4.2 Capital intensity increases in downstream value capture

Table 5 Column 1 shows that university papers have an around 2% lower probability of using a scientific instrument, even within the same year, field and journal. Column 5 shows that a university paper's instruments are around $53,000 less expensive (or 21% of the sample mean). This difference widens by around 60% and 90% respectively for Columns 2 and 6 when I limit the sample to highly cited publications only (those in the top 5% of forward paper citations). From this, I interpret that quality-based sorting is insufficient to explain stagnant university capital intensity. If quality were driving the inter-sectoral gaps in capital intensity, they should have narrowed for comparisons for top papers: I observe the opposite.

[TABLE 5 HERE]

Columns 3 and 7 test the corollary that fields where capital is especially productive at originating inventions (i.e., greater $\psi'(\theta)$) drive the industry-academia capital gap. $\psi'(\theta)$ is measured by the field-year level coefficient estimates of an OLS specification that regresses share of papers cited by patents against share of papers mentioning a capital equipment.[28] The standard errors in these columns are bootstrapped as $\psi'(\theta)$ is an estimated regressor. I find that the university capital intensity gap to firms widens by 50.3% for fields with a standard deviation steeper invention-equipment gradient measured through equipment use (Column 3), and by 2.2% for gradient measured through equipment cost (Column 7).

The baseline model assumes university and corporate scientists draw from the same distribution of taste for glory (λ). If we instead assume that scientists with greater taste for glory sort into academia ($\lambda_{univ} > \lambda_{corp}$) per Roach and Sauermann (2010) and Sauermann and Roach (2014), the coefficient estimates would be conservative estimates of ($\frac{\theta^*}{\gamma}$). This is because university scientists, by virtue of their greater λ endowment, would compensate for a dearth in γ. The true $\frac{\theta^*}{\gamma}$ would then have to be greater to net out the empirical pattern we find in Table 5.[29]

Use of own science in patent — I test the first prediction of Table 1 by regressing capital

[28] The "NPL-Eq. Use Gradient" variable refers to $\hat{\kappa}$ from $Pr(CitedbyPatents)_{ft} = \kappa Pr(Equipment\ Use)_{ft} \times \zeta_f + \alpha Pr(Equipment\ Use)_{ft} + \tau_t + \zeta_f + \epsilon_{ft}$. "NPL-Eq. Cost Gradient" is defined analogously for equipment costs. Appendix Figure B4 plots presents the field-level $\hat{\kappa}$ that enter this regression.

[29] I require capital to increase glory ($\phi'(\theta) > 0$). The full proof is found in Appendix Model Section A.3.2

intensity (θ^*) against three measures of downstream appropriability (γ) that are plausibly unrelated to researcher quality (q). First, I limit the paper sample to those cited by patents and construct a dummy indicating whether a paper has been cited by the author's focal organization ("Cit by Own Patent"). The underlying assumption is that organizations with greater value capture would be more likely to use their own science. From Column 4 of Table 5, I find that being cited by your own patent is associated with a 2.8% greater likelihood of using a scientific instrument and use of $49,000 costlier instrument (Column 5). Furthermore, the university instrument gap to firms is driven by own-science use: for papers that are not cited by own patents, the university-industry gap in capital intensity is around 63% (Column 4) and 54% (Column 8) smaller. That is, in research where firms do not have a marked downstream appropriability advantage, the capital intensity of research between the two sectors become more similar.

[TABLE 6 HERE]

Patent Stock Market Returns — Table 6 Columns 1 and 2 report results from regressing the capital intensity of U.S. public firms' papers against the added stock market value they add while using science in their inventions. A standard deviation greater stock market value capture measure (estimated using Equation 2) is associated with a 2.4% (8.5% of the sample mean) greater likelihood of using instruments in the firm's paper (Column 1) and use of $78,000 (22% of the sample mean) more expensive equipment (Column 2).[30]

Academic patent reassignments — Third, I measure value capture at the university researcher level by measuring how proficient a researcher is at selling her patents in markets for technology (MFT). For each university researcher with a patent, I measure the share of patents that are reassigned to an outside firm (i.e., traded) to proxy for her downstream value capture capability. Critically, I add researcher dummies to mitigate concerns that some researchers generate inherently higher quality research. The residual differences in patent trade can therefore proxy within-researcher changes in downstream appropriability that may be caused by being located in an innovation hub with a concentration of downstream innovators or a stronger technology transfer office (Bikard & Marx, 2019; Lerner, Manley, Stein,

[30] Results are reported for firm-field level measures of stock market value capture, but also hold for firm-level measures where the fixed effects in Equation 2 are applied at the firm level instead of the firm-field level.

& Williams, 2025). Columns 3 and 4 of Table 6 present the results. I find that an academic that sells patents is around 5% more likely to use a scientific instrument relative to the sample mean (Column 3) and use a $30,000 more expensive equipment. In sum, the evidence suggests that the capital intensity of scientific research responds to the downstream appropriability of researchers.

I consider two alternative explanations. First, it is possible that firms, in addition to enjoying greater downstream value capture ($\gamma_c > \gamma_u$), may be more proficient at using capital equipment (that is, $\psi'_{university}(\theta) < \psi'_{corporate}(\theta)$. Universities typically place an epistemic hierarchy that rewards codified knowledge more than tacit expertise to operate scientific instruments. Exceptions can be found: universities that house core facilities with standing staff, for instance, can preserve long-term technical expertise that would otherwise be lost in a PI-centric system that is reliant on individual faculty members (Bovenberg, 2023; Oettl, 2012). By and large, however, firms that operate large industrial research laboratories seem more likely to prioritize such longer-term expertise (Arora, Belenzon, Patacconi, & Suh, 2020).

Empirically, I find mixed results. Comparing Table 4 Columns 2 and 3, I find that firms have an around 37% steeper $\psi'(\theta)$ slope than universities. On the other hand, the 2SLS results show the corporate slope to be 23% flatter than the university's (note, though the F-statistics are not strong for the corporate subsample).[31] Yet again, 2SLS specifications that replace the NPL citation-based measure of commercialization with a dummy indicating whether the researcher has a Patent-Paper Pair reveal firm 2SLS coefficients to be 2-3 times greater than universities' (Appendix Tables C2 and C3). Universities and firms may well differ in their proficiency with equipment, and this may partly explain differences in capital intensity. The aim of this paper, however, is not to dispel such differences, but to highlight the role of an overlooked mechanism: downstream appropriability. To isolate downstream factors, the measurement of value capture focuses on commercial returns *after* invention occurs: the own-science use (Column 4,8 of Table 5), stock market value add, and reassignment-based measures of value capture in Table 6 are all predicated on the existence of a patent that builds on a paper, rather than the proficiency with which such inventions can be produced.

[31] Appendix Table C1 replicates this result by measuring capital intensity with the use dummy ("Scientific Instrument Dummy") and also finds the university 2SLS coefficient (1.343) to be greater than the firm one (.267).

A second alternative explanation stems from limitations of bibliographic data: to publish results from research is a choice, and firms may approach disclosing internal research in peer-reviewed scientific publications differently from universities. On the one hand, firms may have an incentive to "say less", withholding the publication of their best research as trade secrets. On the other hand, firms may view publications as directly intertwined with their scientific reputation, which in turn affects their ability to recruit the best talents from universities. Google and IBM's quantum research disputes over claims of quantum supremacy/advantage or big tech firms' avid publication in AI journals points to this motivation (Sauermann & Cohen, 2010; Stern, 2004). Concretely, these reputational concerns may lead to a quality floor for corporate publications. The former possibility is less concerning as it results in a conservative bias: we are observing that firms are outspending universities in instruments in spite of publishing only their least impressive papers. The latter possibility of a publication quality floor from corporations has been mitigated, though not perfectly, by the results in Columns 2 and 6, which limit the sample to the top 5% most cited papers for each field and year. Here, we found that top publications of universities still under-use instruments compared to comparable corporate publications.

4.3 Novelty of university science deepens with capital intensity

I predict in Table 1 (Prediction 2) that there will be a deeper division of scientific labor in capital intensive domains of science, where academics specialize deeper into projects that yield greater glory. While forward paper citations may proxy for glory, they also reflect raw quality (q). Therefore, I proxy glory by the textual novelty of papers from Arts, Melluso, and Veugelers (2025), who create word embeddings of abstracts found in OpenAlex publications through the SPECTER algorithm. Paper novelty is defined as one minus the maximum cosine similarity between a paper's abstracts and all papers' abstracts published five years prior to it (Arts, Melluso, & Veugelers, 2025, p.6). I predict that university scientists engage in more novel science, especially more so when capital intensity of the paper is greater.

[TABLE 7 HERE]

In Table 7 Columns 3 and 4, I regress the number of papers in the top decile of novelty

scores against capital intensity and author type. I find that university authors produce in general 7% more novel papers compared to corporate counterparts, but the gap widens by around twice as when researchers use scientific instruments. By contrast, I find that for inventive relevance, the opposite result holds (Columns 1 and 2): universities are less likely to conduct research relevant for invention, but the gap grows when we compare within capital intensive researchers. Capital intensity is correlated with greater specialization of universities into "glory"-yielding work with greater scientific novelty and corporations into "gold"-yielding work with greater inventive relevance.

To summarize, scientific instruments help hasten inventions based on science. Firms seize on these inventive opportunities more eagerly than universities by investing in capital equipment. The academia-industry gap in capital investments reflect corresponding gaps in downstream value capture. Lacking downstream appropriability, academics wishing to remain in capital intensive domains seem to work on scientifically more novel topics. I infer that the rising capital intensity of modern science has deepened a division of scientific labor between academia and industry.

5 Discussion and Conclusion

Why is academic science harder to commercialize than corporate science? I have argued that universities under-invest in scientific capital because they lack the competitive downstream value capture capability that would justify the expense. Where firms can recoup the cost of an expensive equipment through manufacturing, sales, and proprietary use of the resulting inventions, universities cannot. Academics instead select into less capital-intensive, more abstract projects. The result is a widening division of scientific labor: firms specialize in capital-intensive "gold," universities in capital-light "glory."

Whether this should worry us is ambiguous. On the one hand, it is an efficient division of labor along the lines Vannevar Bush envisioned in his linear model (Bush, 1945): universities work on abstract problems while industry handles prototyping and scaling. On the other, there are grounds for concern. Private research is far less likely to be disclosed and diffused than academic research, where Mertonian norms of open communication prevail (Dasgupta

& David, 1994). Applied progress may also benefit from the diverse avenues of attack that academic entry may provide (Cohen & Klepper, 1992; Murray, Aghion, Dewatripont, Kolev, & Stern, 2016).

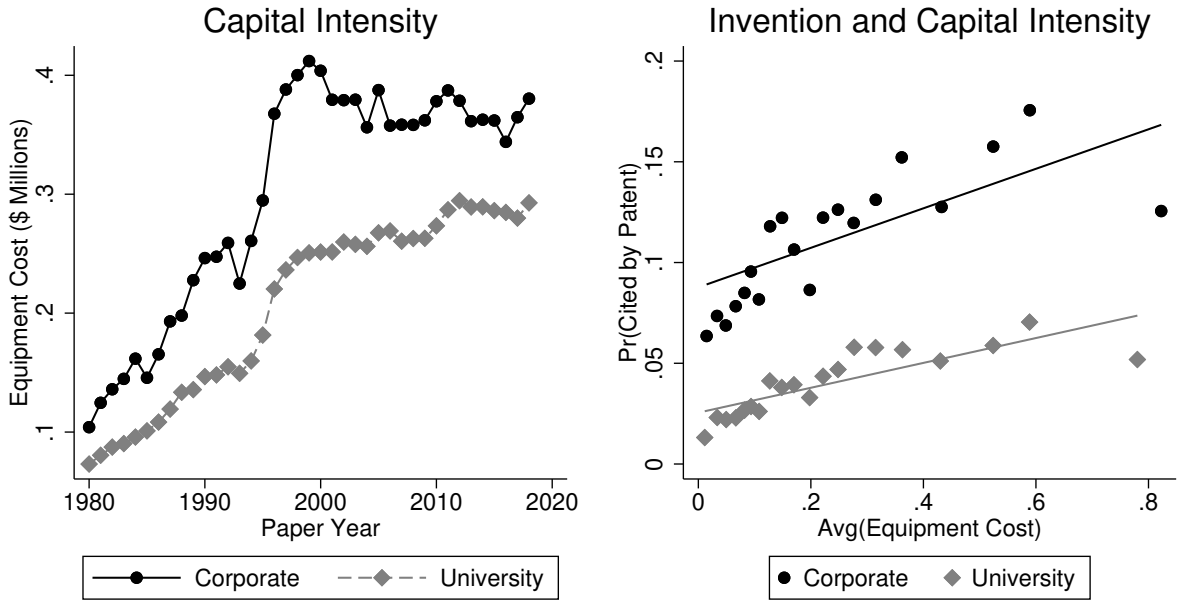
Beyond the contributions stated in the introduction, my work has two broader implications. First, it highlights capital as a new dimension of the "burden of knowledge" in the natural sciences that must be shouldered for frontier discoveries. Jones (2009) argues that the accumulation of knowledge increases the time it takes for researchers to reach the frontiers of human knowledge, raising the cost of entry into discovery. I propose a complementary, physical burden: while equipment can create shortcuts to the frontier by embodying abstract knowledge, their price can also impose steep fixed costs. Purchasing a commercial electron microscope from a vendor, for instance, saves the scientist decades of electron optics research that was required to bend and focus electrons to render accurate images at the nano-scale. At the same time, the price tag of such instruments raises barriers to discovery.

Second, I add to a broader growing innovation literature linking downstream conditions to upstream research. Beginning with Gans, Hsu, and Stern (2002), this work shows that the commercialization environment shapes the choices scientists make upstream (Kim, 2024; Suh, 2024; Tranchero, 2024). My contribution is to identify capital intensity as an important channel: downstream appropriability governs how much physical capital a researcher will commit, and therefore how close her science sits to application. Upstream experiments are not exogenous inputs into the linear pipeline; they are chosen in anticipation of the downstream conditions that determine their payoff.

An upshot identified in the introduction was that downstream demand-side interventions may be promising avenues through which capital intensity in academia could be raised. I end with two caveats: first, the "glory" chasing ambitious work that university researchers do without regard for application may expand our understanding of nature farther and plant the seeds for future applied research. Second, it is precisely the curiosity-driven approach that allows universities to maintain their status as training ground for scientific human capital (Dasgupta & David, 1994). A unilateral push to incentivize gold-chasing research in academia may risk marring both missions which have been uniquely pursued by universities.

Figures and Tables

Figure 1: Corporate-University Gap in Capital Intensity and Commercialization



Notes: The left line graph plots the annual average equipment cost of scientific papers from 1980 to 2018, by the type of author. The right binned scatterplot graphs the share of corporate and university papers cited by patents against the average equipment cost of the paper's OpenAlex scientific field & year.

Table 1: Empirical Tests

	Level of Analysis	Dependent Variable	Regressor
Assumption: Capital intensity yields more inventions ($\psi'(\theta)\|_q > 0$)			
	Paper	NPL Citations, PPP	Equipment Use & Cost
	Researcher panel	NPL Citations, PPP	Equipment Use & Cost, instrumented by local funding shocks
Prediction 1: Capital intensity increases in downstream value capture ($\frac{\partial \theta^*}{\partial \gamma} > 0$)			
	Paper	Equipment Use & Cost	Use of own science in patent
	Firm-field	Equipment Use & Cost	Patent stock market value-add
	Researcher panel (University only)	Equipment Use & Cost	Academic patent reassignments
Prediction 2: Capital intensity sorts more academics into "glory" ($\lambda_u(\theta^*, q) > \lambda_c^*(\theta^*, q)$)			
	Researcher Panel	Paper Textual Novelty	University affiliation $\times$ Equipment Use & Cost

Table 2: Summary Statistics

	Panel A: Paper-level Descriptives (Cross Sectional)									
	Corporate					University				
	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max	Obs
Year	2004.88	9.88	1980.00	2018.00	470143	2004.61	10.02	1980.00	2018.00	5764715
Cited by Paten	11.27	31.63	0.00	100.00	448911	4.04	19.68	0.00	100.00	5482021
Patent Paper Pair	4.25	20.18	0.00	100.00	470143	1.03	10.11	0.00	100.00	5764715
Scientific Equipment Cost	0.34	0.85	0.00	13.93	470143	0.24	0.70	0.00	18.57	5764715
Scientific Equipment Dummy	24.38	42.94	0.00	100.00	470143	18.86	39.12	0.00	100.00	5764715
Forward Paper Citations	1.16	3.21	0.00	397.73	470143	0.91	2.09	0.00	702.61	5764715
Number of Coauthors	7.03	21.73	1.00	5363.00	470143	5.20	36.30	1.00	5104.00	5764715
Cited by Own Patent	74.58	43.54	0.00	100.00	116071	67.11	46.98	0	100.00	716979
	Panel B: Researcher-level Descriptives (Panel)									
	Corporate (551,605 researchers)					University (2,515,717 researchers)				
	Mean	S.D.	Min	Max	Obs	Mean	S.D.	Min	Max	Obs
Year	2006.72	8.91	1980.00	2018.00	1312405	2005.35	9.81	1980.00	2018.00	9011690
Cited by Patent	25.72	43.71	0.00	100.00	1312405	12.78	33.38	0.00	100.00	9011690
Patent Paper Pair	10.71	30.92	0.00	100.00	1312405	3.44	18.22	0.00	100.00	9011690
Scientific Equipment Dummy	28.84	38.92	0.00	100.00	1312405	22.67	37.15	0.00	100.00	9011690
Paper Equipment Cost	0.44	0.85	0.00	12.93	1312405	0.32	0.73	0.00	18.57	9011690
Nearby Equipment Funding (Other Fields)	5.82	28.40	0.00	554.33	1312405	4.18	24.46	0.00	579.16	9011690
Nearby Equipment Funding (Focal Field)	1.24	7.69	0.00	170.75	1312405	0.79	6.52	0.00	170.75	9011690
No. Textually Novel Papers	0.23	0.57	0.00	19.00	1312405	0.20	0.49	0.00	25.00	9011690
No. Papers	3.26	4.52	1.00	215.00	1312405	2.34	2.95	1.00	215.00	9011690
Forward Paper Citations	1.17	2.99	0.00	397.93	1312405	0.87	1.95	0.00	598.36	9011690
Number of Coauthors	11.58	61.40	1.00	5363.00	1312405	10.20	84.31	1.00	5363.00	9011690

Notes: The table splits the summary statistics by type of affiliation at the paper level (Panel A) and researcher-year level (Panel B). For Panel A, "Cited by Patent" is a dummy equal to 100 if a paper is cited by a patent within 5 years of publication. "Patent Paper Pair" is equal to 100 if the paper has a corresponding patent pair. The "Scientific Equipment Dummy" is a dummy equal to 100 if the paper's text mentions at least one scientific equipment and zero otherwise. "Paper Equipment Cost" sums the cost of all equipment mentioned in the paper. "Forward Paper Citations" normalizes all forward citation received by peer-reviewed scientific papers in the paper's year by average citations received in the paper's Open Alex field-year. "Number of Coauthors" counts the number of unique authors listed in the paper, sourced from the Dimensions dataset. "Cited by own Patent" is defined only for papers cited by patents according to Marx and Fuegi (2020) and equals 100 if the paper has been cited at least one of the the paper authors' focal organization. For Panel B, these measures are averaged at the paper author-year level. Additionally, "Nearby Equipment Funding" measures the distance-decayed federal equipment grant funding for the researcher-year (details on calculations are in footnote 25). "Focal Field" refers to the modal field of the researcher's publication history; "Other Fields" refers to all other fields. "No. Textually Novel Papers" refers to the number of papers by the author-year that are in the top decile of textual novelty scores from Arts, Melluso, and Veugelers (2025). "No. Papers" refers to the number of papers by the author-year.

Table 3: Capital Intensity and Science-based Invention (Paper Level)

Dependent Variable	Pr(Cited by Patent)				Pr(Patent Paper Pair)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Paper Twins	All	Paper Twins	All	Paper Twins	All	Paper Twins
Scientific Equipment Dummy	1.654	2.582			0.651	1.269		
	(0.044)	(1.317)			(0.016)	(0.885)		
Paper Equipment Cost			0.800	0.888			0.340	0.802
			(0.026)	(0.604)			(0.010)	(0.443)
Forward Paper Citations	1.417	1.123	1.417	1.127	0.213	0.577	0.213	0.578
	(0.222)	(0.226)	(0.222)	(0.225)	(0.032)	(0.154)	(0.032)	(0.154)
Number of Coauthors	0.001	-0.105	0.001	-0.104	0.001	0.077	0.001	0.075
	(0.000)	(0.090)	(0.000)	(0.090)	(0.000)	(0.052)	(0.000)	(0.051)
Average of Dep Var	4.512	23.656	4.512	23.656	1.239	4.378	1.239	4.378
Year Dummies	Yes	No	Yes	No	Yes	No	Yes	No
Field Dummies	Yes	No	Yes	No	Yes	No	Yes	No
Journal Dummies	Yes	No	Yes	No	Yes	No	Yes	No
Twin Pair Dummies	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.099	0.811	0.099	0.811	0.032	0.611	0.032	0.612
Number of Obs	7,092,327	5,804	7,092,327	5,804	7,435,615	6,258	7,435,615	6,258

Notes: Table presents Linear Probability Model (LPM) estimates regressing invention against capital intensity at the scientific paper level. Dependent variable in Columns 1-4 is a dummy equal to 100 if the paper is cited by a patent within 5 years of its publication and zero otherwise; in Columns 5-8 it is equal to 100 if the paper has a patent pair and zero otherwise (Marx & Fuegi, 2020). The "Scientific Equipment Dummy" is equal to one if the paper's text mentions at least one scientific equipment. "Paper Equipment Cost" sums the cost of all equipment mentioned in the paper. "Forward Paper Citations" normalizes all forward citation received by peer-reviewed scientific papers in the paper's year by average citations received in the paper's Open Alex field-year. "Number of Coauthors" counts the number of unique authors listed in the paper, sourced from the Dimensions dataset. Columns 1,3,5, and 7 include dummies for year and field; robust standard errors are included. The sample for Columns 2,4,6 and 8 only includes papers on simultaneous discoveries from (Marx & Hsu, 2022) and adds dummies for the pair ID of the discovery ("Twin Pair Dummies"); standard errors are clustered at the pair ID level. Sample period is from 1980 to 2018 throughout this paper unless stated otherwise.

Table 4: Capital Intensity and Science-based Invention (Researcher Level)

	OLS			IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Univ	Firm	All (FS)	All	Univ (FS)	Univ	Firm (FS)	Firm
Paper Equipment Cost	1.166	1.137	1.364		43.315		44.696		11.997
	(0.023)	(0.025)	(0.081)		(16.651)		(16.507)		(58.628)
Nearby Equipment Funding (Other Fields)				0.000		0.000		0.000	
				(0.000)		(0.000)		(0.000)	
Nearby Equipment Funding (Focal Field)	0.004	0.005	-0.018	0.000	-0.018	0.000	-0.019	0.000	-0.020
	(0.003)	(0.003)	(0.009)	(0.000)	(0.010)	(0.000)	(0.011)	(0.000)	(0.015)
Forward Paper Citations	2.625	2.521	2.529	0.015	1.983	0.015	1.848	0.012	2.405
	(0.065)	(0.065)	(0.099)	(0.001)	(0.259)	(0.001)	(0.260)	(0.001)	(0.690)
Number of Coauthors	-0.000	-0.001	-0.001	0.000	-0.005	0.000	-0.005	0.000	-0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.004)
Average of Dep Var	13.126	13.026	27.872	0.318	13.126	0.321	13.026	0.444	27.872
F-Stat					29.965		31.079		1.621
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Researcher Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.343	0.344	0.423		.		.		.
Number of Obs	9,563,478	8,005,336	1,010,491	9,563,478	9,563,478	8,005,336	8,005,336	1,010,491	1,010,491

Notes: Unit of analysis is at the researcher-year level. Columns 1-3 run OLS specifications regressing invention against capital intensity. Column 1 includes all researchers; Column 2 includes only researchers affiliated with a university; Column 3 includes only affiliated with a corporation. The dependent variable (DV) is measured by a dummy equal to 100 if the author has a paper cited by a patent within 5 years of its publication and zero otherwise. Capital intensity is measured as the average "Paper Equipment Cost" of papers published by the researcher-year. Columns 4-9 run two-stage least squared analogues of these regressions that instrument "Paper Equipment Cost" with distance-decayed equipment funding in fields external to the researcher's field — "Nearby Equipment Funding (Other Fields)". The DV for the first stage regressions in Columns 4,6,8 is the average paper equipment cost of a researcher-year; for the second state regressions in Columns 5,7,9, it is identical to the DV in Columns 1-3. A researcher's field is defined as the modal field where she publishes in. I control for the amount of distance-decayed equipment funding in the researcher's focal field with "Nearby Equipment Funding (Focal Field)". "Forward Paper Citations" and "Number of Coauthors" take the averages of paper-level measures published by the researcher-year. Standard errors are clustered at the researcher level. Disambiguated researcher IDs, their affiliation types, and grant funding data are obtained from the Dimensions dataset. Field data is obtained from OpenAlex and linked through DOIs.

Table 5: Capital Intensity and Value Capture (Paper Level)

Dependent Variable	Scientific Equipment Dummy				Paper Equipment Cost			
	(1) All	(2) Highly Cited	(3) $\psi'(\theta)$	(4) NPL Cited	(5) All	(6) Highly Cited	(7) $\psi'(\theta)$	(8) NPL Cited
Univ Author	-0.020	-0.032	-0.044	-0.009	-0.053	-0.104	-0.091	-0.032
	(0.001)	(0.002)	(0.010)	(0.003)	(0.001)	(0.006)	(0.022)	(0.006)
Univ Author × NPL-Eq. Use Gradient			-0.102					
			(0.046)					
NPL-Eq. Use Gradient			0.100					
			(0.070)					
Univ Author × NPL-Eq. Cost Gradient							-0.011	
							(0.108)	
NPL-Eq. Cost Gradient							-0.112	
							(0.207)	
Cit by Own Patent × Univ Author				-0.014				-0.038
				(0.003)				(0.006)
Cit by Own Patent				0.040				0.082
				(0.003)				(0.006)
Forward Paper Citations	0.004	-0.000	0.009	-0.000	0.009	0.001	0.019	0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Number of Coauthors	0.000	0.000	-0.000	0.003	0.000	0.000	0.000	0.006
	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)	(0.005)	(0.002)
Average of Dep Var	0.193	0.254	0.193	0.302	0.250	0.388	0.250	0.417
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	No	No	Yes	Yes	No	Yes
Journal Dummies	Yes	Yes	No	No	Yes	Yes	No	Yes
R^2	0.236	0.247	0.011	0.210	0.198	0.218	0.013	0.178
Number of Obs	6,234,742	320,737	6,234,856	832,474	6,234,742	320,737	6,234,856	832,474

Notes: This table presents OLS estimates regressing measures of capital intensity against measure of value capture at the paper level. Dependent variable in Columns 1-4 is a dummy equal to 100 if a paper mentions a scientific equipment; in Columns 5-8 it is the total cost of all equipment mentioned in the paper. "NPL-Eq. Use Gradient" refers to the field-year level coefficient of regressing share of cited papers against share of equipment-mentioning papers. Standard errors in specifications including this variable are clustered at the scientific field level and bootstrapped using 500 replications. The sample in Columns 2 and 6 are limited to papers that are in the 5% of field-normalized forward paper citations The sample in Column 4 and 8 is limited to papers that are cited by patents. "Cit by Own Patent" is a dummy equal to one if the paper has been cited by at least one patent assigned to an author's organization. The rest of the variable definitions are identical as Table 3.

Table 6: Capital Intensity and Value Capture

	Value Capture (Firm Level)		Value Capture (Researcher Level)	
	(1)	(2)	(3)	(4)
Dependent Variable	1(Use)	Equipment Cost	1(Use)	Equipment Cost
Corporate Value Capture	0.022	0.072		
	(0.011)	(0.024)		
Share of Patents Traded			0.017	0.030
			(0.008)	(0.017)
Forward Paper Citations	0.000	0.002	0.002	0.006
	(0.002)	(0.006)	(0.001)	(0.002)
Team Size	0.006	0.021	0.000	0.001
	(0.001)	(0.003)	(0.000)	(0.000)
Average of Dep Var	0.284	0.398	0.342	0.442
Year Dummies	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	No	No
Firm Dummies	Yes	Yes	No	No
Researcher Dummy	No	No	Yes	Yes
R^2	0.326	0.351	0.542	0.541
Number of Obs	13,432	13,432	66,611	66,611

Notes: This table presents OLS estimates regressing measures of capital intensity against measures of value capture at the organizational level. Unit of analysis for Columns 1 and 2 is the firm-field-year. Sample is limited to U.S. public firms with at least one scientific publication. Dependent variable for Column 1 is the share of corporate papers that use scientific equipment; for Column 2 it is the average cost of those equipment. "Corporate Value Capture" refers to the $\widehat{value_capture}_{mf}$ estimate obtained at the firm-field level from estimating equation 2. Standard errors for these columns are bootstrapped using 500 replications. Unit of analysis for Columns 3 and 4 is researcher-year. Sample is limited to university researchers with at least one patent. "Share of Patents Traded" refers to the share of patents granted in the focal year which were eventually sold (reassigned) to an outside entity. Standard errors for these columns are clustered at the researcher level.

Table 7: Scientific Novelty and Capital Intensity (Researcher Level)

	Pr(Cited by Patent)		Novel Papers	
	(1)	(2)	(3)	(4)
Scientific Equipment Dummy × Univ Author	-0.030		0.018	
	(0.001)		(0.001)	
Paper Equipment Cost × Univ Author		-0.013		0.005
		(0.000)		(0.000)
Scientific Equipment Dummy	0.098		0.012	
	(0.001)		(0.001)	
Paper Equipment Cost		0.036		0.003
		(0.000)		(0.000)
Univ Author	-0.022	-0.023	0.014	0.018
	(0.000)	(0.000)	(0.000)	(0.000)
Forward Paper Citations	0.031	0.031	-0.006	-0.006
	(0.001)	(0.001)	(0.000)	(0.000)
Number of Coauthors	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Papers	0.019	0.021	0.053	0.054
	(0.000)	(0.000)	(0.000)	(0.000)
Average of DV	0.101	0.101	0.187	0.187
Year Dummies	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	Yes	Yes
R^2	0.118	0.110	0.105	0.104
Number of Observations	10,330,068	10,330,068	10,655,998	10,655,998

Notes: This table presents OLS specifications regressing count measures of invention and scientific novelty against capital intensity, interacted with author type at the researcher-year level. The dependent variable in Columns 1 and 2 is a dummy equal to one if the researcher publishes a paper that is cited in patents. In Columns 3 and 4, the dependent variable is the count of papers in the top decile of the textual novelty measure (*cosine_max*) in Arts, Melluso, and Veugelers (2025) The rest of the variable definitions are identical to Table 4. Standard errors are clustered at the researcher level.

References

Aghion, P., Dewatripont, M., & Stein, J. C. (2008). Academic freedom, private-sector focus, and the process of innovation. *The RAND Journal of Economics*, *39*(3), 617–635.

Agrawal, A., & Goldfarb, A. (2008). Restructuring Research: Communication Costs and the Democratization of University Innovation. *American Economic Review*, *98*(4), 1578–1590.

Ahmed, N., Wahed, M., & Thompson, N. C. (2023). The growing influence of industry in AI research. *Science*, *379*(6635), 884–886.

Arora, A., Belenzon, S., Cioaca, L., Sheer, L., Shin, H., & Shvadron, D. (2024). *DISCERN 2.0: Duke Innovation & SCientific Enterprises Research Network*. Zenodo.

Arora, A., Belenzon, S., Patacconi, A., & Suh, J. (2020). The changing structure of American innovation: Some cautionary remarks for economic growth. *Innovation Policy and the Economy*, *20*(1), 39–93.

Arora, A., Belenzon, S., Patacconi, A., & Suh, J. (2025). The reorganization of the American innovation ecosystem and the challenge of translating science. *Industrial and Corporate Change*, *34*(6), 1206–1228.

Arora, A., Belenzon, S., & Suh, J. (2022). Science and the Market for Technology. *Management Science*, *68*(10), 7176–7201.

Arts, S., Melluso, N., & Veugelers, R. (2025). Beyond Citations: Measuring Novel Scientific Ideas and their Impact in Publication Text. *The Review of Economics and Statistics*, 1–33.

Barbosu, S., & Teodoridis, F. (2025). *Catalysts of discovery: How technologies are shaping the future of science and innovation* (1st ed.). Palgrave Macmillan Cham.

Baruffaldi, S., & Gaessler, F. (2026). The Returns to Physical Capital in Knowledge Production: Evidence from Lab Disasters. *American Economic Journal: Applied Economics*, *18*(1), 248–285.

Bikard, M. (2020). Idea twins: Simultaneous discoveries as a research tool. *Strategic Management Journal*, *41*(8), 1528–1543.

Bikard, M., & Marx, M. (2019). Bridging Academia and Industry: How Geographic Hubs Connect University Science and Corporate Technology. *Management Science*.

Bovenberg, D. (2023). *Craft Knowledge and the Advancement of Science: The Role of Scientific Support Occupations in Shared Research Facilities*.

Bush, V. (1945). Science: The endless frontier. *Transactions of the Kansas Academy of Science (1903-)*, *48*(3), 231–264.

Chip History Center. (n.d.). GCA – mann 4800 direct step on wafer system.

Cohen, W. M., & Klepper, S. (1992). The tradeoff between firm size and diversity in the pursuit of technological progress. *Small Business Economics*, *4*(1), 1–14.

Cohen, W. M., Sauermann, H., & Stephan, P. (2020). Not in the Job Description: The Commercial Activities of Academic Scientists and Engineers. *Management Science*, *66*(9), 4108–4117.

Committee on Advanced Research Instrumentation & Committee on Science, Engineering, and Public Policy. (2006). *Advanced research instrumentation and facilities*. National Academies Press. Washington, DC.

Dasgupta, P., & David, P. A. (1994). Toward a new economics of science. *Research policy*, *23*(5), 487–521.

Ding, W. W., Levin, S. G., Stephan, P. E., & Winkler, A. E. (2010). The Impact of Information Technology on Academic Scientists' Productivity and Collaboration Patterns. *Management Science*, *56*(9), 1439–1461.

Dresselhaus, M. S., & Terrones, M. (2013). Carbon-Based Nanomaterials From a Historical Perspective. *Proceedings of the IEEE*, *101*(7), 1522–1535.

Furman, J. L., & Stern, S. (2011). Climbing atop the Shoulders of Giants: The Impact of Institutions on Cumulative Research. *American Economic Review*, *101*(5), 1933–1963.

Ganguli, I., & Murciano-Goroff, R. (2025). Price shocks and scientific production: Evidence from university procurement contracts. *Academy of Management Proceedings*, *2025*(1), 16925.

Gans, J. S., Hsu, D. H., & Stern, S. (2002). When Does Start-Up Innovation Spur the Gale of Creative Destruction? *The RAND Journal of Economics*, *33*(4), 571–586.

Graham, S. J., Marco, A. C., & Myers, A. F. (2018). Patent transactions in the marketplace: Lessons from the uspto patent assignment dataset. *Journal of Economics & Management Strategy*, *27*(3), 343–371.

Hartmann, P., & Henkel, J. (2019). *The Rise of Corporate Science in AI* [Working Paper].

Hecht, J. (2005). *Beam: The race to make the laser*. Oxford University Press.

Helmers, C., & Overman, H. G. (2017). My Precious! The Location and Diffusion of Scientific Research: Evidence from the Synchrotron Diamond Light Source. *The Economic Journal*, *127*(604), 2006–2040.

Hill, R., & Stein, C. (2025). Race to the Bottom: Competition and Quality in Science. *The Quarterly Journal of Economics*, *140*(2), 1111–1185.

Johnstone, B. (2007). *Brilliant!: Shuji Nakamura and the revolution in lighting technology*. Prometheus Books.

Jones, B. F. (2009). The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *The Review of Economic Studies*, *76*(1), 283–317.

Jung, H. J., & Lee, J. " (2014). The impacts of science and technology policy interventions on university research: Evidence from the U.S. National Nanotechnology Initiative. *Research Policy*, *43*(1), 74–91.

Kim, S. (2024). Shortcuts to Innovation: The Use of Analogies in Knowledge Production.

Klopsteg, P. E. (1957). *Instrumentation in Bio-Medical research* (Publication 472). National Academy of Sciences–National Research Council. Washington, DC.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665–712.

Lacetera, N. (2009). Different Missions and Commitment Power in R&D Organizations: Theory and Evidence on Industry-University Alliances. *Organization Science*, *20*(3), 565–582.

Lerner, J., Manley, H., Stein, C., & Williams, H. (2025, April 22). *The wandering scholars: Understanding the heterogeneity of university commercialization*.

Levinson, H. (2019). Lithography Costs. *PM304*, 455–475.

Marx, M., & Fuegi, A. (2020). Reliance on science: Worldwide front-page patent citations to scientific articles. *Strategic Management Journal*.

Marx, M., & Hsu, D. H. (2022). Revisiting the Entrepreneurial Commercialization of Academic Science: Evidence from "Twin" Discoveries. *Management Science*, *68*(2), 1330–1352.

Masclans, R. (2026, March 26). *Science, startups, and the problem of value capture: Thin acquisition markets, weak outside options*.

McKeon, J., & Boudou, J. (2024, June 17). *Innovation Under Resource Constraints: Supercomputing in Scientific Research*.

Murray, F. (2010). The Oncomouse That Roared: Hybrid Exchange Strategies as a Source of Distinction at the Boundary of Overlapping Institutions. *American Journal of Sociology*, *116*(2), 341–388.

Murray, F., Aghion, P., Dewatripont, M., Kolev, J., & Stern, S. (2016). Of Mice and Academics: Examining the Effect of Openness on Innovation. *American Economic Journal: Economic Policy*, *8*(1), 212–252.

Murray, F., & Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge?: An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior & Organization*, *63*(4), 648–687.

Nakamura, S. (2014). Background story of the invention of efficient blue InGaN light emitting diodes.

Nenni, D., & McLellan, P. (2013). *FABLESS: The transformation of the semiconductor industry. Sl: SemiWiki. Com*. SemiWiki.com.

Oettl, A. (2012). Reconceptualizing Stars: Scientist Helpfulness and Peer Performance. *Management Science*, *58*(6), 1122–1140.

Polanyi, M. (1962). THE REPUBLIC OF SCIENCE: Its Political and Economic Theory. *Minerva*, *1*(1), 54–73.

Price, D. J. d. S. (J. d. S. (1986). *Little science, big science– and beyond*. Columbia University Press.

Riggs, W., & von Hippel, E. (1994). Incentives to innovate and the sources of innovation: The case of scientific instruments. *Research Policy*, *23*(4), 459–469.

Roach, M., & Sauermann, H. (2010). A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. *Research Policy*, *39*(3), 422–434.

Rosenberg, N. (1992). Scientific instrumentation and university research. *Research Policy*, *21*(4), 381–390.

Rosenberg, N. (1994). *Exploring the black box: Technology, economics, and history*. Cambridge University Press.

Sanderson, S. W., & Simons, K. L. (2014). Light emitting diodes and the lighting revolution: The emergence of a solid-state lighting industry. *Research Policy*, *43*(10), 1730–1746.

Sauermann, H., & Cohen, W. M. (2010). What makes them tick? Employee motives and firm innovation. *Management Science*, *56*(12), 2134–2153.

Sauermann, H., & Roach, M. (2014). Not all scientists pay to be scientists: PhDs' preferences for publishing in industrial employment. *Research Policy*, *43*(1), 32–47.

Serrano, C. J., & Ziedonis, R. (2018). *How redeployable are patent assets? evidence from failed startups*. National Bureau of Economic Research.

Stephan, P. E. (1996). The Economics of Science. *Journal of Economic Literature*, *34*(3), 1199–1235.

Stern, S. (2004). Do scientists pay to be scientists? *Management science*, *50*(6), 835–853.

Suh, J. (2024, August 21). *Swinging for the Fences: Startup Novelty as a Response to Entry Costs **.

Teodoridis, F. (2018). Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise. *Management Science*, *64*(8), 3625–3648.

Tranchero, M. (2024). Finding Diamonds in the Rough: Data-Driven Opportunities and Pharmaceutical Innovation. *Academy of Management Proceedings*, *2024*(1), 13751.

Tranchero, M., Fons-Rosen, C., & Fleming, L. (2025, August). *Scientific malpractice in alzheimer's research: Systematic evidence and impacts on pharmaceutical firms*.

von Hippel, E. (1976). The dominant role of users in the scientific instrument innovation process. *Research Policy*, *5*(3), 212–239.

Appendix A A simple model of researcher project choice

A.1 Setup

I present a simple model of research project choice to formalize the intuition presented in Section 2. A scientist of one of two institutional types $\tau \in \{\text{university, corporate}\}$ chooses capital intensity $\theta \in [0, 1]$ of her research project. The payoff is given as the sum of "glory" and "gold" net of costs:

$$U_\tau(\theta, q) \;=\; \lambda \cdot S(\theta, q) \;+\; \gamma_\tau \cdot G(\theta, q) \;-\; C(\theta, q) \tag{A1}$$

"Glory" — $S(\theta, q) = q \cdot \phi(\theta)$ represents payoffs from scientific recognition through priority and novelty. $\phi(\theta)$ is the scientific reputation from using capital. I assume capital-intensity in general produces results that can increase scientific credit ($\phi'(\theta) > 0$). $\lambda \sim F(0, 1)$ weights the importance of "glory" for the researcher and can refer to idiosyncratic taste for scientific reputation or the ability to theorize novel findings based on empirical results. I assume equal distributions of λ across all researcher types.

"Gold" — $G(\theta, q) = q \cdot \psi(\theta)$ represents returns from downstream commercialization. $\psi(\theta)$ refers to inventions that result from the use of capital; γ refers to downstream value capture. I impose two assumptions: first, $\psi'(\theta) > 0$: capital-intensive projects are closer to invention; second, $\gamma_{univ} < \gamma_{corp}$, since academics do not possess the manufacturing plants, sales organizations or IP infrastructure that incumbent firms maintain.[32]

"Costs" — $C(\theta, q) = \theta^2/2q$ represents the costs of capital-intensive research. The cost function is convex in θ and decreasing in q: more talented scientists are better able to manage large-scale projects, giving them a comparative advantage in capital-intensive work. This drives quality sorting.

A.2 Results

The scientist's problem is:

$$\max_{\theta \in [0,1]} \quad \lambda q \phi(\theta) \;+\; \gamma_\tau q \psi(\theta) \;-\; \frac{\theta^2}{2q} \tag{A2}$$

The first-order condition characterizing an interior optimum $\theta^*_\tau(q)$ is:

$$\lambda q \phi'(\theta^*) \;+\; \gamma_\tau q \psi'(\theta^*) \;=\; \frac{\theta^*}{q} \tag{FOC}$$

The left side is the marginal benefit of increasing capital intensity, decomposed into glory and gold gradients. The right side is the marginal cost, which is linear in θ and decreasing in q. The second-order condition requires $\lambda q \phi''(\theta^*) + \gamma_\tau q \psi''(\theta^*) - 1/q < 0$, which we maintain throughout. We derive three predictions that organize the empirical analysis.

Proposition 1 (Quality sorting)**.** $\partial \theta^*_\tau / \partial q > 0$*. Higher-quality scientists choose more capital-intensive projects.*

[32] For simplicity, I normalize $\gamma_u = 1$ and assume $\gamma_c > 1$

Proof. Applying the implicit function theorem to (FOC):

$$\frac{\partial \theta^*}{\partial q} = \underbrace{\frac{\lambda\phi'(\theta^*) + \gamma_\tau \psi'(\theta^*) + \theta^*/q^2}{1/q - \lambda q \phi''(\theta^*) - \gamma_\tau q \psi''(\theta^*)}}_{>0 \text{ by SOC}} \tag{A3}$$

From (FOC), the marginal benefit equals the marginal cost at the optimum, so the numerator reduces to $\theta^*/q^2 > 0$. The denominator is positive by the second-order condition. □

The intuition is that high-q scientists face lower marginal costs of capital-intensive work: the cost function $C(\theta, q) = \theta^2/2q$ is supermodular in $(\theta, -q)$, meaning the marginal cost of θ falls in q.

Proposition 2 (Corporate research is more capital intensive)**.** *$\theta_c^*(q) > \theta_u^*(q)$ for all q, especially for fields with greater $\psi'(\theta^*)$.*

Proof. Differentiating (FOC) with respect to γ_τ:

$$\frac{d\theta^*}{d\gamma_\tau} = \underbrace{\frac{\lambda q \psi'(\theta^*)}{1/q - \lambda q \phi''(\theta^*) - \gamma_\tau q \psi''(\theta^*)}}_{>0 \text{ by SOC}} > 0 \tag{A4}$$

since $\psi'(\theta^*) > 0$ by assumption. Because $\gamma_c > \gamma_u$, corporate scientists choose strictly higher capital intensity than university scientists of equal quality. A corollary is that fields with greater $\psi'(\theta^*)$ will show a greater capital gap between university and industry.

□

Proposition 3 (University selection into glory)**.** *For quality q and capital intensity θ^*, let $\lambda_\tau^*(\theta^*, q)$ be the glory weight that rationalizes the choice θ^* for a type-τ scientist (the λ solving* (FOC)*). Then*

$$\lambda_u^*(\theta^*, q) > \lambda_c^*(\theta^*, q).$$

University scientists are revealed to place greater weight on glory for the same capital intensity.

Proof. Solving (FOC) for λ at (θ^*, q) gives

$$\lambda_\tau^*(\theta^*, q) = \frac{\theta^*/q - \gamma_\tau q\, \psi'(\theta^*)}{q\, \phi'(\theta^*)}.$$

Differencing across types with $\gamma_u = 1 < \gamma_c$,

$$\lambda_u^* - \lambda_c^* = \frac{(\gamma_c - 1)\, \psi'(\theta^*)}{\phi'(\theta^*)} > 0,$$

since $\gamma_c > 1$, $\psi'(\theta^*) > 0$, and $\phi'(\theta^*) > 0$. Monotonicity of θ^* in λ follows from $d\theta^*/d\lambda = q\phi'(\theta^*)/(-H_\theta) > 0$, where $-H_\theta > 0$ is the SOC term. □

A.3 Extensions

A.3.1 Heterogeneous returns to capital and the IV estimand.

Add a price of capital p and an invention equation. The scientist solves

$$\max_{\theta} \ \lambda q\,\phi(\theta) + \gamma q\,\psi(\theta) - \frac{p\,\theta^2}{2q},$$

with policy $\theta^*(q;p)$ satisfying $\partial\theta^*/\partial q > 0$ (quality sorting) and $\partial\theta^*/\partial p < 0$. Inventive output, proxied by NPL citations, is

$$Y(\theta, q) = q\,\psi(\theta), \qquad \psi' > 0.$$

A funding shock Z lowers the effective price, $p = \bar{p} - Z$. Define the marginal product of capital in invention, α and the change in capital in response to a change in its price ω,

$$\alpha(q) \ \equiv \ \frac{\partial Y}{\partial \theta}\Big|_{\theta^*(q)} = q\,\psi'\big(\theta^*(q)\big), \qquad \omega(q) \ \equiv \ \frac{\partial \theta^*}{\partial Z} = -\frac{\partial \theta^*}{\partial p} > 0.$$

Assumption 1. $\alpha'(q) > 0$: the return to capital rises with quality. This follows from output-side complementarity, $\partial^2 Y/\partial\theta\partial q = \psi'(\theta) > 0$.

Assumption 2 (First-stage selection on quality)**.** $\omega'(q) > 0$: higher-quality scientists expand capital use more when the price falls. In the constant-gradient case $\theta^* = q^2K/p$, $\omega(q) = q^2K/p^2$.

Proposition 4 (The IV over-weights high-return scientists)**.** *Let $q \sim G$. A marginal shift in Z identifies the IV (Wald) estimand*

$$\beta_{IV} = \frac{dE[Y]/dZ}{dE[\theta]/dZ} = \frac{E[\alpha(q)\,\omega(q)]}{E[\omega(q)]} = \int \alpha(q)\,dW(q), \qquad dW(q) \equiv \frac{\omega(q)\,dG(q)}{E[\omega]}.$$

Under Assumptions 1–2,

$$\beta_{IV} - \underbrace{E[\alpha(q)]}_{\text{average effect } \beta_{ATE}} = \frac{\mathrm{Cov}\big(\alpha(q), \omega(q)\big)}{E[\omega(q)]} > 0.$$

The IV estimand strictly exceeds the population-average return to capital. Because α and ω depend on q and not on γ, the gap arises within every institutional type.

The density $dW(q) \propto \omega(q)\,dG(q)$ is the subpopulation the instrument moves. Note that never-takers that have no interest in empirical work and always-takers with maximal $\theta = 1$ (high-γ researchers) will receive zero weight ($\omega(q) = 0$) and drop out of β_{IV}.

The IV therefore estimates the return on the responsive, "high-quality" margin, with implicit population shifted toward high q relative to G. Together with classical measurement error attenuating β_{OLS} toward zero, $\beta_{IV} > \beta_{OLS}$.

A.3.2 Sorting on Taste for Glory

The baseline model assumes scientist tastes to be drawn from the same distribution $\lambda_f, \lambda_u \sim F$. In reality, scientists may sort across institutional sectors partly on the basis of how much they value scientific recognition relative to financial return (Roach & Sauermann, 2010; Sauermann

& Roach, 2014). This subsection allows λ to vary across scientists and shows that the reduced-form gap in capital intensity between corporate and university scientists is a downward-biased estimand of the structural γ wedge from Proposition 2.

I assume taste-based sorting: $\lambda_u > \lambda_c$, where λ_τ denotes the taste of the scientist observed in sector τ. I also assume that scientific instruments on average enable glory-pursuant research ($\phi'(\theta) > 0$). Differentiating the FOC with respect to λ yields:

$$\frac{\partial \theta^*}{\partial \lambda} = \frac{\phi'(\theta^*)}{-U_{\theta\theta}} > 0,$$

That is, higher taste for glory also raises the optimal capital intensity. Holding λ fixed across scientist types, the theorized gap in capital intensity (θ) driven by gaps in downstream appropriability ($\gamma_c - \gamma_u > 0$) is as follows:

$$\Delta^* \equiv \theta^*(\lambda, \gamma_c) - \theta^*(\lambda, \gamma_u).$$

However, the reduced-form gap available in the empirical comparisons will have heterogeneous λs by sector:

$$\hat{\Delta} \equiv \theta^*(\lambda_c, \gamma_c) - \theta^*(\lambda_u, \gamma_u),$$

Proposition 5 (Downward bias of the reduced-form γ estimand)**.** *Under $\psi'(\theta) > 0$, $\phi'(\theta) > 0$, and $\lambda_u > \lambda_c$,*

$$\hat{\Delta} < \Delta^*.$$

Proof. Add and subtract $\theta^*(\lambda_u, \gamma_c)$:

$$\hat{\Delta} = \underbrace{\left[\theta^*(\lambda_u, \gamma_c) - \theta^*(\lambda_u, \gamma_u)\right]}_{=\Delta^*} - \underbrace{\left[\theta^*(\lambda_u, \gamma_c) - \theta^*(\lambda_c, \gamma_c)\right]}_{\text{the } \lambda \text{ adjustment}}.$$

The λ adjustment is strictly positive: $\partial\theta^*/\partial\lambda > 0$ together with $\lambda_u > \lambda_c$ gives $\theta^*(\lambda_u, \gamma_c) > \theta^*(\lambda_c, \gamma_c)$. Therefore $\hat{\Delta} < \Delta^*$. □

Empirical comparisons of corporate and university capital intensity identify the reduced-form gap $\hat{\Delta}$ rather than the structural γ wedge Δ^*. The two factors are in opposition: The γ wedge pushes corporate scientists toward higher θ, while the λ wedge — through the equilibrium sorting that places lower-λ types in the corporate sector — pulls them toward lower θ relative to what they would choose with the academic taste profile. The observation that corporate scientists nevertheless work at higher capital intensities implies the γ wedge dominates. The magnitude of $\hat{\Delta}$ is a conservative estimate.

Appendix B Data Appendix

B.1 Identifying Costly Scientific Instruments

B.1.1 Federal Instrument Purchase Grants

I use the Dimensions.ai grants database to obtain all U.S. federal grants administered to principal investigators in the United States. Of 6,312,091 total grants in the database, I focus on those related to the US government (GRID ID: "grid.451285.f"). A total of 927 sub-organizations across the federal scientific establishment are identified through the Dimensions GRID database. Around 1.35 million grants from 1980 to 2020 were input to the OpenAI Batch API with the following instructions:[33]

Listing 1: gpt-4o-mini prompt for extracting equipment information from U.S. government grants.

```
prompt = f'''This is an abstract of a grant proposal in the natural sciences: {cell}.
---
Please organize the data into a tab-separated table.
Each line in the table must be split by a newline character (\n).
If you cannot find information for an item, list it as "NuN" and move on to the next item.
If the grant proposes to acquire the instrument, indicate "acq" under "I_PROPOSAL";
if the grant proposes to use an existing instrument, indicate "use";
if the grant does not contain any scientific instruments, indicate "FP".
Indicate the type of scientific instrument under "I_TYPE".
Indicate the manufacturer of the scientific instrument under "I_MANUFACTURER".
Indicate the model number of the scientific instrument under "I_MODEL_NAME".
If the acquisition is for a completely new system, indicate "new" under "DENOVO";
If the acquisition is for an upgrade, renovation or repair of an existing system, indicate "old" under DENOVO".
Indicate whether the scientific instrument will be purchased from a manufacturer or developed internally under "ACQ_TYPE":
If purchased, state "buy"; if internally developed, state "make"; if unclear, state "unclear".

Create a new line for each instrument you find.
This is the format of the output. DO NOT DEVIATE:
I_TABLE\nI_PROPOSAL\tI_TYPE\tI_MANUFACTURER\tI_MODEL_NAME\tDENOVO\tACQ_TYPE\n--Your content here --
```

This creates a candidate list of 248,758 grants for which the acquisition of scientific instruments is mentioned. Many of these grants propose to lease equipment or build them in-house. To ensure consistent measurement between researchers, I clean these out and focus only on purchases of systems from outside vendors, where prices are less dependent on researcher taste or quality. This leaves us with 88,251 grants that concern the purchase of a system. Of these, 83,809 concern the purchase of new systems (the remainder refer primarily refer to upgrades or expansions of existing instruments).[34]

[33] Specifically, I use the 2024-07-18 version of gpt-4o-mini.

[34] Of these, 12,517 declare a manufacturer name that I use to spot-check prices on used lab equipment vendors such as labx.com.

The equipment mentioned in the 83,809 grants are then manually cleaned and grouped together. Three categories of equipment are dropped from the sample: the first concern IT-related software and hardware expenditures.[35] While compute is a critical physical input the grant abstracts are usually not specific about the type of system acquired and the scale at which the acquisition is happening. Therefore, these systems are omitted from the data. The second category concerns non-IT equipment that are too broadly mentioned to reliably measure price data on. For instance, abstracts will propose to purchase boules of specialized material such as neodymium that are melted down, cell lines and animal models used for in vivo experiments that - these items are either too idiosyncratic project-by-project to gauge reliable price data, or require scale data (in the case of crystals or gases) to measure capital intensity (i.e., size and number of boules or tanks purchased), which is rarely available in grant abstracts.[36] After eliminating these items, we cluster the equipment into like category so that a similarly named instrument is not double-counted when joined to the ngrams in General Index. New name variants are also added using the National Nanotechonlogy Coordinated Infrastructure (NNCI) website so that common acronyms (e.g., "XRD" for x-ray diffractometer, "UPLC" for ultra-performance liquid chromatography, or "CVD" for chemical vapor deposition) are included.

After the checks, 9,759 grants containing 4,679 instruments remain. There are 47 sub-types of instruments clustered under 24 broader types that fall under three broad categories (imaging, metrology and processing), as shown in Table B1. The price of an equipment is deduced from the awarded amount for the grants that propose to purchase it. The per-equipment funding amounts are shown in Figure B3. We take the median of this value to construct the "Paper Equipment Cost" variable used in the analysis. The capital intensity of scientific papers is deduced by matching the equipment name to abstract and full-text ngrams available in the General Index database.

B.1.2 AZO Networks

To mitigate concerns that U.S. federal grants data has uneven coverage of capital equipment across fields, I gather data on scientific instruments from AZO networks, a comprehensive industry publication for lab equipment manufacturers.[37] The AZO network comprises AZO Nano, AZO Materials, AZO Quantum and AZO Optics. I scrape the vendor directories for each website, comprising 94 firms fielding 354 equipment ranging from 3D printers to zeta potential analyzers. Unlike the federal grants data, the data from AZO networks lacks price data; they are also current only as of the data collection period (April to October of 2024), and therefore may miss legacy systems that were retired prior to the period. I stem the instruments names from AZO and match them to the General Index ngrams. At the paper level, the correlation between AZO networks-based measure of capital use and the grants-based measure is 0.35.[38] On average, the grants data identifies more papers as equipment users than AZO networks.

[35] This category includes terms such as “software package,” “compute server,” “computer graphics workstation,” “computer interface,” “computer laboratory,” “computer server,” “computer workstation,” “CPU server,” “cyber-security software,” “data analysis software,” “database management system,” and “GPU nodes.”

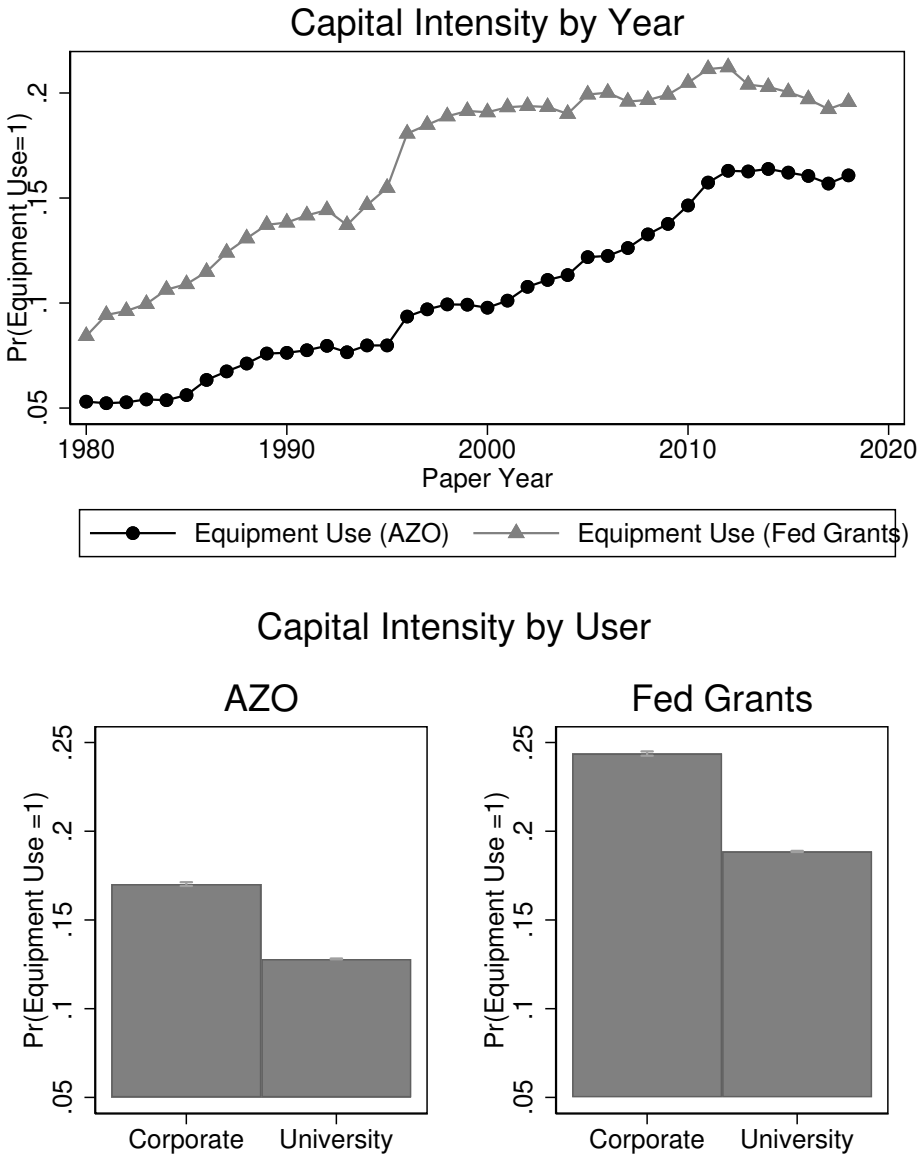
[36] Other examples in this category include "neutron beam," "solar cell,” “sonar system,” “total station,” “tracking system,” “video camera,” “3-D seismic reflection system,” “acoustic source,” “air sampler,” “air source heat pump,” and “animal services.”

[37] https://www.azonetwork.com/

[38] 491,203 papers are identified as using equipment by both datasets; 5,661,318 are identified as using none by both datasets; the grants data identifies 868,273 equipment-using papers that the AZO data fails to identify; AZO identifies 415,119 that the grants data do not identify.

The line graph in Figure B1 shows that the grants-based capital intensity measure is above the AZO-based line. The capital gap between university and industry is preserved, however: the bar graphs in the bottom of Figure B1 shows that corporate papers are more likely to use equipment identified in AZO networks compared to university papers.

Figure B1: Capital Intensity, AZO vs Federal Grants Data

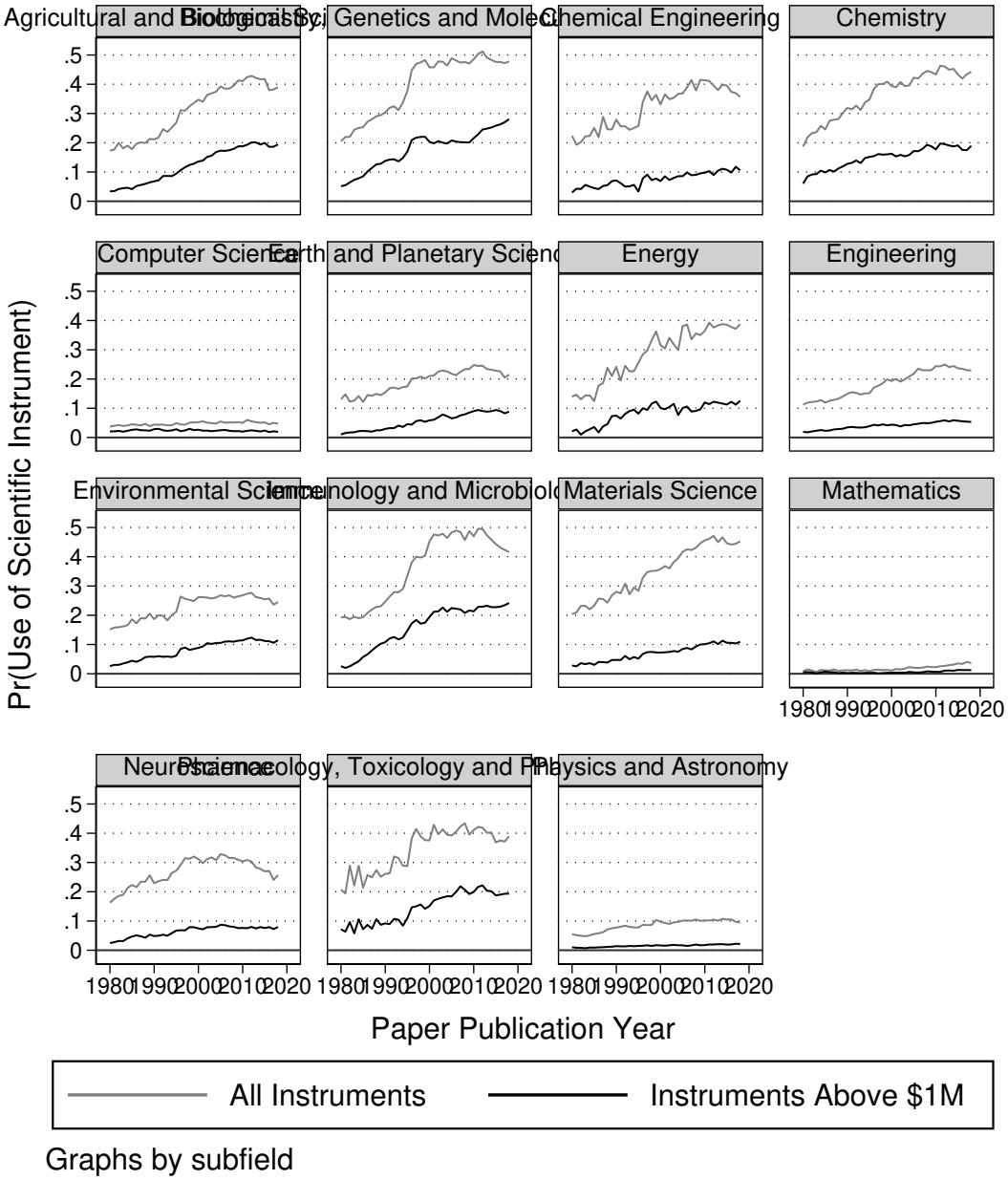


Notes: The top panel plots the share of papers that mention a capital equipment identified through the AZO Networks data (black circle marker) and through federal grants data (grey triangle marker) over time. The bottom bar graphs plot the share of corporate and university papers that use capital equipment according to AZO networks (left) and federal grants (right).

B.2 Descriptives on Scientific Equipment

B.2.1 Equipment categories and costs

Figure B2: Use of Scientific Equipment, by Scientific Field



Notes: The gray line plots the share of papers in each scientific subfield using scientific instruments found in U.S. federal grant documents. the black line plots the same for instruments that cost above $1 million. Scientific subfields are sourced from the OpenAlex database. Further details on identifying instruments is found in Section 3.

Figure B3: Costs of Scientific Equipment (Sub-type)

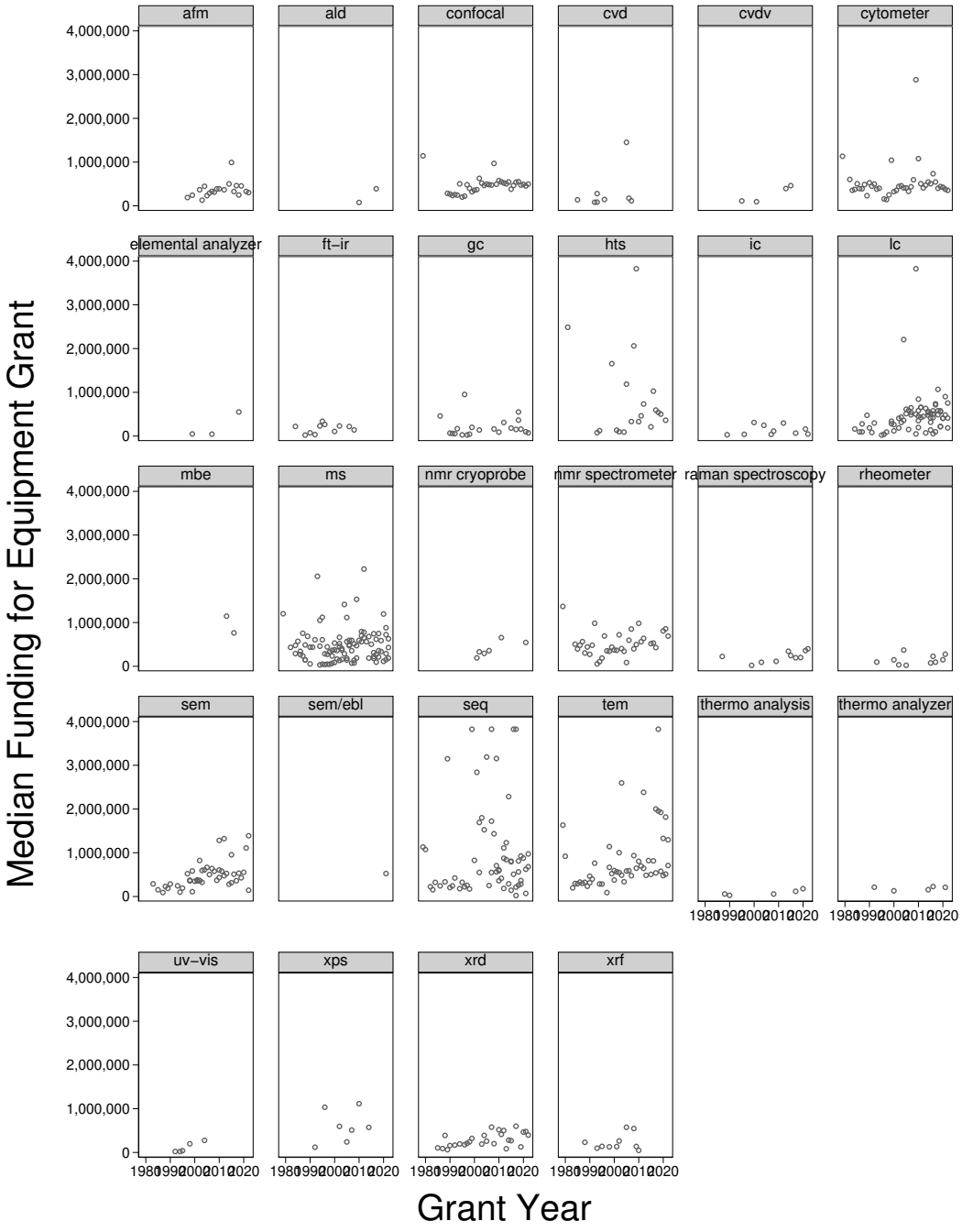


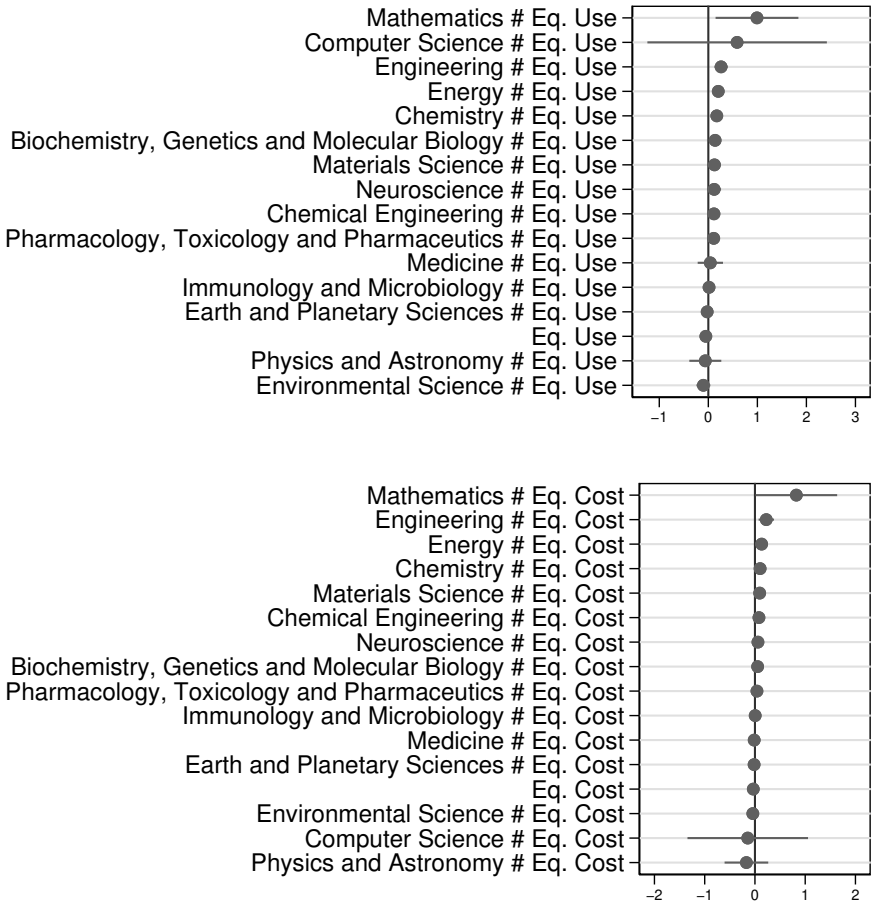
Table B1: Cost Data by Equipment (Sub-type)

Category	Type	Subtype	Purchase Grants	Average Funding
imaging	Atomic Force Microscope		41	$ 366,012
imaging	Confocal Microscope		458	$ 468,581
imaging	Scanning Electron Microscope	Environmental Scanning Electron Microscopy	7	$ 435,335
imaging	Scanning Electron Microscope	Focused Ion Beam Scanning Electron Microscopy	6	$ 1,059,322
imaging	Scanning Electron Microscope		85	$ 396,361
imaging	Transmission Electron Microscope	Cryo-electron Microscopy	14	$ 1,548,358
imaging	Transmission Electron Microscope	Scanning Transmission Electron Microscopy	4	$ 717,727
imaging	Transmission Electron Microscope		139	$ 892,432
metrology	Cytometer		249	$ 531,445
metrology	Elemental Analyzer		3	$ 214,614
metrology	Fourier Transform Infrared Spectroscopy		14	$ 170,310
metrology	Gas Chromatography	Gas Chromatography-Mass Spectroscopy	7	$ 172,060
metrology	Gas Chromatography		19	$ 220,509
metrology	High Throughput Screening		39	$ 981,197
metrology	Ion Chromatography		12	$ 134,974
metrology	Liquid Chromatography	Fast Protein Liquid Chromatography	2	$ 124,812
metrology	Liquid Chromatography	Gas Chromatography-Liquid Chromatography	1	$ 278,541
metrology	Liquid Chromatography	Gel Permeation Chromatography	1	$ 186,321
metrology	Liquid Chromatography	High-Performance Liquid Chromatography	46	$ 315,617
metrology	Liquid Chromatography	Liquid Chromatography-Mass Spectrometry	24	$ 468,958
metrology	Liquid Chromatography	Ultra-High Performance Liquid Chromatography	10	$ 455,424
metrology	Liquid Chromatography	Ultra-Performance Liquid Chromatography	5	$ 376,414
metrology	Liquid Chromatography		26	$ 993,231
metrology	Mass Spectroscopy	Gas Chromatography-Mass Spectrometry	39	$ 211,924
metrology	Mass Spectroscopy	Inductively Coupled Plasma	39	$ 341,970
metrology	Mass Spectroscopy	Secondary Ion Mass Spectrometry	7	$ 877,329
metrology	Mass Spectroscopy	Time-of-Flight	3	$ 550,276
metrology	Mass Spectroscopy		486	$ 648,546
metrology	Nuclear Magnetic Resonance	Cryoprobe	6	$ 396,199
metrology	Nuclear Magnetic Resonance	Spectrometer	123	$ 517,434
metrology	Raman Spectroscopy		13	$ 219,149
metrology	Rheometer		16	$ 148,929
metrology	Gene Sequencer	High-Throughput	18	$ 585,001
metrology	Gene Sequencer	Next Generation	45	$ 471,852
metrology	Gene Sequencer		631	$ 1,547,636
metrology	Thermo Analyzer		7	$ 87,819
metrology	Thermo Analyzer		6	$ 187,420
metrology	Ultraviolet-visible Spectroscopy		5	$ 106,867
metrology	X-ray Photoelectron Spectroscopy		8	$ 598,675
metrology	X-ray Diffraction		63	$ 291,764
metrology	X-ray Fluorescence		13	$ 230,114
thin film processing	Atomic Layer Deposition		3	$ 234,066
thin film processing	Chemical Vapor Deposition	Liquid-Phase	1	$ 137,430
thin film processing	Chemical Vapor Deposition	Metalorganic	2	$ 227,383
thin film processing	Chemical Vapor Deposition		6	$ 376,221
thin film processing	Molecular Beam Epitaxy		2	$ 954,746

B.2.2 Scientific instrument use, by field

Figure B4 correlates share of papers used in inventions (measured by NPL citations) against two measures of capital intensity (share of papers using capital equipment & average equipment cost per paper) at the scientific field level. Concretely, the figure plots the coefficient estimates of $\hat{\kappa}$ from $Pr(CitedbyPatents)_{ft} = \kappa Pr(EquipmentUse)_{ft} \times \zeta_f + \alpha Pr(EquipmentUse)_{ft} + \tau_t + \zeta_f + \epsilon_{ft}$ for field f and year t. $\hat{\kappa}$ enters as "NPL-Eq. Cost Gradient" in Columns 3 and 7 of Table 5.

Figure B4: NPL-Capital Intensity Gradient by Scientific Field



Notes: This figure plots the coefficient estimates of a scientific field-year level OLS specification regressing share of papers cited by patents against share of paper using a capital equipment (top panel) and average capital equipment cost mentioned in papers (bottom paenl).

B.3 Measuring Downstream Value Capture

B.3.1 Corporate value capture measure (patent stock market value)

To measure the $Corporate\ Value\ Capture$ variable for U.S. public firms in Table 6, I run an OLS specification regressing the stock market value of patents citing science against firm-

field dummies while controlling for the cited scientific article. I begin with 415,383 paper-patent citation pairs that consist of 161,569 patents citing 54,518 papers (corporate patents are drawn from the DISCERN database and linked to the patent stock market value database from Kogan, Papanikolaou, Seru, and Stoffman (2017)). There are 1,996 firms citing science in 16 fields. Tables B2 and B3 show the top five firms by value capture measure.

Table B2: Top 5 Corporate Value Capture Firms by Field (1/2)

Rank	Field	Firm Name	Equipment Use Share	Equipment Cost ($1M)	Value Capture
1	Agricultural and Biological Sciences	ILLUMINA INC	1.00	3.10	2.75
2	Agricultural and Biological Sciences	PFIZER INC	0.37	0.60	2.22
3	Agricultural and Biological Sciences	THERMO FISHER SCI INC	0.80	2.38	2.15
4	Agricultural and Biological Sciences	AMGEN INC	0.54	1.20	2.00
5	Agricultural and Biological Sciences	ABBVIE INC	0.67	0.73	2.00
1	Biochemistry, Genetics and Molecular Biology	CHEVRON CORP	0.67	0.21	2.48
2	Biochemistry, Genetics and Molecular Biology	WEYERHAEUSER CO	0.30	0.39	2.22
3	Biochemistry, Genetics and Molecular Biology	THERMO FISHER SCI INC	0.56	1.35	2.18
4	Biochemistry, Genetics and Molecular Biology	SERES THERAPEUT INC	1.00	4.54	2.14
5	Biochemistry, Genetics and Molecular Biology	AMGEN INC	0.47	0.93	2.11
1	Chemical Engineering	EXXON MOBIL CORP	0.50	0.11	2.06
2	Chemical Engineering	PHILLIPS 66	0.00	0.00	1.77
3	Chemical Engineering	CHEVRON CORP	0.00	0.00	1.67
4	Chemical Engineering	FORD MOTOR CO	0.20	0.57	1.49
5	Chemical Engineering	HALLIBURTON CO	1.00	0.15	1.21
1	Chemistry	AMGEN INC	0.70	1.49	2.68
2	Chemistry	WARNER LAMBERT CO	0.68	1.11	2.40
3	Chemistry	ALTRIA GRP INC	0.67	1.63	2.25
4	Chemistry	PFIZER INC	0.57	0.92	2.15
5	Chemistry	LILLY ELI & CO	0.62	0.90	2.13
1	Computer Science	AMGEN INC	0.00	0.00	2.57
2	Computer Science	HOLOGIC INC	0.00	0.00	2.26
3	Computer Science	GTE CORP	0.04	0.06	2.20
4	Computer Science	TIME WARNER INC	0.00	0.00	1.95
5	Computer Science	CHEVRON CORP	0.00	0.00	1.91
1	Earth and Planetary Sciences	TEXACO INC	0.00	0.00	2.85
2	Earth and Planetary Sciences	CHEVRON CORP	0.12	0.11	2.27
3	Earth and Planetary Sciences	EXXON MOBIL CORP	0.14	0.13	1.82
4	Earth and Planetary Sciences	ATLANTIC RICHFIELD CO	1.00	0.65	1.67
5	Earth and Planetary Sciences	CONOCOPHILLIPS	0.09	0.08	1.58
1	Energy	CHEVRON CORP	0.00	0.00	2.75
2	Energy	EXXON MOBIL CORP	0.17	0.11	1.30
3	Energy	LINDE PLC	0.00	0.00	1.14
4	Energy	LOCKHEED MARTIN CORP	1.00	3.13	0.81
5	Energy	GE	0.00	0.00	0.32
1	Engineering	PFIZER INC	0.41	0.35	2.90
2	Engineering	AMGEN INC	0.20	1.37	2.37
3	Engineering	CELGENE CORP	0.00	0.00	2.18
4	Engineering	BIOMET INC	0.50	0.40	2.03
5	Engineering	ILLUMINA INC	0.56	0.69	1.96

Table B3: Top 5 Corporate Value Capture Firms by Field (2/2)

Rank	Field	Firm Name	Equipment Use Share	Equipment Cost ($1M)	Value Capture
1	Environmental Science	EXXON MOBIL CORP	0.24	0.26	3.88
2	Environmental Science	CHEVRON CORP	0.30	0.29	3.68
3	Environmental Science	ALTRIA GRP INC	0.67	1.41	3.11
4	Environmental Science	SCHLUMBERGER LTD	0.17	0.10	2.95
5	Environmental Science	MICROSOFT CORP	0.00	0.00	2.61
1	Immunology and Microbiology	WARNER LAMBERT CO	0.00	0.00	3.42
2	Immunology and Microbiology	CERNER CORP	0.00	0.00	2.31
3	Immunology and Microbiology	AMGEN INC	0.25	0.44	2.14
4	Immunology and Microbiology	LILLY ELI & CO	0.30	0.50	2.04
5	Immunology and Microbiology	BIOGEN INC	0.45	0.92	1.99
1	Materials Science	GENENTECH INC	0.50	0.23	2.38
2	Materials Science	LILLY ELI & CO	0.33	0.32	2.26
3	Materials Science	ALTRIA GRP INC	0.37	0.22	2.22
4	Materials Science	CHEVRON CORP	0.60	0.29	2.09
5	Materials Science	GILEAD SCI INC	1.00	0.32	1.98
1	Mathematics	BRISTOL MYERS SQUIBB CO	0.05	0.08	1.71
2	Mathematics	EXXON MOBIL CORP	0.00	0.00	1.59
3	Mathematics	ABBVIE INC	0.00	0.00	1.41
4	Mathematics	ABBOTT LAB	0.00	0.00	1.23
5	Mathematics	AT&T INC	0.00	0.00	0.71
1	Medicine	SERES THERAPEUT INC	1.00	2.47	2.47
2	Medicine	DYNAVAX TECH CORP	0.21	0.20	2.40
3	Medicine	KING PHARM INC	0.00	0.00	2.16
4	Medicine	PFIZER INC	0.21	0.28	2.14
5	Medicine	AMGEN INC	0.17	0.30	2.03
1	Neuroscience	AMGEN INC	0.37	0.59	2.29
2	Neuroscience	DUPONT	0.36	0.28	2.27
3	Neuroscience	CELGENE CORP	0.00	0.00	2.21
4	Neuroscience	BIOGEN INC	0.50	0.43	2.20
5	Neuroscience	ABBVIE INC	0.46	0.34	1.99
1	Pharmacology, Toxicology and Pharmaceutics	AMGEN INC	0.58	0.42	2.76
2	Pharmacology, Toxicology and Pharmaceutics	GILEAD SCI INC	0.19	0.28	2.68
3	Pharmacology, Toxicology and Pharmaceutics	ABBVIE INC	0.51	0.53	2.18
4	Pharmacology, Toxicology and Pharmaceutics	IMMUNEX CORP	1.00	1.31	2.07
5	Pharmacology, Toxicology and Pharmaceutics	CELGENE CORP	0.51	0.41	2.00
1	Physics and Astronomy	FACEBOOK INC	0.00	0.00	1.81
2	Physics and Astronomy	GEN DYNAM CORP	0.11	0.19	1.81
3	Physics and Astronomy	ALTRIA GRP INC	1.00	0.40	1.77
4	Physics and Astronomy	EXXON MOBIL CORP	0.25	0.24	1.48
5	Physics and Astronomy	VIAVI SOLUT INC	0.50	0.28	1.46

B.3.2 University patent reassignment

To measure share of reassigned patents, I collect USPTO patents matched to university researchers through the Dimensions patent dataset. There are a total of 167,225 patents issued to 99,106 academics throughout my sample period. I then match this to patent reassignment data after cleaning out reassignments unrelated to Markets for Technology (MFT) transactions following the procedure from (Arora, Belenzon, & Suh, 2022): I start with the USPTO Assignment Dataset (Graham, Marco, & Myers, 2018) and exclude assignments due to name changes, security interests. I also exclude reassignments that are likely between an employee and an employer or between subdivisions within the same organization following Arora, Belenzon, and Suh (2022) and Serrano and Ziedonis (2018). Around 4.1% of university patents are found to be "traded" to outside entities under this measure. I calculate the share of traded patents by researcher and patent grant year. This enters the "Share of Patents Traded" vari-

able in Columns 3 and 4 of Table 6. For further context, Tables B4 and B5 collapse the data at the university level by linking the researcher to her home institution based on Dimensions affiliation linkages at the time of patent issuance.

Table B4: Top 5 Patent Reassigning Universities by Field (1/2)

Rank	Field	University	Number of Patents	Share of Reassigned Patents	Equipment Use Share	Equipment Cost ($1M$)
1	Agricultural and Biological Sciences	North Carolina State University	156	0.06	0.40	691,253
2	Agricultural and Biological Sciences	Cornell University	225	0.03	0.40	866,070
3	Agricultural and Biological Sciences	University of Florida	146	0.03	0.41	787,486
4	Agricultural and Biological Sciences	Iowa State University	195	0.03	0.45	727,330
5	Agricultural and Biological Sciences	Michigan State University	224	0.02	0.43	721,655
1	Biochemistry, Genetics and Molecular Biology	Albert Einstein College of Medicine	210	0.36	0.47	656,280
2	Biochemistry, Genetics and Molecular Biology	Virginia Commonwealth University	118	0.11	0.37	492,518
3	Biochemistry, Genetics and Molecular Biology	University of North Carolina System	145	0.10	0.39	513,582
4	Biochemistry, Genetics and Molecular Biology	University of Washington	507	0.08	0.46	875,086
5	Biochemistry, Genetics and Molecular Biology	Indiana University Ð Purdue University Indianapolis	122	0.08	0.34	489,680
1	Chemistry	Brigham Young University	111	0.25	0.58	685,691
2	Chemistry	Stanford University	169	0.07	0.50	604,642
3	Chemistry	University of South Florida	114	0.06	0.37	491,929
4	Chemistry	University of Florida	176	0.05	0.51	634,799
5	Chemistry	Harvard University	120	0.03	0.37	443,042
1	Computer Science	New York University	101	0.06	0.00	3,509
2	Computer Science	Columbia University	226	0.03	0.01	15,998
3	Computer Science	Stanford University	135	0.01	0.04	41,255
4	Computer Science	Massachusetts Institute of Technology	287	0.01	0.03	29,800
5	Computer Science	Carnegie Mellon University	155	0.01	0.04	42,083
1	Engineering	University of New Mexico	157	0.16	0.24	179,214
2	Engineering	Virginia Tech	391	0.14	0.22	202,045
3	Engineering	University of Delaware	178	0.09	0.19	106,270
4	Engineering	Brigham Young University	191	0.09	0.24	217,275
5	Engineering	University of Maryland, College Park	200	0.08	0.31	290,782

Table B5: Top 5 Patent Reassigning Universities by Field (2/2)

Rank	Field	University	Number of Patents	Share of Reassigned Patents	Equipment Use Share	Equipment Cost ($1M$)
1	Immunology and Microbiology	University of Florida	103	0.05	0.31	481,546
2	Immunology and Microbiology	Johns Hopkins University	124	0.05	0.35	556,202
3	Immunology and Microbiology	Harvard University	420	0.04	0.38	572,721
4	Immunology and Microbiology	Yale University	179	0.04	0.34	603,910
5	Immunology and Microbiology	University of California, Los Angeles	106	0.04	0.39	680,770
1	Materials Science	University of Minnesota	141	0.10	0.59	481,571
2	Materials Science	University of Florida	224	0.09	0.41	278,077
3	Materials Science	University of California, Santa Barbara	142	0.08	0.49	416,362
4	Materials Science	Tufts University	176	0.06	0.51	499,887
5	Materials Science	Northwestern University	432	0.06	0.50	439,888
1	Medicine	Albert Einstein College of Medicine	176	0.33	0.29	457,932
2	Medicine	Tufts University	101	0.16	0.26	387,415
3	Medicine	University of New Mexico	117	0.12	0.24	328,875
4	Medicine	Wayne State University	103	0.10	0.17	177,587
5	Medicine	Yale University	274	0.09	0.26	356,761
1	Neuroscience	University of South Florida	105	0.07	0.30	227,242
2	Neuroscience	University of California, San Francisco	116	0.05	0.30	463,569
3	Neuroscience	University of MichiganÐAnn Arbor	173	0.05	0.38	442,768
4	Neuroscience	University of Florida	124	0.04	0.25	344,444
5	Neuroscience	Johns Hopkins University	109	0.03	0.25	300,740
1	Physics and Astronomy	North Carolina State University	116	0.14	0.38	287,290
2	Physics and Astronomy	University of New Mexico	172	0.13	0.24	162,314
3	Physics and Astronomy	University of California, Berkeley	109	0.06	0.22	128,490
4	Physics and Astronomy	University of California, Santa Barbara	371	0.02	0.39	243,534
5	Physics and Astronomy	Harvard University	128	0.02	0.30	285,393

Appendix C Robustness Tests

The following table replicate the result in Table 4 using alternative measures of capital intensity and invention. Table C1 replaces the instrumented capital intensity measure to a dummy that indicates whether a scientist publishes a paper that uses a scientific equipment. Tables C2 and C3 replace the dependent variable to a dummy indicating whether the author has a paper with a patent pair. The instrumented variable in Table C2 is equipment costs while it is the scientific equipment dummy in Table C3. Both

Table C1: Capital and NPL Citations (Equipment Dummy)

	OLS			IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Univ	Firm	All (FS)	All	Univ (FS)	Univ	Firm (FS)	Firm
Scientific Equipment Dummy	0.023	0.022	0.036		0.977		1.343		0.267
	(0.000)	(0.000)	(0.002)		(0.377)		(0.578)		(1.296)
Nearby Equipment Funding (Other Fields)				0.003		0.002		0.002	
				(0.001)		(0.001)		(0.002)	
Nearby Equipment Funding (Focal Field)	0.004	0.005	-0.017	0.010	-0.009	0.011	-0.014	-0.013	-0.015
	(0.003)	(0.003)	(0.009)	(0.003)	(0.006)	(0.003)	(0.010)	(0.007)	(0.015)
Forward Paper Citations	2.631	2.527	2.533	0.537	2.118	0.532	1.824	0.337	2.455
	(0.065)	(0.065)	(0.099)	(0.017)	(0.209)	(0.018)	(0.311)	(0.027)	(0.449)
Number of Coauthors	-0.000	-0.001	-0.001	0.002	-0.002	0.001	-0.003	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Average of Dep Var	13.126	13.026	27.872	22.708	13.126	23.062	13.026	29.154	27.872
F-Stat					23.166		13.507		1.524
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Researcher Dummies		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.343	0.344	0.423		.		.		.
Number of Obs	9,563,478	8,005,336	1,010,491	9,563,478	9,563,478	8,005,336	8,005,336	1,010,491	1,010,491

Notes: This table replicates the specifications in Table 3 by replacing the independent variable from equipment cost to the equipment use dummy (the dependent variable remains forward patent citations received by the researcher's papers).

Table C2: Capital and Patent Paper Pairs (Equipment Costs)

	OLS			IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Univ	Firm	All (FS)	All	Univ (FS)	Univ	Firm (FS)	Firm
Paper Equipment Cost	0.397	0.408	0.324		4.964		8.580		25.517
	(0.013)	(0.014)	(0.058)		(7.886)		(8.157)		(50.100)
Nearby Equipment Funding (Other Fields)				0.000		0.000		0.000	
				(0.000)		(0.000)		(0.000)	
Nearby Equipment Funding (Focal Field)	0.004	0.005	0.010	0.000	0.001	0.000	0.001	0.000	0.005
	(0.002)	(0.002)	(0.007)	(0.000)	(0.005)	(0.000)	(0.005)	(0.000)	(0.013)
Forward Paper Citations	0.568	0.539	0.619	0.015	0.499	0.015	0.413	0.012	0.326
	(0.016)	(0.017)	(0.031)	(0.001)	(0.121)	(0.001)	(0.127)	(0.001)	(0.583)
Number of Coauthors	0.001	0.000	0.002	0.000	0.000	0.000	-0.001	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.004)
Average of Dep Var	3.803	3.614	11.948	0.318	3.803	0.321	3.614	0.444	11.948
F-Stat					29.965		31.079		1.621
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Researcher Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.309	0.307	0.381		.		.		.
Number of Obs	9,563,478	8,005,336	1,010,491	9,563,478	9,563,478	8,005,336	8,005,336	1,010,491	1,010,491

Notes: This table replicates the specifications in Table 3 by replacing the dependent variable from forward patent citations to patent paper pair dummies (=100 if the researcher publishes at least one paper with a patent pair and zero otherwise).

Table C3: Capital and Patent Paper Pairs (Equipment Dummy)

	OLS			IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Univ	Firm	All (FS)	All	Univ (FS)	Univ	Firm (FS)	Firm
Scientific Equipment Dummy	0.008	0.008	0.011		0.112		0.258		0.567
	(0.000)	(0.000)	(0.001)		(0.178)		(0.251)		(1.104)
Nearby Equipment Funding (Other Fields)				0.003		0.002		0.002	
				(0.001)		(0.001)		(0.002)	
Nearby Equipment Funding (Focal Field)	0.004	0.005	0.010	0.010	0.002	0.011	0.002	-0.013	0.015
	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)	(0.012)
Forward Paper Citations	0.570	0.541	0.619	0.537	0.514	0.532	0.408	0.337	0.431
	(0.016)	(0.017)	(0.031)	(0.017)	(0.097)	(0.018)	(0.134)	(0.027)	(0.374)
Number of Coauthors	0.001	0.000	0.002	0.002	0.001	0.001	-0.000	-0.001	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Average of Dep Var	3.803	3.614	11.948	22.708	3.803	23.062	3.614	29.154	11.948
F-Stat					23.166		13.507		1.524
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Researcher Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.309	0.307	0.381		.		.		.
Number of Obs	9,563,478	8,005,336	1,010,491	9,563,478	9,563,478	8,005,336	8,005,336	1,010,491	1,010,491

Notes: This table replicates the specifications in Table C1 by replacing the dependent variable from forward patent citations to patent paper pair dummies (=100 if the researcher publishes at least one paper with a patent pair and zero otherwise).