The making of high-tech clusters: Evidence from early-mover corporate labs in the American microchip breakthrough

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Abstract

During technological breakthrough, the uncertain nature of innovation often gives rise to unanticipated leader firms that coincidentally outpace their rivals. Do these unanticipated leaders continue to disseminate ideas to the industry after they achieve product market advantage? Using newly digitized corporate lab-level data and a unique natural experiment based on pre-Fairchild semiconductor choices, I test the corporate response to a plausibly unanticipated head start in the American late 1950s' microchip breakthrough. I find: 1) The head start quickly creates early leaders in the microchip industry, marked by persistent influx of citations and significant expansion of product lines. 2) The leader labs persistently produce more advanced inventions and new product designs in their leading research fields. 3) Rather than fencing off these research fields, the leaders disproportionately disclose technical details as public knowledge in industrial associations. The voluntary knowledge diffusion is likely strategic and vertical. I find that the leaders selectively disclose fabrication techniques that may attract downstream users, while limiting the release of experimental details that could benefit horizontal product rivals. 4) The vertical diffusion from leaders is mostly detected from in-person conferences arranged by the Institute of Radio Engineer (IRE), in which the "regional section" policy likely localizes the leader knowledge diffusion to engineers in close vicinity. I find Marshallian externalities indeed likely emerge in leader lab locations.

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1 Introduction

Innovation plays a pivotal role in driving economic development, and the expansion of technology clusters is often propelled by periods of groundbreaking discoveries (Romer, 1990; Schumpeter, 1942; Nelson and Winter, 1982). During revolutionary technological change, early leaders may crucially facilitate the diffusion of breakthroughs. A notable anecdote is how Fairchild Camera and Instrument Corp, an early-mover in microchip, advanced the aggregate technology frontier of micro-electronics industry and sparked the Silicon Valley (Klepper, 2010; Berlin, 2005). Alternatively, however, if early industrial leaders are more engaged in the acquisition of patent monopoly right, then their incentives to preempt and exclude rivals from new markets may lead to stagnated productivity growth and declining business dynamism (Argente et al., 2020; Williams, 2013; Akcigit and Ates, 2023). Therefore, understanding how breakthroughs reshape market structure is a crucial first step to informing the optimal policy in new technological revolution. However, there is still insufficient evidence to explain why firms occasionally disclose crucial techniques to the industry and facilitate cluster formation, especially during early technology breakthroughs.

This paper aims to unveil whether early technology leaders in breakthrough innovation continue to innovate and disseminate ideas after they achieve product market advantage over their rivals, and how the early technology leadership impacts high-tech cluster formation. However, the head start of firms into breakthrough innovation is highly endogenous. To robustly pin down the trajectory of early technology leaders, I focus on one of the most important technological breakthroughs in the US technology history - the 1950s' Fairchild microchip breakthrough[1]. The context of the US microchip breakthrough offers distinctive advantage to study early-mover R&D performance: firstly, the head start of corporate labs in each downstream research field, which has the potential to creatively combine with semiconductor technology, is found to be dependent on the choice of two major semiconductor materials (Silicon and Germanium) before Fairchild emerged. The two semiconductors share similar properties and were close substitutes before the breakthrough (Berlin, 2005; Reid, 2001). Moreover, I find that the ex ante choice of two semiconductors among corporate labs and research fields is orthogonal to most observable corporate and technological characteristics. After microchip breakthrough, Silicon is quickly proven to be the right material for microchip due to superior oxide properties. The identification assumption is that corporate labs holding Silicon patents in a given research field would experience a quasi-exogenous head start over other germanium patent holders in the same research field after the breakthrough. I leverage the setting, and conduct a corporate lab×research field level

[1]Figure A.1 showcases how the early takeoff of high-tech clusters (e.g., Silicon Valley) was associated with the 1957 microchip breakthrough.

difference-in-differences estimation to compare dynamic R&D outcomes between Silicon (head start), and Germanium (counterfactual head start) groups, conditional on the same research field.

Furthermore, I digitize and compile several novel datasets to measure R&D outcomes, including micro product data from each electronics manufacturer, advanced physics publications, historical patents micro data, and corporate industrial conference/working paper/proceeding publications. Using word embedding techniques, I run a cross-walk between their textual descriptions and patent classification scheme. Then, I merge these geo-located data to each corporate R&D lab. This allows me to separately estimate the impact of corporate labs' head start in microchip research on various R&D outcomes, ranging from research ("R") to development ("D") of products, within each specific research field. The corporate conference publication micro data also allow me to capture the disclosure of techniques at a granular lab×research field level. The above data enable me to understand whether early industrial leaders during technology breakthrough continue to radically innovate and disseminate ideas to the industry after they achieve relative product market advantage. I further rule out several caveats that may jeopardise my estimates, including simulaneous shock of the NASA Space Act, the likelihood that close research fields are strategic substitutes, and negative spillover (e.g., business stealing and R&D duplication).

Several interesting findings are unveiled. Firstly, the Silicon head start triggers significant creative combination of microchip technology toward the research field where Silicon patents were held. The head start quickly creates early leaders in the microchip industry, marked by persistent influx of citations and significant expansion of product lines. The leader corporate labs persistently produce more radical inventions and new product designs in their leading research fields, rather than a one-off acquisition of monopoly rights. However, there was no significant effect on the "Pasteur's Quadrant", measured by corporate publications of advanced physics research. Therefore, the early leader R&D seemed highly "applied" by nature, and the reward for obtaining a head-start in microchip breakthrough seemed to concentrate only on the "development" phase of "R&D" process. The finding coincides with the miracle of rapid expansion of product varieties in microchip sectors just after the breakthrough (Klepper, 2010). By 1968, the market size of commercial-use microchip had trumped the military market spurred by NASA procurement (Berlin, 2005; Orton, 2009). New microchip designs were released on a yearly basis from companies such as Texas Instruments and Fairchild (Berlin, 2005).

Furthermore, I demonstrate that after the initial head start, early technology leaders significantly disclose technical details to industrial association, such as the *Institute of Electrical and Electronics Engineers* (IEEE). I demonstrate that the knowledge sharing is unlikely to be spontaneous and automatic knowledge spillover; instead, the knowledge disclosure is likely strategic and vertical: the early leaders selectively disclose fabrication techniques that may attract downstream users, while limiting the release of experimental details that could benefit horizontal product rivals. I also demonstrate that the leader labs are more likely to disclose fabrication techniques when the product designs from their parent firms are likely to become dominant. I argue that the voluntary knowledge diffusion is likely associated with the increased product varieties during technology breakthrough, in which the firm of each design competes to become the dominant design. In a simple conceptual model, early leaders could have an incentive to lower the relative adoption costs for potential downstream users by releasing certain technical details as public knowledge. However, once crucial details are disclosed in public, they also become quasi-public goods that can be absorbed by rivals, explaining why the disclosure appears to be vertical and selective. Furthermore, I rule out several alternative caveats, including the concern that early leaders may publish original findings on IEEE platform, rendering the measure of knowledge disclosure a noisy measure of innovation.

Lastly, I find that the vertical diffusion from leaders is mostly detected from in-person conferences arranged by the Institute of Radio Engineer (IRE), in which the "regional section" policy that requires IRE members to participate within section meetings likely localizes the leader knowledge diffusion. In the Silicon lab located county$\times$research field pairs, the cumulative stock of inventors and corporate assignees are catalyzed to a larger extent, compared with the scenario when there are only Germanium labs. This is a sign that the channels of leader knowledge diffusion are likely to remain localized due to search frictions across space. As a result, early leader located clusters are likely to experience a rise of Marshallian externalities due to the concentration of vertical knowledge diffusion. This could raise the R&D performance of local labs in a persistent way. Robustness checks further demonstrate that the creation of such "Silicon Valleys" is a generalizable phenomenon beyond California and west coast states[2].

This research contributes to the literature on economic geography, economic history and knowledge spillover. Scholars have sought to understand the genesis of high-tech cluster formation and early industrial takeoff (Gross and Sampat, 2022; Mokyr et al., 2022; Kantor and Whalley, 2022; Saxenian, 1994; Giorcelli and Li, 2021). One way to approach the superstar cluster miracle is through the theory of agglomeration economies, whereby co-location of technologically related firms is regarded essential for new ideas to develop and recombine due to spatial frictions in knowledge exchange

[2]Other typical early-mover labs, such as IBM in Poughkeepsie, were also catalysts of local cluster take-off.

(Glaeser, 1999; Catalini et al., 2018; Atkin et al., 2022; Koh et al., 2022; Jaffe et al., 1993; Asheim and Gertler, 2006). Prior work has also shown that breakthrough innovation often imposes extraordinary influence on the churning of high-tech industries across space, and even facilitate the making of new high-tech clusters (Kerr, 2010; Duranton, 2007). However, in the prior literature, knowledge spillover is often treated as a spontaneous and automatic externality which firms have limited control on (Fadeev, 2023). There is also limited evidence to understand how a plausibly unanticipated head start in technological breakthrough impacts firm outcomes and cluster formation. I contribute to this literature by providing a causal estimate of the degree of voluntary knowledge disclosure when firms achieve a head start in technological breakthrough. I demonstrate how the voluntary vertical knowledge disclosure from leader labs may likely explain the rise of Marshallian externalities in leader lab locations.

I also contribute to a series of insightful work by Klepper (1996, 2002, 2010) on the evolution of oligopoly structure during early industrial development. Technology breakthrough (or discontinuities) often changes the trajectory of technology and marks the beginning of a new product cycle (Dosi, 1982). Klepper (1996) discusses the competition and shake-out dynamics of firms from heterogeneous entry cohorts in new product cycles. Klepper (2010) further takes the early rise of Silicon Valley as an example, and explains the cluster takeoff through the perspective of spin-off dynamics. However, the mechanics of knowledge diffusion is still relatively simplified due to the availability of data. The recent work by Giorcelli and Li (2021) demonstrates that spillover in early industrial development is indeed significant, both horizontally and vertically. I contribute to the literature by seeking to unpack the blackbox of knowledge diffusion, and the extent to which leader firms may internalize the externality from new technology. I also discuss how heterogeneous diffusion strategies may lead to diverse downstream product market performance.

This research also provides novel causal evidence to the literature on competition, innovation and growth (Aghion et al., 2001; Acemoglu and Akcigit, 2012; Akcigit and Ates, 2021, 2023). In modern Schumpeterian theories, firms innovate to escape from Schumpeterian competition, especially when they are at technological par with their rivals (Aghion et al., 2001, 2005). When firms progressively obtain greater market share, the innovation intensity is likely to fall (Aghion et al., 2005; Acemoglu and Akcigit, 2012), or the mode of R&D will switch to less radical research (Akcigit and Kerr, 2018). Recent work by Akcigit and Ates (2023) further relates the declining business dynamism to declining knowledge diffusion between leaders and followers. I contribute to this debate by examining whether early industrial leaders strategically reduce the amount of knowledge disclosure, and curb the rate of innovation once they obtain product market advantage over rivals.

The remainder of this article is organized as below: section 2 introduces the setting, data and research design. Section 3 serves as a stage one analysis: I discuss how the Silicon head start quickly creates early leaders in each research field after the breakthrough. Section 4 proceeds to the stage two analysis: I discuss whether early technology leaders continue to innovation after they achieve product market advantage over rivals. Section 5 presents the discussion on knowledge diffusion from these early industrial leaders. Section 6 presents the broader impact on agglomeration. Section 7 excludes several alternative logic and section 8 ends with a brief conclusion.

2 The takeoff of American microchip industry

2.1 Setting

The microchip breakthrough of the 1950s marks one of the most radical innovations in American history (Figure 1). After Fairchild Semiconductor emerged in 1957 (Figure 2), the early microchip industry experienced a rapid influx of circuit innovators, a rapid rise of circuit manufacturers, and a rapid transition of manufacturers from "old tech" such as vacuum tubes to the new general-purpose technology. The early development of new markets also provides an ideal experimental setting to trace out the trajectory of early industrial leaders, and observe their dynamic R&D outcomes and strategic interactions with rivals, especially when the product cycle progresses to later stages.

Estimating the causal effect of a head start in microchip breakthrough on corporate outcomes is empirically challenging. Firstly, by definition, technology leadership is highly research field specific. While Fairchild Semiconductor Division is a leader in bipolar integrated circuit, the company is not a leader in mainframe computer; while Intel is a leader in microprocessor and memory device, the company is not a leader in personal computer. Secondly, anticipatory effects may populate the pre-treatment observations as forward-looking firms may react upon new technological opportunities ahead of technological breakthrough. The third empirical challenge underlies simultaneous demand shocks, such as the 1958 NASA Space Act[3] that raised both the demand for telecommunication products and the productivity of microelectronics sectors closely related to space industries (Kantor and Whalley, 2022). The last empirical challenge lies in the endogeneity of corporate entry decision into new technology. Therefore, the ideal natural experiment must suffice the condition that all confounders are either balanced or time-invariant between head start and follower firms. Moreover, the chance of obtaining the head start should be quasi-random such that simultaneous shocks would

[3]For the purpose of confronting the 1957 launch of Soviet Sputnik I satellite, NASA released waves of post-1958 large procurement contracts to develop American space industries.

not exhibit a systematic pattern. To overcome this, I propose a unique natural experiment to robustly identify the causal effect of a head start in the microchip breakthrough on the subsequent corporate R&D outcomes.

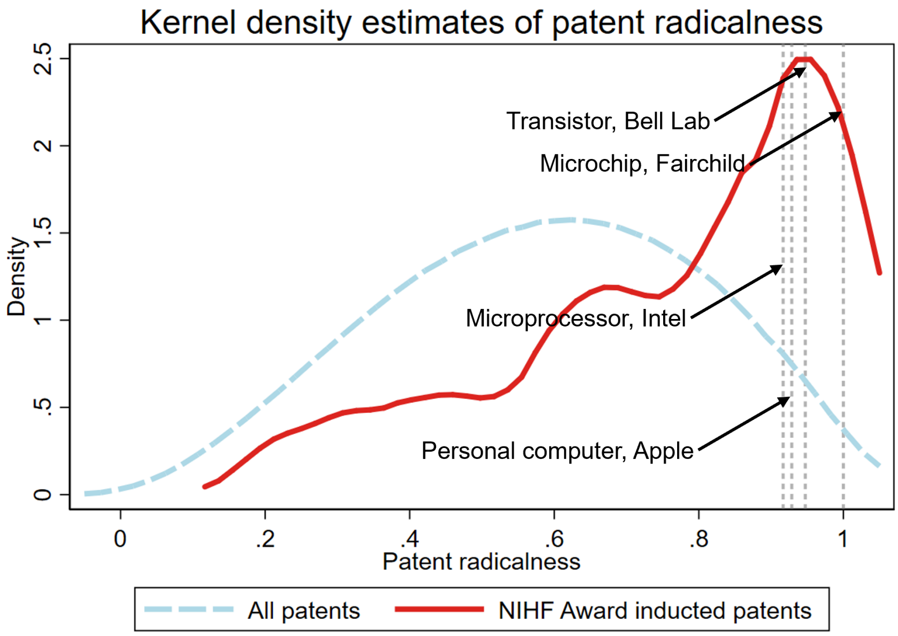
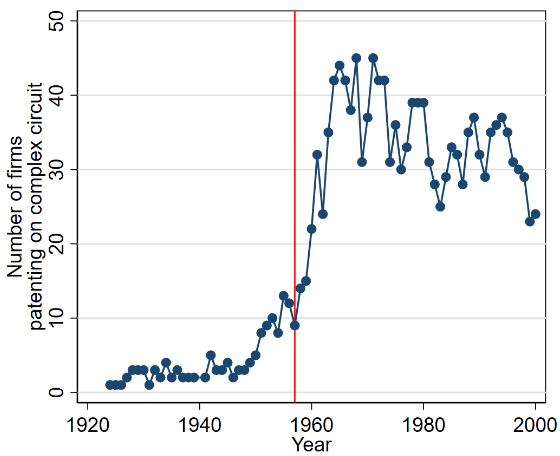


Figure 1: Radicalness of the microchip breakthrough.

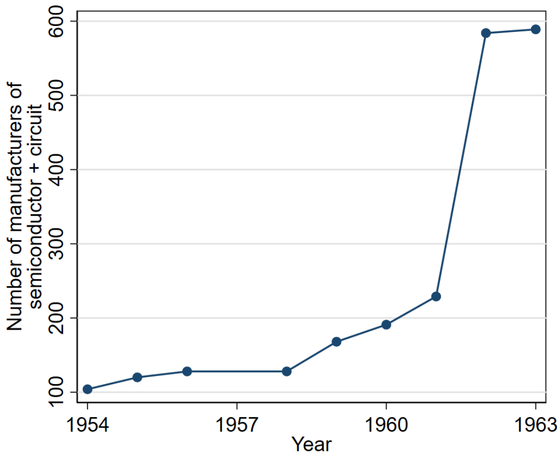
Note: Patent radicalness is defined by the degree to which a patent predates its similar patents. More specifically, I compute the measure by counting the share of Google Patent Similar Documents granted later than the given patent. The "All patents" plot shows the density curve for all patents during 1920-1980. The "NIHF Award inducted patents" plot shows the density curve only for the National Inventors Hall of Fame inducted patents during 1920-1980. Bandwidth = 0.05.

The natural experiment is based on the uncertain nature of innovation during the late 1950s' American microchip breakthrough, in which the choice of semiconductor material among corporate labs and research fields was found to be orthogonal to most observable covariates until Fairchild Semiconductor emerged. Shortly before Fairchild emerged, two types of semiconductors with almost identical properties - Silicon and Germanium - co-existed for semiconductor research[4]. Within 1 year after the founding of Fairchild Semiconductor in 1957, the Fairchild engineers came up with a revolutionary idea, called planar technique, which coated Silicon oxide layer on top of Silicon substrate to protect complex circuits from impurities. The same workflow did not work out for Germanium because of inferior oxide properties (Ye, 2016). The emergence of Fairchild Semiconductor triggered a chain of discoveries that quickly brought Silicon to the front stage as the perfect and the only (back then) material for microchip-based innovations. The key identification assumption is hence that after Fairchild emerged,

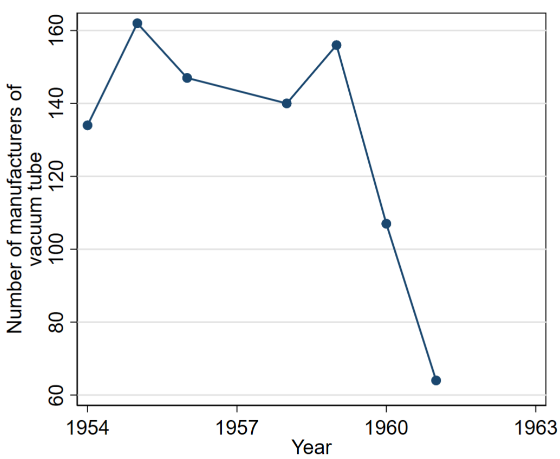
[4]In Appendix Figure C.1, I also plot the dynamic trends of Silicon and Germanium usage in semiconductor research over time to quantitatively support this claim.



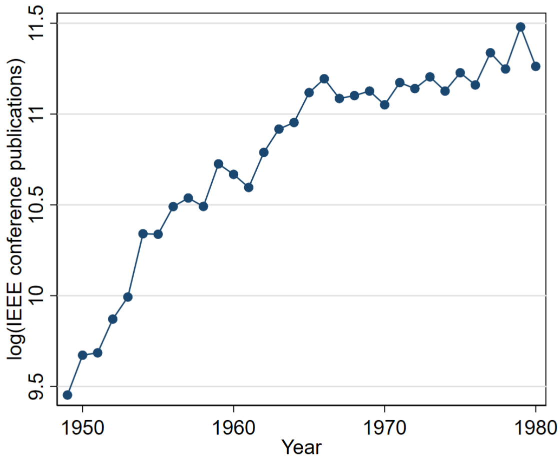
(a) Surge of corporate patentees



(b) Rapid entry of "new tech" manufacturers



(c) Rapid exit of "old tech" manufacturers



(d) Increasing conference publications

Figure 2: The early growth of American microchip industry.

Note: Producer data are digitized and collected from the Institute of Radio Engineer membership directory. Patent data are collected from USPTO and Google Patents. Conference publications data are collected from IEEE Xplore.

corporate labs that held only Germanium patents in a given research field would face creative destruction by the microchip breakthrough, and hence they lose the head start on that research field, compared with corporate labs that held Silicon patents on the same research field. For the Silicon patent holders, the microchip breakthrough exert a force of creative construction on their research, which would provide them with a head start to leverage the microchip technology or implement follow-on innovation on the Fairchild's microchip in the given research field. This creates a quasi-exogenous, within firm variation in the head start of corporate labs into microchip-related research (Figure 3a). I show that when a lab chooses Germanium on a certain research field, it leads to around 41.3% decline in microchip-related patents by the year of 1965 on that research field, which is equivalent to a (conservatively estimated) 3 years delay in the timing to combine the microchip technology into that research field. Moreover, balanced tests confirm that the pre-Fairchild characteristics of Silicon and Germanium-based labs, and their performance in respective research fields, were indeed comparable.

The setting has two additional unique advantages. Firstly, the anticipation of firms ahead of the advent of Fairchild Semiconductor is considered minimal according to archival evidence: the discovery of the "planar" idea was driven not by years of cumulative trial-and-errors corporate research, but instead it was triggered by the resentful breakaway within a group of genius engineers. William Shockley, a Nobel Prize Physics laureate but authoritarian manager, hindered his engineers[5] from exploring other new technology possibilities except for his dedicated project on four-layer diode (Berlin, 2005; Reid, 2001). In 1957, eight talented engineers broke away from Shockley due to personal resentment and formed the Fairchild semiconductor. With unfettered freedom for semiconductor research in the new company, the eights soon unlock the true potential of semiconductors: within just less than half a year since the breakaway, Jean Hoerni (one of the eights) noted down a novel idea in Dec. 1957 to dope semiconductor oxide layer on top of a clean semiconductor (namely, the planar technique) as a solution to carve down complex circuits while preventing contamination of complex junctions (Berlin, 2005; Orton, 2009). The formation of this idea soon unlock unprecedented potential in semiconductor technology and officially kicked off the decades-long transformation of human race to the modern computer age.

Secondly, the historical context provides a distinctive setting to comprehend the role of technology rivalry among early industrial leaders, and how it impacted market structure. In 1958, along with the discovery of the planar-based microchip idea, a parallel, non-planar-based microchip was invented by Texas Instruments (Berlin, 2005; Reid, 2001). The co-discovery and legal dispute over the "first" microchip patent spurred a

[5]The team was consisted of Jean Hoerni, the aforementioned engineer who came up with planar idea; as well as Robert Noyce and Gordon Moore, who brought the planar idea to new height and invented the first Silicon-based microchip.

patent war between the two companies, resulting in intensified technology rivalry in the form of legal impediment to the licensing of conflicted patents toward other companies. The patent war lasted until 1966 when Texas Instruments reached a licensing agreement with Fairchild and brought an end to the legal dispute[6]. By investigating how the exposure to the patent war waged by the two early-movers in microchip (Fairchild & Texas Instruments) impacted other early-movers, I unveil how the attempt to limit technology diffusion trigger the response of competing rivals.

2.2 Data sources

I compile multiple novel historical data from the following sources, and allocate them to each corporate R&D lab:

Historical US patent data: USPTO provides comprehensive bibliography information of all inventions granted since 1976, and OCR (Optical Character Recognition) - extracted textual data for patents granted before 1976. I obtain these aforementioned data and compiles patent forward citations, references, CPC (Cooperative Patent Classification) classes, and inventor names. For patent locations, I compile inventor locations from PatCity (Bergeaud and Cyril, 2022) and HistPat (Petralia et al., 2016) and merge them with the USPTO patent database. The above datasets have geocoded the locations for each historical inventor before 1976;

Corporate R&D labs: Parent firms and locations of corporate R&D labs are collected from the Corporate Author Headings used by the US Atomic Energy Commission in cataloging reports (United States Atomic Energy Commission, 1970), which includes information on the specific location of each R&D establishment as well as the hierarchical relationships between the facilities and the corresponding firms;

Historical product data for electronics manufacturer: I collect, digitize and build a novel site-product level database from Yearbooks of Institute of Radio Engineers (1953-1963), IRE membership directories, and the directory of electronics manufacturers from 1953-1963 (Institute of Radio Engineers, 1963) (Figure 4). New product manuals published by each firm in each business unit are also digitized and collected from the Electronics Industries trade journal (also known as the Tele-Tech). The trade journal is a professional magazine released by Chilton Co., a company famous for providing market research services for readers such with professional background in electronics and automotive.

IEEE conference publications: I download from IEEE Xplore (ieeexplore.ieee.org) the abstracts and bibliographic data for historical IEEE conference publications (in-

[6]Hence, rather than licensing directly from Fairchild, other companies needed to invent their own versions of microchip-related patents to adopt the technology into production.

Key events in 1957:

- Shockley breakaway (Sept. 1957)
- Fairchild Semiconductor Div emerged
- Fairchild's early discovery of planar technique (key basis of microchip) (Dec. 1957)

Labs	Research fields	1954-1957	1958-	
		Pre breakthrough era	**Post breakthrough, microchip era**	
1	A	Patents had NOT used Silicon	Delay	Start using microchip
2	B	Patents had NOT used Silicon	Delay	Start using microchip
2	C	Patents had used Silicon		Start using microchip
3	A	Patents had used Silicon		Start using microchip

Key event in 1954:
Both Silicon and Germanium entered mass use and production

(a) Timeline.

Corporate lab	Research field (Patent CPC code)	Semiconductor choice (Pre-Fairchild, 1953-1957)	Treatment group (head start in microchip research)
Bell Telephone Laboratory (lab of Morris, New Jersey)	Solid state device	Had used Silicon	Actual head start
	Bipolar integrated circuit	Had only used Germanium	Counterfactual head start
	Substation equipment, e.g. for use by subscribers	Had used Silicon	Actual head start
...	...	...	...

(b) Workflow to define Silicon/Germanium groups.

Figure 3: Introduction of empirical setting.

Note: Figure 3a displays time frame of events. Figure 3b displays the structure of data.

cluding conferences, meetings, conventions and symposium) for 1900-2000.

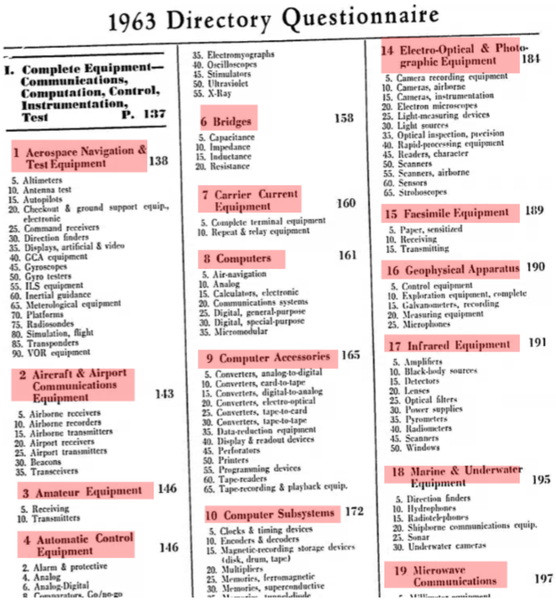
Advanced physics basic research publications: I download historical abstract and bibliography data for all publications in American Physics society during the year of 1940-1980 (https://www.aps.org/).

Besides these data, I collect county socio-economic indicators from Historical, Demographic, Economic, and Social Data compiled by Inter-university Consortium for Political and Social Research (ICPSR) (Haines, 2010). I also collect NASA prime procurement data over 1958-1968 from NASA Historical Data Book (Nimmen et al., 1976) to build a county-level control.

2.3 Data construction

Corporate R&D labs. The list and locations of research establishments are collected from Corporate Author Heading (CAH) (see Figure C.3 in Appendices), coordinated by the Committee on Scientific and Technical Information, Federal Council for Science and Technology. Unlike a simple collection of author affiliations, the CAH report was carefully examined and has cross-referenced the identities of each United States corporate authors based on the COSATI standard, in order to "facilitate exchange of scientific and technical information among government agencies" (United States Atomic Energy Commission, 1970). The report incorporates an extensive range of R&D establishments (corporate authors) that published before 1970. I digitize the location and names of each corporate author and merge them with Google Patent assignees. Owing to the lack of more granular patentee affiliation data, all R&D establishments affiliated to the same assignee, located within the same county, are merged and treated as one single corporate R&D lab. All patents, advanced physics publications, and products developed by the same corporate patentee u at county c are thereby allocated to the corresponding lab v retrieved from CAH.

Research field. I indicate research field by each granular Cooperative Patent Classification (CPC) class (i.e., the part before "/". I term it as 6-digit patent class hereafter.). One advantage of using CPC codes to indicate technology fields of patents is that it provides a nested hierarchical classification structure to arrange categories of technology fields. The issue of having a critical piece of technology under-represented by a given patent class can be much more salient when I use coarsened categories (such as 3-digit CPC, 3-digit USPC, or NBER patent sub-category) to capture technology fields. For example, both the traditional telegraphy and modern microprocessor are located in the same NBER sub-category or 3-digit USPC category. The nature of invention can be massively heterogeneous even within a single 4-digit CPC sub-category (e.g., semiconductor devices (H01L)). For example, the progress from transistor (H01L29/00) to


1963 Directory Questionnaire

I. Complete Equipment—Communications, Computation, Control, Instrumentation, Test P. 137

1 Aerospace Navigation & Test Equipment 138

2 Aircraft & Airport Communications Equipment 143

3 Amateur Equipment 146

4 Automatic Control Equipment 146

6 Bridges 158

7 Carrier Current Equipment 160

8 Computers 161

9 Computer Accessories 165

10 Computer Subsystems 172

14 Electro-Optical & Photographic Equipment 184

15 Facsimile Equipment 189

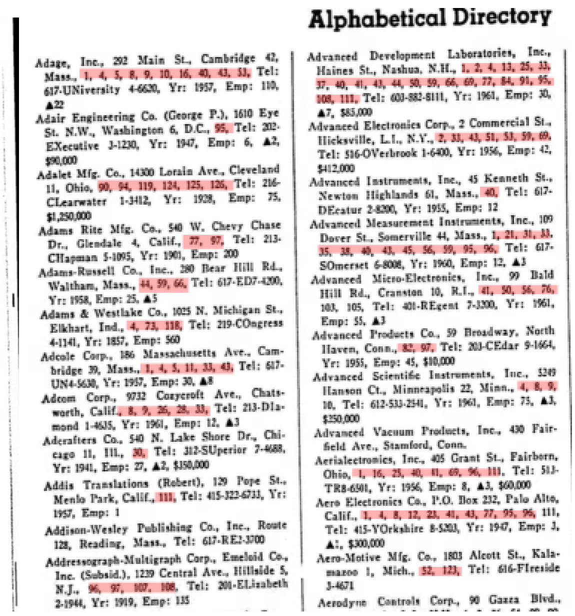
16 Geophysical Apparatus 190

17 Infrared Equipment 191

18 Marine & Underwater Equipment 195

19 Microwave Communications 197

(a) Digitized new product manuals.


Alphabetical Directory

Adage, Inc., 292 Main St., Cambridge 42, Mass., 1, 4, 5, 8, 9, 10, 16, 40, 43, 53, Tel: 617-UNiversity 4-6630, Yr: 1957, Emp: 110, ▲22

Adair Engineering Co. (George P.), 1610 Eye St. N.W., Washington 6, D.C., 95, Tel: 202-EXecutive 3-1230, Yr: 1947, Emp: 6, ▲2, $90,000

Adams Rite Mfg. Co., 540 W. Chevy Chase Dr., Glendale 4, Calif., 77, 97, Tel: 213-CHapman 5-1095, Yr: 1901, Emp: 200

Adams-Russell Co., Inc., 280 Bear Hill Rd., Waltham, Mass., 44, 59, 66, Tel: 617-ED7-4290, Yr: 1958, Emp: 25, ▲5

Advanced Development Laboratories, Inc., Haines St., Nashua, N.H.

Advanced Electronics Corp., 2 Commercial St., Hicksville, L.I., N.Y.

Advanced Instruments, Inc., 45 Kenneth St., Newton Highlands 61, Mass.

Advanced Measurement Instruments, Inc., 109 Dover St., Somerville 44, Mass.

Advanced Micro-Electronics, Inc., 99 Bald Hill Rd., Cranston 10, R.I.

Advanced Products Co., 59 Broadway, North Haven, Conn.

Advanced Scientific Instruments, Inc., 5249 Hanson Ct., Minneapolis 22, Minn.

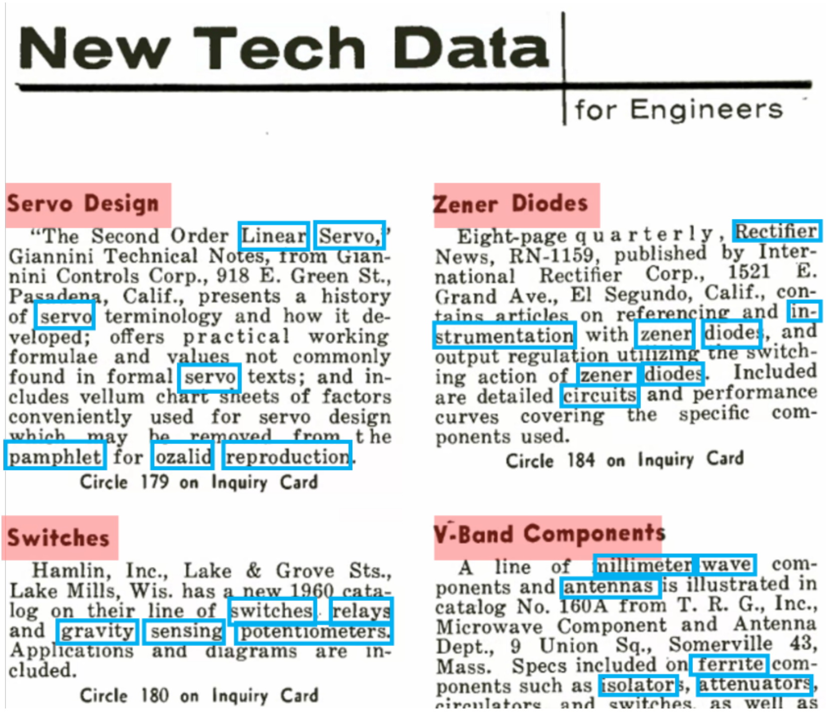
Advanced Vacuum Products, Inc., 430 Fairfield Ave., Stamford, Conn.

Aerialectronics, Inc., 405 Grant St., Fairborn, Ohio

Aero Electronics Co., P.O. Box 232, Palo Alto, Calif.

Aero-Motive Mfg. Co., 1803 Alcott St., Kalamazoo 1, Mich.

(b) Digitized product lines.


New Tech Data for Engineers

Servo Design

"The Second Order Linear Servo," Giannini Technical Notes, from Giannini Controls Corp., 918 E. Green St., Pasadena, Calif., presents a history of servo terminology and how it developed; offers practical working formulae and values not commonly found in formal servo texts; and includes vellum chart sheets of factors conveniently used for servo design which may be removed from the pamphlet for ozalid reproduction.

Circle 179 on Inquiry Card

Switches

Hamlin, Inc., Lake & Grove Sts., Lake Mills, Wis. has a new 1960 catalog on their line of switches, relays and gravity sensing potentiometers. Applications and diagrams are included.

Circle 180 on Inquiry Card

Zener Diodes

Eight-page quarterly, Rectifier News, RN-1159, published by International Rectifier Corp., 1521 E. Grand Ave., El Segundo, Calif., contains articles on referencing and instrumentation with zener diodes, and output regulation utilizing the switching action of zener diodes. Included are detailed circuits and performance curves covering the specific components used.

Circle 184 on Inquiry Card

V-Band Components

A line of millimeter wave components and antennas is illustrated in catalog No. 160A from T. R. G., Inc., Microwave Component and Antenna Dept., 9 Union Sq., Somerville 43, Mass. Specs included on ferrite components such as isolators, attenuators, circulators and switches, as well as

(c) Digitized new product manuals.

Figure 4: Newly digitized product-level datasets.

Note: Data source: IRE Membership directory & Electronics Industries.

integrated circuit with bipolar transistors on a single substrate (H01L27/0755) was already a revolutionary breakthrough that won Jack Kilby the Nobel Prize in Physics and National Hall of Fame Inventors Award. CPC codes for each historical US patent are collected from the Google Patents, in which the classification scheme is realigned retrospectively so that the nature of technology in the same patent class is consistent over time. One concern of using such a granular, 6-digit patent class is the risk of between-field R&D substitution (or negative spillovers) across closely-related research fields. A broad set of spillover checks are displayed in section 3, which suggest that between-research field spillovers are instead positive and statistically insignificant. Hence, these concerns are at worst a downward bias of the estimate of early-mover advantage, which is unlikely to jeopardise the validity of my natural experiment design.

Pre-Fairchild semiconductor choice. I trace the use of Silicon/Germanium in each corporate lab and research field (6-digit patent class) by semi-manually searching through all textual data from their historical patents. The detailed workflow is further explained step-by-step in Appendix C.2. All patents with priority date from 1954 (the year both Silicon and Germaniun had started mass production) to 1957 are searched[7]. Figure 3b presents an example of the data: As Bell Lab (Morris county) had not used Silicon and only used Germanium in bipolar integrated circuit (H01L27/00) within the time range, I classify the lab×research field pair [Bell Lab (Morris county) × bipolar integrated circuit] as in the Germanium group (i.e., all else equal, engineers from Bell Lab (Morris county) were expected to experience delay in conducting planar-based microchip research on bipolar integrated circuit). As Bell Lab (Morris county) had used Silicon in the other research fields from the example I show in Figure 3b, I classify these lab×research field pairs as in Silicon group (i.e., all else equal, engineers from Bell Lab (Morris county) were not expected to experience delay in conducting planar-based microchip research on solid state device and substation equipment).

Outcome variables. The key outcome of interest is the R&D performance of each corporate lab on each research field. Furthermore, the novel datasets I collected enable me to separate the "R" and "D" in R&D activities. Therefore, the impact of head start in microchip research on corporate R&D activities can be accurately decomposed according to stages of research. I use abstracts data for conference/physics publications and textual description data of CPC codes to build a cross-walk[8] between research fields

[7]To avoid mechanical issues from counting the same patent in both left- and right-hand sides of patent regression, inventors that filed these pre-Fairchild Si/Ge patents are excluded out of all patent-based dependent variables. All the following estimates on patent outcome regressions should therefore be interpreted as the effect of a head start in microchip research on the universe of corporate inventors that were not directly involved in pre-Fairchild Silicon/Germanium research.

[8]I first use word embedding approach to convert each token into a numeric coordinate. Then, I weight each token by TF-IDF (Term Frequency - Inverse Document Frequency) score, and compute a weighted average of all tokens in each single abstract/CPC description document. Therefore, each abstract/CPC text description document is converted to a numeric coordinate. Lastly, I compute

(6-digit CPC codes) and IEEE/advanced physics publication data. Only the matches with cosine similarity score above 90% of the universe of all possible matches are kept as successful cross-walks. Similarly, I use TF-IDF (Term Frequency - Inverse Document Frequency)[9] weighted keyword matching to create a cross walk between 133 electronics product categories (Figure 4) and CPC codes, so that only meaningfully important product-CPC code matches are obtained. The list of compiled product categories is displayed in Appendix C.1.

As a result, I focus on five major outcome variables at the corporate lab×research field level: (1) count of product lines (measured by product modules) to capture product market performance; (2) Life-long citations of the most cited patent to capture of "local" technology frontier of each lab in each research field; (3) Number of advanced physics publications to capture basic research progress; (4) Number of new product manuals to capture newly commercialized innovation (new product designs); (5) Number of IEEE conference/meeting paper/proceeding publications to capture public knowledge disclosure. Specifically, I further divide the IEEE publications into two categories: the ones mentioning fabrication details that could be of interest to downstream users, and the ones that mention experimental details that could be related to corporate trade secrets. Additional analyses further divide the variable into conference/convention/symposiums publications, where face to face communication is needed; and the general journal publications. The exercise will be explained in following sections.

2.4 Baseline model specification

The baseline model takes the form of equation (1):

$$Y_{vft} = \alpha + \beta \text{Head start}_{vf} \times \mathbf{1}\{t \geq 1957\} + \mu_{vf} + \lambda_{ut} + X_{vt} + \varepsilon_{vft} \tag{1}$$

where v is an index for corporate lab. f is an index for research field. t is an index for year. u stands for the parent firm of lab v. $\mathbf{1}\{t \geq 1957\}$ is a post-Fairchild time dummy, coded as 1 when the calendar year has progressed beyond the emergence of Fairchild Semiconductor in 1957. Head start$_{vf}$ is a binary variable indicating whether or not a given corporate lab×research field pair belongs to Silicon/Germanium group. For better exposition of the head start (Silicon (dis-)advantage in R&D), I set Germanium group as the benchmark (0) and Silicon group as the "treated" (1). μ_{vf} are corporate lab×research field two-way fixed effects, which absorb $\mathbf{1}\{t \geq 1957\}$, Head start$_{vf}$, and all the time-invariant confounders. ε_{vft} is the error term. λ_{ut} is two-way firm×year FE.

pair-wise cosine similarity scores between abstracts and CPC text description document.

[9]TF-IDF is an approach to weight the importance of each token in a document based on Term Frequency and Inverse Document Frequency.

The inclusion of λ_{ut} absorbs all unobservable firm-level confounders such as size, debts and revenues and overall R&D spending. The time period runs from 1953 to 1965, and the panel is balanced in nature as I keep only the corporate labs that had survived through the entire research period[10].

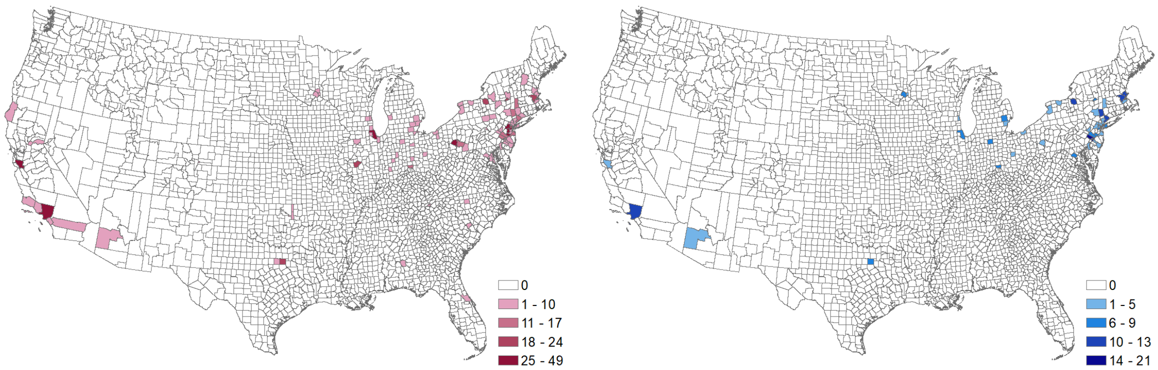
As robustness checks, I include a set of controls (for simplicity, I term the set of controls weighted by coefficients as X_{vt}) including: 1) a binary NASA county variable interacted with year fixed effects: the NASA variable is coded as 1 when the county c where lab v was located would be awarded a prime NASA contract in 1958-1968; 2) a binary county-level advanced physics institute/university variable interacted with year fixed effects: the binary institute/university variable is coded as 1 when the lab is located in the top 10% counties c where most advanced physics publications were produced during 1953-1957; 3) the number of advanced physics publications in lab$\times$research field vf at year t. Robustness check has ensured that the advanced physics publications control indeed follows parallel trend. Y_{vft} is a set of dependent variables explained earlier.

Another concern endangering this identification strategy is somewhat similar to exclusion restriction - the choice of Silicon over Germanium may impact outcomes through other channels, regardless of any head-start in microchip research. This may be concerning if the use of Silicon before Fairchild implies a higher share of foresighted inventors (e.g., more potential Noyces and Moores), or more weight on explore over exploit in doing Silicon research. These unobservable factors may raise patenting and hence bias upward the effect of a head start in microchip research. To test for whether these concerns exist, I further conduct a falsification test by keeping only those lab$\times$research field pairs in which no microchip-related patents are detected. Upon this modified sample of *de facto* never-adopters (or late-mover in the microchip breakthrough), the effect of Silicon choice becomes both statistically and economically near 0 on all R&D outcome variables (detailed falsification tests are displayed in Appendix section D.2. On the one hand, the test verifies that apart from an early head start in microchip research, there were no any other obvious channels by which pre-Fairchild semiconductor choice could change R&D performance (exclusion restriction); on the other hand, the test rules out the concern that some unobservable latent traits in Silicon labs could induce simultaneous increase in R&D performance after Fairchild Semiconductor emerged. Furthermore, I will also discuss a series of alternative explanation for the estimated effect in section 3, and none of the alternative logic seems to vastly jeopardise the estimated early-mover advantage in R&D.

[10] The post period may be adjusted in individual exercise performed later.

2.5 Stylized facts

The sample distribution is mapped in Figure 5. The spatial distribution of lab×research field pairs is relatively balanced, which is a piece of suggestive evidence that there were no obvious first-nature geographical characteristics biasing the selection of labs into Silicon and Germanium before Fairchild Semiconductor emerged. To systematically test for the quasi-random selection assumption, Figure 6 displays the mean differences of covariates across Silicon and Germanium groups before Fairchild Semiconductor emerged. Evidence shows that the use of Silicon/Germanium in each corporate lab and research field seemed uncorrelated with prior innovation capacities, *ex ante* locational characteristics, and pre-Fairchild R&D outcome variables.



(a) Silicon (b) Germanium

Figure 5: Distribution of sample.

Note: The number indicates the count of corporate lab×research field pairs.

Figure 7 plots the trends of key outcome variables, respectively for Silicon and Germanium groups over time. A constant value equivalent to pre-1957 mean from each group is subtracted from each outcome variable to better compare the dynamic trends. The binned scatter pre-trends of the two groups indeed overlap in scale before Fairchild Semiconductor emerged, which supports the parallel trend assumption.

Figures 7a and 7b show that Silicon patent holders on average experience greater citations influx from other firms, and greater expansion of their product lines after the breakthrough. Figure 7c shows that Silicon labs also produce more new product manuals, a proxy for newly commercialized innovation, than Germanium labs do. Several surprising facts are also unveiled. Rather than reducing the rate of innovation after a sizable advantage in the product market, the Silicon labs continue to produce radical new patents, measured by patents granted earlier than 50% of its Google Similar Documents (Figure 7d). Moreover, compared with Germanium labs, the Silicon labs also release more technical details in IEEE on the research fields where they hold Silicon patents before the breakthrough (Figure 7e). The evidence casts interesting question

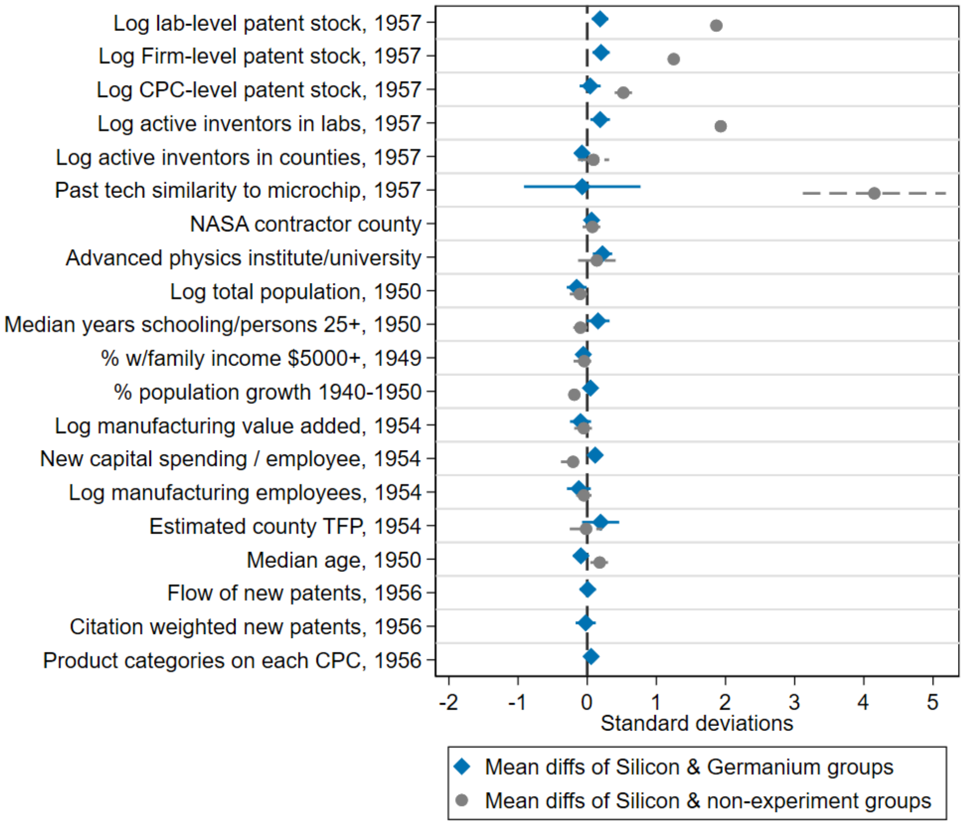
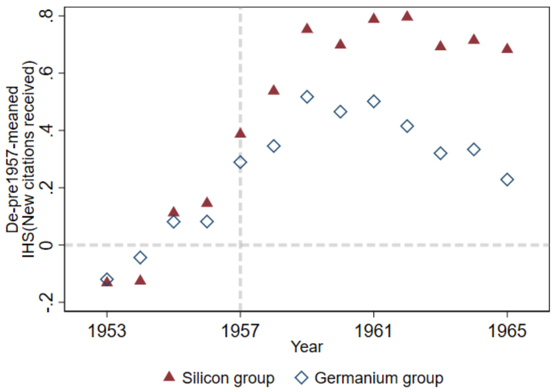
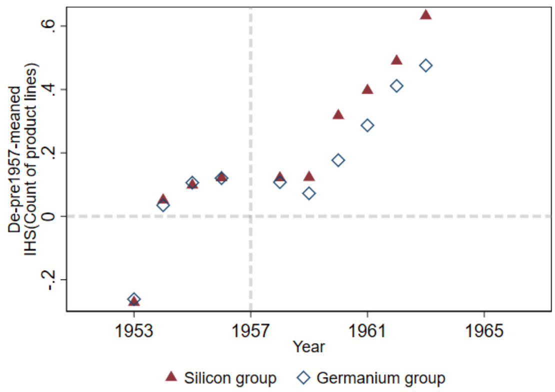


Figure 6: Balancing test

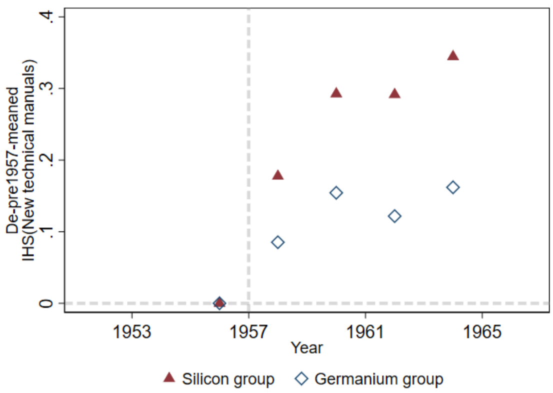
Note: Figure 6 reports the corporate lab×research field level t-tests for covariate mean differences. The year of each covariate is taken at the closest year before Fairchild Semiconductor emerged, depending on data availability. "Patent stock" is defined as cumulative count of all patents invented during 1953-1957. "Past tech similarity to microchip" is a technology-class level indicator, measuring the fraction of patents similar to microchip patents (according to Google Patent: Similar Documents) from each research field during 1953-1957 (for details, see C.1). "NASA contractor county" is a binary county-level variable, coded as 1 when the county where a lab belongs to would receive a prime contract during 1958-1967. "Advanced physics institute/university" is a binary county-level variable, coded as 1 when the lab is located in the top 10% counties where most advanced physics publications were produced during 1953-1957. Covariates from "Log total population" to "Median age" are county-level indicators. Due to considerable efforts needed for the data collection of "Non-experiment group", for "Flow of new patents", "Citation weighted new patents" and "Product categories on each CPC", I only display the mean differences of Silicon and Germanium groups. Mean differences values are standardized in units of standard deviations. "Non-experiment group" refers to all the other corporate lab×research field pairs in which neither Silicon nor Germanium semiconductor had been detected in patents during 1954-1957. Standard error is clustered at the county×research field level and confidence intervals are reported at the 95% level.



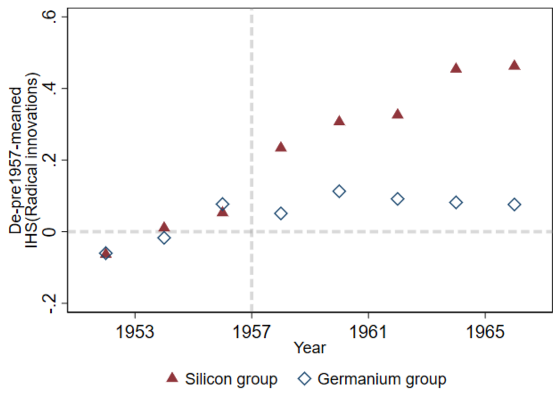
(a) New citations received



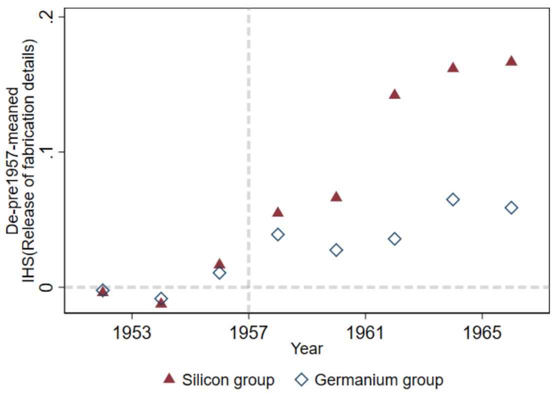
(b) Count of product lines



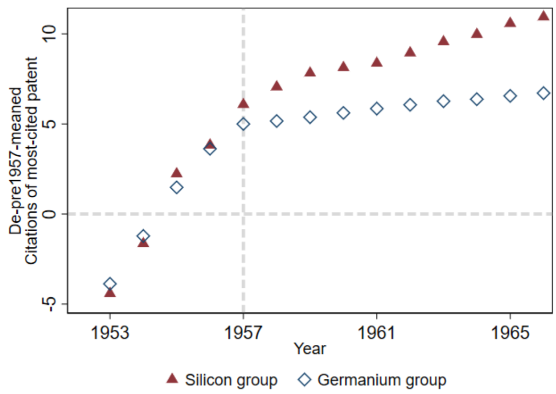
(c) New product manuals



(d) Flow of radical innovation



(e) Release of technical details



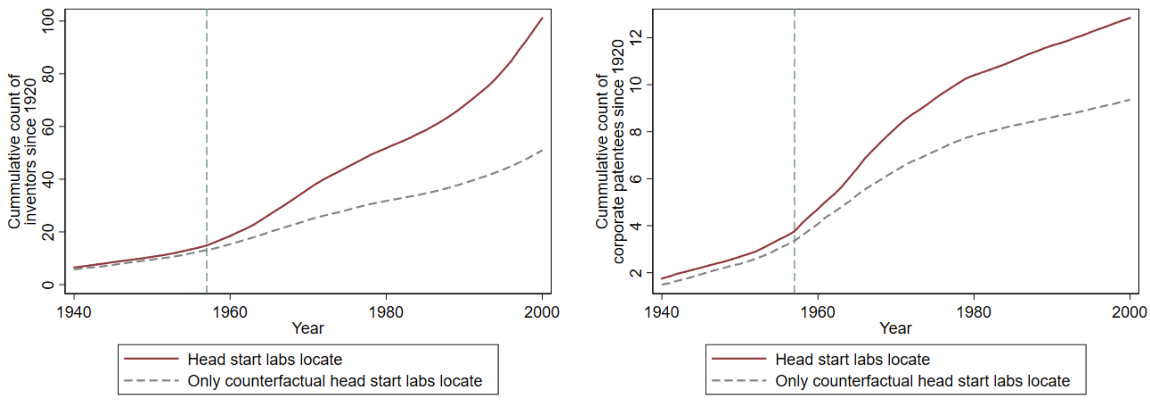
(f) Life-long citations of the most-cited patent

Figure 7: Demeaned scatter plot on key outcome variables.

Note: Figures display the time trend of mean values for each key outcome variable. Before the aggregation to group-level means, each observation is a corporate lab×research field×year unit. A constant value equivalent to pre-1957 mean from each group is subtracted from each outcome variable to better compare the dynamic trends.

on the standard innovation models where the problem of market failure often leads to the classic incentive problem in private R&D spending. Lastly, Figure 7f plots the time trends for life long citations of the (cumulative) most-cited patent as a proxy for the local technology possibility frontier for each lab. The preliminary evidence suggests the Silicon labs experienced a decade-long, persistent advancement of the lab-level technology frontier in respective research fields.

Moving from micro to a more aggregated perspective, Figure 8 displays the cumulative stock of inventors and corporate patent assignees over time in the "head start" counties×research fields where Silicon lab×research fields are located before the breakthrough, and "non head start" counties×research fields where only Germanium lab×research fields are located before the breakthrough. Preliminary evidence shows that the head start clusters experience rapid expansion in both measures after the microchip breakthrough.



(a) Cumulative stock of inventors (b) Cumulative stock of corporate patentees

Figure 8: Takeoff of Silicon lab located county×research field pairs.
Note: Figure 8a displays the count of total new patents per year in each county×research field. Figure 8b displays the cumulative count of corporate patentees in each county×research field. All dates are taken from patent priority dates.

Causal evidence is presented in the following sections to unveil the trajectory of early technology leaders in microchip breakthrough.

3 The rise of early technology leaders

3.1 Silicon and early exposure to microchip breakthrough

After the microchip breakthrough, how significant is the head start of Silicon patent holders over their Germanium rivals in the same research field? Additionally, are Silicon patent holders more likely to anticipate the arrival of Fairchild and the subsequent breakthrough? I illustrate the extent of the head start by quantifying the timing of each lab's exposure to microchip within their respective research fields[11] (Microchip_{vft}). Then, I regress Microchip_{vft} on the Silicon dummy as illustrated in equation (2):

$$\text{Microchip}_{vft}\mid_{t=T} = \zeta_0 + \zeta_1 \text{Silicon}_{vf} + \theta_u + X_{vf} + \varepsilon_{vf} \tag{2}$$

where $\text{Microchip}_{vft}\mid_{t=T}$ incorporates: 1) a binary variable indicating whether lab v have developed a microchip-related[12] patent in year $t = T$ on research field f (Table 1 columns (1) - (3)); 2) the cumulative count of microchip-related patents in year $t = T$, lab v, on research field f (Table 1 column (4)); 3) the year (priority date) of the first microchip-related patent of lab v on research field f (Table 1 column (5)). The coefficients from columns (1), (3) - (5) are all positive and statistically significant at 1% level, which suggests that the Silicon patent holders are indeed associated with significantly earlier exposure to microchip technology, irrespective of the indicator chosen to capture the exposure. For example, by 1965, there has been an around 18.2% increase in the probability for Silicon patent holders to develop at least 1 patents related to microchip in each research field where they held Silicon patents before Fairchild emerged. This is equivalent to an approximately 41.3% increase in the stock of microchip-related patents by 1965, and a conservatively estimated[13] 3-year advantage in producing the first microchip related patent. In column (2), I fix $T = 1957$, and the result suggests that before Fairchild emerges, Silicon patent holders were not disproportionately producing microchip-related patents in the research fields where they held Silicon patents. Therefore, no evidence is found to suggest significant pre-Fairchild anticipation of the microchip breakthrough among the selected lab$\times$research field pairs.

3.2 The rise of early industrial leaders

In this section, I unveil to what extent the power of creative construction and destruction shapes the market selection for early industrial leaders after the early product

[11] I restrict the sample to the research fields where inventors have already patented with semiconductor before Fairchild emerged.

[12] The reason of using microchip related patents is that the keyword "microchip" was not widely used at the early stage of microchip era. For example, Texas Instruments preferred the term "integrated circuit" and Fairchild preferred "semiconductor circuit complexes". To capture early efforts in microchip research as much as possible, I first identify a set of "confident" microchip patents using keyword detection of a combination of terms such as "transistor", "integrate", "circuit", "semiconductor" and "oxide layer". And then I collect similar patents to these "confident" microchip patent from Google Patents Similar Documents.

[13] This is a conservative estimate because Table 1 column (5) is conditional on the labs that have at least patented once with microchip technology throughout the entire research period.

Table 1: Pre-Fairchild semiconductor choice and the speed of applying microchip to new patents.

	(1) Entry status t=1965	(2) Entry status t=1957	(3) Entry status t=1965	(4) IHS(Cuml. count) t=1965	(5) Entry year t=1965
Silicon	0.182***	0.017	0.159***	0.413***	-3.011***
	(0.038)	(0.013)	(0.041)	(0.088)	(0.712)
Firm FE	N	N	Y	Y	Y
Controls	N	N	Y	Y	Y
Obs.	1061	1061	1039	1039	494
R^2	0.039	0.001	0.172	0.241	0.186

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: a binary variable indicating whether or not lab v has started microchip patents in research field f by 1965 (columns (1) and (3)) and by 1957 (column (2)); inverse hyperbolic sine of lab v's cumulative stock of microchip-related patents in research field f by 1965 (column (4)); lab v's year of the first microchip-related patent in research field f (column (5)). "t=X" means only a cross-section of sample in year X are kept. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

market shake-out. Does the head start predict early technology leadership in the microchip industry? To illustrate this, I estimate equation (1) by first taking new citations received from other firms as an outcome variable. Patent citation has attracted mixed interpretation from recent years. For example, citations are often commonly viewed as a proxy for knowledge flows, either intentional or unintentional (Jaffe et al., 1993; Hall et al., 2001; Fadeev, 2023). Citations can also be a noisy indicator of actual knowledge diffusion, as they may be affected by idiosyncratic choices from the assigned patent examiners (Kuhn et al., 2023; Hall et al., 2001). I hence step back from giving citation measure a concrete conceptual definition, and interpret the influx of citation in a given firm as a signal that the firm's knowledge stock is likely satisfying more potential demand in the market for ideas. I present estimates of β from the dynamic version of equation (1) in Figure 9. Static estimates are displayed in Table 2. In Panel A, Figure 9b shows that after the breakthrough, Silicon labs instantly attract a greater amount of external citations compared with Germanium labs in the same research field, and the effect persists throughout the entire first 8 years. The influx of citations to the Silicon labs is economically sizable: columns (1) - (3) from Table 2 shows that the surge of citation influx is not sensitive to the controls and the effect on average amounts to 1.761 (approximately 32.4%) more citations. The finding suggests that after the breakthrough, knowledge stock from Silicon labs is increasingly more demanded than that of Germanium labs in the market for ideas, conditional on the same research field.

Next, I unveil the product market performance of corporate labs by switching the outcome variable to the count of product lines on each research field. Figure 9a shows that the head start not only predicts significant leadership measured by the attraction of citations, but also a surge of product lines in Silicon labs, compared with the Germanium labs that patent in the same research field. On average, the head start raises 1.764 (equivalent to 32.4%) more product lines after the breakthrough. The finding confirms that after an around 2 years' lag, the head start gives Silicon labs a significant product market advantage over the Germanium rivals in the same research field.

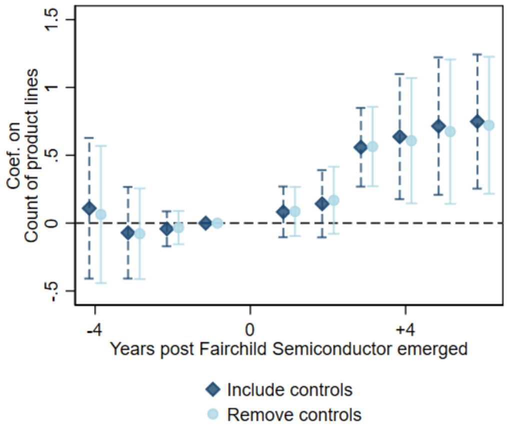
Table 2: Baseline results: the rise of early industrial leaders after microchip breakthrough.

	New citations received			Count of product lines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Y_{vft}	Y_{vft}	IHS(Y_{vft})	Y_{vft}	Y_{vft}	IHS(Y_{vft})
Silicon × Post	1.777***	1.761***	0.324***	0.482***	0.482***	0.137***
	(0.368)	(0.352)	(0.053)	(0.159)	(0.157)	(0.037)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y	Y
Controls	N	Y	Y	N	Y	Y
Mean(Y_{vft}|Silicon)	4.415	4.415	4.415	2.803	2.803	2.803
Obs.	13507	13507	13507	10390	10390	10390
R^2	0.770	0.774	0.757	0.869	0.872	0.885

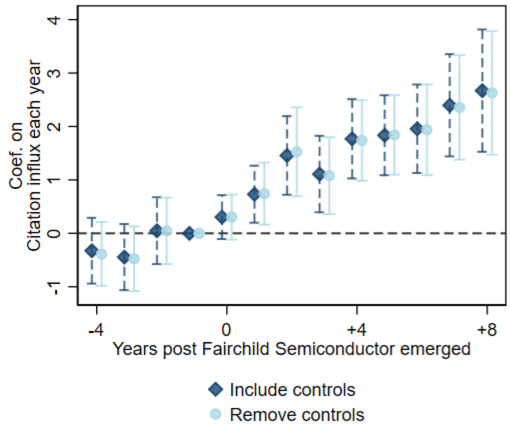
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: new forward citations received for each year in each lab×research field pair (columns (1) - (3)); count of product lines for each year in each lab×research field pair (columns (4) - (6)). IHS(Y_{vft}) indicates that the dependent variables are in the form of inverse hyperbolic sine. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

Panel B of Figure 9 checks if the advantage of Silicon labs in product market could reflect any other alternative explanations. For example, the pre-Fairchild choice of Silicon over Germanium may impact Silicon lab outcomes through other channels beyond the head start in microchip. I restrict the sample by including only labs that have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f. If any latent properties of Silicon labs induce greater product market performance or greater external demand for ideas, the estimated impact of the head start should remain sizable on the two outcomes even after the sample restriction. Figure 9c and 9d display the results after sample exclusion. The effects of choosing Silicon over Germanium mostly shrink to statistically and economically near 0 when only the microchip "never-adopters" are kept. The tests verify that the head start indeed mostly reflects an early-mover advantage in the microchip breakthrough, but unlikely the other pre-Fairchild latent confounders.

A. Full sample

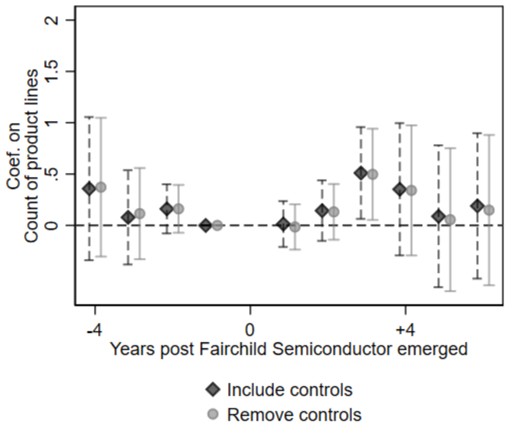


(a) Count of product lines

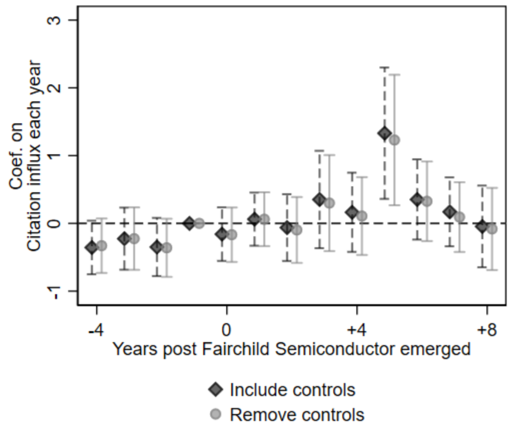


(b) New citations received

B. Conditional on lab×research fields where no microchip patents are observed



(c) Count of product lines (never-adopter)



(d) New citations received (never-adopter)

Figure 9: Head start and the rise of early technology leaders.
Note: Panel A shows the dynamic effects of the head start on corporate outcomes, and how the effect shrinks to near zero when no microchip is actually used throughout the research period. Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit. For Panel B, the sample consists only of labs that have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f.

3.3 Caveats of alternative mechanisms

Caveats of R&D allocation. However, so far the empirical model has not yet factored in the reallocation of R&D factors between corporate labs and between research fields. Such reallocation could lead to over-estimation of the "net effect" of head start if the following scenarios occurred: (1) Local congestion: conditional on the same research field and all else being equal, if co-located labs share the same local factor market and the supply of inventors is inelastic, the rise of R&D in one lab could divert researchers away from the other co-located labs, resulting in a decline in R&D from the co-located Germanium labs after the microchip breakthrough; (2) Within-firm R&D re-allocation: a corporate manager may re-assign more R&D tasks from Germanium labs to Silicon labs after the microchip breakthrough, resulting in a decline in R&D from Germanium labs affiliated to the same firm; (3) Between-research field substitution: if close research fields are likely to be strategic substitutes, the rise in R&D in "head start" research fields (i.e., where a given lab held Silicon patents and then develops a head-start after the microchip breakthrough) may draw R&D from the other research fields (i.e., where the the same lab has no head start in microchip research). Alternatively, if close research fields are likely to be strategic complements, the rise in R&D in one field may facilitate R&D from the other close research fields. The former case could render the coefficients from Table 2 an over-estimation of early technology leadership.

Appendix Table D.7 further checks for the above three types of hidden interactions, and all these "spillover" estimates remain statistically insignificant. Hence, no evidence seems to support the above hypotheses. For patent outcomes, all three types of spillovers are positive. Hence, the between-lab, between-technology reallocation is at worst a downward bias of the estimate of early-mover advantage on patent inventions, which is unlikely to jeopardise the validity of my natural experiment design.

Regarding outcomes of product development, the only slight caveat underlies the scenario of within-firm allocation. While the coefficient is negative, the estimate remain statistically insignificant and the magnitude (around -5.9%) does not outweigh the estimated effect from Table 2 (13.7%). The test suggests that conditional on the same research field, a firm was likely to internally re-assign production away from its Germanium labs to its Silicon labs after microchip breakthrough. Therefore, the estimated rise of product development in early-mover labs should be interpreted with slight caution as it could incorporate some extent of the demise of commercialization in the non head start labs from the same firm.

The NASA Space Act. One important caveat is that simultaneous demand shocks from NASA 1958 Space Act may favor leaders in microchip research. If NASA procurement disproportionately benefit early industrial leaders, estimates from equations 1 may be upward-biased, even when parallel trend assumption holds. Analyses from Tables 2 and Figure 9 seem to some extent ease the concern when NASA controls are included, and the estimates are not sensitive to such inclusion. However, fixed effects cannot rule out lab-specific demand and productivity shocks that were time variant. Robustness checks that simply remove prime NASA contractors out of the sample are also not sufficient, due to the rise of massive subcontracting since 1960s. To test this alternative channel, I collect all NASA patents during 1957-1980, and calculate the textual similarity between these NASA patents and all the other non-NASA patents. All labs that had ever filed a patent with textual similarity to NASA >0.8 are defined as doing research related to NASA. Then, I exclude all these lab×research fields from the sample. Based on this sub-sample, I rerun equation (1). Estimates are displayed in Panel A, Table E.4 in Appendix, and the estimated product market advantage for the Silicon group remains consistent with Table 2.

Moreover, the Small Business Investment Act was established in 1958 to advocate for public contracts to place increasing emphasis on small firms and technology followers that were underrepresented in the technology and scientific industries. Recent studies also show that publicly funded innovations tend to produce greater spillovers for smaller firms (Dyevre, 2023). If NASA contracts indeed facilitated the performance of Germanium labs more than Silicon labs[14], the Space Act could therefore introduce a downward bias, rendering my estimates at worst a conservative reflection of early leadership. In Appendix Table E.4, Panel B, I conduct a set of heterogeneity tests to examine the effects within and outside of NASA prime contractor locations. The results show that being located in a NASA prime contractor location indeed closes the product market performance gap between Silicon and Germanium labs.

4 Do early leaders persistently innovate?

One of the most striking aspects of the modern US economy is the decreasing innovation incentives among industrial leaders (Akcigit and Ates, 2021; Argente et al., 2020). Although patents from industrial leaders are still rising, recent work shows that a large proportion of these patents tend to be strategic: leaders patent to deter rivals from entering new markets, often with limited commercialization efforts behind these patents (Argente et al., 2020). The dynamics can be captured by a creative destruction model with step-by-step innovation, where a leading firm progressively loses the incentive to innovate once it outpaces its rivals in a technology race and gains a larger share of the product market (Akcigit and Ates, 2023; Aghion et al., 2001). However, contrary to view of the stagnated business dynamism, a rapid expansion of the US commodity

[14] Early technology leaders were often reluctant to engage directly with military or state bureaucracy to avoid red tape and over-intervention in R&D (Berlin, 2005).

microchip market was witnessed in mid 1960s. By 1968, the market size of commercial-use microchip had trumped the military market spurred by NASA procurement (Berlin, 2005; Orton, 2009). New designs were continuously released on a yearly basis from top industrial leaders such as Texas Instruments and Fairchild (Berlin, 2005). Such rapid product development following microchip breakthrough was highly unlikely without persistent learning, innovation and spillover from early industrial leaders, as the creation of application sectors and complementary assets should be gradual and incremental (Helpman and Trajtenberg, 1994, 1996).

Do the leader firms continue to innovate after they achieve product market advantage over their rivals? To illustrate this, I modify the baseline equation (1) as equation (3):

$$\begin{aligned} Y_{vft} = \alpha + \beta_1 \text{Silicon}_{vf} \times \mathbb{1}\{1957 \leq \text{t} \leq 1961\} + \beta_2 \text{Silicon}_{vf} \times \mathbb{1}\{1962 \leq \text{t} \leq T\} + \\ \mu_{vf} + \lambda_{ut} + X_{vt} + \varepsilon_{vft} \end{aligned} \tag{3}$$

where the post period is further split into two sub-periods based on the emergence of product market advantage estimated by Figure 9a, using 1961 as the cutoff. For the dependent variable, I use the following outcomes: 1) the life-long citations of the cumulatively most-cited patent of lab v in research field f in each year. The variable provides a proxy for the citations achieved by each lab's "best" patent by a given year on each research field; 2) the flow of new product manuals released by lab v in research field f in each two-year period. The variable provides a proxy for the newly commercialized innovation in the form of new product designs.

Figure 10a and 10b reports the dynamic estimates and Table 3 reports the static ones. For the equation on life-long citations outcome, I further extend the post period to year + 12 to check for whether the innovation from leader labs likely disappears in the long run.

4.1 Persistent advance of lab technology frontier

Figure 10 and Table 3 estimate the dynamic and static versions of model (3) with OLS. The tests of pre-trends from Figure 10a suggest no signs of violation of the parallel trend assumption. Columns (1) - (3) sequentially include the controls and take the form of inverse hyperbolic sine. Such modifications produce negligible changes on the economic significance of my estimates. Results show that for the first period before 1961, the head start leads to a persistent advancement in the quality of best patent in Silicon labs' leading research fields. The effect is equivalent to an around 16.2% increase in the citations to the most cited patent, compared with citations received by the "best" patent of Germanium labs in the same research fields. Moreover, after 1962 when product market advantage is significantly detected, the head start advances the frontier of lab to a even larger extent: for the second period after 1961, the citations on the most cited patent increase by 19.9% for the early leaders. Figure 10a further plots out the dynamic effects to the longer run. The evidence shows that for the corporate labs that develops a head start in research field f, they likely persistently innovate and produce new patents more demanded by the industry.

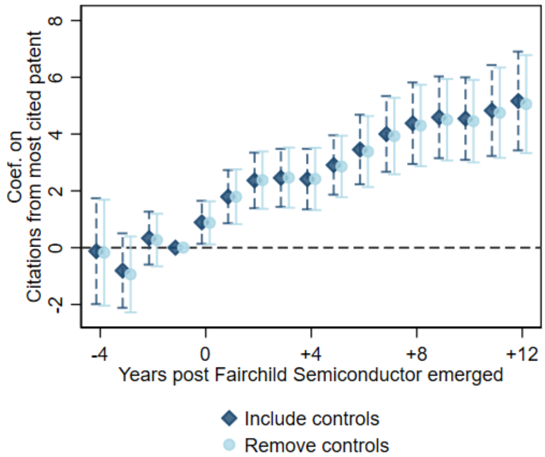
4.2 New product designs

The persistent innovation from early leaders is not only reflected by patent citations. The early leaders likely continue to commercialize their innovations and produce new designs to the market, which prospers the product varieties in the microchip industry. Table 3, columns (4) - (6) show that early leaders indeed produce significantly more product designs in their leading research fields where the head start is achieved. And the effect is even more significant after the product market advantage becomes certain. Column (6) takes the inverse hyperbolic sine transformation, and the effect is equivalent to an around 13.5% increase in the flow of new product manuals. Figure 10b plots the dynamic effect on product development. The result shows that taking new product designs as a proxy for commercialized innovation, the effect is minimal from the start, but it peaks after the Silicon labs develops product market advantage over their rivals.

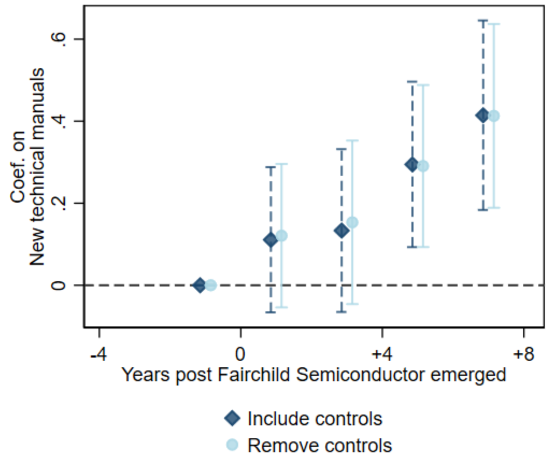
4.3 Radical innovation

In growth theory with heterogeneous firms and heterogeneous innovation, the larger firms are often presumed to undertake less radical innovation that generates new clusters of innovation while rendering the old ones obsolete; instead, they are presumed to develop more incremental innovation that generates process improvement (Akcigit and Kerr, 2018). However, this does not seem to be the case during the early microchip breakthrough. The evidence I have summarized so far shows that early leaders carry out even more new product designs and more "advanced" patents after they progressively obtain a larger product market advantage over time. Do new patents from early leaders become progressively less radical? To answer this question, I construct two new outcome variables: 1) flow of radical inventions, defined by patents granted earlier to $> 50\%$ of their Google Similar Documents; 2) flow of ordinary innovations, defined by patents granted earlier than to $\leq 50\%$ of their Google Similar Documents.

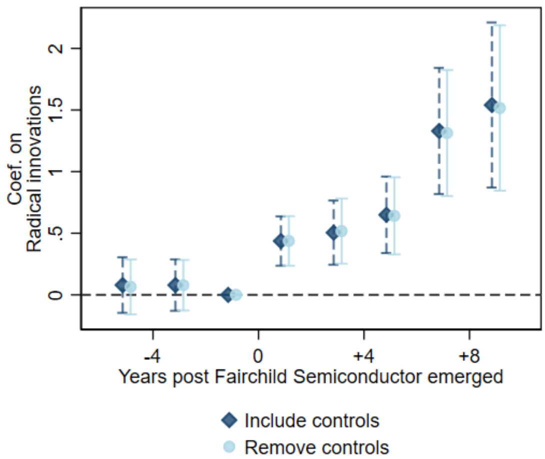
Figure 10c estimate the dynamic effects of head start on the flow of radical innovation, which suggests no sign of pre-trend. Figure 10d further compares dynamic



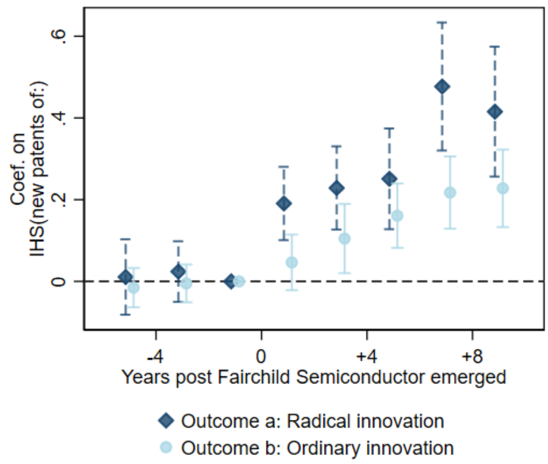
(a) Life-long citations of the most-cited patent



(b) New product manuals



(c) Radical innovation



(d) Radical vs ordinary innovation

Figure 10: Dynamic effects of corporate head start on R&D outcomes.

Note: Figure shows the dynamic effects of the head start on multiple corporate R&D outcomes. Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

Table 3: Head start and long-run corporate R&D during microchip breakthrough.

	Panel A. Persistent innovation & idea commercialization.					
	Life-long citations of most-cited pat.			New product manuals		
	(1)	(2)	(3)	(4)	(5)	(6)
	Y_{vft}	Y_{vft}	IHS(Y_{vft})	Y_{vft}	Y_{vft}	IHS(Y_{vft})
Silicon $\times$ $\mathbb{1}\{1957 \leq t \leq 1961\}$	2.199***	2.134***	0.162**	0.137	0.122	0.031
	(0.467)	(0.466)	(0.078)	(0.089)	(0.090)	(0.037)
Silicon $\times$ $\mathbb{1}\{1962 \leq t \leq T\}$	4.368***	4.384***	0.199**	0.352***	0.355***	0.135***
	(0.690)	(0.693)	(0.081)	(0.103)	(0.106)	(0.049)
Lab×research field FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	Y	N	Y	Y
Mean(Y_{vft}|Silicon)	23.667	23.667	23.667	0.619	0.619	0.619
Obs.	17408	17408	17408	5195	5195	5195
R^2	0.934	0.935	0.827	0.775	0.779	0.797

	Panel B. Radical and ordinary innovation					
	Flow of radical innovation			Flow of ordinary innovation		
	(7)	(8)	(9)	(10)	(11)	(12)
	Y_{vft}	Y_{vft}	IHS(Y_{vft})	Y_{vft}	Y_{vft}	IHS(Y_{vft})
Silicon $\times$ $\mathbb{1}\{1957 \leq t \leq 1961\}$	0.430***	0.416***	0.198***	0.125**	0.122**	0.082**
	(0.092)	(0.089)	(0.039)	(0.062)	(0.061)	(0.033)
Silicon $\times$ $\mathbb{1}\{1962 \leq t \leq T\}$	1.187***	1.189***	0.384***	0.415***	0.408***	0.202***
	(0.256)	(0.253)	(0.068)	(0.094)	(0.093)	(0.041)
Lab×research field FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	Y	N	Y	Y
Mean(Y_{vft}|Silicon)	1.007	1.007	1.007	0.458	0.458	0.458
Obs.	9351	9351	9351	9351	9351	9351
R^2	0.535	0.545	0.599	0.520	0.525	0.558

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of life-long citations of the most-cited patent for each year in each lab×research field (columns (1) - (3)), count of new product manuals for each 2 years in each lab×research field (columns (4) - (6)); count of radical innovations for each 2 years in each lab×research field pair (columns (7) - (9)), count of ordinary innovations for each 2 years in each lab×research field pair (columns (10) - (12)). IHS(Y_{vft}) indicates that the dependent variables are in the form of inverse hyperbolic sine. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

effects of the head start on the flow of radical innovation, versus the effects on the flow of ordinary innovation. Outcomes in Figure 10d are converted into inverse hyperbolic sine to better compare the two effects. Results show that: 1) Comparing early leaders with the counterfactual early leaders, there is no sign that Silicon labs have progressively curbed the rate of radical innovation. Instead, Silicon labs persistently undertake more radical innovation than the Germanium labs in the same research field, even after product market advantage become significant. 2) Comparing radical innovation with ordinary innovation, there is no sign that Silicon labs have progressively switched toward the latter over time. Instead, Panel B, Table 3 shows that the effects of head start on radical innovation (19.8%, 38.4%) trump the effects on ordinary innovation (8.2%, 20.2%) in both the two post periods. The early leaders in the microchip industry has at least maintained the rate of radical innovation since the microchip breakthrough.

4.4 Channels of persistent innovation

The persistence of innovation could be attributed to three possible mechanisms through which early-mover advantage impacts R&D. (1) Firstly, the head start during technology breakthrough may imply higher likelihood of winning the microchip patent race in each downstream research field. Hence, the "champion" firms could become more able to appropriate future innovation rents from research fields where they had head-start over rivals, while avoiding the Schumpeterian competition that dissipates rents from innovation. (2) Secondly, the head start in microchip research could facilitate the formation of intangible capital through within-firm learning and training. The accumulation of intangible capital and skills could thereby facilitate persistent innovation. (3) Thirdly, the head start in microchip research could induce strategic interactions between the leader firms and their rivals beyond simply the Schumpeterian competition. Strategic response to rivals could also intensify R&D investment.

The first mechanism alone is unlikely to fully explain the dynamic leadership advantage in R&D. In Figure 10, the time paths of effect on all innovation outcomes trace out a pattern with stable, progressive rise, instead of a one-off increase just after Fairchild Semiconductor emerged. In section 7, I further exclude the alternative explanation that early-mover advantage on patent inventions was only from the "champion" of patent race in each research field. Combining the above evidence, the results imply that early-movers' post-Fairchild surge of patents was unlikely the result of a one-off acquisition of proprietary right.

If the second mechanism (i.e., learning and intangible capital) holds, the head start in microchip research should impact firm R&D performance beyond production of patents. To examine this, I also look at the outcome of corporate basic research and then I check on the effect of the head start varies with corporate human capital.

Corporate basic research mainly serves three purposes: 1) reducing the marginal costs of internal inventions (Arora et al., 2023); 2) forming corporate human capital (Arora et al., 2023); 3) enabling more effective commercialization of firm innovation (Akcigit et al., 2021). In the specific context of my research, the US universities and basic research institutes were laggard behind global scientific frontier led by advanced physics institutes from Europe (Arora et al., 2021a). Therefore, firms had an extra incentive to internalize basic research functions. If the head start in microchip stimulated corporate basic research, and hence facilitated the accumulation of human capital within corporate labs, early-mover advantage in R&D could be persistent. Appendix Figure D.2 shows that, comparing with Germanium labs on the same research field, Silicon labs on average produced slightly lower advanced physics papers per year on the given research field where they obtained head start. When I implement a heterogeneity check with respective to the number of senior engineers in each lab, the estimates also remain statistically similar Appendix Table E.6. There is therefore no significant evidence that star scientist or corporate basic research determine the success of early technology leaders.

In the following section, I test the third mechanism by unveiling a likely strategic attempt from leader firms to control the diffusion of knowledge in public, and how the voluntary diffusion may determine their product market success.

5 Voluntary knowledge diffusion from early leaders

5.1 A simple conceptual framework

Ideas are non-rival by nature (Arrow, 1972). The presence of knowledge spillovers may discourage private R&D (Bloom et al., 2013; Arora et al., 2021b; Akcigit and Ates, 2021). Therefore, firms often have an incentive to impede knowledge spillouts by hiding critical trade theory from patents (Fadeev, 2023). However, if an early technology leader internalizes the response of downstream users, which could either innovate upon the leader's dominant design or seek cheaper, competing designs from rivals, then the leader firms potentially has an incentive to outcompete their rivals by vertically diffusing more technical details related to their designs toward potential users. The relative costs for potential downstream users to choose the leader's design could fall after such voluntary disclosure of critical details. As the disclosed knowledge from leaders also likely becomes quasi-public goods, the rivals would also learn from the early leader's design and hence refine their own competing design. Therefore, the diffusion from early leaders will theoretically rise until a point when the marginal costs of knowledge leak-out matches the marginal benefit of winning over downstream users from rivals. Such strategies are not rare during early industrial take-off, as seen in the royalty-free declaration by Tesla to build complementary assets and downstream application sectors in the electric vehicle sector. For the context of early microchip industry, I will first provide causal evidence that unveils a generic pattern of vertical voluntary knowledge diffusion from early technology leaders. Next, I will provide in-depth case studies of the two most advanced leaders, Fairchild and Texas Instruments, and demonstrate how the decision to diffuse may potentially ignite drastically diverse response from rivals.

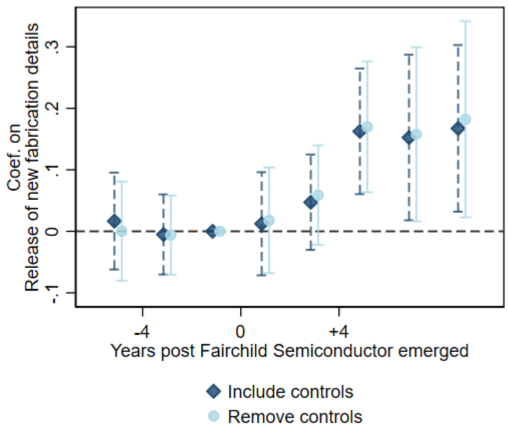
5.2 Public knowledge disclosure

Figure 11 and Table 4 present evidence of such strategies: within the first 4 years when leader product market advantage is still uncertain, I detect no statistically significant rise of knowledge disclosure on fabrication techniques from Silicon labs. From year 5 onward, Silicon labs are significantly disclosing more new technical details regarding fabrication processes than Germanium labs do on the same research field (Figure 11a). However, a cautionary remark should be noted as the outcomes only capture the observable knowledge disclosure from IEEE, but not the informal disclosure happening through informal meetings. Section 6 complements the analysis by looking at the county-level estimates, on which I discuss how the informal disclosure from early leaders could potentially target engineers in close adjacency.

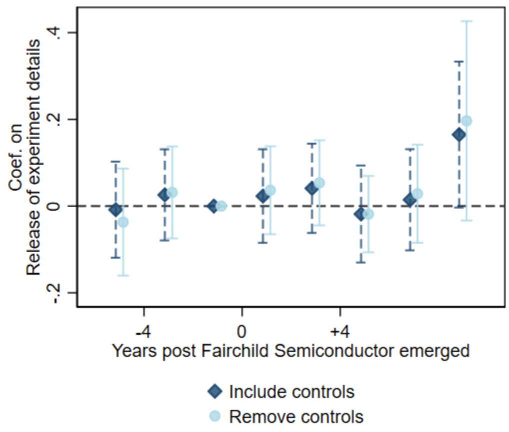
If the pattern of knowledge disclosure follows the theoretical prediction, several features should be observed from data. Firstly, the leader labs are likely to selectively disclose knowledge that reduce marginal costs from downstream users, but not the knowledge that could benefit rivals competing for the dominant design. To test for this prediction, I switch the outcome variable as the release of experimental details in IEEE from lab v in research field f in year t. Results from Figure 11b and column (3), Table 4 confirms the prediction. Silicon labs indeed do not disproportionately disclose details of their experiments from their leading research fields.

Secondly, the leader labs should be more likely to raise the voluntary vertical diffusion on a leading research field when the product designs from their parent firms are likely to become dominant. To test this prediction, I run a heteorgeneity-by-market share check in Figures 11c, 11d, and Panel B, Table 4. Results show that whether the leader lab disclose new fabrication details to public is highly dependent on whether their parent firms have ex ante product lines on their leading research field before the breakthrough. The heterogeneity does not appear when I switch the outcome as the release of experimental details.

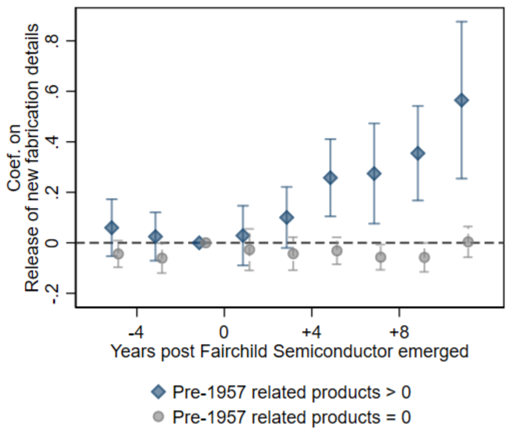
Two concerns may remain: firstly, if the leaders publish original findings on IEEE platform, the measure of knowledge disclosure could be conflated with the measure of innovation. To rule out this concern, I first re-do the analysis by conditioning on the



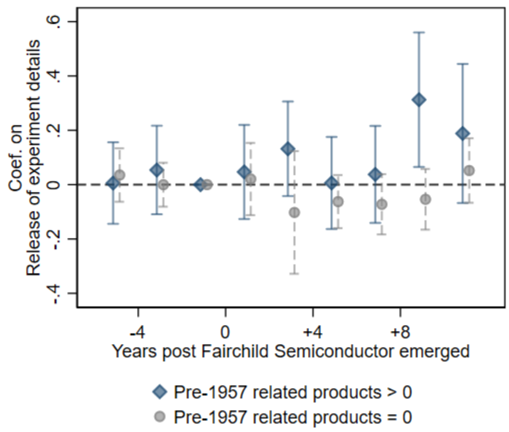
(a) Release of fabrication details



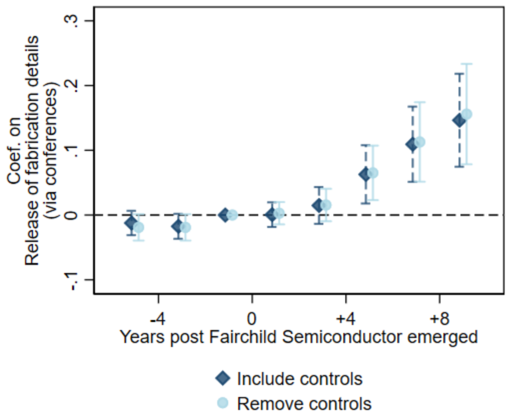
(b) Release of experiment details



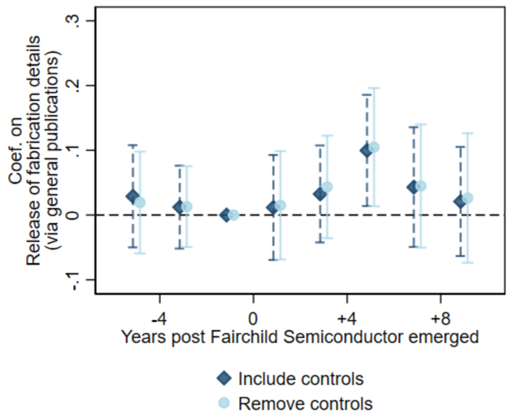
(c) Vertical diffusion by market share



(d) Horizontal diffusion by market share



(e) Vertical diffusion via face-to-face



(f) Vertical diffusion via publications

Figure 11: Voluntary knowledge disclosure.

Note: Figure shows dynamic effects of the head start on voluntary knowledge diffusion. Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

Table 4: Voluntary knowledge disclosure from leader corporate labs.

	A. Voluntary knowledge disclosure					
	(1)	(2)	(3)	(4)	(5)	(6)
	Release of fabric.	Release of fabric. pre microchip adoption	Release of experim.	Release of fabric. (residualized)	Release of fabric. via face-to-face	Release of fabric. via publications
Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$	0.026	0.010	0.026	-0.005	0.018***	0.008
	(0.022)	(0.022)	(0.034)	(0.022)	(0.007)	(0.021)
Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.157***	0.023	0.048	0.091**	0.116***	0.041
	(0.047)	(0.024)	(0.037)	(0.041)	(0.027)	(0.027)
Lab×research field FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Mean(Y_{vft}|Silicon)	0.389	0.248	0.513	0.000	0.087	0.301
Obs.	8312	7226	8312	8312	8312	8312
R^2	0.750	0.725	0.793	0.002	0.485	0.711

	B. Vertical diffusion heterogeneity by market share					
	(7)	(8)	(9)	(10)	(11)	(12)
	Release of fabric.		Release of fabric. (residualized)		Release of fabric. via face-to-face	
	Parent firms' pre-1957 product lines related to research field f:					
	> 0	$= 0$	> 0	$= 0$	> 0	$= 0$
Silicon × Post	0.178***	-0.007	0.106**	-0.031	0.118***	-0.004
	(0.052)	(0.016)	(0.046)	(0.020)	(0.023)	(0.007)
Lab×research field FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Mean(Y_{vft}|Silicon)	0.594	0.061	0.000	0.000	0.135	0.011
Obs.	5056	3200	5056	3200	5056	3200
R^2	0.760	0.654	0.024	0.393	0.523	0.348

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Panel A tests the effect of head start on corporate release of technical details. Dependent variables are: count of IEEE publications on fabrication details for each 2 years in each lab×research field pair (columns (1), (2), (7) and (8)), count of IEEE publications on experiment details for each 2 years in each lab×research field pair (column (3)); the residualized count of IEEE publications on fabrication details for each 2 years in each lab×research field pair (column (4), (9) and (10)); count of IEEE conference publications on fabrication details for each 2 years in each lab×research field pair (columns (5), (11) and (12)), count of IEEE non-conference publications on fabrication details for each 2 years in each lab×research field pair (columns (6)). Column (2) is conditional on the observations of which lab v have not yet utilized microchip on research field f in year t. Panel B tests the effect heterogeneity by prior market share. Columns (7), (9) and (11) are conditional on the labs of which parent firm u had already developed product lines on research field f during 1953-1957; columns (8), (10) and (12) are conditional on the labs of which parent firm u had not developed any product lines on research field f during 1953-1957. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

observations in periods when the first microchip-related patent has not yet been invented by each lab in research field f before year $t+1$. The exercise illustrates whether knowledge disclosure could potentially pre-date the actual exposure to microchip breakthrough from each lab. Evidence from column (2), Table 4 shows that the effect of head start on disclosure indeed shrinks to statistically insignificant. Next, I find that the existence of leader knowledge disclosure remains robust after residualizing the outcomes by regressing the disclosure variable on new patent flow (Column (4), Table 4). The above tests likely rule out the first concern.

The second concern is the risk of mis-measuring disclosure. When firms publish in conference/meeting paper publications on IEEE, the purpose may not be the disclosure of information, but instead it may be to leverage their publications as a ticket to attend the IEEE conferences. I check this hypothesis by matching each lab×research field pair to all the another labs working in the same research field from my sample. In doing so, I create a set of focal lab×target lab×research field triads. Next, I investigate whether the head start of a "focal lab" on the research field raises the frequency of "target lab" to attend IEEE conferences. Appendix Table E.7 presents the result, and the estimate is statistically near 0, indicating that the outcome is unlikely explained by scouting, but more likely by disclosure.

5.3 Counterfactuals without public knowledge disclosure

The conceptual framework also predicts that the vertical knowledge disclosure from the "candidates" of dominant designs may facilitate rapid expansion of downstream application sectors since the microchip breakthrough, due to lower marginal cost of using the technology. To verify this mechanism, I further restrict the sample to research fields that are not covered by the scope of IEEE, the largest professional association for knowledge exchange. Then, I re-estimate the key results conditional on the scenario in which the largest platform of knowledge disclosure is absent. Table 5 shows that when IEEE coverage is absent, the disclosure of technical details via IEEE mechanically shrinks to near 0. However, it does not prevent Silicon labs from obtaining their technology leadership: the head start still leads to sizable influx of citations (column (4)), significant radical innovation (column (2)), and persistent advance in the local technology frontier (column (3)).

However, the absence of IEEE platform tends to shut down the channels for leader labs to achieve downstream product market advantage (column (5)): the effect on the count of product lines shrink to statistically near 0 in both two post periods. Moreover, the Silicon labs no longer commercialize their innovations better than the Germanium labs do, conditional on the same research field.

Table 5: Conditional on research fields without IEEE conference coverage.

	A. Voluntary knowledge disclosure					
	(1) Release of fabric.	(2) Flow of radical innovation	(3) Life-long cit.	(4) New citations received	(5) Count of product lines	(6) New product manuals
Silicon $\times$ $\mathbb{1}\{1957 \leq t \leq 1961\}$	-0.006	0.264**	2.571***	0.418	0.136*	-0.071
	(0.013)	(0.116)	(0.766)	(0.383)	(0.080)	(0.060)
Silicon $\times$ $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.014	0.578*	3.805***	1.312**	0.051	-0.006
	(0.011)	(0.333)	(1.034)	(0.566)	(0.165)	(0.060)
Lab×research field FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs.	4815	4815	8959	6955	5350	2675
R^2	0.371	0.512	0.923	0.705	0.887	0.702

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Only observations of which research fields have no IEEE coverage throughout the entire period are kept. Dependent variables are: the residualized count of IEEE publications on fabrication details for each 2 years in each lab×research field pair (column (1)), count of radical innovations for each 2 years in each lab×research field pair (column (2)), count of citations of the most-cited patent for each year in each lab×research field pair (column (3)), new citations received from different firms for each year in each lab×research field (columns (4)), count of product lines for each year in each lab×research field (column (5)), count of new product manuals for 2 years in each lab×research field (column (6)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

Case studies evidence Additionally, I supplement the above analyses by proposing two case studies: in the first one, I unveil how competing leaders respond to the impediment to technology diffusion[15], proxied by a large scale impediment of licensing during 1962-1965, with even more intense radical innovation and commercialization of new designs. In the second case, I estimate how co-presenting with Fairchild, a typical leader that deeply engages in conference publications, may lead to a shift toward Fairchild's microchip design. Findings are displayed in appendix sections D.4 and D.8. The phenomenon is probably caused by a rapid expansion of product varieties during early product life cycle (Klepper, 1996), and a expanding technology space where the marginal cost of exploring alternative designs is relatively lower. This offers downstream users a wide range of options to choose from. In a nutshell, the evidence shows how the attempt to limited technology diffusion may instead lead to greater expansion of competing product designs which potentially jeopardise the leader advantage in product market.

[15] As explained earlier in the context setting, the patent lawsuit from Texas Instruments impeded the licensing microchip-related patents to all actual or imaginary rivals (Lojek, 2007).

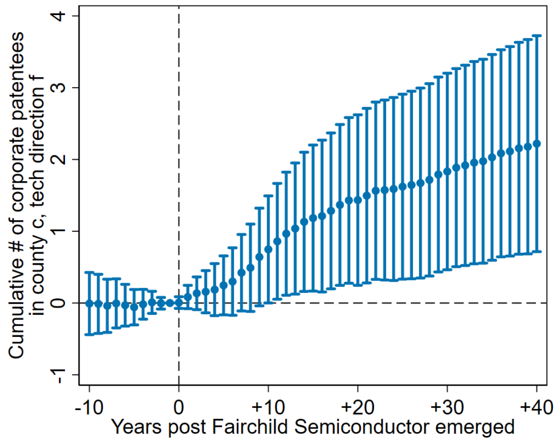
6 Catalysts of agglomeration (TBC)

How localized is the vertical knowledge diffusion? At the centre of agglomeration theories underlies the key notion that knowledge and information exchange decays with distance due to frictions in social interactions (Storper and Venables, 2004). The role of distance could localize the diffusion from leaders to close vicinity, and hence catalyze local Marshallian externalities. To test this, I rerun the equation (3), and switch the outcome as count of IEEE publications related to fabrication techniques via formal conferences/symposiums/conventions arranged by *Institute of Radio Engineer*. Figure 11e displays the result. In Figure 11f, I further displays the estimates when outcome switches to general publications in which no in-person meetings are needed. Findings show that the vertical diffusion from leaders is mostly detected from in-person conferences arranged by the Institute of Radio Engineer, rather than general publications where no face-to-face meetings are necessary. As mentioned above, the publications outcome only captures the observable disclosure via formally documented meetings. Does the unobservable disclosure, which mostly come via information meetings and gatherings, likely follow the same pattern? The institutional context of the Institute of Radio Engineer provides a likely mechanism that localizes these information meetings and gatherings further in close geography: by 1963, the institute divide members from United States into more than 70 "regional sections" to better facilitate the exchange of knowledge (Institute of Radio Engineers, 1963). According to the policy, each regional section is expected to arrange at least 5 meetings per year; otherwise, the regional section faces the risk of cancellation (Institute of Radio Engineers, 1963).

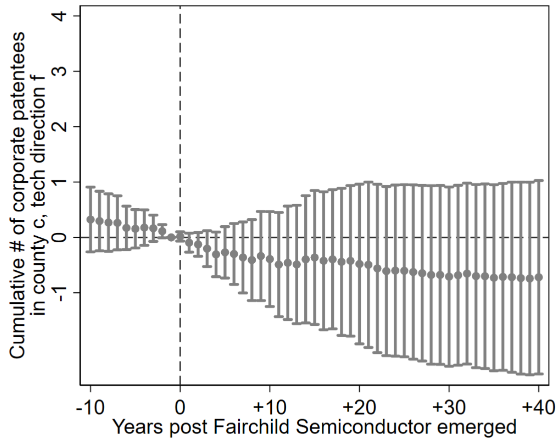
Stylized facts presented in Figure 8 support the creation of Marshallian externalities. To verify this, I conduct a county×research field level regression taking the form of equation (4):

$$Y_{cft} = \alpha + \sum_{j=1940}^{1955} \delta_j \mathbb{1}\{t=j\} \times \text{Silicon}_{cf} + \sum_{k=1957}^{1980} \delta_k \mathbb{1}\{t=k\} \times \text{Silicon}_{cf} + \mu_{cf} + \gamma_t + \varepsilon_{cft} \tag{4}$$

where c stands for county. The dependent variable Y_{cft} is the cumulative count of corporate patentees in county c, research field f in year t. Silicon_{cf} is the treatment dummy, coded as 1 when the county c had a record of using Silicon on research field f during 1954-1957, and 0 if only Germanium was used. $\mathbb{1}\{cf \in Silicon\}$ can be interpreted as a proxy for whether county c was an Silicon lab located county on research field f before Fairchild Semiconductor emerged. Figure 12a displays the dynamic effects of equation (4). Evidence from Figure 12a shows that early-mover places indeed experienced a sizable expansion in the local pool of corporate patentees. To verify if the persistent entry of new corporate patentees was indeed related to head start in microchip breakthrough, I run a falsification test in Figure 12b, in which only county×research fields where the first microchip patent had not been started before 1962 are kept. After restricting the sample to these *de facto* late-mover places, the dynamic trend of agglomeration in Figure 12a is reversed. The above evidence lends support to the hypothesis that early-mover labs played a pivotal role in catalyzing early agglomeration forces. (More analyses will be carried out to test the effect heterogeneity to the enforcement of "regional sections" policy.)



(a) Full sample



(b) Placebo early-mover places.

Figure 12: Early-mover places as incubator of follow-on corporate patentees.
Note: Each observation is a county×research field pair. Standard errors are clustered at the county×research field level. Confidence intervals are displayed at the 95% level. In figure 12b, only county×research field pairs in which the first microchip patent had not been started until 1962 are kept.

7 Other alternative explanations

In previous sections, I have already shown that the observed effects from the head start is unlikely to be biased upward by the NASA Space Act, concerns of exclusion restriction, and mis-measurement of public knowledge disclosure. In this section, I further conduct a series of robustness checks to rule out several alternative explanations for the observed leader R&D patterns during the microchip breakthrough.

7.1 Specificity to California

Is the effect specific to Silicon Valley, an agglomeration that has pioneered the global frontier ICT technologies ever since 1960s? To test for this channel, I rerun equation (1) and exclude all the labs from California and Texas (states where Fairchild and Texas Instruments were located) (Columns 3-4 in Appendices Table E.1). The effect still remains positive and significant.

7.2 The triumph of large agglomerations?

Another potential explanation is that prior military contracts (Gross and Sampat, 2022) could have explained the early formation of clusters, and then spur the early leaders in the microchip breakthrough. In Appendix section E.4, I test this view by first looking at the sorting bias of these early-movers. Evidence shows that most of the early leaders in microchip instead emerge in counties with relatively smaller population in 1950. Next, I run a heterogeneity check to see if the estimates of key results change across counties with higher population density and overall population. The result suggests slightly negative linkages between the effects of head start and various ex ante population measures.

7.3 Does winner take all?

In the previous sections, I unveiled how head start in microchip research facilitated firm learning, altered firm strategies, and catalyzed agglomeration economies. However, an alternative explanation is that early-mover advantage in R&D was simply a reward of winning the microchip patent race (i.e., winner takes all (Bobtcheff et al., 2017; Fudenberg et al., 1983; Hill and Stein, 2019)). To test for this alternative explanation, I construct a "non-champion" sub-sample by first obtaining the "champion" corporate labs with the highest cumulative microchip-related patents in each research field in 1965; then I exclude these "champion" corporate lab×research fields out of the full sample. The equation (1) is re-estimated on this "non-champion" sub-sample, and the estimates are displayed in Appendix Table E.2. The result suggests that patent race is not a game of first-mover-takes-all; instead, even when an innovator missed out proprietary right of patenting microchips in a new research field, the Silicon head start on that research field still brought the innovator closer to technological frontier and facilitates idea commericalization.

8 Conclusion

This paper unveils that an approximately 3 years head start of a corporate lab over the rival in the same research field triggers persistent R&D, learning, product development and vertical knowledge disclosure to the public, as opposed to a one-off acquisition of patent proprietary right. Once a corporate lab achieves a head start after the microchip breakthrough, the early-mover advantage in both the rate and radicalness of subsequent applied research persists. The early leaders also continue to product new product designs on their leading research fields. Furthermore, the likely strategic knowledge sharing enables early industrial leaders to consolidate the dominant design over their rivals. As knowledge diffusion decays with distance, early technology leaders play a pivotal role in catalyzing early agglomeration forces across space.

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Appendices

A Historical context

The Shockley breakaway Early in 1948, Santa Clara, a county located in the north of California, which is commonly referred to as the birthplace of the great "Silicon Valley" today, was still far from being called a superstar region that stands at the frontier of cutting edge technology. In late 1940s, the war-time research contracts had kicked off the development of cutting-edge telecommunication technologies in a variety of emerging agglomerations, including northern California, Houston, Dallas and Cleveland. As one of these locations, Santa Clara had not yet achieved the status of a thriving hub for innovation and entrepreneurship that it enjoys today. It was during this time that two key events unfolded, which ultimately jump-started Silicon Valley and set the stage for modern American semiconductor technology.

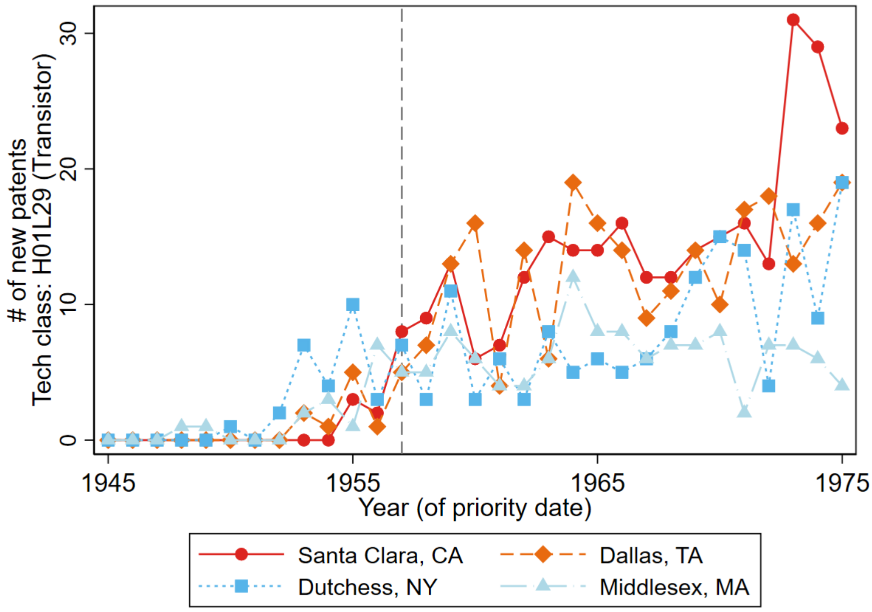
William Shockley, a Nobel laureate and a pioneer in solid-state physics, played a pivotal role in spawning the seed of future growth in Silicon Valley. In 1955, Shockley, along with a team of talented engineers, founded the Shockley Semiconductor division in Mountain View, California. His division attracted some of the brightest minds in the field. Shockley's semiconductor division, however, faced numerous challenges, both technological and managerial. His authoritarian leadership created a tense working environment. Although his engineers had foreseen that smaller, programmable microelectronic devices were the future of semiconductor technology, these early research efforts were largely discouraged as Shockley was dedicated to his four-layer-diode project - in which few Shockley employees saw any future. In Oct. 1957, the personal resentment between Shockley and his genius engineers finally led to a break-away, which soon left profound impact on the progress of American technologies. This group of dissenting employees, known as the "Traitorous Eight," left Shockley's division to establish their own company, Fairchild Semiconductor.

With unfettered freedom for semiconductor research in the new company, the eights soon unlock the true potential of semiconductors: within just 2 months since the Shockley breakaway, Jean Hoerni (one of the eights) noted down a novel idea in Dec. 1957 to dope semiconductor oxide layer on top of a clean semiconductor (namely, the planar process), which provided a solution to carve down complex circuits while preventing contamination of complex junctions. The formation of this idea soon unlock unprecedented potential in semiconductor technology and officially kicked off the decades-long transformation of human race to the modern computer age. After a year of refinement and in May 1959, the first US patent for this technique was filed to the

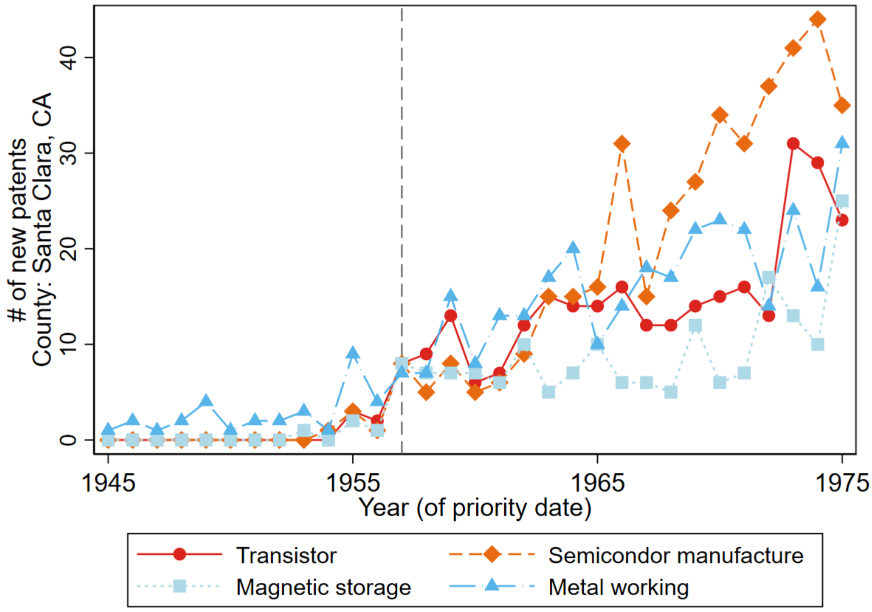
USPTO office and in July 1959, the breakthrough patent of microchip was filed by Robert Noyce (one of the eights) based on Hoerni's planar idea. The planar-microchip idea has been so pervasive in almost every segment of modern high-tech sectors ever since its invention to even today.

Silicon v.s. Germanium: the horse-race in semiconductor In a timeline parallel to the breakaway of the "Fairchild Eight," a technology horse race between two types of semiconductors was silently ongoing. In 1948, William Shockley, John Bardeen and Walter Brattain in Bell Lab first invented the transistor - a small device to amplify current in circuits. This marked the moment when Silicon, an abundant semiconductive element from the Earth's crust, and Germanium, another element with highly similar semiconductive properties and lying just above Silicon in the periodic table, occupied the central stage in the early spark of information age. Germanium, with its superior electrical conductivity at room temperature, initially gained widespread acceptance within manufacture stage in the early years (1948-1953) for the first commercial transistor radios and early computer systems. In 1954, the first practical Silicon-based transistor were demonstrated to public in an IEEE conference by Gordon Teal, a director of Texas Instruments. This marked a significant milestone in semiconductor technology history as it paved the way for the mass production of Silicon transistors. Between 1954-1957, the two material co-existed for use in both the inventions and in the mass production of transistor devices.

Just two months after the Fairchild eights broke away from Shockley and started the exploration of faster and smaller electronic devices, the Hoerni's planar idea came, which not only spurred the microchip but also revolutionized the use of Silicon. Semiconductor oxide had been viewed as redundancy in semiconductor devices, because it grew naturally on the surface of pure semiconductors and needed to be washed away to net out the impurities (Orton, 2009). With Hoerni's planar approach, Silicon oxide can be used to protect the underneath Silicon junctions from contamination and electrical leakage and hence paved the way for miniaturization and mass integration of transistors within a single piece of Silicon microchip (Berlin, 2005). However, the same process cannot be replicated upon Germanium because of inferior oxide properties (for example, the oxide growing process is difficult to control and the oxide is water soluble.) (Ye, 2016). Figure C.1 shows that soon after Fairchild Semiconductor emerged, the horse race between Germanium and Silicon had a clear winner. Germanium, although significant in the early stages of semiconductor development, couldn't overcome its incompatibility with single-crystalline microchips and gradually faded into the background since 1960s. Silicon, as an ideal material to realize the microchip breakthrough, became the foundation of modern semiconductor technology and kick-started the United States invention golden age.



(a) Cross-county comparison conditional on the same technology (H01L29/00)



(b) Cross-technology comparison conditional on the same county (Santa Clara)

Figure A.1: Trends of patent statistics pre- and post-Fairchild Semiconductor emerged.

Note: The vertical dashed line indicates the year of 1957 when Fairchild Semiconductor Division emerged. Patent dates are evaluated at the priority date[a]

[a]Priority date is the earliest filing date in a family of patent applications. Therefore, a priority date is often the most proximate date to capture the timing of new idea discovery.

B A simple model (TBC)

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C Data appendix

C.1 Supplementary data

Patent locations Each patent is geo-coded based on the inventor-declared locations in patent bibliography information (see Figure C.2a in Appendices). The workflow allocates the location information provided from PatCity (Bergeaud and Cyril, 2022) and HistPat (Petralia et al., 2016) to each inventor, and prioritizes the location with a higher accuracy score. The order of the assignment workflow is specified as follows:

Order 1: USPTO: for all patents granted after 1976;

Order 2: HistPat: accuracy band = High;

Order 3: PatCity: accuracy band = High;

Order 4: HistPat: accuracy band = Medium;

Order 5: PatCity: accuracy band = Medium;

Order 6: HistPat: accuracy band = Low.

Similarity to microchip Similarity to microchip is calculated at the research field level. The indicator is defined as the fraction of patents similar to microchip patents in a research field. Similar patents are defined by collecting the Google Patent "Similar Documents" record for all microchip patents, and the patents with microchip patents in their "Similar Documents" record.

List of product categories The 133 electronics product modules collected and compiled from Yearbooks of Institute of Radio Engineers (1953-1963) (Institute of Radio Engineers, 1963) include:

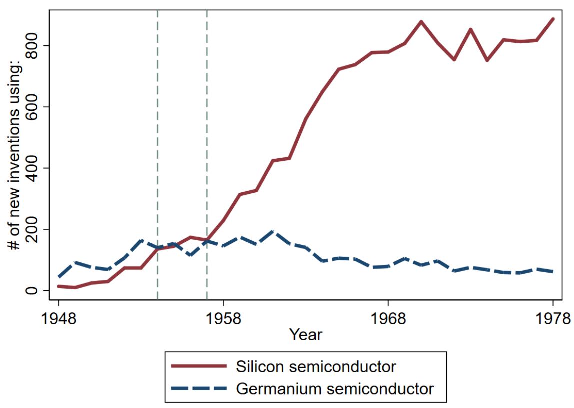
[1] Aerospace Navigation & Test [2] Amateur [3] Amplifiers [4] Antenna Accessories [5] Attenuators [6] Audio Frequency Test [7] Automatic Control [8] Batteries [9] Bio-Medical [10] Blowers & Cooling Fans [11] Bridges [12] Broadcast Receivers [13] Broadcast Transmitters [14] Cabinets, Consoles & Enclosures [15] Cable & Wire [16] Capacitors [17] Carrier Current [18] Ceramics [19] Chassis & Racks [20] Chemicals & Compounds [21] Circuits [22] Coils [23] Computer Accessories [24] Connectors [25] Consulting Engineers [26] Control [27] Converters [28] Cooling Devices [29] Core Materials [30] Crystals & Accessories [31] Decades [32] Delay Lines [33] Distribution [34] Educa-

tion [35] Electro-Optical & Photographic [36] Electronic Control [37] Electronic Control Equip [38] Emergency Communications [39] Energy Conversion Devices [40] Equalizers [41] Fabricators & Custom Builders [42] Facsimile [43] Ferrimagnetic Materials [44] Filters [45] Fuses [46] Gasses & Vapors [47] General Laboratory & Supplies [48] General Test [49] Generators [50] Geophysical Apparatus [51] Graphic Recorders [52] Hardware & Findings [53] Heating [54] Hermetic Seals [55] Indicating Instruments (Panel Meters & Timers) [56] Induction Heating [57] Industrial Sound Systems [58] Infrared [59] Insulating & Shielding Materials [60] Jacks & Plugs [61] Laboratories & Custom Builders [62] Laboratories Standards Of Frequency & Time [63] Lacquers, Paints, Compounds & Waxes [64] Lights & Displays (Indicator) [65] Loudspeakers [66] Machinery [67] Magnetic Amplifiers [68] Marine [69] Materials & Fabrication Distribution [70] Materials, [71] Materials, Electrooptical [72] Materials, Ferrimagnetic [73] Materials, Semiconductor [74] Measurement [75] Metals [76] Meters (Indicating Instruments) [77] Microphones [78] Microwave [79] Mobile [80] Molded Products [81] Monitor [82] Motors [83] Nuclear [84] Oscilloscopes [85] Phonograph, Pick-Ups, Record Changers, Etc [86] Pilot & Indicator Lights [87] Plastic Moldings [88] Point-To-Point [89] Power Circuit Components [90] Prime Movers [91] Printed & Packaged Circuits [92] Production Aids [93] Publishing [94] Radar-Microwave Receivers [95] Receivers [96] Recorders [97] Rectifiers [98] Rectifiers, Vacuum Tube [99] Regulators [100] Relays [101] Resistors [102] Services For The Broadcaster [103] Servo-Mechanisms [104] Shielding Materials [105] Single Sideband [106] Sockets [107] Solder [108] Sound Systems [109] Studio [110] Switches [111] Telegraph & Teleprinter [112] Telemetering [113] Television [114] Terminals [115] Test & Measuring [116] Thermal Devices [117] Thermostats [118] Tools [119] Transducers [120] Transformers [121] Transmission & Distribution [122] Transmitters [123] Tubes, Entertainmenttype [124] Tubes, Industrial-Type [125] Tubes, Receiving [126] Tubes, Rectifying [127] Tubes, Special Purpose [128] Tubes, Transmitting [129] Tubing [130] Tuners [131] Utilization [132] Vacuum Tube [133] Waveguides & Accessories.

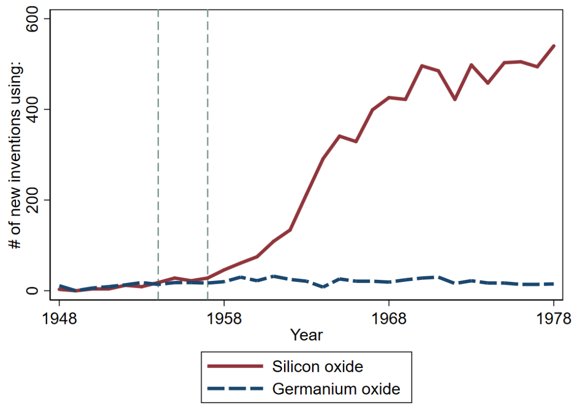
C.2 Defining Silicon and Germanium groups

To start with, I classify corporate lab×research field pairs into two groups based on the pre-Fairchild use of semiconductor material (observed in patent texts).

Step 1: Extracting the original components of a patent Early historical patents did not display a clear structure in texts, and hence the review of "prior arts" is often combined with the description of original work conducted by the patent inventors. The key challenge of this step thereby lies in the extraction of accurate information from historical patent documents and how to leave out confounding information (e.g., discussion of prior arts) that did not represent the actual innovation of a patent. To overcome this, I employ a variety of regular expressions and separates patent claims



(a) Choice of Silicon v.s. Germanium



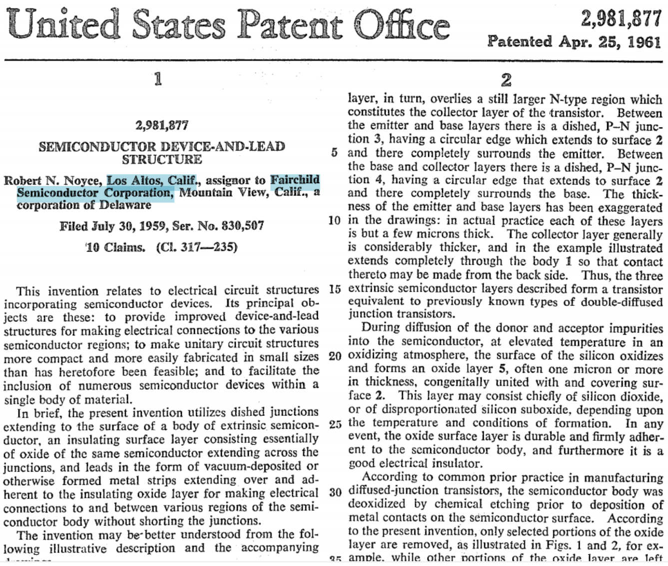
(b) Oxide patents

Figure C.1: Patents using Silicon and Germanium over time.

Note: The first vertical dashed line marks 1954, and the second vertical dashed line marks 1957.

from historical patent texts, where the inventors declared the most original part of the invention that warrant intellectual property protection (see Figure C.2b in Appendices). An additional feature of patent texts is that crucial structures or components of a graphed design are often indexed with numbers for inventors to further elaborate on (for details see Figure C.4 in Appendices). I exploit this feature and extract the texts with these structures and extract all the sentences that incorporate such numeric elements (e.g., Figure C.4b in Appendices). I further compile all the above textual information, which is supposed to capture the most original ingredients of a patent. Based on this, I proceed with the following natural language processing workflow.

Step 2: Detecting semiconductor choices If a corporate R&D lab has a provisional semiconductor patent shortly before Fairchild discovered the disruptive idea for planar-based microchip, the post-Fairchild efforts for that lab are more likely to be path-dependent on that specific semiconductor material which are utilized in ongoing research. Based on the extracted "original textual information" following step 1, I conduct keyword detection on these strings to capture the semiconductor choice of each granted patent. All patents with priority dates starting between 1954-1957 (after both Silicon and Germanium transistors entered mass production and before Shockley breakaway) are collected. A patent i is defined as using Silicon if the term "Silicon" appears in the patent claim or graph descriptive texts of her patent in research field f. If the patent had not declared Silicon in the claims and graph descriptions of the patent p on research field f, but mentions the term "Germanium", the patent is defined as Germanium patents. For patents that mention neither material within the above machine extracted "original textual information", I conduct a manual classification on these remaining ambiguous patents based on whether one semiconductor was valued more than the other in key structures of the invention, and hence manually subdivides these pat-



United States Patent Office

2,981,877
Patented Apr. 25, 1961

1

2,981,877

SEMICONDUCTOR DEVICE-AND-LEAD STRUCTURE

Robert N. Noyce, Los Altos, Calif., assignor to Fairchild Semiconductor Corporation, Mountain View, Calif., a corporation of Delaware

Filed July 30, 1959, Ser. No. 830,507

10 Claims. (Cl. 317—235)

This invention relates to electrical circuit structures incorporating semiconductor devices. Its principal objects are these: to provide improved device-and-lead structures for making electrical connections to the various semiconductor regions; to make unitary circuit structures more compact and more easily fabricated in small sizes than has heretofore been feasible; and to facilitate the inclusion of numerous semiconductor devices within a single body of material.

In brief, the present invention utilizes dished junctions extending to the surface of a body of extrinsic semiconductor, an insulating surface layer consisting essentially of oxide of the same semiconductor extending across the junctions, and leads in the form of vacuum-deposited or otherwise formed metal strips extending over and adherent to the insulating oxide layer for making electrical connections to and between various regions of the semiconductor body without shorting the junctions.

The invention may be better understood from the following illustrative description and the accompanying

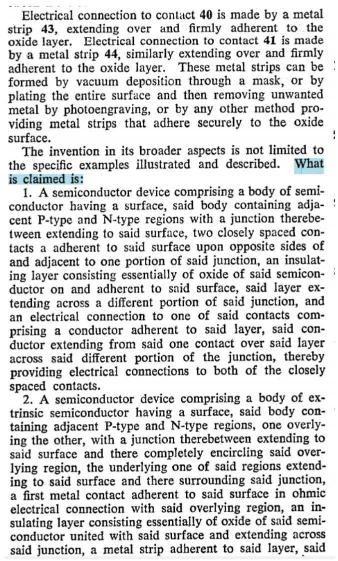
2

layer, in turn, overlies a still larger N-type region which constitutes the collector layer of the transistor. Between the emitter and base layers there is a dished, P–N junction 3, having a circular edge which extends to surface 2 and there completely surrounds the emitter. Between the base and collector layers there is a dished, P–N junction 4, having a circular edge that extends to surface 2 and there completely surrounds the base. The thickness of the emitter and base layers has been exaggerated in the drawings: in actual practice each of these layers is but a few microns thick. The collector layer generally is considerably thicker, and in the example illustrated extends completely through the body 1 so that contact thereto may be made from the back side. Thus, the three extrinsic semiconductor layers described form a transistor equivalent to previously known types of double-diffused junction transistors.

During diffusion of the donor and acceptor impurities into the semiconductor, at elevated temperature in an oxidizing atmosphere, the surface of the silicon oxidizes and forms an oxide layer 5, often one micron or more in thickness, congenitally united with and covering surface 2. This layer may consist chiefly of silicon dioxide, or of disproportionated silicon suboxide, depending upon the temperature and conditions of formation. In any event, the oxide surface layer is durable and firmly adherent to the semiconductor body, and furthermore it is a good electrical insulator.

According to common prior practice in manufacturing diffused-junction transistors, the semiconductor body was deoxidized by chemical etching prior to deposition of metal contacts on the semiconductor surface. According to the present invention, only selected portions of the oxide layer are removed, as illustrated in Figs. 1 and 2, for example, while other portions of the oxide layer are left

(a) Inventor location & assignee



Electrical connection to contact 40 is made by a metal strip 43, extending over and firmly adherent to the oxide layer. Electrical connection to contact 41 is made by a metal strip 44, similarly extending over and firmly adherent to the oxide layer. These metal strips can be formed by vacuum deposition through a mask, or by plating the entire surface and then removing unwanted metal by photoengraving, or by any other method providing metal strips that adhere securely to the oxide surface.

The invention in its broader aspects is not limited to the specific examples illustrated and described. What is claimed is:

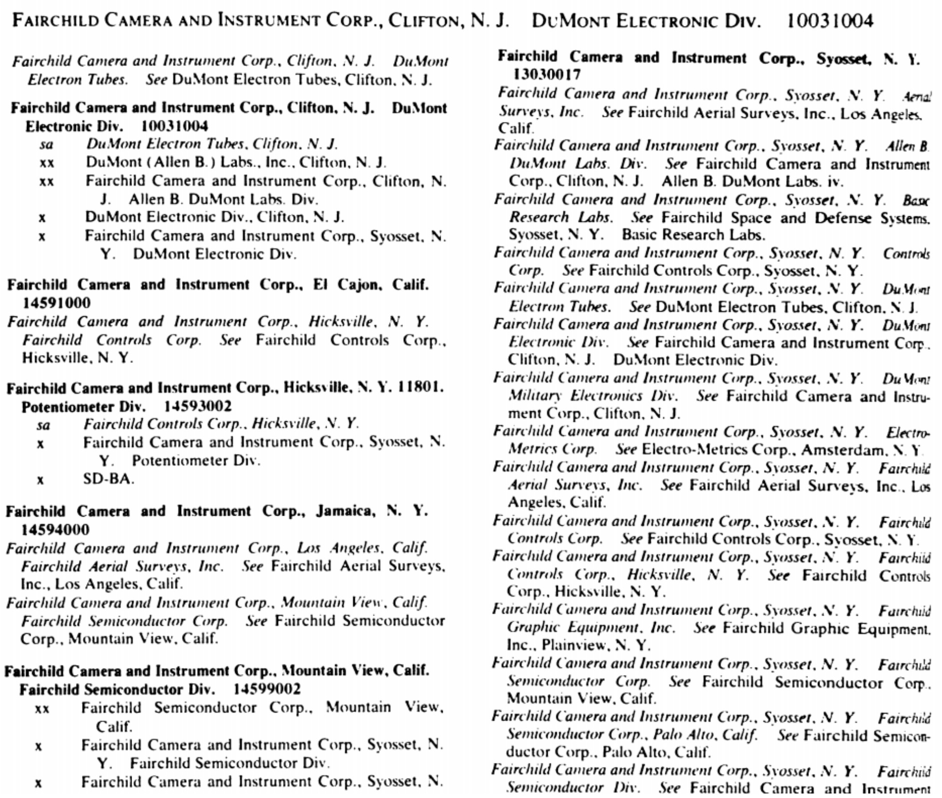
1. A semiconductor device comprising a body of semiconductor having a surface, said body containing adjacent P-type and N-type regions with a junction therebetween extending to said surface, two closely spaced contacts a adherent to said surface upon opposite sides of and adjacent to one portion of said junction, an insulating layer consisting essentially of oxide of said semiconductor on and adherent to said surface, said layer extending across a different portion of said junction, and an electrical connection to one of said contacts comprising a conductor adherent to said layer, said conductor extending from said one contact over said layer across said different portion of the junction, thereby providing electrical connections to both of the closely spaced contacts.

2. A semiconductor device comprising a body of extrinsic semiconductor having a surface, said body containing adjacent P-type and N-type regions, one overlying the other, with a junction therebetween extending to said surface and there completely encircling said overlying region, the underlying one of said regions extending to said surface and there surrounding said junction, a first metal contact adherent to said surface in ohmic electrical connection with said overlying region, an insulating layer consisting essentially of oxide of said semiconductor united with said surface and extending across said junction, a metal strip adherent to said layer, said

(b) Claims

Figure C.2: An example of patent bibliography and claims in Robert Noyce's patent on microchip (US2981877).

Note: Data source: USPTO.



FAIRCHILD CAMERA AND INSTRUMENT CORP., CLIFTON, N. J. DUMONT ELECTRONIC DIV. 10031004

Fairchild Camera and Instrument Corp., Clifton, N. J. DuMont Electron Tubes. *See* DuMont Electron Tubes, Clifton, N. J.

Fairchild Camera and Instrument Corp., Clifton, N. J. DuMont Electronic Div. 10031004
- *sa* *DuMont Electron Tubes, Clifton, N. J.*
- xx DuMont (Allen B.) Labs., Inc., Clifton, N. J.
- xx Fairchild Camera and Instrument Corp., Clifton, N. J. Allen B. DuMont Labs. Div.
- x DuMont Electronic Div., Clifton, N. J.
- x Fairchild Camera and Instrument Corp., Syosset, N. Y. DuMont Electronic Div.

Fairchild Camera and Instrument Corp., El Cajon, Calif. 14591000

Fairchild Camera and Instrument Corp., Hicksville, N. Y. Fairchild Controls Corp. *See* Fairchild Controls Corp., Hicksville, N. Y.

Fairchild Camera and Instrument Corp., Hicksville, N. Y. 11801. Potentiometer Div. 14593002
- *sa* *Fairchild Controls Corp., Hicksville, N. Y.*
- x Fairchild Camera and Instrument Corp., Syosset, N. Y. Potentiometer Div.
- x SD-BA.

Fairchild Camera and Instrument Corp., Jamaica, N. Y. 14594000

Fairchild Camera and Instrument Corp., Los Angeles, Calif. Fairchild Aerial Surveys, Inc. *See* Fairchild Aerial Surveys, Inc., Los Angeles, Calif.

Fairchild Camera and Instrument Corp., Mountain View, Calif. Fairchild Semiconductor Corp. *See* Fairchild Semiconductor Corp., Mountain View, Calif.

Fairchild Camera and Instrument Corp., Mountain View, Calif. Fairchild Semiconductor Div. 14599002
- xx Fairchild Semiconductor Corp., Mountain View, Calif.
- x Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Semiconductor Div.
- x Fairchild Camera and Instrument Corp., Syosset, N.

Fairchild Camera and Instrument Corp., Syosset, N. Y. 13030017

Fairchild Camera and Instrument Corp., Syosset, N. Y. Aerial Surveys, Inc. *See* Fairchild Aerial Surveys, Inc., Los Angeles, Calif.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Allen B. DuMont Labs. Div. *See* Fairchild Camera and Instrument Corp., Clifton, N. J. Allen B. DuMont Labs. iv.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Basic Research Labs. *See* Fairchild Space and Defense Systems, Syosset, N. Y. Basic Research Labs.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Controls Corp. *See* Fairchild Controls Corp., Syosset, N. Y.

Fairchild Camera and Instrument Corp., Syosset, N. Y. DuMont Electron Tubes. *See* DuMont Electron Tubes, Clifton, N. J.

Fairchild Camera and Instrument Corp., Syosset, N. Y. DuMont Electronic Div. *See* Fairchild Camera and Instrument Corp., Clifton, N. J. DuMont Electronic Div.

Fairchild Camera and Instrument Corp., Syosset, N. Y. DuMont Military Electronics Div. *See* Fairchild Camera and Instrument Corp., Clifton, N. J.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Electro-Metrics Corp. *See* Electro-Metrics Corp., Amsterdam, N. Y.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Aerial Surveys, Inc. *See* Fairchild Aerial Surveys, Inc., Los Angeles, Calif.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Controls Corp. *See* Fairchild Controls Corp., Syosset, N. Y.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Controls Corp., Hicksville, N. Y. *See* Fairchild Controls Corp., Hicksville, N. Y.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Graphic Equipment, Inc. *See* Fairchild Graphic Equipment, Inc., Plainview, N. Y.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Semiconductor Corp. *See* Fairchild Semiconductor Corp., Mountain View, Calif.

Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Semiconductor Corp., Palo Alto, Calif. *See* Fairchild Semiconductor Corp., Palo Alto, Calif.

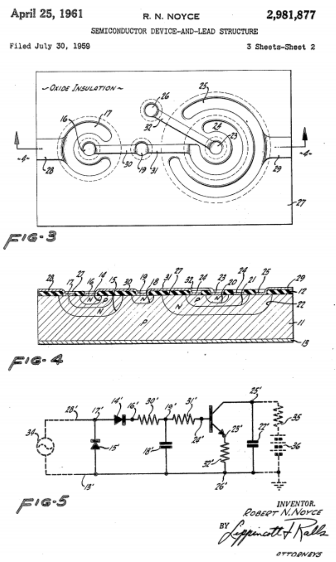
Fairchild Camera and Instrument Corp., Syosset, N. Y. Fairchild Semiconductor Div. *See* Fairchild Camera and Instrument

Figure C.3: Corporate Author Heading.

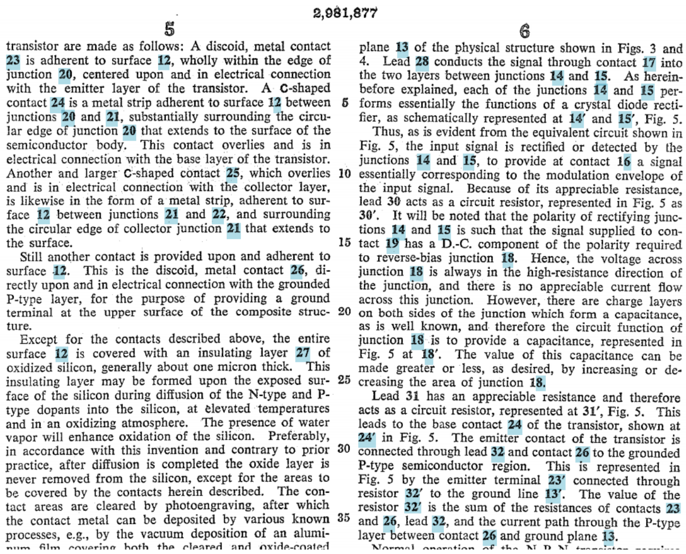
Note: Data source: Corporate Author Headings Used by the US Atomic Energy Commission in Cataloging Reports. United States Atomic Energy Commission, Division of Technical Information.

ents into Silicon and Germanium groups. Lastly, to rule out irrelevant resin-related patents where the term "Silic", "Silicone", "Silicon Oil" etc are frequently referred to, this detection of "Silicon" is conditional on patent full texts having matched a regular expression related to "semiconductor."

Step 3: Assigning corporate lab×research field pairs into Silicon and Germanium groups The focal sample for lab-level analyses is defined by searching all the aforementioned corporate lab×research field pairs {c,f}, in which the lab v had successfully applied at least one of the two kinds of semiconductors into corresponding research fields f between 1954-1957. The Silicon group therefore consists of the subsample in which lab v had started research[16] using Silicon in research field f during 1954-1957; the Germanium group consists of the subsample in which lab v had not engaged in Silicon-based semiconductor research, but had utilized Germanium semiconductor on research field f during 1954-1957. I further condition the remaining sample on the "survivor" (or "stayer") labs, defined as the labs that had patented at least once before 1954 and at least once after 1967. The final sample consists of 643 corporate lab×research field pairs for Silicon group and 402 corporate lab×research field pairs for Germanium group.



(a) Patent graph



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transistor are made as follows: A discoid, metal contact 23 is adherent to surface 12, wholly within the edge of junction 20, centered upon and in electrical connection with the emitter layer of the transistor. A C-shaped contact 24 is a metal strip adherent to surface 12 between junctions 20 and 21, substantially surrounding the circular edge of junction 20 that extends to the surface of the semiconductor body. This contact overlies and is in electrical connection with the base layer of the transistor. Another and larger C-shaped contact 25, which overlies and is in electrical connection with the collector layer, is likewise in the form of a metal strip, adherent to surface 12 between junctions 21 and 22, and surrounding the circular edge of collector junction 21 that extends to the surface.

Still another contact is provided upon and adherent to surface 12. This is the discoid, metal contact 26, directly upon and in electrical connection with the grounded P-type layer, for the purpose of providing a ground terminal at the upper surface of the composite structure.

Except for the contacts described above, the entire surface 12 is covered with an insulating layer 27 of oxidized silicon, generally about one micron thick. This insulating layer may be formed upon the exposed surface of the silicon during diffusion of the N-type and P-type dopants into the silicon, at elevated temperatures and in an oxidizing atmosphere. The presence of water vapor will enhance oxidation of the silicon. Preferably, in accordance with this invention and contrary to prior practice, after diffusion is completed the oxide layer is never removed from the silicon, except for the areas to be covered by the contacts herein described. The contact areas are cleared by photoengraving, after which the contact metal can be deposited by various known processes, e.g., by the vacuum deposition of an alumi-

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plane 13 of the physical structure shown in Figs. 3 and 4. Lead 28 conducts the signal through contact 17 into the two layers between junctions 14 and 15. As hereinbefore explained, each of the junctions 14 and 15 performs essentially the functions of a crystal diode rectifier, as schematically represented at 14′ and 15′, Fig. 5.

Thus, as is evident from the equivalent circuit shown in Fig. 5, the input signal is rectified or detected by the junctions 14 and 15, to provide at contact 16 a signal essentially corresponding to the modulation envelope of the input signal. Because of its appreciable resistance, lead 30 acts as a circuit resistor, represented in Fig. 5 as 30′. It will be noted that the polarity of rectifying junctions 14 and 15 is such that the signal supplied to contact 19 has a D.-C. component of the polarity required to reverse-bias junction 18. Hence, the voltage across junction 18 is always in the high-resistance direction of the junction, and there is no appreciable current flow across this junction. However, there are charge layers on both sides of the junction which form a capacitance, as is well known, and therefore the circuit function of junction 18 is to provide a capacitance, represented in Fig. 5 at 18′. The value of this capacitance can be made greater or less, as desired, by increasing or decreasing the area of junction 18.

Lead 31 has an appreciable resistance and therefore acts as a circuit resistor, represented at 31′, Fig. 5. This leads to the base contact 24 of the transistor, shown at 24′ in Fig. 5. The emitter contact of the transistor is connected through lead 32 and contact 26 to the grounded P-type semiconductor region. This is represented in Fig. 5 by the emitter terminal 23′ connected through resistor 32′ to the ground line 13′. The value of the resistor 32′ is the sum of the resistances of contacts 23 and 26, lead 32, and the current path through the P-type layer between contact 26 and ground plane 13.

(b) Graph components indexed in text

Figure C.4: An example of patent graph descriptive texts in Robert Noyce's patent on microchip (US2981877).
Note: Data source: USPTO.

[16]The date that a research project is started is approximated by patent priority date.

Similar Documents

Publication	Publication Date	Title
US2981877A	1961-04-25	Semiconductor device-and-lead structure
US3029366A	1962-04-10	Multiple semiconductor assembly
US3199002A	1965-08-03	Solid-state circuit with crossing leads and method for making the same
US3581161A	1971-05-25	Molybdenum-gold-molybdenum interconnection system for integrated circuits
US3506893A	1970-04-14	Integrated circuits with surface barrier diodes
US3722079A	1973-03-27	Process for forming buried layers to reduce collector resistance in top contact transistors
US3489961A	1970-01-13	Mesa etching for isolation of functional elements in integrated circuits
US3443176A	1969-05-06	Low resistivity semiconductor underpass connector and fabrication method therefor
US3409812A	1968-11-05	Space-charge-limited current triode device
US3506502A	1970-04-14	Method of making a glass passivated mesa semiconductor device
US3500143A	1970-03-10	High frequency power transistor having different resistivity base regions

Figure C.5: An example of Google Patents Similar Documents.

Note: Data source: Google Patents.

Table C.1: A sample of NIHF Inductees.

Inventor	Awarded invention	U.S. Patent No.
Thomas Alva Edison	Electric Lamp	223898
Nikola Tesla	Electro-Magnetic Motor	381968
William B. Shockley; Walter H. Brattain; John Bardeen	Transistor	2502488;2524035
George R. Stibitz	Digital Computer	2668661
Robert N. Noyce	Integrated Circuit	2981877
Jean A. Hoerni	Method of Manufacturing Semiconductor Devices	3025589
Gordon Moore	Method for Fabricating Transistors	3108359
Jack S. Kilby	Integrated Circuit	3138743
Robert H. Dennard	Dynamic Random Access Memory (DRAM)	3387286
Steve Wozniak	Personal Computer	4136359

Note: Data source: National Inventors Hall of Fame.

Table C.2: A sample of CPC patent class - IEEE publication crosswalk.

Research field (Patent class)	Cosine similarity	Titles of the 5 most similar IEEE publications
Transistor	0.9249088	Proposed process modifications for dynamic bipolar memory to reduce emitter-base leakage current
	0.9211423	The insulated-gate field-effect transistor
	0.9161273	Computerized Model for Response of Transistors to a Pulse of Ionizing Radiation
	0.9159416	The silicon insulated-gate field-effect transistor
	0.9156585	A New Semiconductor Tetrode-The Surface-Potential Controlled Transistor
Digital computer	0.9596612	Computer Architecture for Process Control
	0.9520213	Automation and data bases in an industrial laboratory
	0.9485689	Design Aspects of Computer Control in Discrete Manufacturing
	0.9478114	Automation of computer panel wiring
	0.9468003	The Illinois Pattern Recognition Computer-ILLIAC III
Data storage	0.9458047	A High-Speed Permanent Storage Device
	0.9374053	Digital Measurement of Ferrite Hysteresis Loops
	0.9370347	Storage devices
	0.9355929	Soniscan: A ferroacoustic thin-film memory
	0.9348686	Semipermanent Storage by Capacitive Coupling
Obtaining Gallium or Arsenide	0.9645047	Gallium-arsenide high-temperature diodes
	0.9645047	Double diffused gallium arsenide transistors
	0.8945064	Current instabilities in gallium arsenide
	0.8939393	The Electroacoustic Gain Interaction in III-V Compounds: Gallium Arsenide
	0.8896928	High voltage, high Q epitaxial gallium arsenide diodes
Synchronous motors or generators	0.9788419	Synchronous Starting of Generator and Motor
	0.9227040	Harmonics of the Salient-Pole Synchronous Machine and Their Effects
	0.9026061	Characteristics of a synchronous inductor motor
	0.8830651	Measurement of the Subtransient Impedances of Synchronous Machines
	0.8826016	Overvoltages in Polyphase Induction Motors During Single-Phase Operation
Television systems	0.9503268	A Portable Color TV Camera System
	0.9467243	Video Processing in the PC-100 Color Television Camera
	0.9462234	A Digitally Controlled Miniature Color Camera
	0.9446854	A Multi-Camera Network Using Radio-Linked Double-System Sound Synchronization
	0.9433047	Television Mobile-Unit Design

Note: .

Table C.3: A sample of CPC patent class - American Physical Society publications crosswalk.

Research field (Patent class)	Cosine similarity	Titles of the 5 most similar American Physical Society publications
Transistor	0.9236749	Analysis of the Tunneling Measurement of Electronic Self-Energies Due to Interactions of Electrons and Holes with Optical Phonons in Semiconductors
	0.9140938	Acoustoelectric interaction of surface phonons in semiconductors: Isotropic approximation
	0.9130029	Transition from Electrode-Limited to Bulk-Limited Conduction Processes in Metal-Insulator-Metal Systems
	0.9112310	Internal Field Emission at Narrow Silicon and Germanium XXXXX Junctions
	0.9100799	Metallic Interfaces. II. Influence of the Exchange-Correlation and Lattice Potentials
Digital computer	0.9221531	Computer Programs for Electronic Wave-Function Calculations
	0.8943759	Analytic Wave Functions. II. Atoms with XXXX Electrons
	0.8908075	Computer renormalization-group technique applied to the Hubbard model
	0.8808629	The Electronic Structure of XXXXX
	0.8714705	Photoproduction of XXXXX Mesons in Hydrogen
Nitrates of sodium, potassium or alkali metals	0.9515612	The Optical Constants of Sodium and Potassium
	0.9472586	Ferroelectricity in Potassium Nitrate at Room Temperature
	0.9281366	Cyclotron Resonance in Potassium Tantalate
	0.9254999	Sodium Chloride at Very High Pressures
	0.9214754	Enhancement of the \$F\$- and \$V\$-Bands in Sodium Chloride Containing Calcium
Optical device moderating light	0.9348301	Optical Detection of Magnetic Resonance in Alkali Metal Vapor
	0.9340387	Electromagnetic response in strong magnetic fields. II. Particle polarization and mode structure for parallel propagation
	0.9298490	New Kapitza heat-transfer model for liquid XXXXX
	0.9289458	Sidebands of the XXXX-Center-Induced Infrared Absorption Spectra of Alkali-Halide Crystals
	0.9273539	Filamentary Tracks Formed in Transparent Optical Glass by Laser Beam Self-Focusing. II. Theoretical Analysis

Note: .

Table C.4: A sample of CPC patent class - product module crosswalk.

Research field (Patent class)	Cosine similarity	Titles of the 5 most similar product modules
Transistor	0.8896392	Semiconductor device
	0.8748108	Ceramics
	0.8732234	Magnets
	0.8700579	Voltage regulator
	0.8677803	Power supplies
Vacuum tubes	0.8115727	Tubes, receiving
	0.7670012	Vacuum tube parts
	0.7455317	Tubes, industrial type
	0.7323446	Tubes, transmitting
	0.7248049	Sockets
Cathode ray/electron beam tubes	0.9175377	Cathode-Ray Oscilloscope
	0.8682057	Circuits
	0.8634396	Magnets
	0.8607054	Relays
	0.8548090	Microwave components/radar test/communication
Synchronous motors or generators	0.7714706	Motors
	0.7305673	Transformers
	0.7144562	Generators
	-	-
	-	-
Digital computer	0.9064396	Computer & subsystems
	0.8768654	Circuits
	0.8656022	Recorders
	0.8656022	Converters
	0.8464447	Relays
DC-AC power input conversion	0.9194738	Transformers
	0.8873087	Power supplies
	0.8838387	Amplifiers
	0.8790170	Rectifiers
	0.8752302	Converters
Frequency (spectra) measurement	0.8580460	Measurement
	0.8525186	Audio/radio frequency test
	0.8385479	Filters
	0.8232363	Microwave components/radar test/communication
	0.8228763	General test

Note: .

D Supplementary evidence

D.1 Radical and ordinary patents

Table D.1: Radical and ordinary patents.

	A. Radical innovation				
	(1)	(2)	(3)	(4)	(5)
	>50%	>60%	>70%	>80%	>90%
Silicon × Post	0.863***	0.687***	0.486***	0.308***	0.127***
	(0.167)	(0.142)	(0.106)	(0.073)	(0.034)
μ_{vf}	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Obs.	8312	8312	8312	8312	8312
R^2	0.522	0.504	0.492	0.465	0.391
	B. Ordinary innovation				
	(1)	(2)	(3)	(4)	(5)
	<50%	<40%	<30%	<20%	<10%
Silicon × Post	0.265***	0.156***	0.106***	0.033*	0.007
	(0.074)	(0.050)	(0.034)	(0.018)	(0.005)
μ_{vf}	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Obs.	8312	8312	8312	8312	8312
R^2	0.537	0.511	0.490	0.422	0.282

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of radical innovations for each 2 years in each lab×research field pair (panel A), count of ordinary innovations for each 2 years in each lab×research field pair (panel B). The criteria for defining radical and ordinary patents are adjusted in each column. ">X%" means that the patent is granted earlier than X% of its Google Patents similar documents; "<X%" means that the patent is granted later than X% of its Google Patents similar documents. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

D.2 Testing exclusion restriction

Table D.2: Falsification test on corporate R&D outcomes.

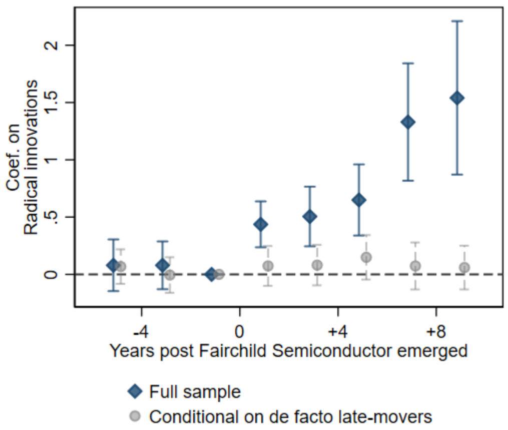
	Conditional on de facto late-movers in microchip:					
	(1)	(2)	(3)	(4)	(5)	(6)
	New patent flow	Citation weighted new pat.	Radical innovation	Ordinary innovation	Count of product lines	New product manuals
Silicon × Post	0.057	0.998	0.067	-0.001	0.067	0.115
	(0.053)	(0.633)	(0.087)	(0.035)	(0.182)	(0.151)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs.	4914	4914	3024	3024	3780	1890
R^2	0.546	0.396	0.554	0.488	0.889	0.799

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. The sample consists only of "de facto late-mover" labs, defined as the labs which have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f. Dependent variables are: count of new patents for each year in each lab×research field pair (column (1)); count of citation weighted new patents for each year in each lab×research field pair (column (2)); count of radical innovations for each 2 years in each lab×research field pair (column (3)), count of ordinary innovations for each 2 years in each lab×research field pair (columns (4)), count of product modules for each year in each lab×research field (columns (5)), count of new product manuals for 2 years in each lab×research field (column (6)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

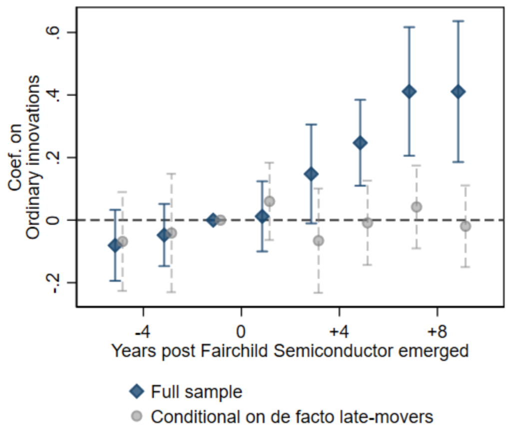
Table D.3: Falsification test on voluntary knowledge diffusion.

	Conditional on de facto late-movers in microchip:				
	(1)	(2)	(3)	(4)	(5)
	Release of fabric.	Release of experim.	Release of fabric. (residualized)	Release of fabric. via face-to-face	Release of fabric. via publications
Silicon × Post	-0.026	-0.009	-0.033	0.014	-0.040
	(0.031)	(0.034)	(0.032)	(0.010)	(0.030)
μ_{vf}	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Obs.	3024	3024	3024	3024	3024
R^2	0.752	0.791	0.168	0.476	0.700

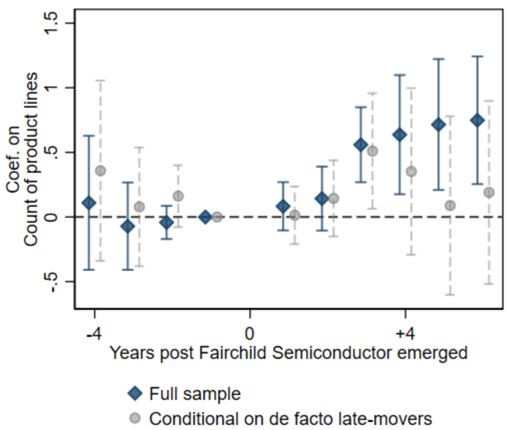
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. The sample consists only of "de facto late-mover" labs, defined as the labs which have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f. Dependent variables are: count of IEEE publications on fabrication details for each 2 years in each lab×research field pair (column (1)), count of IEEE publications on experiment details for each 2 years in each lab×research field pair (column (2)); the residualized count of IEEE publications on fabrication details for each 2 years in each lab×research field pair (column (3)); count of IEEE conference publications on fabrication details for each 2 years in each lab×research field pair (columns (4)), count of IEEE non-conference publications on fabrication details for each 2 years in each lab×research field pair (columns (5)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.



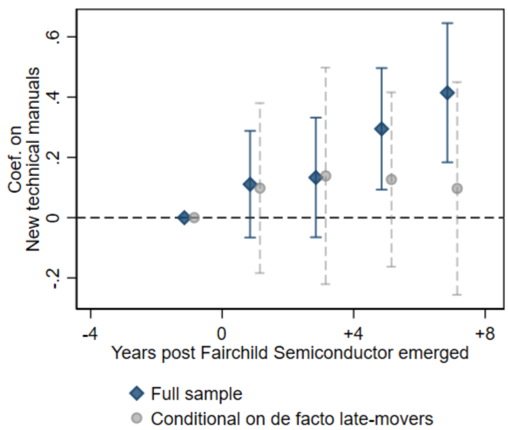
(a) Radical innovation



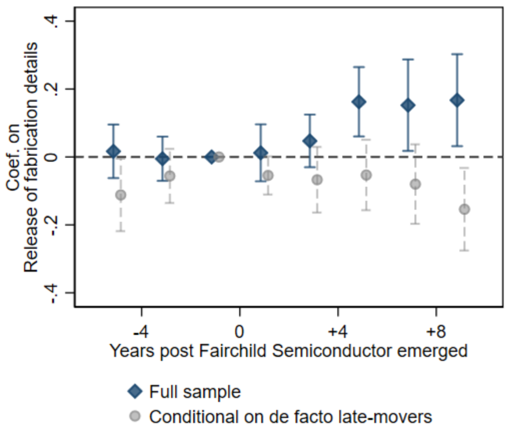
(b) Ordinary innovation



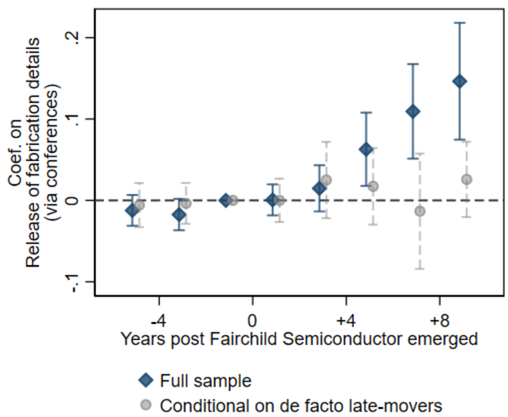
(c) Count of product lines



(d) New product manuals



(e) Release of fabrication details



(f) via face-to-face

Figure D.1: Falsification test.

Note: Figure shows dynamic effects of the head start on multiple corporate R&D outcomes, and how the effects from the head start shrink to near zero when no microchip is actually used. Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit. For the "Conditional on de facto late-movers" event study plot, the sample consists only of labs that have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f.

Table D.4: Estimating pre-Fairchild selection bias for new product manuals.

	(1)	(2)	(3)	(4)
	New product manuals		IHS(New product manuals)	
Silicon	0.029	0.032	0.027	0.028
	(0.042)	(0.044)	(0.026)	(0.027)
Research field FE	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	N	Y	N	Y
Obs.	833	833	833	833
R^2	0.437	0.470	0.441	0.484

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Only pre-1957 observations are kept to estimate the size of selection bias. Dependent variables are count of new product manuals for 2 years in each lab×research field (columns (1) and (2)), and the same variable taking the inverse hyperbolic sine transformation (columns (3) and (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

D.3 Corporate basic research as time-varying confounders

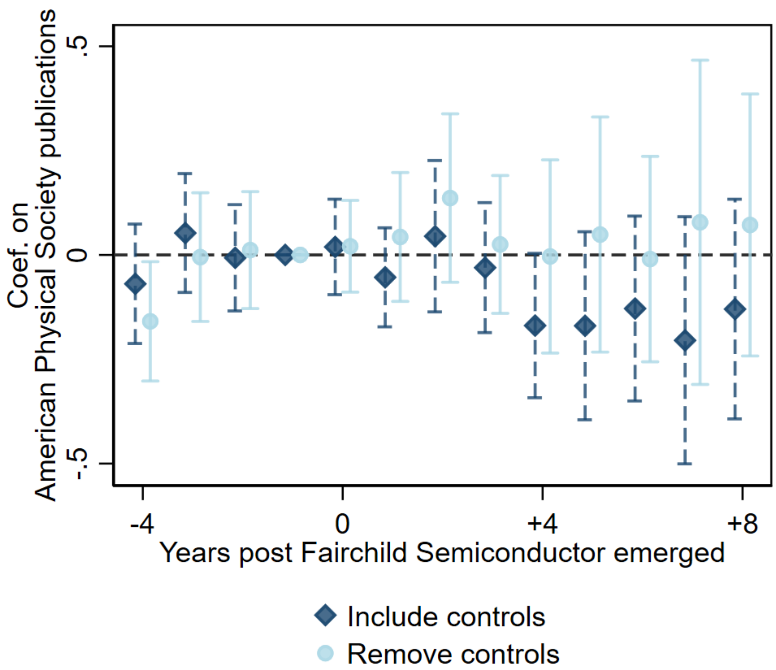


Figure D.2: Time-varying change of corporate basic research in Silicon and Germanium groups.

Note: Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

D.4 The 1960s microchip patent war

Patent Appeal No. 8182
United States Court of Customs and Patent Appeals

Noyce v. Kilby

416 F.2d 1391 (C.C.P.A. 1970)
Decided Jan 29, 1970

Patent Appeal Nos. 8182, 8205.

November 6, 1969. Rehearing Denied January 29, 1970.

Roger S. Borovoy, attorney of record, Mountain View, Cal., for appellant and cross-appellee J. Harold Kilcoyne, Washington, D.C., and Lawrence B. Dodds, Great Neck, N.Y., of counsel.

Ellsworth H. Mosher, Washington, D.C., for appellee and cross-appellant. Samuel M. Mims, Jr., Dallas, Tex., and Stevens, Davis, Miller Mosher, Washington, D.C., of counsel.

Before RICH, Acting Chief Judge, McGUIRE Judge, sitting by designation, and ALMOND, BALDWIN and LANE, Judges.

ALMOND, Judge.

These are cross-appeals from the decision of the Board of Patent Interferences awarding priority of invention as to counts 1-4 to Kilby and counts 5 and 6 to Noyce in Interference No. 92,841

hereinafter stated, we find that the counts in issue are not supported by the '602 application, and therefore *reverse* the decision of the board as to counts 1-4 in No. 8182 and *affirm* it as to count C in No. 8205.

[2] As to count 5, which was also involved in No. 8205, Kilby withdraws his appeal in his brief here and the appeal therefore is dismissed as to that count.

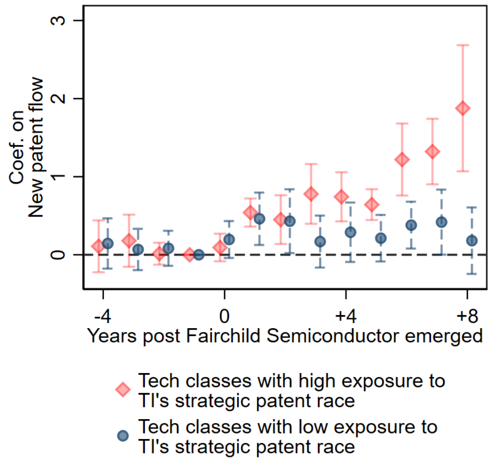
[3] Issued June 23, 1964 as patent No. 3, 138,743.

The subject matter in issue is a semiconductor device including an electrical lead or connection thereto, which device is suitable for use in
1392 integrated electronic *1392 circuits of very small size.[4] Count 1 is representative:

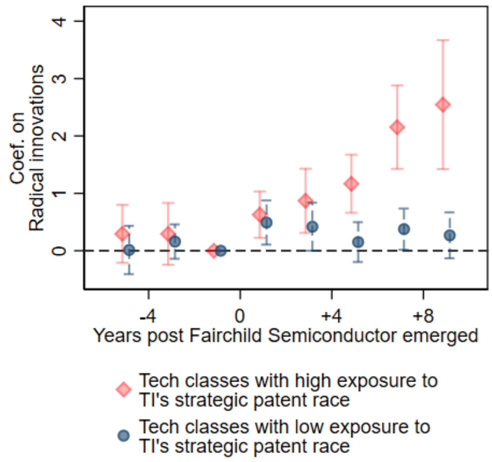
[4] As an example of the minute size of the circuits, the dimensions of the semiconductor wafer of Fig. 6a of the Kilby '602 application, which figure is reproduced and discussed hereinafter, are

Figure D.3: Patent appeal of the 1960s microchip patent war.

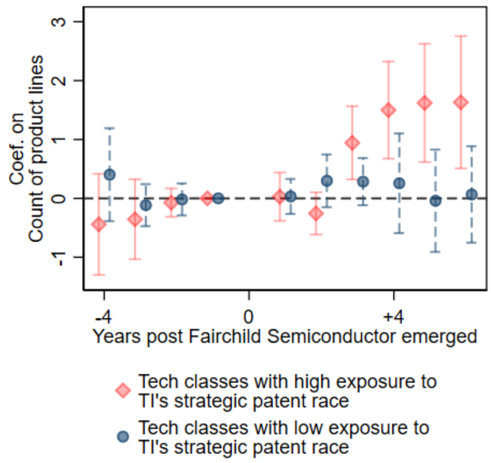
Note: Data source: Casetext.



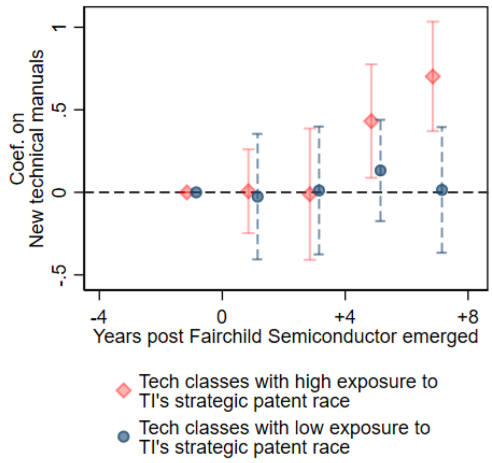
(a) New patent flow



(b) Radical innovation



(c) Count of product lines



(d) New product manuals

Figure D.4: Intense corporate response to the 1960s' TI patent war.

Note: Figure shows dynamic effects of the head start on multiple corporate R&D outcomes, and how the effects from the head start varies in research fields with high/low exposure to the 1960's microchip patent race. Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

$$Y_{vft} = \alpha + \beta_1 \text{Head start}_{vf} \times \mathbb{1}\{1957 \leq \text{t} \leq 1961\} + \beta_2 \text{Head start}_{vf} \times \mathbb{1}\{1962 \leq \text{t} \leq 1965\} + \beta_3 \text{Patent race}_f \times \text{Head start}_{vf} \times \mathbb{1}\{1957 \leq \text{t} \leq 1961\} + \beta_4 \text{Patent race}_f \times \text{Head start}_{vf} \times \mathbb{1}\{1962 \leq \text{t} \leq 1965\} + \beta_5 \text{Patent race} \times \gamma_t + \mu_{vf} + \lambda_{ut} + X_{vt} + \varepsilon_{vft} \quad (5)$$

Table D.5: Backfired patent race: response of non-TI corporate labs to TI's patent war.

	(1) New patent flow	(2) Radical innova-tion	(3) Count of product lines	(4) New product manuals
Silicon $\times$ $\mathbb{1}\{1957 \leq \text{t} \leq 1961\}$	0.260**	0.306**	0.533*	-0.069
	(0.115)	(0.149)	(0.300)	(0.160)
Silicon $\times$ $\mathbb{1}\{1962 \leq \text{t} \leq 1965\}$	0.351**	0.442**	0.023	0.162
	(0.171)	(0.223)	(0.380)	(0.152)
Patent Race $\times$ Silicon $\times$ $\mathbb{1}\{1957 \leq \text{t} \leq 1961\}$	0.353***	0.332**	0.394**	0.210
	(0.085)	(0.136)	(0.165)	(0.155)
Patent Race $\times$ Silicon $\times$ $\mathbb{1}\{1962 \leq \text{t} \leq 1965\}$	1.210***	1.725***	1.261***	0.442**
	(0.189)	(0.275)	(0.448)	(0.201)
Patent Race$\times$Year FE	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Mean(Y_{vft}|Silicon)	0.672	0.898	2.782	0.643
Obs.	9399	5784	7230	3615
R^2	0.575	0.567	0.874	0.792

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab$\times$research field$\times$year unit. Only research fields patented by Texas Instruments are kept. "Patent race" is a research field level, time-invariant binary variable. It is coded as 1 when the research field of Texas Instruments is overlapped with Fairchild before the 1963 litigation, and 0 when no overlap is detected. Only the corporate labs affiliated not with Texas Instruments or Fairchild are included in the sample. Upon the baseline equation, Patent race $\times$ Silicon $\times$ Post, and Patent race $\times$ Year FE are included. Patent race $\times$ Head start are absorbed by μ_{vf}. Dependent variables are: count of new patents for each year in each lab$\times$research field pair (column (1)), count of radical innovations for each 2 years in each lab$\times$research field pair (columns (2)), count of product modules for each year in each lab$\times$research field (columns (3)), count of new product manuals for 2 years in each lab$\times$research field (column (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab$\times$research field.

Table D.6: Backfired patent race: response of non-TI corporate labs to TI's patent war.

	(1) Radical innovation	(2) Ordinary innovation	(3) Count of product lines	(4) New product manuals
Silicon $\times$ $\mathbb{1}\{1957 \leq t \leq 1961\}$	-0.033	0.010	0.192	-0.338***
	(0.114)	(0.039)	(0.243)	(0.124)
Silicon $\times$ $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.046	0.011	-0.588*	-0.273**
	(0.225)	(0.051)	(0.301)	(0.124)
Litigation risk $\times$ Silicon $\times$ $\mathbb{1}\{1957 \leq t \leq 1961\}$	1.282***	0.202***	1.589***	1.470***
	(0.165)	(0.060)	(0.228)	(0.161)
Litigation risk $\times$ Silicon $\times$ $\mathbb{1}\{1962 \leq t \leq 1965\}$	3.592***	0.139**	4.084***	2.175***
	(0.422)	(0.057)	(0.726)	(0.236)
Litigation risk $\times$ Year FE	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Mean(Y_{vft}|Silicon)	0.804	0.123	2.600	0.582
Obs.	7576	7576	9470	4735
R2	0.553	0.344	0.876	0.790

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. "Litigation risk" is a research field level, time-invariant continuous variable ranging from 0 - 1. It captures the exposure of research fields to conflicted terms mentioned in the Noyce v Kilby patent appeal, with 1 indicating the highest exposure. Upon the baseline equation, Litigation risk × Silicon × Post, and Litigation risk × Year FE are included. Litigation risk × Head start are absorbed by μ_{vf}. Dependent variables are: count of radical innovations for each 2 years in each lab×research field pair (column (1)), count of ordinary innovations for each 2 years in each lab×research field pair (columns (2)), count of product modules for each year in each lab×research field (columns (3)), count of new product manuals for 2 years in each lab×research field (column (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

D.5 Non-negative spillover and strategic complementarity

Table D.7: Spillover checks.

	A. Spillover of head start to co-located labs					
	(1)	(2)	(3)	(4)	(5)	(6)
	New patent flow		Citation weighted new pat.		Count of product lines	
	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})
Silicon$_{cf}$ × Post	0.262**	0.088	2.036**	0.141	0.567	0.159*
	(0.130)	(0.058)	(1.032)	(0.113)	(0.393)	(0.083)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	N	N	Y	N	N	Y
Controls	N	Y	Y	N	Y	Y
Obs.	6015	6015	6015	6015	4010	4010
R^2	0.568	0.585	0.446	0.518	0.875	0.894

	B. Are close research fields strategic complements or substitutes?					
	(7)	(8)	(9)	(10)	(11)	(12)
	New patent flow		Citation weighted new pat.		Count of product lines	
	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})
Silicon$_{vF}$ × Post	0.161	0.065	1.085	0.114	0.927***	0.256***
	(0.099)	(0.045)	(0.996)	(0.103)	(0.335)	(0.074)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	N	N	Y	N	N	Y
Controls	N	Y	Y	N	Y	Y
Obs.	6015	6015	6015	6015	4010	4010
R^2	0.567	0.585	0.446	0.518	0.876	0.895

	C. Between-lab reallocation within the same parent firm					
	(13)	(14)	(15)	(16)	(17)	(18)
	New patent flow		Citation weighted new pat.		Count of product lines	
	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})
Silicon$_{uf}$ × Post	0.145	0.075*	0.977	0.160*	-0.207	-0.059
	(0.090)	(0.042)	(0.936)	(0.089)	(0.331)	(0.091)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	N	N	Y	N	N	Y
Controls	N	Y	Y	N	Y	Y
Obs.	5985	5985	5985	5985	3990	3990
R^2	0.567	0.585	0.445	0.517	0.875	0.893

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Only the counterfactual head start group (Germanium corporate lab×research field pairs) is kept as the sample. For panel A, "Silicon" is a county×research field level treatment dummy. The value takes 1 when the county×research field had patented with Silicon during 1954-1957, and 0 otherwise. Similarly, for panel B, "Silicon" is a lab×higher-order research field (4-digit CPC class) level treatment dummy; for panel C, "Silicon" is a parent firm×research field level treatment dummy. The estimates capture the magnitude of spillover from certain "treated" labs to respective "untreated" labs. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1), (2), (7), (8), (13), (14)), citation weighted count of new patents for each year in each lab×research field pair (columns (3), (4), (9), (10), (15), (16)), and count of product modules for each year in each lab×research field (columns (5), (6), (11), (12), (17), (18)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

D.6 Sensitivity to non-linear estimation method

Table D.8: Restimation of key results based on QML Poisson fixed effect regression.

	(1)	(2)	(3)	(4)	(5)	(6)
	New patent flow			Radical innovation		
Silicon × Post	0.940***	0.940***	0.964***	1.048***	1.048***	1.079***
	(0.250)	(0.250)	(0.253)	(0.267)	(0.267)	(0.269)
Firm FE×Post	Y	N	N	Y	N	N
Silicon	Y	Y	Y	Y	Y	Y
λ_{ut}	N	Y	Y	N	Y	Y
Controls	N	N	Y	N	N	Y
Obs.	13068	11355	11355	7853	6884	6884
	(7)	(8)	(9)	(10)	(11)	(12)
	Count of product lines			Release of fabric. via face-to-face		
Silicon × Post	0.133***	0.133***	0.172***	0.613**	0.613**	0.683**
	(0.049)	(0.049)	(0.044)	(0.298)	(0.298)	(0.304)
Firm FE×Post	Y	N	N	Y	N	N
Silicon	Y	Y	Y	Y	Y	Y
λ_{ut}	N	Y	Y	N	Y	Y
Controls	N	N	Y	N	N	Y
Obs.	9212	7959	7959	4641	2776	2776

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) - (3)), count of radical innovations for each 2 years in each lab×research field pair (columns (4) - (6)), count of product modules for each year in each lab×research field (columns (7) - (9)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (columns (10) - (12)). "Controls" indicate whether or not a set of control variables are included. The model is estimated with clustered Poisson. To avoid non-concavity in non-linear estimation, a "Silicon" dummy are inserted in place of μ_{vf}. The controls include: 1) a NASA county dummy; 2) an advanced physics institute/university county dummy; 3) count of advanced physics publications for each year in each lab×research field.

D.7 Continuous measure of Silicon exposure

Table D.9: Restimation of key results with continuous Silicon exposure.

	(1) New patent flow	(2) Radical innovation	(3) Count of product lines	(4) Release of fabric. via face-to-face
# of pre-Fairchild Silicon patents × Post	0.256***	0.394***	0.072***	0.041***
	(0.023)	(0.046)	(0.021)	(0.007)
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Obs.	13507	8312	10390	8312
R^2	0.537	0.540	0.871	0.493

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. The sample consists of exactly the same lab×research field pairs as in the baseline model (Table **??**). "# of pre-Fairchild Silicon patents" is a continuous "Head start" variable, indicating the count of Silicon patents in each lab×research field during 1953-1957. Dependent variables are: count of new patents for each year in each lab×research field pair (column (1)), count of radical innovations for each 2 years in each lab×research field pair (column (2)), count of product modules for each year in each lab×research field (column (3)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (column (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

D.8 A case study: meeting with the Fairchild

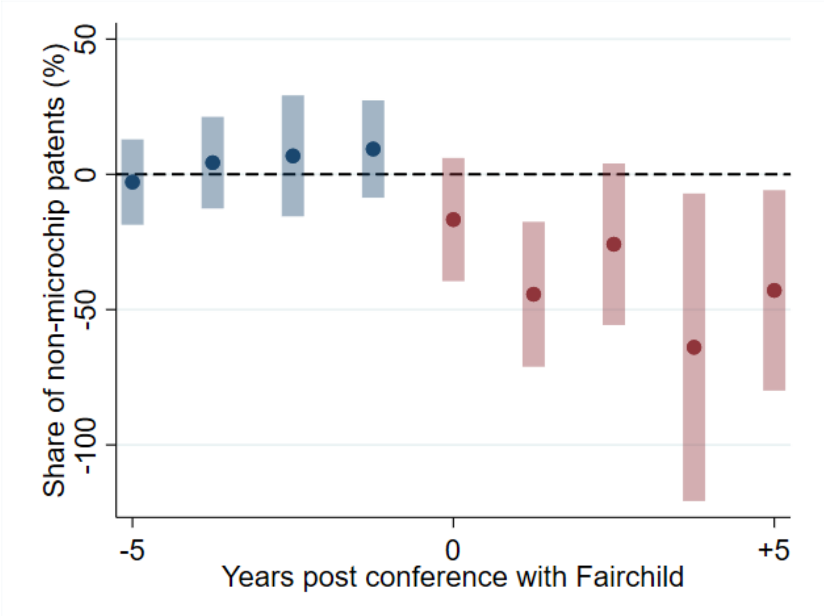


Figure D.5: Share of patents irrelevant to microchip after co-presenting work with Fairchild.

Note: Standard errors are clustered at the research field level. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

E Ruling out alternative explanations

E.1 Specificity to the Silicon Valley

Table E.1: Specificity to California.

	(1) Drop SC	(2) Drop ties with SC	(3) East coast	(4) Drop SC	(5) Drop ties with SC	(6) East coast
	New patent flow			Radical patents		
Silicon × Post	0.564***	0.466***	0.506***	0.885***	0.722***	0.747***
	(0.113)	(0.109)	(0.103)	(0.176)	(0.152)	(0.154)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs.	13325	10725	9373	8200	6600	5768
R^2	0.523	0.489	0.549	0.521	0.512	0.531
	(7) Drop SC	(8) Drop ties with SC	(9) East coast	(10) Drop SC	(11) Drop ties with SC	(12) East coast
	Count of product lines			Release of fabric. via face-to-face		
Silicon × Post	0.490***	0.579***	0.520***	0.084***	0.090***	0.097***
	(0.160)	(0.204)	(0.182)	(0.017)	(0.020)	(0.019)
μ_{vf}	Y	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs.	10250	8250	7210	8200	6600	5768
R^2	0.871	0.849	0.886	0.487	0.434	0.509

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Corporate labs located in Santa Clara county are excluded from columns (1), (4), (7) and (10). Corporate labs that had ever collaborated with inventors from Santa Clara are excluded from columns (2), (5), (8) and (11). Only corporate labs located in east coast states are kept in columns (3), (6), (9) and (12). Each observation is a corporate lab×research field×year unit. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) - (3)), count of radical innovations for each 2 years in each lab×research field pair (columns (4) - (6)), count of product modules for each year in each lab×research field (columns (7) - (9)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (columns (10) - (12)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

E.2 Winner takes all

Table E.2: Excluding the champion lab from each research field.

	(1) New patent flow	(2) Radical innovation	(3) Count of product lines	(4) Release of fabric. via face-to-face
Silicon × Post	0.641***	1.021***	0.663***	0.101***
	(0.108)	(0.174)	(0.234)	(0.020)
Controls	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Obs.	7176	4416	5520	4416
R^2	0.590	0.583	0.874	0.544

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. I construct the sample by first obtaining the "champion" corporate labs with the highest cumulative microchip-related patents in each research field until 1965; then I exclude these top corporate labs from each research field. Dependent variables are: count of new patents for each year in each lab×research field pair (column (1)), count of radical innovations for each 2 years in each lab×research field pair (column (2)), count of product modules for each year in each lab×research field (column (3)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (column (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

Table E.3: First-mover (dis-)advantage.

	(1) New patent flow	(2) Radical innovation	(3) New product manuals	(4) Count of product lines	(5) Release of fabric. (residualized)
Silicon $\times$ Post	0.654***	1.006***	0.103	0.046	0.062
	(0.192)	(0.283)	(0.192)	(0.235)	(0.070)
μ_{vf}	Y	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Mean()	1.112	1.450	0.772	3.158	0.000
Obs.	4043	2488	1555	3110	2488
R^2	0.608	0.601	0.846	0.891	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. I only keep lab×research fields in which lab v had produced patents similar to microchip before Fairchild emerged. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) and (5)), count of radical innovations for each 2 years in each lab×research field pair (columns (2) and (6)), count of product modules for each year in each lab×research field (columns (3) and (7)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (columns (10) and (12)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

E.3 NASA Space Act

Table E.4: Sensitivity to NASA Space Act.

	A. Excluding potential NASA (sub-)contractors.			
	(1)	(2)	(3)	(4)
	New patent flow	Radical innovation	Count of product lines	Release of fabric. via face-to-face
Silicon × Post	0.546***	0.850***	0.490***	0.089***
	(0.119)	(0.192)	(0.165)	(0.021)
Controls	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Obs.	8879	5464	6830	5464
R^2	0.513	0.539	0.906	0.535
	B. Effect heterogeneity by prime NASA contractor counties.			
	(5)	(6)	(7)	(8)
	New patent flow	Radical innovation	Count of product lines	Release of fabric. via face-to-face
Silicon × Post	0.738***	1.150***	0.532**	0.053***
	(0.169)	(0.250)	(0.256)	(0.020)
NASA County × Silicon × Post	-0.303**	-0.444**	-0.072	0.033
	(0.150)	(0.217)	(0.253)	(0.024)
NASA County × Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Obs.	13507	8312	10390	8312
R^2	0.522	0.520	0.872	0.482

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Panel A checks if key estimates are sensitive to the exclusion of potential NASA (sub-)contractor labs from places with prime NASA contracts during 1958-1968. Potential NASA (sub-)contractors are defined as labs with patents similar to NASA patents. Panel A checks if the effects are heterogeneous to counties with high/low exposure to NASA prime contracts. Upon the baseline equation, NASA County × Silicon × Post, and NASA County × Year FE are included. NASA County × Head start are absorbed by μ_{vf}. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) and (5)), count of radical innovations for each 2 years in each lab×research field pair (columns (2) and (6)), count of product modules for each year in each lab×research field (columns (3) and (7)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (columns (10) and (12)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

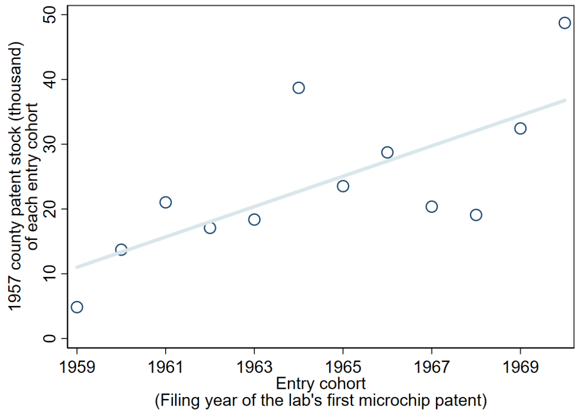
E.4 The triumph of not-that-large cities

Table E.5: Heterogeneity to 1950 county population.

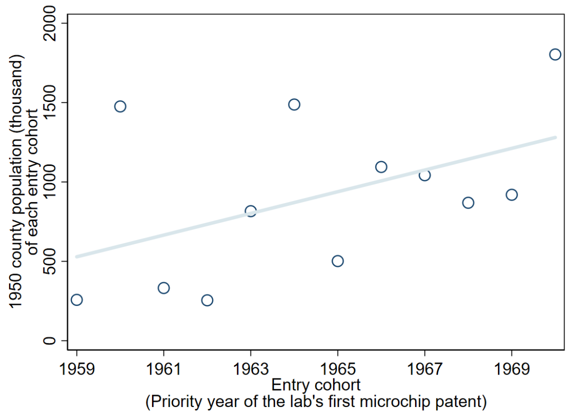
	(1) New patent flow	(2) Citation weighted new pat.	(3) Radical innovation	(4) Cumulative # of microchip pat.
Silicon × Post	0.519***	5.025***	0.822***	0.952***
	(0.108)	(1.071)	(0.166)	(0.226)
ln(1950 pop. density) × Silicon × Post	-0.350***	-3.798***	-0.645***	-0.673***
	(0.115)	(1.056)	(0.168)	(0.233)
ln(1950 pop. density) × Year FE	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Obs.	13507	13507	8312	17663
R^2	0.523	0.417	0.521	0.442

	(5) New patent flow	(6) Citation weighted new pat.	(7) Radical innovation	(8) Cumulative # of microchip pat.
Silicon × Post	0.505***	4.922***	0.806***	0.926***
	(0.103)	(1.025)	(0.158)	(0.221)
ln(1950 total pop.) × Silicon × Post	-0.071*	-0.784*	-0.103*	-0.088
	(0.038)	(0.419)	(0.053)	(0.071)
ln(1950 total pop.) × Year FE	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Obs.	13507	13507	8312	17663
R^2	0.523	0.416	0.520	0.443

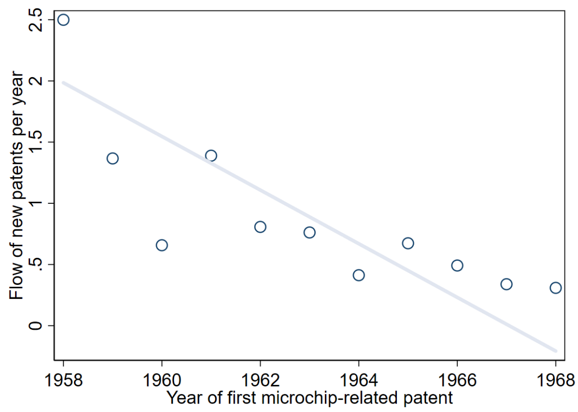
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) and (5)), count of radical innovations for each 2 years in each lab×research field pair (columns (2) and (6)), count of product modules for each year in each lab×research field (columns (3) and (7)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (columns (4) and (8)). "ln(1950 pop. dens)" indicates log population density of each county from the 1950 census. "ln(1950 total pop.)" indicates log total population of each county from the 1950 census. The interaction terms - county population variables × Head start - are absorbed by μ_{vf}. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.



(a) Home county total patent stock



(b) Home county log population



(c) Entry cohort and new patent flow

Figure E.1: Negative sorting across space.

Note: The horizontal axes from both figures denote the entry cohort of corporate labs into microchip research, measured by year of first microchip patent from each lab. The vertical axes of E.1a and E.1b presents characteristics of counties where each cohort of labs were located before Fairchild Semiconductor emerged. Figure E.1a displays the cumulative count of patents in corresponding lab-located counties in 1957; the vertical axis of E.1b presents the total population in corresponding lab-located counties in 1950.

E.5 Senior engineers and corporate absorptive capacity

Table E.6: Effect heterogeneity by count of senior IRE members.

	(1) New patent flow	(2) Radical innovation	(3) Count of product lines	(4) Release of fabric. via face-to-face
Silicon × Post	0.488***	0.769***	0.391	0.061***
	(0.110)	(0.145)	(0.256)	(0.022)
IRE senior members ×	-0.020	-0.039**	-0.005	0.002
Silicon × Post	(0.014)	(0.017)	(0.017)	(0.002)
IRE senior members × Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Obs.	7423	4568	5710	4568
R^2	0.493	0.515	0.882	0.495

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. "IRE senior members" is a lab-level variable, indicating the count of IRE senior members in a given corporate lab during 1953-1956. The interaction term IRE senior members × Head start are absorbed by μ_{vf}. Dependent variables are: count of new patents for each year in each lab×research field pair (column (1)), count of radical innovations for each 2 years in each lab×research field pair (column (2)), count of product modules for each year in each lab×research field (column (3)), count of IEEE conference publications on fabrication details for 2 years in each lab×research field (column (4)). "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.

E.6 Scouting via conferences

Table E.7: Scouting through conferences.

	(1)	(2)	(3)	(4)
	Release of fabric. of matched rivals		Release of fabric. via face-to-face of matched rivals	
	Y_{vft}	IHS(Y_{vft})	Y_{vft}	IHS(Y_{vft})
Silicon $\times$ $\mathbb{1}\{1957 \leq \text{t} \leq 1961\}$	-0.015	-0.059	-0.011	-0.009
	(0.045)	(0.067)	(0.011)	(0.009)
Silicon $\times$ $\mathbb{1}\{1962 \leq \text{t} \leq 1965\}$	0.048	-0.061	0.028	0.015
	(0.080)	(0.049)	(0.031)	(0.020)
Controls	Y	Y	Y	Y
μ_{vf}	Y	Y	Y	Y
λ_{ut}	Y	Y	Y	Y
Obs.	18720	7234	18720	18720
R^2	0.428	0.435	0.204	0.217

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of overall IEEE publications on fabrication details for 2 years from matched competing labs in the same research field (columns (1) and (2)); count of IEEE conference publications on fabrication details for 2 years from matched competing labs in the same research field. "Controls" indicate whether or not a set of control variables are included. The controls include: 1) a NASA county dummy interacted with year fixed effects; 2) an advanced physics institute/university county dummy interacted with year fixed effects; 3) count of advanced physics publications for each year in each lab×research field.