# Instrumental Burden: Rising Capital Intensity in Science and Consequences for Science

March 1, 2026

> *I need a gram of radium to continue my research, but I cannot buy it; radium is too dear for me.*
>
> - Marie Curie

## 1 Introduction

In recent decades, the promise of science to drive transformative innovations and productivity growth has been challenged by a growing disconnect between theoretical discovery and commercial application. This paper highlights a critical yet underexplored factor: the rising capital intensity of scientific research. Modern applied science increasingly depends on access to sophisticated, high-cost instruments — from cryo-electron microscopes and mass spectrometers to high-throughput screening platforms — whose acquisition and operation require substantial fixed investments. This capital burden can act as an entry barrier, shaping which researchers and institutions are able to participate in translation-oriented research.

I propose that these rising costs have reshaped the landscape of university-based applied science. Whereas industrial laboratories can absorb the cost of cutting-edge instrumentation as part of their value capture strategies, many academic researchers face binding budget constraints that restrict access to such tools. Using newly assembled data on over 10,000 federal grants for scientific instruments and a vendor directory of research equipment, I construct a comprehensive dataset to measure the diffusion and cost of major instruments across fields and time. I then match this data to more than seven million scientific publications authored in the United States to track how capital requirements have influenced patterns of research output, collaboration, and commercialization.

I establish several patterns from the data: first, scientific instruments seem to help with

the commercialization of science, even after controlling for the type of research using pairs of simultaneous discoveries (Bikard, 2020; Marx & Fuegi, 2020). Second, corporations are more likely to use costly instruments than universities. Third, universities are especially less likely to engage in commercially relevant research (as measured through patent citations) in more instrument-intensive fields. Alternative explanations for the university-to-corporate gap are considered: first, the results are not likely to be driven by universities' "taste" for abstract problems without applied components: scientific impact is increasing in the use of instruments regardless of author affiliation. Second, I mitigate concerns that firm publications may be higher quality due to reputational concerns by showing the industry-university instrument gap to hold for "home-run" papers receiving high publication forward citations. Finally, I find that scientists priced out of capital intensive fields choose more "exploratory" science which is more novel than corporates'.

With the retrenchment of basic research at major American firms in recent decades and a growing division of innovative labor between university and industry, identifying structural impediments to translating academic knowledge has become a pressing question (Arora, Belenzon, Patacconi, & Suh, 2020). By identifying a growing "instrumental burden" imposed by modern science on translational research, this paper contributes to our understanding of structural challenges related to the commercialization of science. The rest of the paper proceeds as follows: Section 2 conducts a qualitative survey of the role of instruments in translational science and the changing composition of their users; Section 3 presents the data on instruments and their users; Section 4 presents the empirical results; Section 5 concludes.

## 2 Translation of Science and the Rising Cost of Instruments

The translation of science into practical applications requires the ability to empirically test out the metes and bounds of a theory. Scientific instruments are the means with which such tests are built, executed, and measured, so that learning for future improvements occur. This section begins first presents signs that modern science has become more reliant on scientific instruments which are becoming more expensive. I then predict that rising fixed costs of conducting translational research deepens a division of scientific labor between universities

which specialize deeper into exploratory science and corporations which focus on incremental science closer to application.

## 2.1 Modern science's growing reliance on costly instruments

Throughout history, scientific instruments have been critical to advancing knowledge about nature. Before the advent of sophisticated telescopes and microscopes, science had been synonymous with natural philosophy, relying primarily on folk observations of natural regularities such as the movement of celestial bodies to the naked eye or the recombination of hereditary traits in breeds of domesticated plants and animals (Garber, 2006). The limitations were clear: neither the phlogiston theory of combustion nor the humoral theories of disease could be tested out with these rudimentary methods of observation, rendering them unfalsifiable speculations about the cosmos. The fabrication of more advanced instruments that began in the Scientific Revolution allowed for the manipulation (vacuum pumps, centrifuges, microtomes, furnaces, and flasks) and observation (telescopes, microscopes, barometers, spectrometers) of natural phenomena. This enabled scientists to design experiments that allowed them to reject older theories about nature and advance new theories which would in turn be tested by future empiricists. 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).

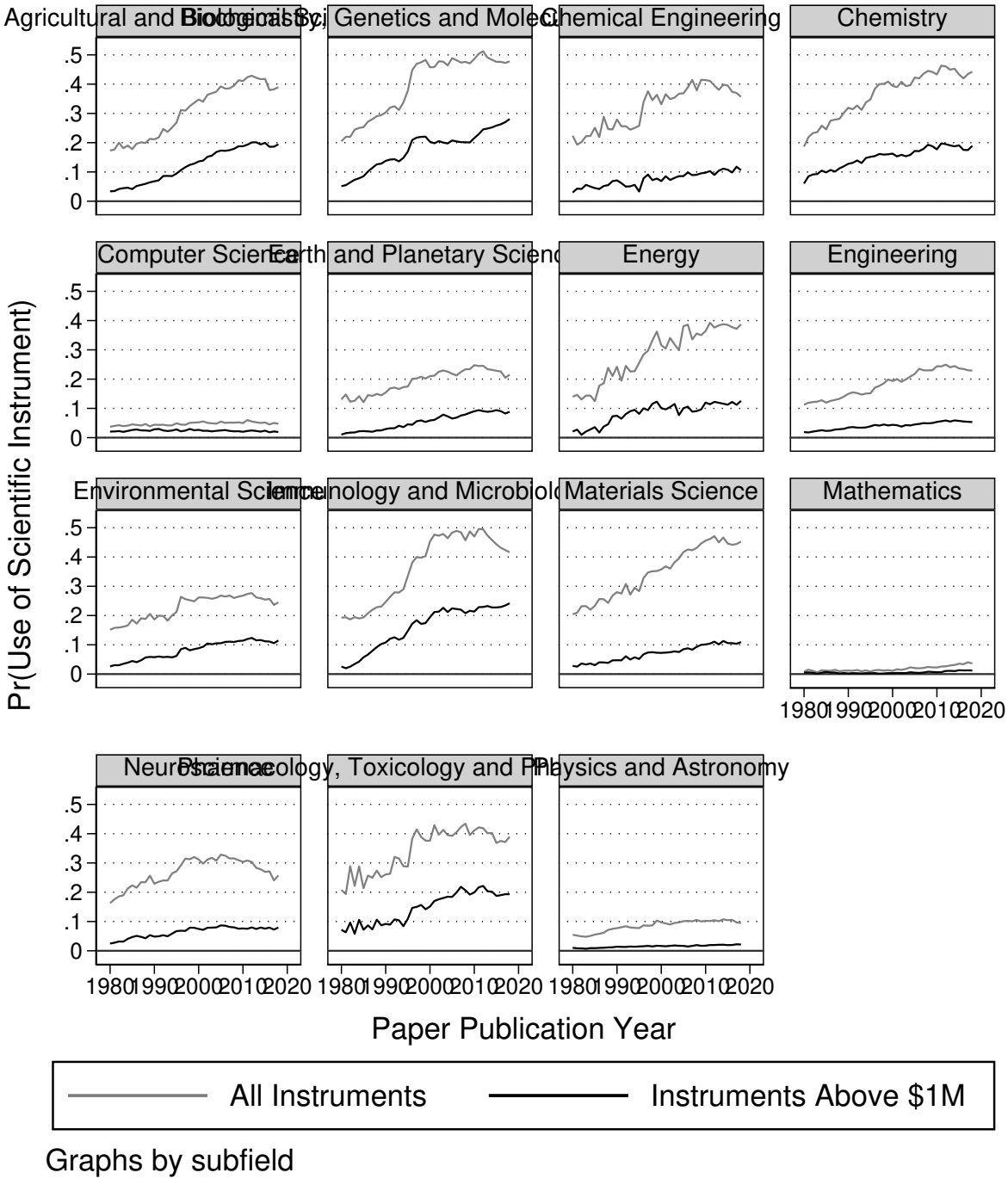
Due to their importance in advancing theory, scientists have increasingly demanded better instruments: the demand for greater resolution, speed, and more diverse modalities in turn pulled more instruments into existence. To overcome the limits of a compound microscope that takes in visible light, Ernst Ruska and Max Knoll invented the transmission electron microscope (TEM) which could resolve 2-dimensional images at the nanometer level. The first commercially available TEM would be built by Siemens in 1938. The first commercial scanning electron microscope (the Model B) that allowed nanometer resolution in 3D was marketed by

RCA in 1940. Because of the use of electrons, samples for electron microscopy required a conductive coating in a vacuum environment, which limited the types of samples that could be examined. Moreover, images were still taken via film, which needed to be stitched together by technicians. The 1980s hence saw the integration of charged coupled devices (CCDs) which allowed for digitized image collection. The Scanning Tunneling Microscope (1981) and Atomic Force Microscope (1986) were invented at IBM to measure atomic level smoothness of hard disk drives, copper interconnects and later 2D materials such as fullerenes. 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.[1]

In addition, instruments have diffused rapidly across fields. Nuclear Magnetic Resonance (NMR), for instance, was invented in 1938 by Isidor Rabi (a physicist) to study magnetic spin in atomic nuclei. However, this method was quickly adopted as a fundamental tool for analytical chemistry. The imaging of liquids and solids of different densities through NMR also enabled the invention of the modern Magnetic Resonance Imaging (MRI) machines used in medicine. Ion implantation - the procedure by which charged particles are smashed into a surface - was first invented by Ernest Rutherford to study the structures of atoms and later adopted in particle accelerators. Nowadays, the primary user of ion implantation techniques is the semiconductor industry, where dopants are placed on silicon wafers to modulate threshold voltages of transistors. As more scientists make use of superior methods to manipulate and measure phenomena, access to instruments is becoming a necessary condition to publishing in the physical and life sciences.

[1] 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)

Figure 1: Use of Scientific Instruments, 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.

The gray line in Figure 1 plots the share of peer-reviewed articles in a scientific field that mention a scientific instrument in its abstract and full text from 1980 to 2020.[2] 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 roughly a doubling of instrument intensity in the four decades observed. In the black line, which limits instrument use to those costing above $1 million, the life sciences show the largest increases: whereas under 5% of papers in biochemistry or genetics used such instruments, the share rises to close to half in the 2020s. This is not only consistent with the re-purposing of instruments from physics and chemistry that was discussed above, but also with the diffusion of new instruments such as gene sequencers that were accelerated during the Human Genome Project.

## 2.2 The consequences of greater instrument costs

The rise in scientific instrument costs can be conceptualized as an increase in the minimum efficient scale (MES) of research.[3] This leads to three empirical predictions. First, for universities, higher MES (without a commensurate increase in funding) would result in diminished entry into applied fields in general, and greater concentration among universities, as Matthew effects skew funding toward a handful of elite institutions. Second, in contrast, private firms may exploit rising MES as an opportunity to fence off potential competitors and appropriate value from their internal research. Corporations would hence redouble their investment in instruments-heavy science. Third, academics that persist in capital-intensive fields would substitute away from incremental topics (which are in direct competition with firms) and into novel topics that face fewer competition in the publication process. In sum, the rising capital intensity of science may deepen a "division of scientific labor" whereby firms double down on downstream research closer to application ("exploitative" science) and universities specialize in novel topics upstream that are farther from application ("exploratory" science).

[2]The list of instrument names are obtained from federal grants provided for the purchase of costly instruments. The grant sizes range from $15,000 to $15 million in 2017 dollars. Further details on how data on instruments (and their use) was collected are available in Section 3.

[3]The burden from fixed capital investments is similar to a "burden of knowledge" studied by Jones (2009).

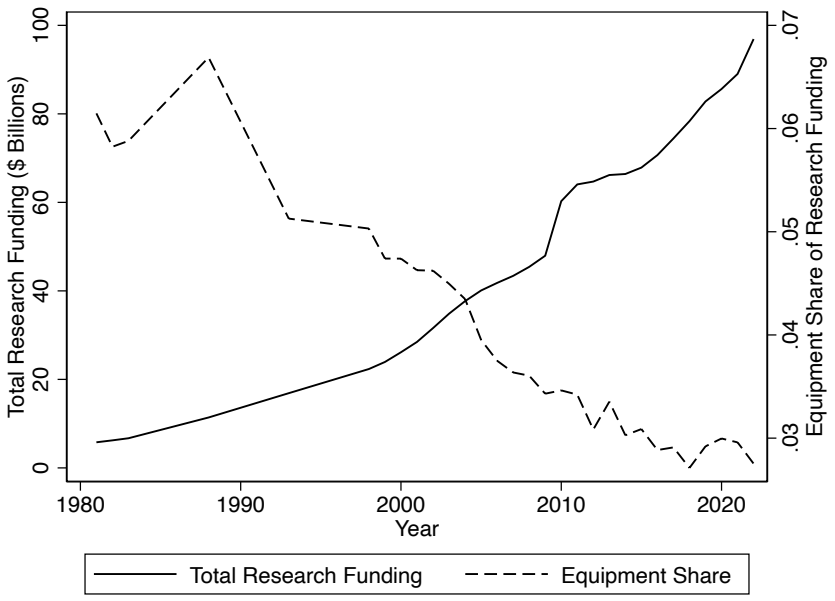
### 2.2.1 Academic research withdraws from instruments

Public funding agencies responsible for equipping labs in academia have striven to keep pace with rising capital intensity in science, but often fell short. This has meant a concentration of scarce funds in a handful of elite institutions that received priority. The primary scientific 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.

In spite of these efforts, however, the aggregate data show that public funding for instruments at universities has fallen as a share of total R&D funding: According to data from the Higher Education Research and Development Survey conducted by the National Science Foundation, federal funds for equipment as a share of total funding fell from just under 7% to 3% in the past four decades (Dashed line in Figure 2). Moreover, government-led initiatives such as the National Nanotechnology Critical Infrastructure (NNCI) programs tend to cluster around a dozen or so elite institutions, potentially increasing disparities between universities.

R&D funding for universities has traditionally been concentrated. In Computer Science, for instance, 81% of all funding went to the top 50 institutions on average. However, funding for instruments is even more concentrated: the average gini coefficient for equipment funding (0.85) is around 11% higher than the gini coefficient for total R&D funding (0.76). Moreover, this wedge between instrument-specific and total research funding concentration is a recent phenomenon: In Figure 2, we find that the top 50 institutions' share of total R&D has fallen in all fields of science (though less in the life sciences, where concentration was lowest to begin with). However, the top 50 universities' share of facilities and equipment funding has decreased far less. With the exception of the life sciences, the gap between instrument and

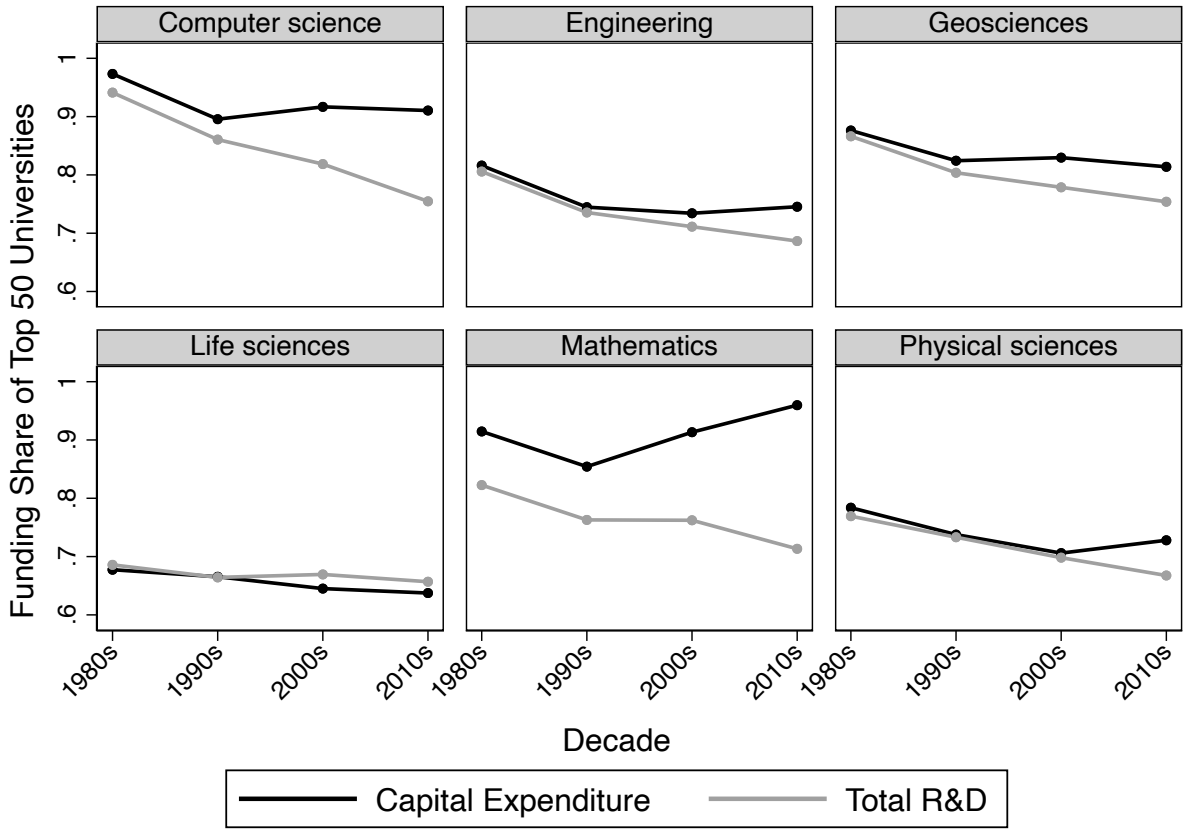
Figure 2: Federal Research Funding to Universities (Total vs Equipment)




*Notes:* This solid line plots the total research funding (deflated to 2017) received by U.S. universities from 1980 to 2020. The dashed line divides expenditures for capitalized R&D equipment funding by total funding. Data from 1980 to 2009 is sourced from the Academic R&D Expenditures Survey; data from 2010-2022 is sourced from the Higher Education Research and Development Survey that succeeded it. All degree granting universities that perform $150,000 or more research and development activities are included in the survey. Data is sourced from the National Science Foundation's Public Use Data Files (https://ncses.nsf.gov/surveys/higher-education-research-development/2023).

total R&D concentration has steadily widened in the past four decades.[4] The concentrated support for instrument funding in a few elite institutions, though rational, may reduce the diversity of approaches toward tackling a commercialization problem by precluding some universities from contributing to applied problems (Cohen & Klepper, 1992). Reduced diversity in research avenues is all the more concerning because the true value of a research agenda, theoretical or empirical, is difficult to predict ex ante.

Figure 3: Instrument vs Total R&D Funding Concentration, by Fields




*Notes:* This figure plots the share of university R&D funding that goes to the top 50 recipients each decade. The shares of the top 50 universities are calculated first and then averaged for each decade (where "1980s" refers to 1980-1989 and so on). The gray line plots this for total R&D expenditure, while the black line plots this for equipment expenditures only. Data source is the same as Figure 2.

[4] "Capital Expenditure" from fiscal years 1979-89 refers to "movable furnishings and scientific equipment, facilities ancillary or integral to R&D efforts, and special separate facilities to house Science & Engineering apparatus." All items with a monetary value of $500 and above were included. The survey item was revised to "expenditures for research equipment" since.

### 2.2.2 Corporations commit further into instrument-heavy research

In stark contrast, firms that are engaged in science seem to have responded with more, not less, investments in scientific instruments. Per Arora, Belenzon, Patacconi, and Suh (2020), we learn that the share of U.S. firms publishing in the sciences has dropped over the four decades. However, the firms that have persisted in the sciences seem to have updated their laboratories with the latest instruments. Far from shunning change, 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). While the use of HTS systems in industry is commonplace, it is exceptionally 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 pharma/biotech.

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). Indeed, Ahmed, Wahed, and Thompson (2023) show evidence that the number of parameters used in corporate AI papers outnumber university counterparts by three orders of magnitude, suggesting a distinct scale advantage at corporations.

In both cases, firm investments in scientific instruments can be rationalized as an attempt to appropriate greater value from internal research. In the life sciences, investing in instruments can help win a priority race. The starkest display of this motive (though ultimately unsuccessful due to competition from the Human Genome Project) was displayed in Celera corporation's efforts to sequence a proprietary dataset of the human genome from 1999 to 2001 (Williams, 2013). The firm reportedly purchased 300 units of Perkin Elmer's ABI Prism 3700

gene sequencers (costing $300,000 per unit) and developed a new method to sequence genes - “shotgun sequencing” - that would fragment the genome into smaller pieces and reassemble them into whole later.[5] In the case of AI research, investment in physical infrastructure likely helps firms extend their lead time against competitors (Cohen, Nelson, & Walsh, 2000).

### 2.2.3 Instrument costs shift direction of academic research

How would academics “priced out” of fields dominated by expensive instruments respond? In an analogous setting where upstream startups with a new discovery decide on a commercialization strategy between licensing and downstream market entry, Gans, Hsu, and Stern (2002) and Teece (1986) show that startups would be better off cooperating with downstream firms than to compete head on. Hence, academics wishing to maintain the same type of work (and stay in Donald Stokes’ “Pasteur’s Quadrant”) would need to cooperate with firms to gain access to their equipment (Stokes, 1997).[6] Others may decide to pivot their work towards less capital intensive areas that promise fewer applications but better satisfy scientific curiosity and garner peer recognition (i.e., “Bohr’s Quadrant” work).

The increasing capital intensity of silicon semiconductor research shows researchers choosing the latter option. Thanks to competition among leading chip manufacturers vying to pack more transistors in a smaller area, instrument manufacturers have introduced increasingly sophisticated photolithography systems. 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. The price of the first lithography system (the GCA DSW 4800) was 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.[7] As such, research using advanced lithography systems became prohibitively expensive for most universities. Though

[5] See https://www.wired.com/2000/07/gene-researchers-get-snppy/

[6] Conversely, firms may use the prospect of instrument use as a lever to sway academic research to areas of interest (Shvadron, 2024).

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

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.

Academic groups responded to the rising capital costs for silicon-based semiconductor research by specializing either 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 compounded semiconductors that promised optical applications. III-V semiconductors such as Gallium Arsenide (GaAs) and Gallium Nitride (GaN), for instance, 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). While still requiring some investment in equipment (especially in metrology), research away from silicon transistors promised greater scientific recognition from peers.

To summarize, anecdotal evidence suggests that as science advances, it increasingly relies on advanced scientific instruments. Academic survey data shows that support for procuring new instruments has fallen as a share of total R&D, and has become more uneven among institutions. While firms may have on average withdrawn from science, the ones that remained seem to have upgraded their instruments on par with (and oftentimes leading) the state of the art. I theorize that the rising capital intensity of science in effect increases the minimum efficient scale of "translational" science that connects abstract theories to practice. For academia, where a corresponding funding push was absent, this may have resulted in diminished entry of (especially smaller) universities to commercially applicable research. Academic instead focus on novel, exploratory research that garner scientific recognition, possibly at the expense of commercializability. For firms, investing in instruments may have been seen as a downstream complementary asset enabling value capture from internal research.

To examine these predictions and establish stylized facts, we require systematic data

on the cost and use of scientific instruments by academic and corporate users, which is the subject of the next section.

# 3 Data

I combine information on scientific instruments, the papers that use these instruments, the authors of these papers, and their commercialization.

## 3.1 Scientific Instruments

Two challenges need to be overcome to construct a comprehensive dataset on costly scientific instruments. First, the range of instruments used by modern science is vast and is beyond the domain of any single subject matter expert. Second, instrument 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 instruments. I complement this data using an instrument vendor directory published by an industry publication.

**Instrument Purchase Grants** — I collect 1,353,220 grants that were made by the 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 the batch mode on 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 instrument must be mentioned. If a grant has multiple instruments mentioned, it prohibits ascribing the grant amount to a single instrument. Second, the grant should not propose to upgrade or maintain an existing instrument possessed by the principal investigator (PI). While the maintenance and renovation of existing instruments are important, the customized nature of these modifications makes it difficult to price them consistently across researchers.

After finding 11,847 grants that fit this description, we manually check whether the size of the grant realistically estimates the price of the identified instruments. A common issue arises when the name of an instrument is too generic, such as "microscope", "laser" and "camera".

For this reason, we exclude purchase grants of data and compute infrastructure (e.g., Linux clusters, cloud computing environments, supercomputers, workstations) because their prices fluctuate widely (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. We 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).

There are two sources of bias on these instrument 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 instrument. 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. I conduct checks using PI-grant level microdata for 45 R1 universities from the IRIS UMETRICS dataset and find such biases to be minor and uncorrelated with field, funding agency, or university characteristics.[8]

**AZO Networks** — We complement the grants data by scraping a vendor directory from an instruments industry publication, AZO Networks. AZO collects comprehensive information of the latest equipment and their manufacturers. We manually scrape the instrument model and manufacturer information for AZO Nano (228 entries), Materials (1,289), Quantum (64) and Optics (228). We 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.

[8]Details on the IRIS data are available here: https://iris.isr.umich.edu/research-data/2024datarelease/ Release of specific details are pending approval.

### 3.2 Scientific Papers

**General Index** — I measure use of instruments by whether an author of a scientific paper mentions the focal instrument 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.[9]

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.[10] The stemmed ngrams are then exact-matched against the General Index ngrams, yielding papers that mention scientific instruments.

**Dimensions.ai and OpenAlex** — We limit the set of science and engineerring papers to those published between 1980 and 2020 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.

To study heterogeneity by institutional endowment, I rank U.S. universities by their receipt of federal funds from 1980 to 2020 (as recorded in Dimensions.ai) and classify those within the top 50 as "top" and those outside as the "rest".[11] To study heterogeneity by the type of corporate author, we also match these papers to OpenAlex through DOIs and then to the DISCERN database to find which of these papers are linked to a publicly listed U.S. headquartered firm. We use the SCImago Journal Rank (SJR) as well as relative citation ratios

[9] The data was downloaded via https://archive.org/details/GeneralIndex.

[10] 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.

[11] The analyses in Section 4 are not sensitive to changing this cutoff to the top 25 or the top 100 institutions.

(RCRs) provided by Dimensions to proxy for the scientific quality of papers.[12] I measure the commercialization of science by patent citations received by papers, using data provided by Marx and Fuegi (2020). The main paper sample consists of 7,462,076 papers, 429,367 (6%) of which are authored by corporations. Around 25% of all papers mention use of at least one scientific instrument.

# 4 Empirical Results

We follow the discussion in Section 2 to guide the empirics. I first test whether instruments help with the commercialization of science, controlling for field, year, and type of discovery. Second, I find that science has become more capital intensive, and that universities have limited access to instruments compared to firms due to funding constraints. Third, I show evidence that scientific instruments are downstream complementary assets which help firms to appropriate value for internal research. Finally, I show that universities in instrument-heavy fields pivot toward research that is less commercializable but more novel, consistent with a division of scientific labor with corporations.

## 4.1 How do instruments affect the translation of science?

Table 1 presents results from a linear probability model that regresses whether a paper is cited by a patent within 5 years of its publication. Column 1 finds that papers which use instruments are associated with a 2% higher likelihood of being cited by a patent, after controlling for patent citations and team size (proxied by the number of coauthors mentioned in the paper). Column 4 shows that using a standard deviation more expensive instrument is associated with a 1.1% greater likelihood of being cited by patents. Columns 2 and 5 add dummies for journals and find the coefficient magnitude to decrease by 28% and 32% relative to Columns 1 and 4 respectively (the direction and significance of the results hold). Still, it is possible that papers within the same field, year, and journal that use instruments may reflect unobserved differences in the resources, connections, and research potential of authors. To further mitigate these concerns, Columns 3 and 6 limit the sample to 5,742 papers on twin discoveries. Marx

[12] RCRs divide the number of forward citations received by a paper by the average forward citations received by all papers in the same field and year.

and Hsu (2022) replicate the method pioneered by Bikard (2020) which identifies papers on the same scientific discoveries published in the same year.[13] Interestingly, paper twins tend to be close to five times more likely to be cited by patents in their unconditional means (23.8% 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 42.8% relative to the sample mean in Column 1, but only around 3.2% in Column 3). However, the coefficients in Column 3 and 6 are still positive and significant: even within paper twins, the use of instruments is associated with a higher likelihood of commercialization.

Table 1: Instrument Cost and Commercialization of Science

| | Pr(Cited by Patent) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | All | Paper Twins | All | All | Paper Twins |
| Scientific Instrument Dummy | 1.935 | 1.388 | 2.497 | | | |
| | (0.022) | (0.024) | (1.366) | | | |
| ln(Paper Instrument Cost) | | | | 0.147 | 0.098 | 0.191 |
| | | | | (0.002) | (0.002) | (0.095) |
| Forward Paper Citations | 5.182 | 4.673 | 5.429 | 5.191 | 4.678 | 5.405 |
| | (0.014) | (0.015) | (1.093) | (0.014) | (0.015) | (1.094) |
| Number of Coauthors | -0.001 | 0.000 | -0.070 | -0.000 | 0.000 | -0.073 |
| | (0.000) | (0.000) | (0.079) | (0.000) | (0.000) | (0.080) |
| Average of Dep Var | 4.517 | 4.517 | 23.772 | 4.517 | 4.517 | 23.772 |
| Year Dummies | Yes | Yes | No | Yes | Yes | No |
| Field Dummies | Yes | Yes | No | Yes | Yes | No |
| Journal Dummies | No | Yes | No | No | Yes | No |
| Twin Pair Dummies | No | No | Yes | No | No | Yes |
| $R^2$ | 0.073 | 0.105 | 0.811 | 0.072 | 0.105 | 0.812 |
| Number of Obs | 7,073,639 | 7,073,527 | 5,742 | 7,073,639 | 7,073,527 | 5,742 |

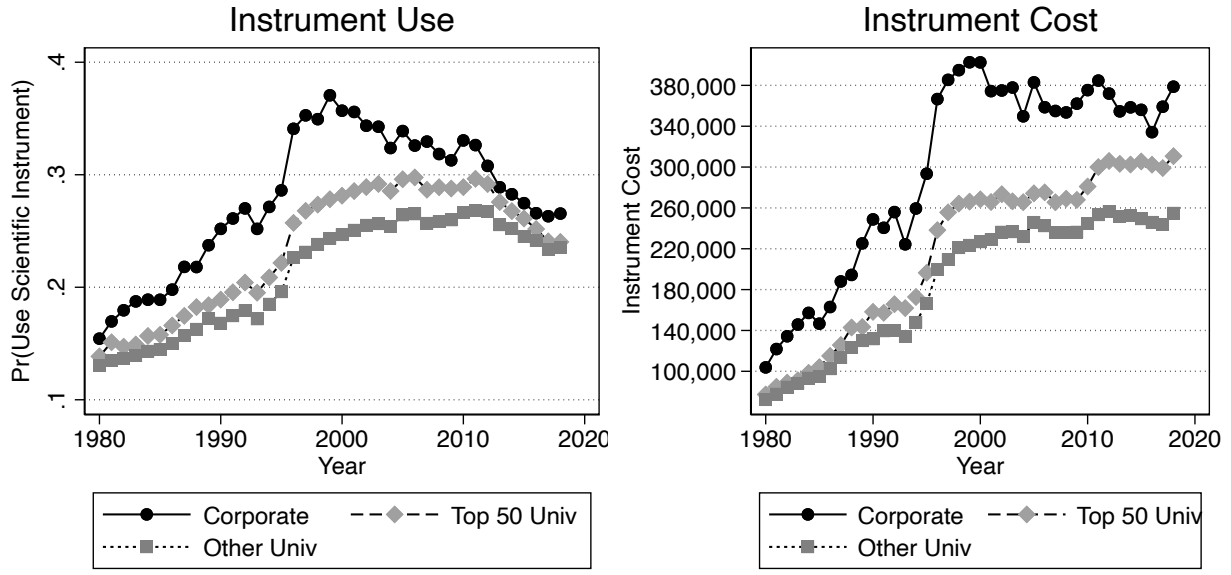
*Notes:* The unit of analysis is at the paper level. All regressions are estimated via Ordinary Least Squares throughout the paper unless stated otherwise. The dependent variable is a dummy indicating whether a paper has been cited by a patent within five years of its publication. "Scientific Instrument Dummy" is equal to 100 if a paper mentions a scientific instrument identified through U.S. federal grants data, and zero otherwise. "ln(Paper Instrument Cost)" sums up the costs of all instruments mentioned and takes one plus the natural logarithm. The sample for Columns 3 and 6 are limited to "paper twins" made available by (Marx & Hsu, 2022). "Forward Paper Citations" normalizes the number of forward citations received by the average forward citations of papers published in the same year and field as the focal paper. "Number of Coauthors" refers to the number of authors found in the paper. Robust standard errors are reported in all columns except Columns 3 and 6, where the standard errors are clustered at the "twin" paper pair level.

[13] 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.

### 4.2 How and why does instrument access differ by sector?

As modern science has become more capital intensive, corporations have stayed ahead of universities in the use of costly scientific instruments. Throughout our sample period, 29.7% of corporate papers mention use of an instrument, while 25.2% of university papers do so. The top panel of Figure 4 shows that this corporate-university "gap" is preserved throughout the sample period, rising somewhat during the 1990s before closing starting from the 2010s. Notably, the gap between the top 50 universities receiving the federal funding (publishing 40.4% of papers in the sample) and the rest of universities (53.8%) also rises around the mid-1990s before closing in the 2010s. Corporate papers on average spend $335,128 on equipment costs, while university papers spend around 29% less, at $238,786. The bottom panel of Figure 4 shows that this cross-sectoral gap is preserved throughout the past four decades. Interestingly, the gap between academia and industry is mostly closed in the 2010s thanks to the top 50 institutions' increased instrument expenditures: for the non-top academic institutions, the gap with corporations holds at around $110,815.

Figure 4: Use of Scientific Instruments, by Author Type




*Notes:* The top panel plots the share of papers that use a scientific instrument, divided by whether the author is corporate or academic. The academic authors are divided by whether they have at least one author from a "Top 50" institution in terms of federal grant funding receipts. The bottom panel plots the average instrument costs (deflated to 2017 dollars). When a paper uses multiple instruments, the instrument costs are summed together at the paper level.

Table 2 replicates this result using OLS regressions where the use of instruments and the logged cost of instruments is regressed against dummies indicating author type (the omitted group is corporate-authored publications). Per Column 1, all academic authors are less likely to use instruments in their papers, even after including the same quality and field controls from Column 1 of Table 1. Figures 2 and 3 spoke to stagnating equipment funding shares and growing concentration in equipment funding in the top 50 institutions. The implication was that even as the state of the art in certain fields require greater capital outlays, non-elite institutions without the benefit of munificent funding will lag top 50 institutions in their instrument use due to a binding budget constraint. This is reflected in the difference between the Top50 vs Other University coefficients: the "Other" group is around 23% less likely to use instruments relative to the "Top 50" group. Column 2 shows that within the same journal, this grows slightly to 36%. And as we limit the set to papers receiving above the 95th percentile of forward citations from peer-reviewed publications in Column 3, the difference holds at around 33%. Columns 4 through 6 replicate these results using dollar values of the instruments used in papers. As before, all types of universities use less expensive instruments on average, though the difference between top 50 and other institutions fluctuates from 7% (Column 4) to 13% (Column 5) to 17% (Column 6) as journal and quality differences are more strictly controlled. In sum, firm publications are more likely than universities' to use scientific instruments. We find that this gap is wider for universities that do not receive ample federal funds, though this "non-elite" penalty diminishes when we limit the sample to top publications only. We may interpret that researchers with exceptional merit at non-elite institutions may still be able to solicit research support to carry out capital intensive research projects.

Table 2: Instrument Use and Costs, by Author Type

| | Instrument Use Dummy | | | ln(Paper Instrument Cost) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | All | Highly Cited | All | All | Highly Cited |
| Top 50 University | -0.030 | -0.011 | -0.024 | -0.576 | -0.263 | -0.442 |
| | (0.001) | (0.001) | (0.003) | (0.009) | (0.009) | (0.035) |
| Other University | -0.037 | -0.015 | -0.032 | -0.617 | -0.298 | -0.519 |
| | (0.001) | (0.001) | (0.003) | (0.009) | (0.009) | (0.036) |
| Forward Paper Citations | 0.046 | 0.026 | | 0.551 | 0.306 | 0.000 |
| | (0.000) | (0.000) | | (0.002) | (0.002) | (.) |
| Number of Coauthors | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Average of Dep Var | 0.247 | 0.247 | 0.321 | 2.514 | 2.514 | 3.437 |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Field Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Journal Dummies | No | Yes | Yes | No | Yes | Yes |
| $R^2$ | 0.118 | 0.288 | 0.297 | 0.095 | 0.237 | 0.241 |
| Number of Obs | 7,415,409 | 7,415,301 | 371,296 | 7,415,409 | 7,415,301 | 371,296 |

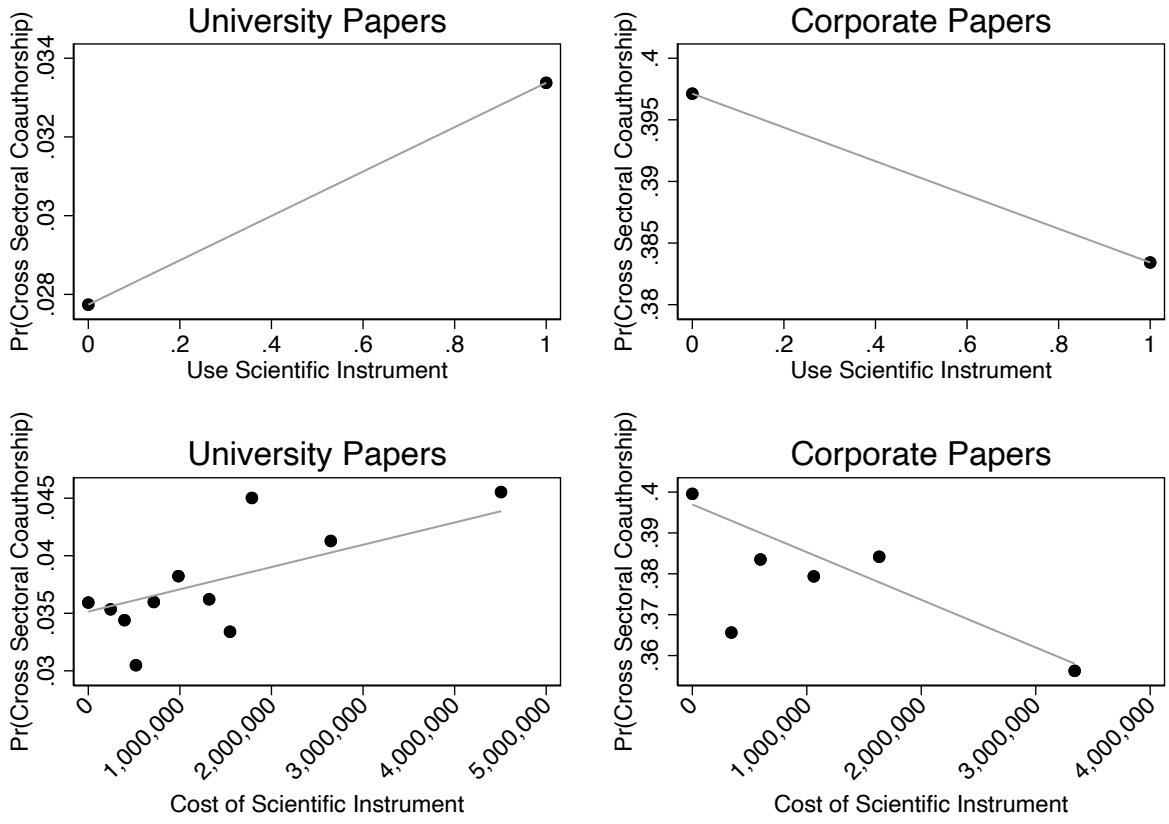
*Notes:* Unit of analysis is at the paper level. The dependent variable in Columns 1-3 is a dummy equal to 1 if the paper mentions at least one scientific instrument; for Columns 4-6, it is equal to the logged total cost of the instruments. "Top 50 University" is a dummy that indicates whether the paper is authored by a university ranked within the top 50 institutions receiving federal research funds. Papers by all other universities are indicated by "Other University". Papers authored by corporate authors constitute the omitted category. Columns 3 and 6 limit the sample to papers whose forward paper citations exceed the 95th percentile in their field and publication year cohort. Robust standard errors are reported.

Further evidence indicative of a budget constraint at universities can be found in the left panels of Figure 5, which show that universities are around 21% more likely to coauthor with corporate authors when their paper uses an instrument. Firms, on the other hand, do not seem to share credit with universities when using scientific instruments, as seen in the right panels. This pattern is consistent with university budget constraints requiring them to find a well-endowed corporate partner to pursue research.

### 4.2.1 Alternative explanation to academic budget constraints

I now consider two alternative explanations of the observed patterns. The first alternative interpretation is that the university-industry gap is driven by a difference in taste rather than budget constraints. If so, the reticence of universities in capital intensive research may represent an efficient division of labor that enables specialization, whereby universities focus on "Bohr's Quadrant" science that is only motivated by curiosity and firms focus on "Pasteur's Quadrant" science that is also motivated by application. However, as discussed in Section 2, there is plenty of credit (in academia) that accrues to scientists that specialize in the empirical

Figure 5: Scientific Instruments and Coauthorships



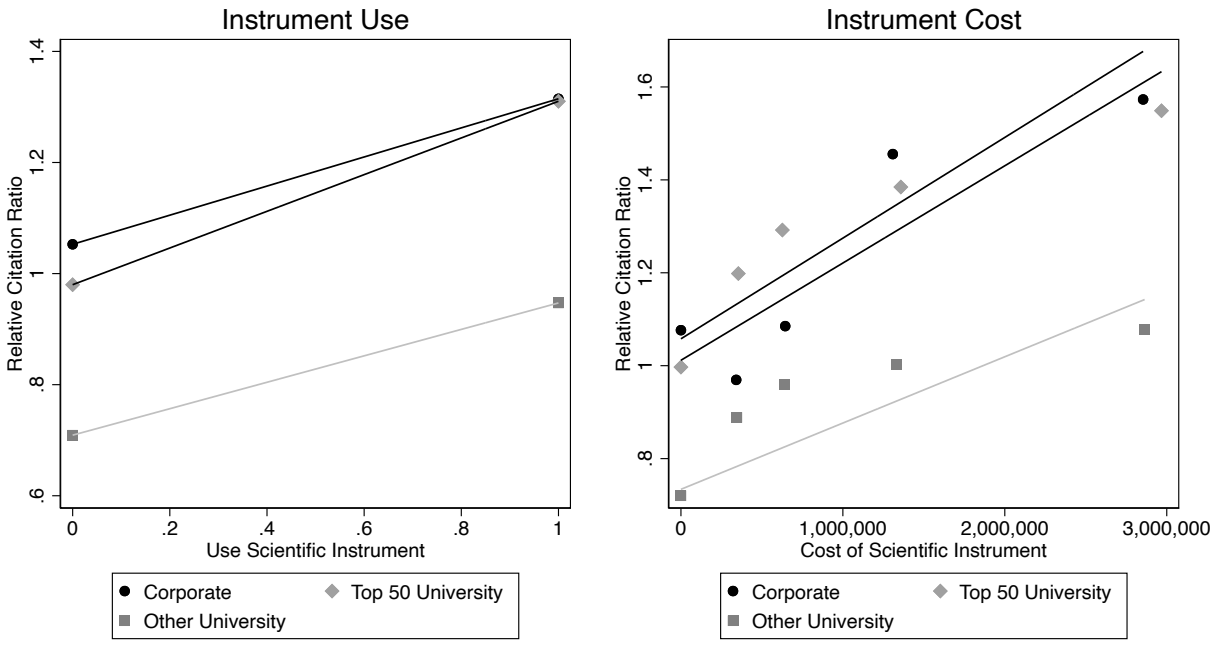

*Notes:* The four binned scatterplots measure the correlation between "cross-sectoral" coauthorships and instrument use. The top left figure limits the sample to papers with university authors and plots the share of papers that are authored jointly with industry-affiliated authors, against whether the paper uses a scientific instrument. The bottom left figure plots the same against the total instrument costs indicated by the paper. The top right figure plots the share of industry publications that are jointly authored with universities against their use of instruments, while the bottom right figure plots this share against the instrument cost of the paper.

validation of theory. Fields where abstract reasoning alone serves as sufficient proof, such as number theory or algebraic geometry, are the exception rather than the norm. Indeed, most of the past Nobel Prizes in Physics would have been impossible without the invention of a new instrument: the prizes for 2018 and 2023 were for superfast (attosecond) lasers, while the 2022 prize went to theorists on quantum computing. The 2017 prize awarded to the detection of gravitational waves would have been impossible without the construction of the Laser Interferometer Gravitational-Wave Observatory (LIGO), while the 2014 prize was given to the Japanese trio that invented blue LEDs.[14] Indeed, Figure 6 shows that the use of scientific instruments (left panel) and their costs (right panel) are associated positively with scientific recognition (as measured by paper forward citations) for all three types of researchers (corporate, top50 and other university authors). Had the sectoral instrument disparity been due to differing taste or preferences, universities should have shown an opposite or null relationship between citations and instruments as the best researchers seek to work on non-instrument heavy problems: for example , in the field "Discrete Mathematics and Combinatorics," an abstract subfield of mathematics, the correlation between instrument cost and forward citations is -0.0015.

The second alternative explanation is that firms are more selective in their decision to disclose internal research through publications, which may introduce biases. 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 can be mitigated, though not perfectly, by the results in Columns 3

[14]The prizes in chemistry show an even heavier reliance on instruments - the 2024 prize for Alphafold, for instance, required heavy investment in large scale data infrastructure to train models on protein folding problems.

Figure 6: Instrument Cost and Scientific Recognition




*Notes:* The binned scatterplot on the left plots average forward paper citations against whether the paper uses a scientific instrument, split by author type: corporate, Top 50 university, and other (non-Top 50) university. The right plot replaces the scientific instrument dummy with the total dollar value of the instruments mentioned in the paper.

and 6 of Table 2, which limit the sample to the top 5% most cited papers for each field and year. Here, we find that top publications of universities still under-use instruments compared to comparable corporate publications.

### 4.3 Why do firms persist in instrument-heavy fields?

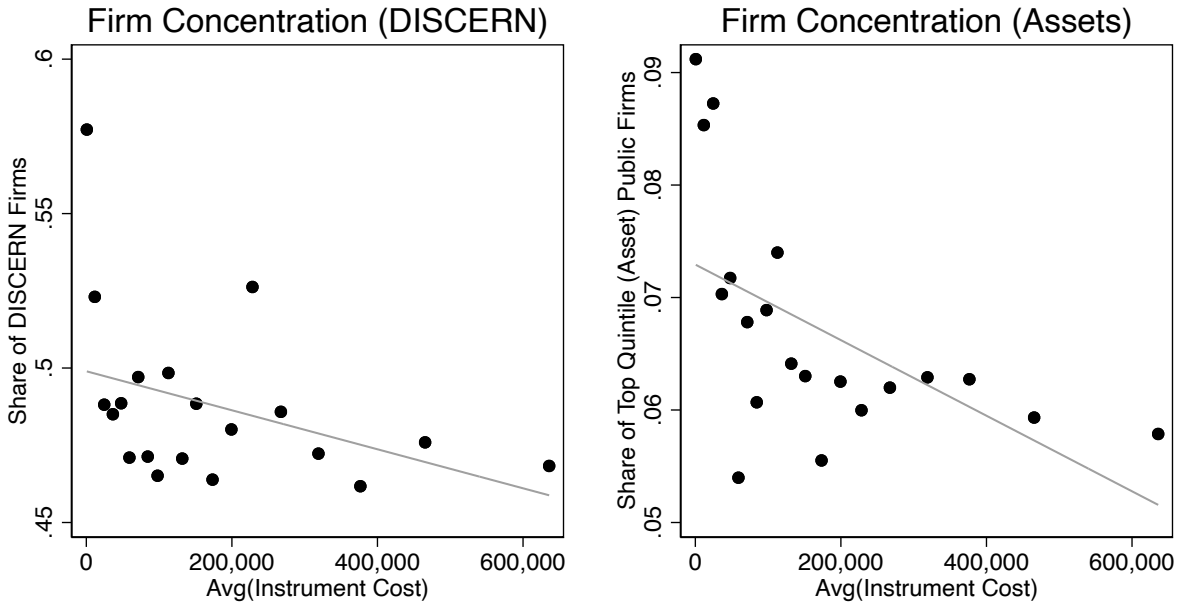
What explains the persistence of the greater capital intensity of corporate papers against academic papers? One reason may be that scientific areas with higher capital intensity offer more technological opportunity. Coupled with the abstention of universities from these fields due to stagnant public support, the promise of a new discovery may incentivize firms to fill a void in academic science. This explains the dominance of large firms within sectors such as Artificial Intelligence, for instance. Arora, Belenzon, Kosenko, Suh, and Yafeh (2024) also explain that the first corporate labs in the U.S. were founded to fill in voids in electrical engineering and polymer chemistry created by a domestic university sector that was still catching up to European standards during the interwar period. However, while a necessary explanation, compensating for stagnant university research in promising fields is insufficient to explain the empirical patterns.

For example, we should expect the largest firms to fill gaps in public science first, as they would be less affected by appropriability concerns thanks to stronger control of downstream markets (Arrow, 1962; Nelson, 1959). However, we find that corporate science is *less* likely to be concentrated in more capital-intensive fields of science. The left binned scatterplot of Figure 7 graphs the share of U.S. listed firm publications in a scientific field and finds that public firm share is greatest for areas with the least capital intensity.[15] The right scatterplot limits the sample to public firm publications and plots the share of large firms (those with top quintile assets) against instrument costs. Similar to the previous plot, there is a negative correlation between instrument intensity and corporate concentration (r=-0.06).

Instead, scientific instruments may serve as value capture devices for firms. Scientific instruments typically have tacit components that rely on "craft knowledge" to operate smoothly (Bovenberg, 2023). For instance, Molecular Beam Epitaxy (MBE) systems are used to create thin films of single crystals for materials science applications. The system forms a vacuum

[15]The listed firm publications are sourced from the DISCERN database (https://discern-project.com).

Figure 7: Instrument Cost and Corporate Concentration of Research




*Notes:* The binned scatterplots correlate measures of concentration against instrument costs at the scientific subfield-year level (there are 166 subfields over 39 years). The left figure plots the share of corporate publications authored by publicly listed firms found in the DISCERN database (Arora, Belenzon, Cioaca, Sheer, Shin, & Shvadron, 2024). The right figure plots the share of DISCERN publications that are authored by firms with assets in the top quintile of their 3 digit SIC and year (firm asset data are sourced from S&P Compustat).

where multiple atom types are heated to sublimation and shot onto a substrate. Operating the machine requires researchers to control multiple parameters such as flux rates of the deposited materials, substrate temperature, background vacuum pressure, growth rate, layer thickness, shutter timings, and the angles of molecular beams striking the substrate. Calibrating these variables represents a high-dimensional choice space of dozens of parameters, each potentially driving the properties of the resulting material. Investment in research using MBEs, therefore, can help sponsoring firms gain knowledge that is difficult for competitors to imitate. A similar motive is observed in a survey of academic life scientists, where material inputs such as cell lines and reagents are used to create "practical excludability" of scientific competition (Cohen & Walsh, 2007; Walsh, Cohen, & Cho, 2007).

Consistent with the value capture view, the right panel of Figure 5 show that corporate papers using (costlier) instruments are less likely to coauthor with universities. Had filling gaps in science been the sole objective, then cost minimizing firms should behaved similarly to universities and partnered with outside institutions when instruments were costlier. As

a more formal test, Table 3 examines whether firms using instruments are especially more likely to use the science in their own patents compared to universities. After limiting the sample to papers that are cited by patents, the dependent variable measures whether the paper was cited by a patent by the same organization (i.e., =1 if an IBM paper is cited by an IBM patent). Column 1 shows that corporate papers are around 4.8% more likely than university papers to be cited by their own patents. Column 2 shows that this tendency is around 1.6% greater when the paper uses a scientific instrument. Replacing the instrument use dummy with instrument costs yields similar results in Columns 3 and 4. The results show that while research organizations using scientific instruments are generally more likely to use the science in their own patents, this tendency is driven chiefly by firms. This is consistent with the interpretation that firms view instruments as value capture devices that help them appropriate returns from conducting science.

Table 3: Instrument Costs and Value Capture, by Author Type

| | Pr(Cited by Own Patent) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Scientific Instrument Dummy | 2.777 | 2.567 | | |
| | (0.115) | (0.121) | | |
| ln(Paper Instrument Cost) | | | 0.176 | 0.163 |
| | | | (0.008) | (0.009) |
| Corporate × Scientific Instrument Dummy | | 1.619 | | |
| | | (0.271) | | |
| Corporate × ln(Paper Instrument Cost) | | | | 0.097 |
| | | | | (0.020) |
| Corporate | 4.826 | 4.155 | 4.800 | 4.358 |
| | (0.154) | (0.191) | (0.154) | (0.180) |
| Number of Coauthors | 0.104 | 0.104 | 0.105 | 0.105 |
| | (0.032) | (0.032) | (0.032) | (0.032) |
| Forward Paper Citations | 0.306 | 0.306 | 0.305 | 0.305 |
| | (0.028) | (0.028) | (0.028) | (0.028) |
| Average of Dep Var | 69.492 | 69.492 | 69.492 | 69.492 |
| Year Dummies | Yes | Yes | Yes | Yes |
| Field Dummies | Yes | Yes | Yes | Yes |
| Journal Dummies | Yes | Yes | Yes | Yes |
| $R^2$ | 0.067 | 0.067 | 0.067 | 0.067 |
| Number of Obs | 897,845 | 897,845 | 897,845 | 897,845 |

*Notes:* Unit of analysis is at the paper level. Sample is limited to papers that are cited by at least one patent within five years of publication. Dependent variable is a dummy equal to 100 if the paper is cited by a patent granted to the same organization as the authors', and zero otherwise. "Corporate" is a dummy equal to one if the paper is authored by a firm. All specifications include year, field and scientific journal fixed effects. Robust standard errors are reported.

To investigate this mechanism further, Figure 8 splits the use of instruments by firm size, as measured by assets. We find that firms in the top asset quintiles within their year and

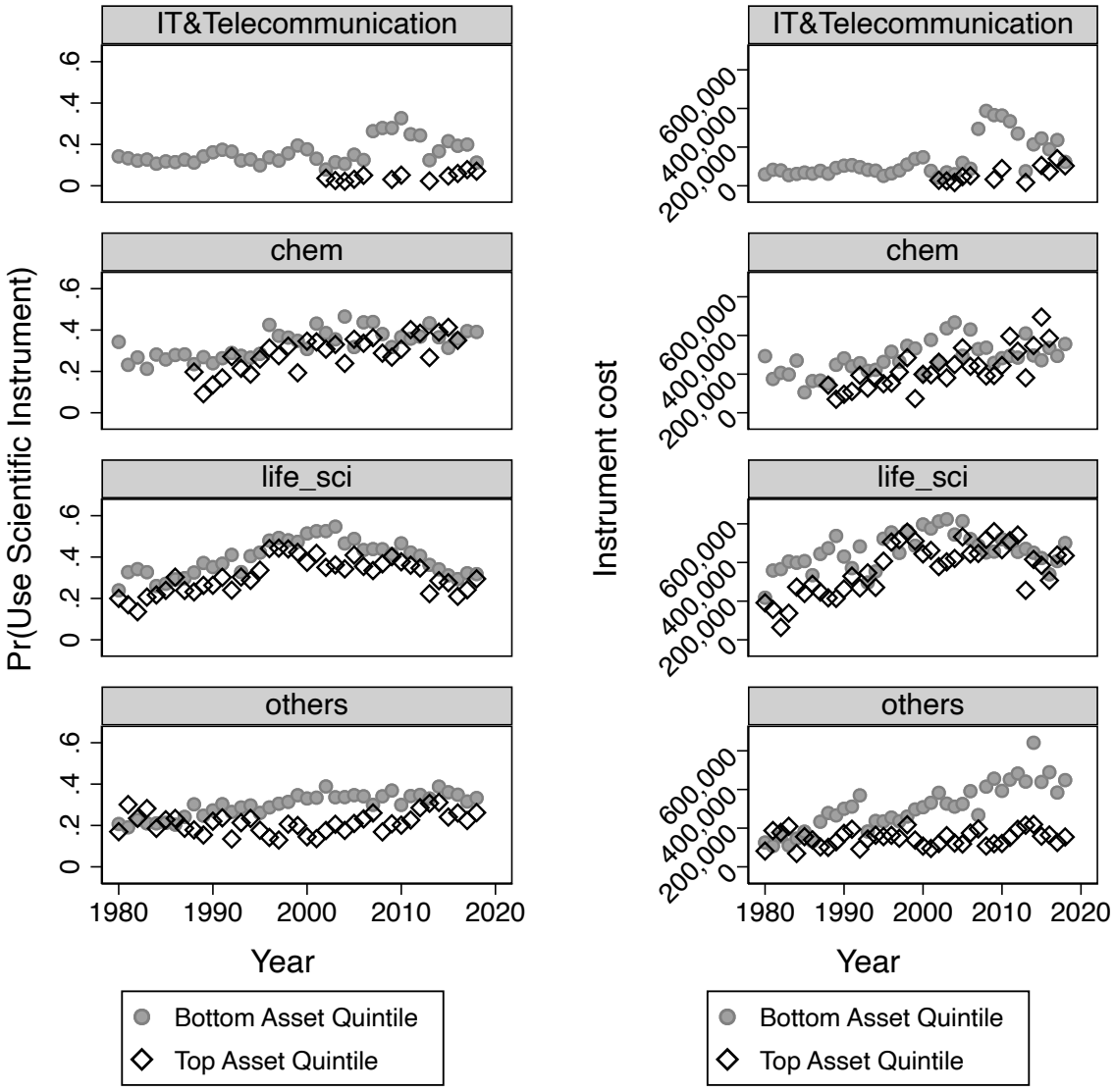
3-digit SIC industry) are less likely to use costly instruments compared to the smallest public firms (in the bottom asset quintile), especially in the ICT sector. I speculate that larger firms have smaller appropriability concerns due to their complementary investments in sales or user data, allowing them to publish work on abstract theory that can be readily spilled out to rivals. Smaller firms, conversely, may consider investments in instrument-heavy fields as reducing susceptibility to imitation because of their tacitness. In areas where these appropriability concerns are lower, such as chemistry or life sciences, the gap induced by firm size is smaller.

### 4.4 Academic science in capital intensive fields pivots away from application

Reduced access to instruments has direct implications for whether universities can continue to participate in "translational research": since instruments are critical to translation and universities have inferior access, papers by academics in capital intensive fields should be less commercializable.

Table 4 regresses a paper's probability of being cited by a patent (i.e., commercial potential) against its institutional provenance and capital intensity of its field. While Column 1 shows that academic papers are around 6-7% less likely to be cited by patents than corporate papers, Column 2 shows that a standard deviation increase in instrument shares is associated with a farther 1.3% decrease in this probability. Controlling for journal fixed effects in Column 3 preserves the direction and significance of the results. Columns 4-6 replace the measure of instrument intensity with logged field-year level average instrument costs and finds similar results. Universities in instrument-intensive fields are less likely to participate in translational research compared to corporations.

Figure 8: Corporate Instrument Use, by Assets




*Notes:* The left figure plots the share of listed firms' publications (from the DISCERN database) each year that use scientific instruments, split by whether the paper was authored by firms in the top asset quintile (diamond markers) or those in the bottom quintile (gray circle markers). The right figure plots average instrument costs similarly.

Table 4: Instrument Cost and Commercialization of Science, by Author Type

| | Pr(Cited by Patent) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Field Instrument Share | 2.063 | 12.379 | 8.816 | | | |
| | (2.664) | (4.375) | (3.620) | | | |
| ln(Field Instrument Cost) | | | | 0.060 | 1.298 | 1.211 |
| | | | | (0.058) | (0.497) | (0.375) |
| University × Field Instrument Share | | -11.160 | -9.971 | | | |
| | | (3.361) | (2.458) | | | |
| University × ln(Field Instrument Cost) | | | | | -1.281 | -1.188 |
| | | | | | (0.482) | (0.360) |
| University | -6.298 | -3.406 | -2.384 | -6.294 | 9.173 | 9.362 |
| | (0.732) | (0.670) | (0.460) | (0.732) | (5.392) | (3.999) |
| Forward Paper Citations | 5.241 | 5.245 | 4.679 | 5.242 | 5.243 | 4.679 |
| | (0.559) | (0.560) | (0.506) | (0.559) | (0.559) | (0.506) |
| Number of Coauthors | -0.001 | -0.001 | -0.000 | -0.001 | -0.001 | -0.000 |
| | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) |
| Average of Dep Var | 4.616 | 4.616 | 4.616 | 4.616 | 4.616 | 4.616 |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Field Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Journal Dummies | No | No | Yes | No | No | Yes |
| $R^2$ | 0.077 | 0.077 | 0.109 | 0.077 | 0.077 | 0.108 |
| Number of Obs | 5,719,662 | 5,719,662 | 5,719,535 | 5,719,662 | 5,719,662 | 5,719,535 |

*Notes:* Unit of analysis is at the paper level. The dependent variable a dummy equal to 100 if the paper is cited by a patent within 5 years of its publication. "Field Instrument Share" divides the number of papers using instruments by total papers in the paper's focal field and publication year. "Field Instrument Cost" takes the average costs of instruments in the paper's focal field and publication year. The definitions for "Top50 University" and "Other University" dummies are identical to Table 2. Papers authored by corporate authors constitute the omitted category. Standard errors are clustered at the scientific subfield level.

We expect researchers moving away from immediate downstream applications to explore more novel topics that do not require expensive lab setups. With the prospect for "gold" (through commercialization) foregone, scientists focus on novel questions that will bring them "ribbons" of scientific prestige (Lam, 2011). Table 5 regresses scientific novelty against whether a paper is authored by an academic. Scientific novelty is measured as one minus the maximum cosine similarity between a paper's abstracts and all papers's abstracts published five years prior to it (Arts, Melluso, & Veugelers, 2025, p.6).[16] Column 1 of Table 5 shows that universities are around 0.7% more novel than corporate papers within the same field and year. However, interacting the share of papers using instruments ("Field Instrument Share") against the university dummy in Column 2, we find that university papers are more novel in capital-intensive fields. Comparing fields in the 75th versus 25th percentile of instrument intensity, university papers are around twice as more novel compared to corporate papers. The

[16]To calculate the cosine similarity measure, Arts, Melluso, and Veugelers (2025) create word embeddings for abstracts found in OpenAlex publications through the SPECTER algorithm.

interaction coefficient between academic papers and capital intensity is diminished by half in Column 3 when we add journal dummies, but still statistically significant. Columns 5 and 6 replicate this result using the average instrument cost of papers by field ("Field Instrument Cost") as the measure of capital intensity.

Table 5: Instrument Cost and Scientific Novelty, by Author Type

| | Paper Abstract Novelty | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Field Instrument Share | -3.754 | -4.602 | -6.426 | | | |
| | (0.134) | (0.181) | (0.176) | | | |
| ln(Field Instrument Cost) | | | | 0.015 | -0.196 | -0.127 |
| | | | | (0.010) | (0.021) | (0.020) |
| University × Field Instrument Share | | 0.919 | 0.408 | | | |
| | | (0.131) | (0.124) | | | |
| University × ln(Field Instrument Cost) | | | | | 0.218 | 0.072 |
| | | | | | (0.019) | (0.018) |
| University | 0.304 | 0.065 | -0.117 | 0.297 | -2.337 | -0.887 |
| | (0.019) | (0.039) | (0.038) | (0.019) | (0.228) | (0.220) |
| Forward Paper Citations | -0.838 | -0.838 | -0.564 | -0.840 | -0.840 | -0.562 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Number of Coauthors | -0.005 | -0.005 | -0.004 | -0.005 | -0.005 | -0.004 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Average of Dep Var | 39.271 | 39.271 | 39.271 | 39.271 | 39.271 | 39.271 |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Field Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Journal Dummies | No | No | Yes | No | No | Yes |
| $R^2$ | 0.061 | 0.061 | 0.189 | 0.061 | 0.061 | 0.189 |
| Number of Obs | 6,013,269 | 6,013,269 | 6,013,149 | 6,013,269 | 6,013,269 | 6,013,149 |

*Notes:* Unit of analysis is at the paper level. The dependent variable is the "Semantic Distance" variable in Arts, Melluso, and Veugelers (2025) which is the inverse of cosine similarity between a focal paper's abstracts and those of all papers five years prior to the focal paper's publication. The definitions for "Field Instrument Share" and "Field Instrument Cost" are identical to Table 4. Papers authored by corporate authors constitute the omitted category. Standard errors are clustered at the scientific subfield level.

In sum, university researchers in capital intensive fields write papers that are commercialized less, but explore newer topics in science. A foundational assumption around the preferences of academic scientists is that they have a taste for "curiosity-driven" science first and foremost (Aghion, Dewatripont, & Stein, 2008; Lacetera, 2009). These results suggest that scientists' choice to explore new areas of science are also affected by the availability of research tools in her disposal.

# 5 Discussion and Conclusion

Pushing the frontier of the applied sciences has become more instrument intensive. While firms have continued to invest in these instruments, public funding for university equipment purchases has stagnated, resulting in a concentration of costly instruments in a few select institutions. Researchers left out of instrumental support likely relocated to solve more theoretical problems (or problems that require less advanced instruments). The materials sciences embodies this pattern clearly, where intensifying R&D races between semiconductor firms has incentivized academics to search for alternatives to silicon semiconductors. On the one hand, this may represent an efficient division of labor where, per Vannevar Bush's vision of his linear model, universities focus on abstract problems and industry focuses on applied problems related to prototyping and scaling (Bush, 1945). On the other hand, there are also reasons to be pessimistic: private research is far less likely to be disclosed and diffused in the scientific community than academic research, where Mertonian norms prevail. (Applied) Scientific progress may also benefit from more diverse avenues of attack, which the entry of academics could have provided.

I contribute to an older debate in innovation on the role of physical inputs in advancing science. The importance of materials, microscopes, animal models and other tools to affect the direction of science has been highlighted as early as Rosenberg (1992). Follow-on work on the innovative impact of new research tools in motion capture (Teodoridis, 2018) and x-ray crystallography in structural biology (Hill & Stein, n.d.; Kim, 2024; Tranchero, 2024) have generally agreed with the premise that the diffusion of new instruments on balance increases scientific output.

However, prior work has not quantified instrumental gaps between universities and firms, or probed reasons behind the gap. Murray and coauthors' oncomouse studies have shown that asserting intellectual property for new animal models can reduce follow-on innovative effort (Murray, 2010; Murray & Stern, 2007), but leave unanswered why some researchers may still expend resources to acquire them in spite of this "anticommons" effect. I fill this gap by collecting large scale data on instrument use in the U.S. across four decades and suggest that the tacitness of instruments increases the excludability (and thereby appropriability) of

research, which may have incentivized firms to lead investments in instrument-intensive fields.

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# Appendix A Data Appendix

## A.1 Instrument categories and costs

Figure A1: Annual Cost of Select Scientific Instruments

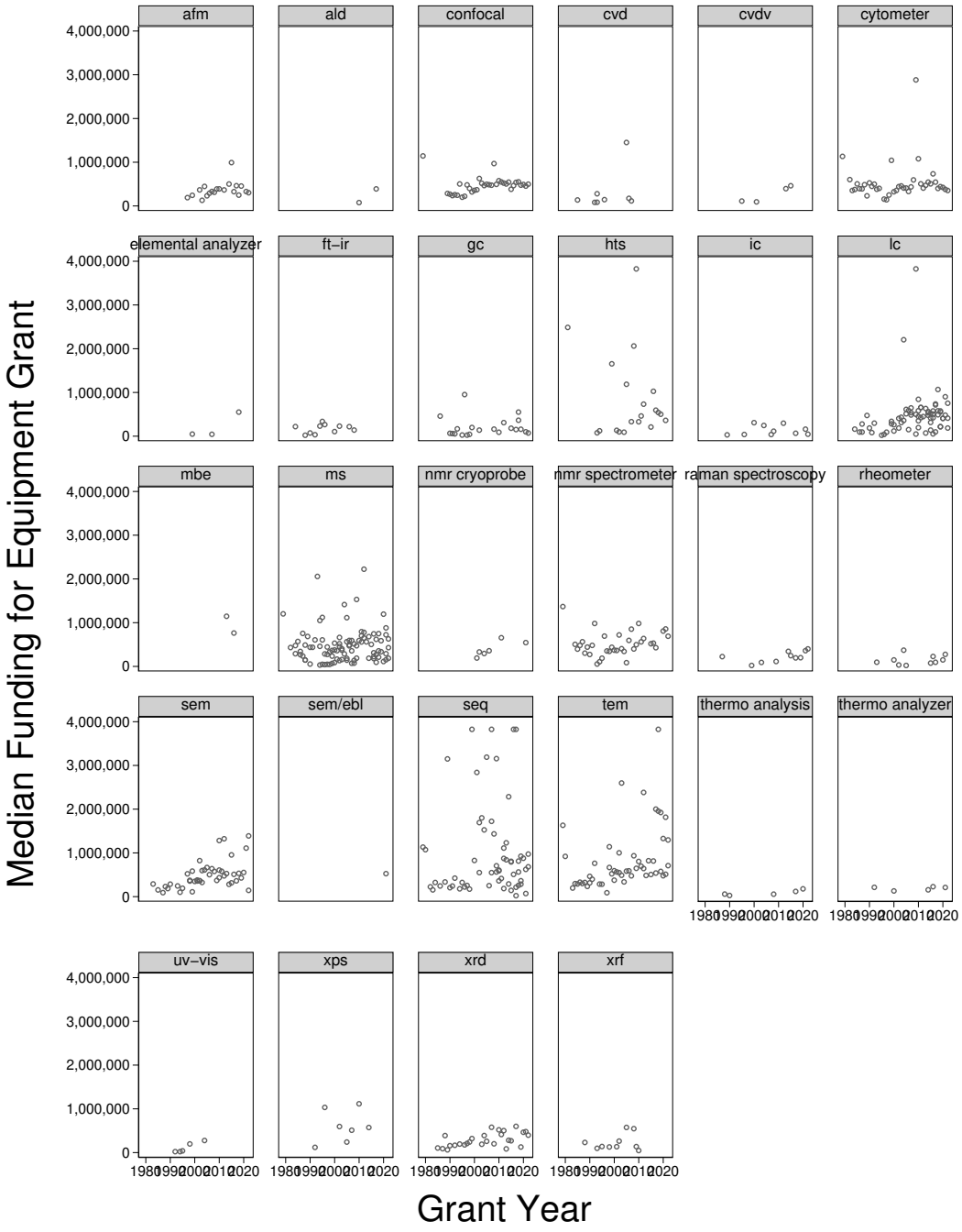


Table A1: Cost Data

| 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 |

## A.2 Scientific instrument use, by field

Figure A2: Use of Scientific Instruments, by Scientific Subfield (Physical Sciences)

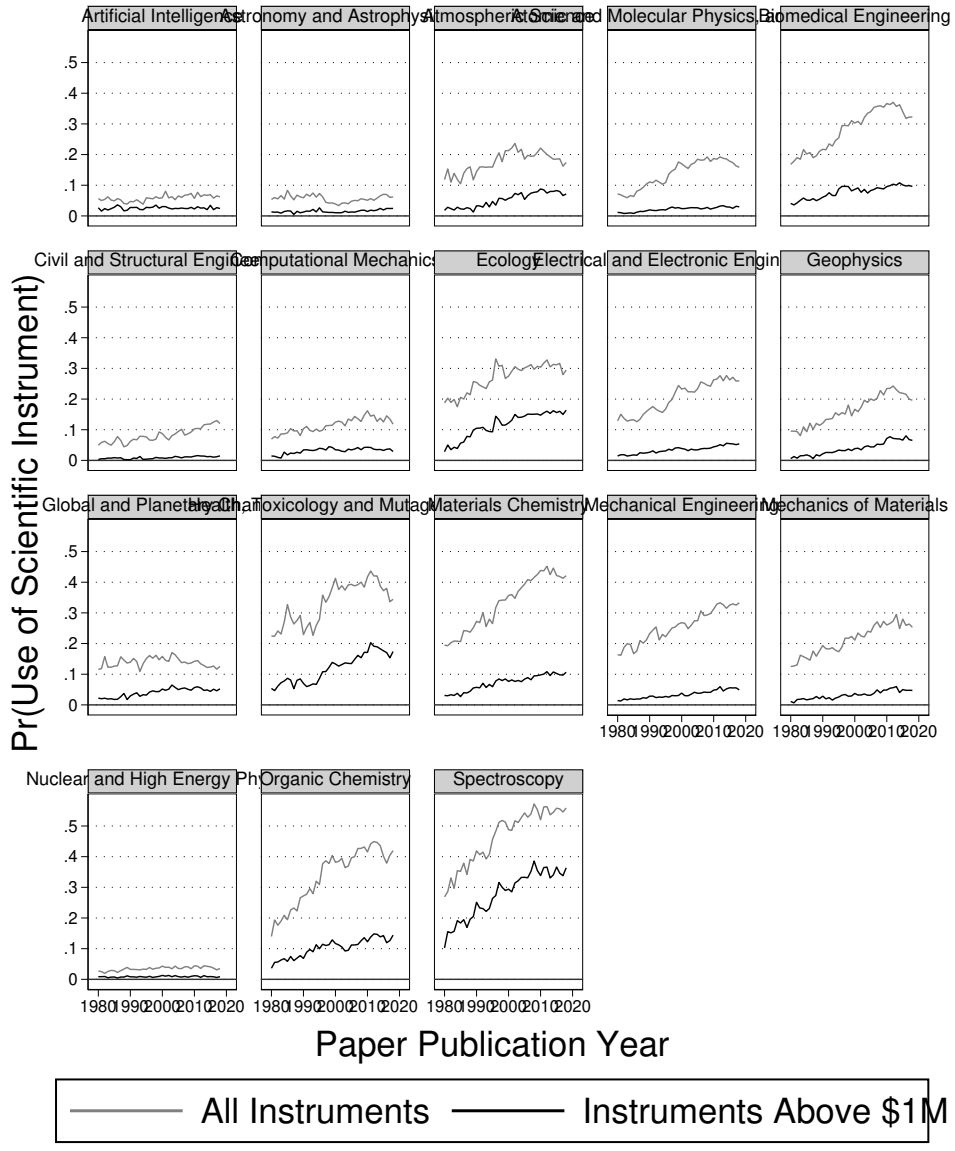
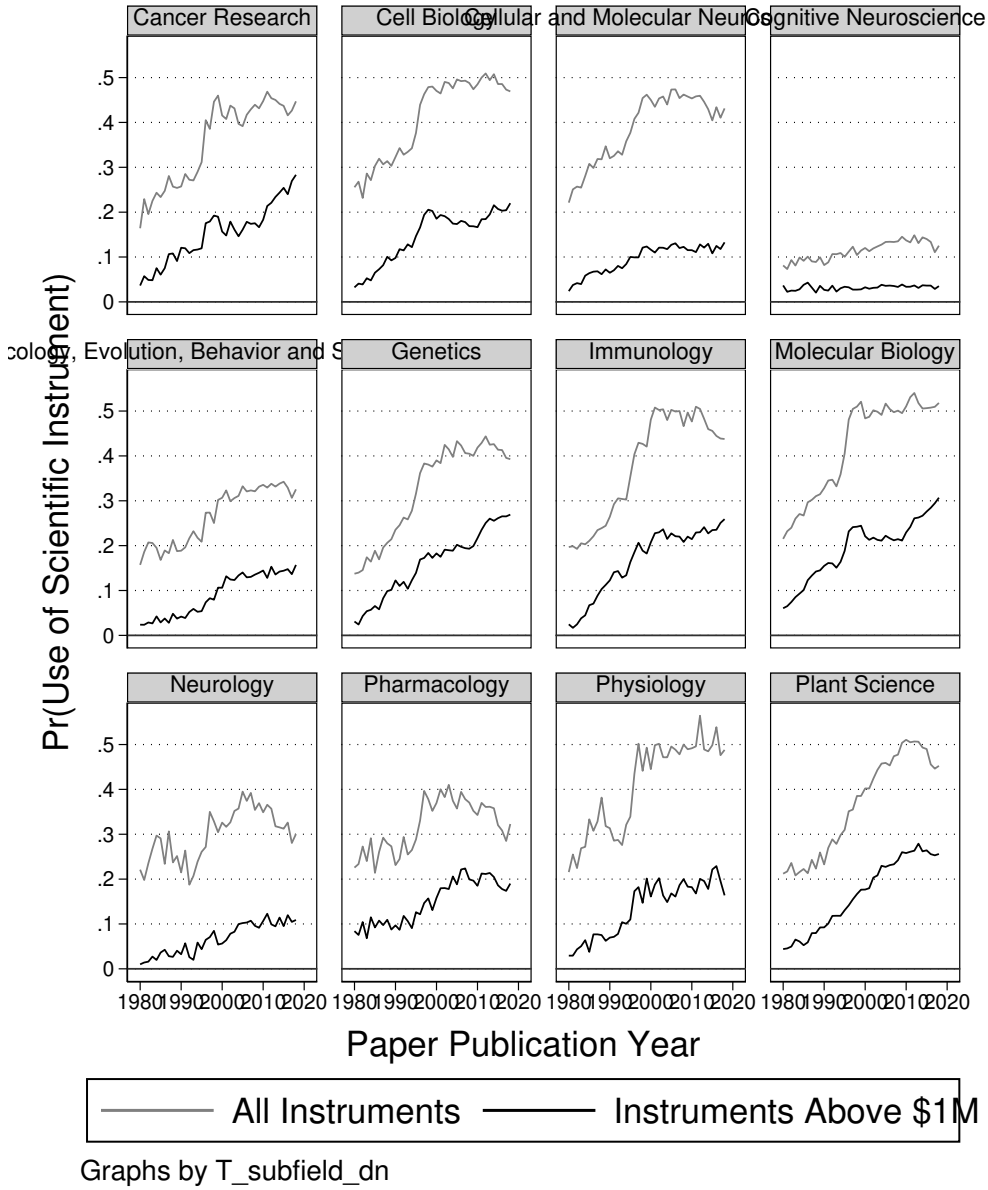


Figure A3: Use of Scientific Instruments, by Scientific Subfield (Life Sciences)



## A.3 Federal Research Funding Concentration

Figures A4, A5 and A6 plot the gini coefficients calculated on the distribution of total (total_rd) funding and funding specific to equipment (eq_rd). In most fields, the black line (which signifies concentration for equipment funding) is above the gray line, consistent with the result in Section 2 that showed a concentration of instrument funding exceeded concentration in total funding.

Figure A4: Federal Research Funding Concentration (Life Sciences)

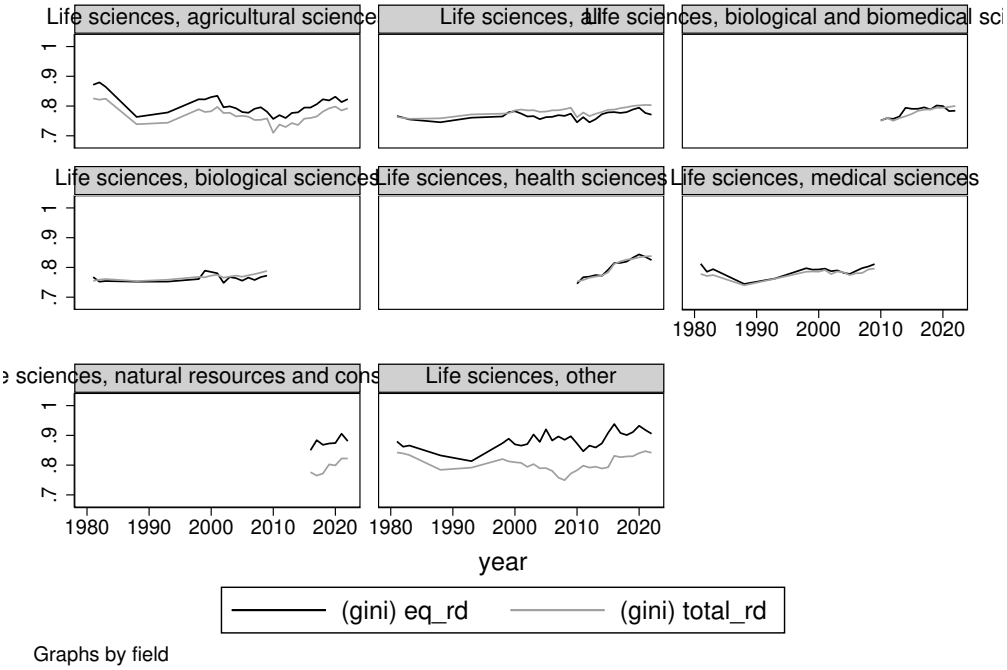


Figure A5: Federal Research Funding Concentration (Physical Sciences)

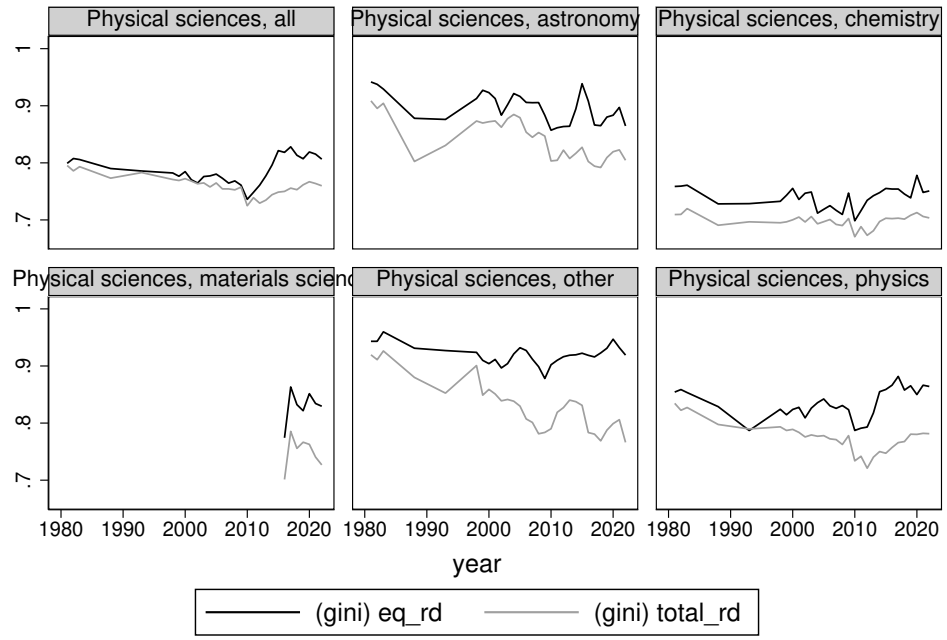



Figure A6: Federal Research Funding Concentration (Engineering)

