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

Jingyuan Zeng†

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Abstract

Technology breakthroughs often give rise to early leader firms in a nascent industry. Do these early leaders cease to share knowledge in public after they achieve product market leadership? Using newly digitized 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 nascent microchip industry, marked by persistent increase of top patents' quality and expansion of product lines. 2) Product differentiation surges: the early leaders persistently announce new products in their leading research fields. 3) Rather than fencing off these research fields, the leaders selectively present research as public knowledge in professional associations and increase the release of technical data bulletins. I provide a simple theory to illustrate the early leaders' trade-off in public knowledge sharing: on one hand, sharing techniques in public unavoidably benefits rivals; on the other hand, presented techniques resembles persuasive advertisement for new product innovations, raising perceived product differences for downstream adopters. 4) The selective sharing requires face-to-face contacts, which spur "Silicon Valleys" in leader firm locations.

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†London School of Economics. Email: j.zeng15@lse.ac.uk

1 Introduction

Knowledge spillovers are often viewed as a spontaneous process due to the quasi-public good nature of ideas (Arrow, 1962; Bryan and Williams, 2021). However, after technology breakthroughs, early industrial leaders may voluntarily facilitate the diffusion of knowledge. Notable anecdotes include Fairchild and Texas Instruments: Fairchild started to disclose corporate research in the Institute of Radio Engineer just after its successful invention of planar integrated circuit in 1959, and Texas Instruments started to do the same just after its invention of Silicon transistor in 1954 (Grinich and Haas, 1959; MacDonald, 1954). Voluntary knowledge sharing from early industrial leaders appears inconsistent with standard innovation theory, in which industrial leaders are more inclined to preempt and exclude rivals from new technology. Such exclusions are often associated with stagnated productivity growth and declining business dynamism (Argente et al., 2020; Gans et al., 2000; Williams, 2013; Akcigit and Ates, 2023). We still know surprising little about how early leaders are formed and change the way knowledge diffuses after breakthroughs revolutionize a nascent industry.

I provide empirical evidence and a simple theory to explain the trade-off of early industrial leaders on public knowledge sharing. On the one hand, when early leaders disclose corporate research publicly, the shared knowledge becomes quasi-public goods, inevitably benefiting product rivals. On the other hand, early leaders significantly differentiate their products from conventional designs. The latent quality variations motivate higher quality producers to signal the differences to potential downstream users, who may be initially unaware of the implicit technological improvements in new product varieties. Therefore, the disclosure of knowledge by early industrial leaders may be strategic and highly selective. My framework suggests that because selecting the proper types of knowledge to disclose is challenging, early leaders may choose to conduct knowledge disclosure disproportionately through face-to-face channels. This approach helps explain the rise of localized, face-to-face knowledge spillovers in the nascent US microchip industry, with a notable departure from Marshall's claim that knowledge is simply "in the air."

I provide robust evidence for the strategic knowledge sharing of early industrial leaders, and how early industrial leadership likely facilitates agglomeration spillovers. A crucial empirical challenge is that product market leadership is endogenous. To robustly pin down the trajectory of early leaders, I investigate a plausibly unanticipated head start in one of the most radical innovations in the US history - the 1950s' Fairchild Silicon microchip breakthrough[1]. The setting of the US Silicon breakthrough

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

has an unique advantage: the head start of firms in microchip-related research fields is dependent on the *ex ante* latent oxide properties of two major semiconductor materials (Silicon and Germanium). Before Fairchild Semiconductor Division[2] emerged and quickly revolutionized the use of semiconductor, Silicon and Germanium displayed similar properties, shared similar complementary assets, and were close substitutes (Berlin, 2005; Reid, 2001). I find that the pre-Fairchild choice of Silicon and Germanium among corporate labs is indeed orthogonal to most observable corporate and technological characteristics. After Fairchild emerged, Silicon is quickly proven to be the right material for microchip due to the latent oxide properties. Conditional on the same research field, corporate labs that held Silicon patents are significantly more likely to adopt microchip and receive influx of patent citations than the other *ex ante* Germanium-based labs from the same research field. I leverage the setting, and conduct a industrial lab×research field level difference-in-differences estimation to compare various R&D outcomes between Silicon (head start), and Germanium (counterfactual head start) labs, conditional on the same research field.

Several interesting findings are unveiled. Firstly, the Silicon head start triggers significant creative combinations of microchip innovations toward research fields where Silicon patents were held. Subsequently, the Silicon head start quickly creates early leaders in the microchip industry, marked by persistent influx of citations, leadership in patent quality, and expansion of product lines. Moreover, I find that early leaders significantly differentiate their products from conventional designs in their leading research fields. However, there is no significant increase from the "Pasteur's Quadrant", indicated by corporate publications of advanced physics research. Therefore, the reward for obtaining a head start in the Silicon breakthrough seemed to concentrate mostly 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). I further rule out several caveats that may jeopardise my estimates, including simultaneous shock of the NASA Space Act, the risk that close research fields are substitutes in knowledge production function, and negative spillovers (e.g., business stealing and R&D duplication).

With the above empirical setting, I demonstrate that after achieving a head start in the Silicon breakthrough, early leaders significantly present technical details in professional associations, such as the *Institute of Radio Engineers* (IRE). I show that the

[2]Note that Fairchild Semiconductor Division is a branch of a larger corporation, Fairchild Camera and Instrument Corp. For brevity, I term the semiconductor branch as "Fairchild" hereafter.

knowledge sharing is unlikely to be spontaneous and automatic knowledge spillovers; instead, the knowledge disclosure tends to be strategic and vertical: early industrial leaders only increase the disclosure of applied research and technical manufacturing bulletins that may attract downstream users, while limiting the release of theoretical research that could benefit horizontal product rivals. Moreover, I show that the leader labs do not disclose more knowledge in public when they fail to announce new products, or when parent firms have limited *ex ante* productive capacities. Therefore, leader knowledge disclosure is closely associated with the product varieties expansion after the Silicon breakthrough. When it comes to research fields with high frictions in knowledge sharing, Silicon head start still predicts significant innovations, but these innovations from Silicon leaders are much less likely to be commercialized. The above findings suggest that early leaders strategically leverage knowledge disclosure as persuasive advertisement for potential downstream users. Furthermore, I rule out several alternative caveats, including the concern that early leaders may simply re-iterate patent claims in proceeding publications, rendering the measure of knowledge disclosure a noisy measure of patent inventions.

Lastly, I find that the voluntary knowledge sharing from early leaders is mostly detected from in-person conferences. Moreover, evidence shows that after Fairchild emerges, the number of corporate patentees surge in the Silicon leader-located counties. The local effect suggests that agglomeration spillovers indeed emerge in early leader locations, lasting even to the long run. Given that a large proportion of the formal, observable knowledge disclosure originates from the Institute of Radio Engineer (IRE), which imposes a "regional section" policy that facilitates localized informal meetings among IRE members, the regional evidence thereby probably reflects the concentration of informal, non-publication based knowledge diffusion from the early leaders. Robustness checks further demonstrate that the creation of such "Silicon Valleys" is a generalizable phenomenon beyond California and west coast states[3].

This research enriches the empirical work on the economics of technology breakthroughs. Innovation is heterogeneous by nature, and radical innovations are in particular the engine of growth: incremental innovations are often subject to diminishing return, while radical innovations spur new clusters of incremental innovations (Acemoglu et al., 2022; Anderson and Tushman, 1990; Akcigit and Kerr, 2018). The fundamental change of technology paradigm, namely *technology breakthroughs*, leads to both periodical bursts of product innovations (Berlingieri et al., 2024; Dosi, 1982) and technological obsolescence, which diminishes the value of past innovations (Ma, 2021). Apart from changing the rate and direction of innovation, breakthroughs also impose extraordinary

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

impact on the structure and location of high-tech industries (Kerr, 2010; Duranton, 2007; Berkes and Gaetani, 2021). Building on the above insights, this paper further documents in details how early industrial leaders are formed following one of the most critical breakthroughs in the American semiconductor industry, and how the voluntary knowledge sharing from early leaders likely facilitates initial agglomerations forces in places like Silicon Valley.

This research also seeks to enrich the work on the strategic control of knowledge spillout by industrial leaders. Scholars have sought to understand the formation of high-tech industrial clusters through knowledge spillovers (Gross and Sampat, 2022; Mokyr et al., 2022; Kantor and Whalley, 2022; Saxenian, 1994; Duranton, 2007). However, whilst spillovers in early industrial development are indeed significant (Giorcelli and Li, 2021), they are largely characterized as a spontaneous and automatic externality which firms do not control or internalize (Fadeev, 2023; Bloom et al., 2013). Much less is known about whether early leaders may strategically leverage knowledge sharing to set the industrial standard, and what it means for market structure and early industrial development. As an addition to this literature, I reveal that when technology breakthrough expands new product varieties, voluntary knowledge sharing from leader firms is likely to be a significant form of high-tech spillovers. I also approach the agglomeration literature seeking to unveil the origin of high-tech spillovers, whereby knowledge spillovers across firms are regarded essential for new ideas to develop, but the mechanics still remain vague (Glaeser, 1999; Catalini et al., 2018; Atkin et al., 2022; Koh et al., 2022; Jaffe et al., 1993; Asheim and Gertler, 2006).

In doing so, I also contribute to a series of insightful work by Klepper (1996, 2002, 2010) on the evolution of oligopoly structure during early cluster and industry formation. 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 in Klepper's models due to the availability of data. On the one hand, firms have weak incentives to disclose major innovation in patents to avoid imitation from competitors (Anton and Yao, 2004). On the other hand, firms also have strong incentives to share crucial techniques as public goods to facilitate R&D cooperation or collective invention (Arora et al., 2021a; Allen, 1983; Fadeev, 2023). Combining the above literature, I provide evidence and a simple framework to illustrate how early industrial leaders selectively disclose technical details to consolidate their product designs after the breakthrough.

Lastly, I provide novel data and causal evidence to the literature on market structure, innovation, and its commercialization. The modern US economy is plagued with

a puzzling mismatch between stable patent increase and stagnated productivity growth (Gordon, 2018). One possible explanation is that incumbent industrial leaders may strategically restrict the transition from patents to products (Argente et al., 2020), especially when innovation is competence destroying (Tushman and Anderson, 1986; Marx et al., 2014; Gans et al., 2000). As technology leaders progressively gain greater market share, their innovation incentives is likely to change (Aghion et al., 2001; Acemoglu and Akcigit, 2012), marked by the shift of R&D toward less radical research (Akcigit and Kerr, 2018; Cohen and Klepper, 1996). Whilst latest research starts to question whether the limited knowledge spillover between leaders and followers can be a crucial account for the US declining business dynamism (Akcigit and Ates, 2023), empirical evidence remains scarce. I intend to contribute to the empirical literature with several newly digitized datasets to measure corporate R&D outcomes, including product line status and new product announcement data from each electronics manufacturer, new technical bulletins to measure the corporate disclosure of engineering knowledge, and corporate industrial conference/proceeding publications as proxies for corporate knowledge disclosure. Using word embedding techniques, This approach enables me to separately estimate the impact of a corporate head start on various R&D outcomes, ranging from research ("R") to development ("D") of products, within each specific research field. With these data, I provide unambiguous evidence of persistent innovation among incumbent leaders in the early microchip industry.

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 Silicon microchip breakthrough of the 1950s marks one of the most radical innovations in American history (Figure 1). However, estimating the causal effect of a head start in Silicon breakthrough on corporate outcomes is empirically challenging. Firstly, by definition, technology leadership is highly research field specific. While Fairchild 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[4] 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 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.

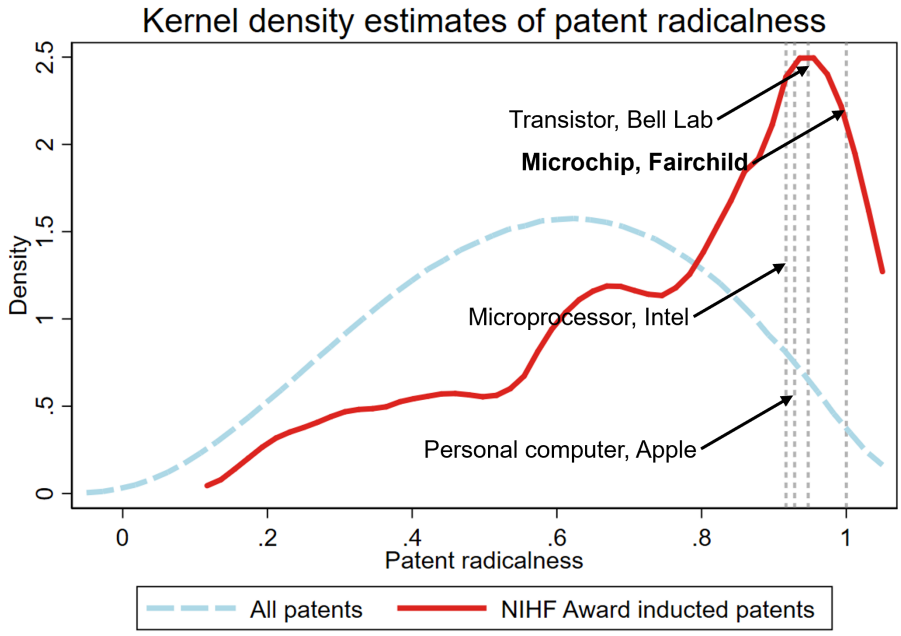


Figure 1: Radicalness of the Fairchild Silicon microchip breakthrough.

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

[4]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.

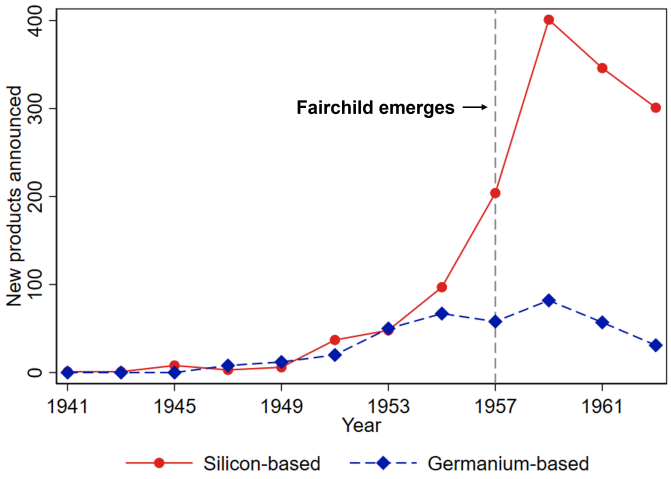
observable covariates until Fairchild Semiconductor emerged. Shortly before Fairchild emerged, two types of semiconductors with almost identical properties and complementary assets - Silicon and Germanium - co-existed for semiconductor research (Figure 2)[5]. Within 1 year after Fairchild Semiconductor emerged in 1957, the Fairchild engineers came up with a revolutionary planar technique, which coated 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. For the Silicon patent holders, the breakthrough reveals the latent value of their past innovations, which provides them with a head start compared with Germanium patent holders from the same research field. The pre-Fairchild semiconductor choice leads to a plausibly exogenous, within firm variation in the head start into microchip-related research (Figure 3a). I show that when a lab chooses Germanium on a certain research field, there will be 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. After Fairchild Semiconductor emerged in 1957 (Figure 2), the early US semiconductor industry experienced a rapid increase of product innovations and public disclosure of corporate research. The early development of new markets 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.

The setting has an additional unique advantage: the anticipation of the advent of Fairchild Semiconductor is likely minimal. The discovery of the "planar" idea was driven not by years of cumulative trial-and-errors corporate research[6], but instead by a resentful breakaway within a group of genius engineers from the Shockley Transistor Lab. William Shockley, a Nobel Prize Physics laureate but authoritarian manager, hindered his engineers[7] 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

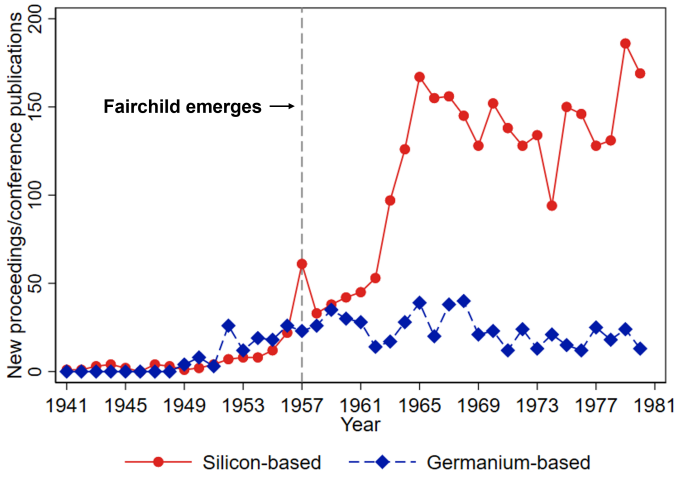
[5]In Appendix Figure C.1, I also plot the dynamic trends of Silicon and Germanium usage in semiconductor research over time to quantitatively support this claim.

[6]From Figure 1, the Silicon microchip patent is among the most radical (or unconventional) inventions in US history.

[7]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.



(a) Expansion of new product varieties.



(b) Increasing research sharing.

Figure 2: The early growth of US semiconductor industry.

Note: Producer data are digitized and collected from several primary professional trade magazines in electronics sector, including *Electronics*, *Electronics Industries*, *Radio Electronics*, *Electronics World* and *Electrical Engineering*. Conference publications data are collected from IEEE Xplore.

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 coat 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 Silicon and officially kicked off the decades-long transformation to the modern computer age.

Key events in 1957:

- The Shockley breakup (Sept. 1957)
- **Fairchild Semiconductor emerged**
- **Hoerni from Fairchild discovered the first Silicon (planar) oxide idea (Dec. 1957)**

R&D labs	Research fields	Patents on Silicon (Y/N)	Exposure to Silicon breakthroughs
		1954-1957	1958-
1	A	No	Frictions in Silicon adoption → Exposure to Silicon innovations
2	B	No	Frictions in Silicon adoption → Exposure to Silicon innovations
2	C	Yes	Exposure to Silicon innovations
3	A	Yes	Exposure to Silicon innovations

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)
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.

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 further construct a novel, granular textual database to capture innovation commercialization in the microchip industry. I collect, digitize and build a novel lab-product level database compiled 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). I collect the announcement of new products in each business unit from several primary electronics trade journals, such as *Electronics*, the *Electronics Industries* trade journal (also known as the *Tele-Tech*). The trade journal was a professional magazine released by Chilton Co., a company famous for providing market research services for readers with professional background in electronics and automotive. In addition, I also collect and digitize data on new product announcement from the *Electrical Engineering*, which is another professional journal associated with the *American Institute of Electrical Engineer*. The other product announcements are collected from *Electronics World* and *Radio Electronics*.

For public knowledge disclosure, I collect the announcement data for new technical bulletins (a proxy for the release of engineering techniques, such as new technical data and guidebooks). I also collect the disclosure of applied and theoretical research from conference/proceeding publication records in IEEE. I download from IEEE Xplore (ieeexplore.ieee.org) the abstracts and bibliographic data for historical IEEE conference publications (including conferences, meetings, conventions and symposium) for 1900-2000.

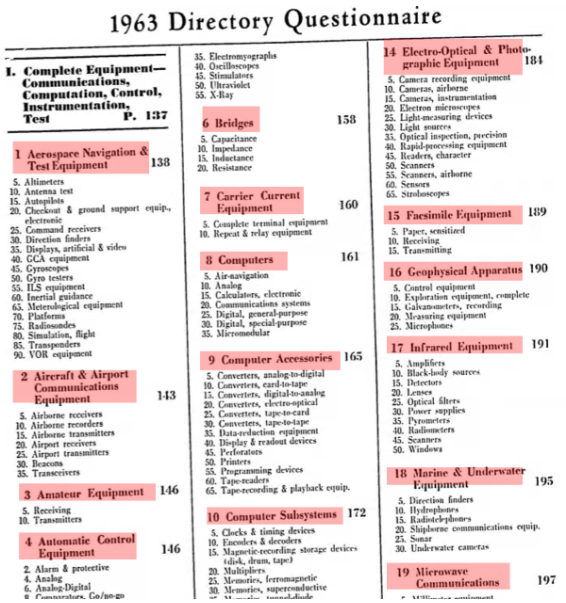
Advanced physics basic research publications: I download historical abstract and bibliography data for all publications in American Physics society during the year of 1940-1980 (https://www.aps.org/).

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.

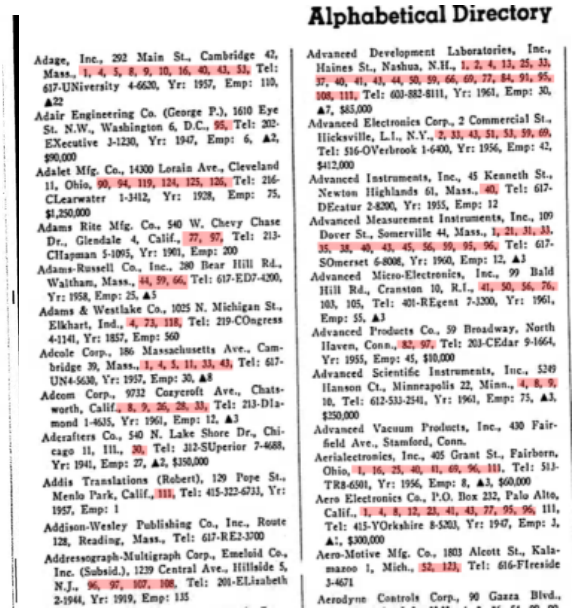
2.3 Data construction

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 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



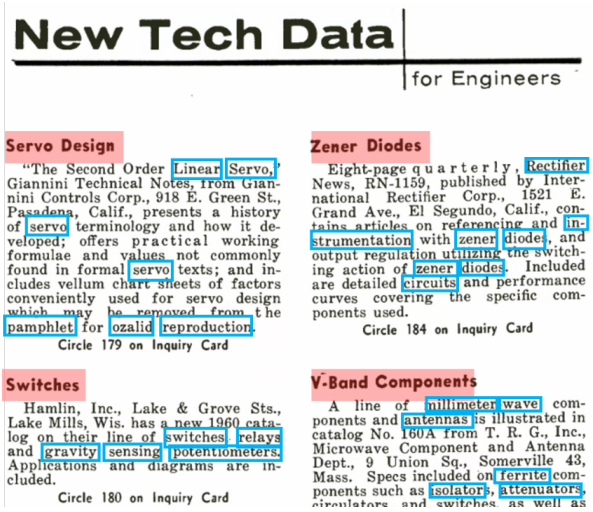
(a) Digitized product lines.



(b) Product lines - corporate lab mapping.



(c) Digitized new product announcements.



(d) Digitized new technical bulletins.

Figure 4: A sample of newly digitized product-level datasets.

Note: Data source: IRE Membership directory (4a and 4b); Tele-Tech and Electronics Industries (4c and 4d).

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[8]. 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[9] between research fields (6-digit CPC codes) and IEEE/advanced physics publication data. Only the matches

[8]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.

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

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)[10] 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 new product announcements to capture newly commercialized innovation (new product varieties); (4) Number of new technical bulletins (e.g., technical data and guidebooks) to capture the public disclosure of downstream, engineering techniques; (5) Number of IEEE conference/meeting paper/proceeding publications to capture public disclosure of corporate research. Specifically, I further divide the IEEE publications into two categories: *applied research disclosure*, defined as the ones mentioning fabrication details that could be of interest to downstream users; and *theoretical research disclosure*, defined as the ones that mention a certain theory. 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

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

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

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. Silicon_{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). To compare outcomes of Silicon labs with Germanium labs within the same research field, I include μ_{vf}, which

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

are research field×lab fixed effects. μ_{vf} absorb $\mathbf{1}\{t \geq 1957\}$, Silicon$_{vf}$, and all the time-invariant confounders at the research field level. ε_{vft} is the error term. λ_{ut} is two-way firm×year FE. The inclusion of λ_{ut} absorbs all unobservable firm-level confounders such as size, overall R&D spending, and the likelihood of obtaining public contracts. The baseline time period runs from 1953 to 1965, but also varies according to data availability when it comes to specific outcomes[11]. The panel is balanced in nature as I condition the analyses on the corporate labs that had survived through 1953-1965.

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×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.

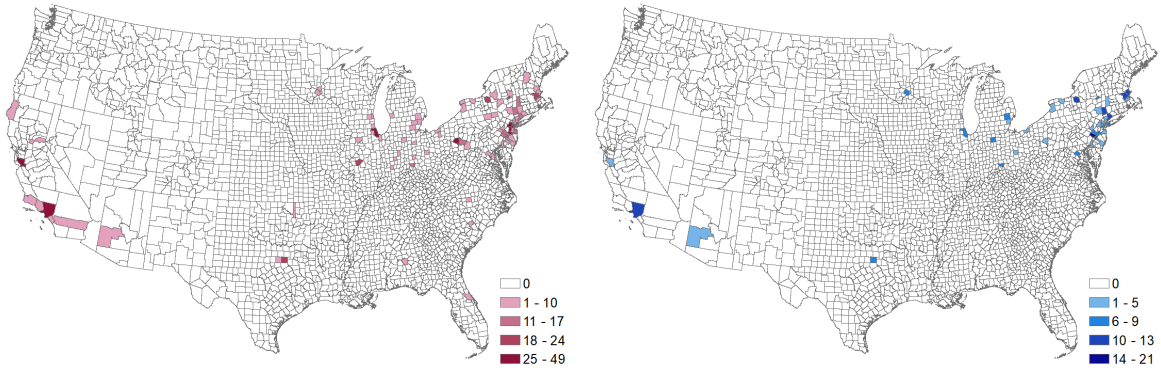
Another concern endangering this identification strategy is somewhat similar to exclusion restriction - the choice of Silicon over Germanium may impact outcomes through other channels, regardless of any head-start in microchip-related research. This may be concerning if the use of Silicon before Fairchild 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×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

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

vastly jeopardise the estimated early-mover advantage in R&D.

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 persistent leadership in top patent quality in respective research fields, and greater expansion of their product lines after the Silicon breakthrough, marked by the emergence of Fairchild. The expansion of product lines is consistent with evidence from Figure 7c), where new products increase to a large extent for the Silicon group after the breakthrough. Several surprising facts are also unveiled. Figure 7d shows that the Silicon labs release more new technical bulletins. The Silicon labs also release more applied research in IEEE on the research fields where they hold Silicon patents before the breakthrough (Figures

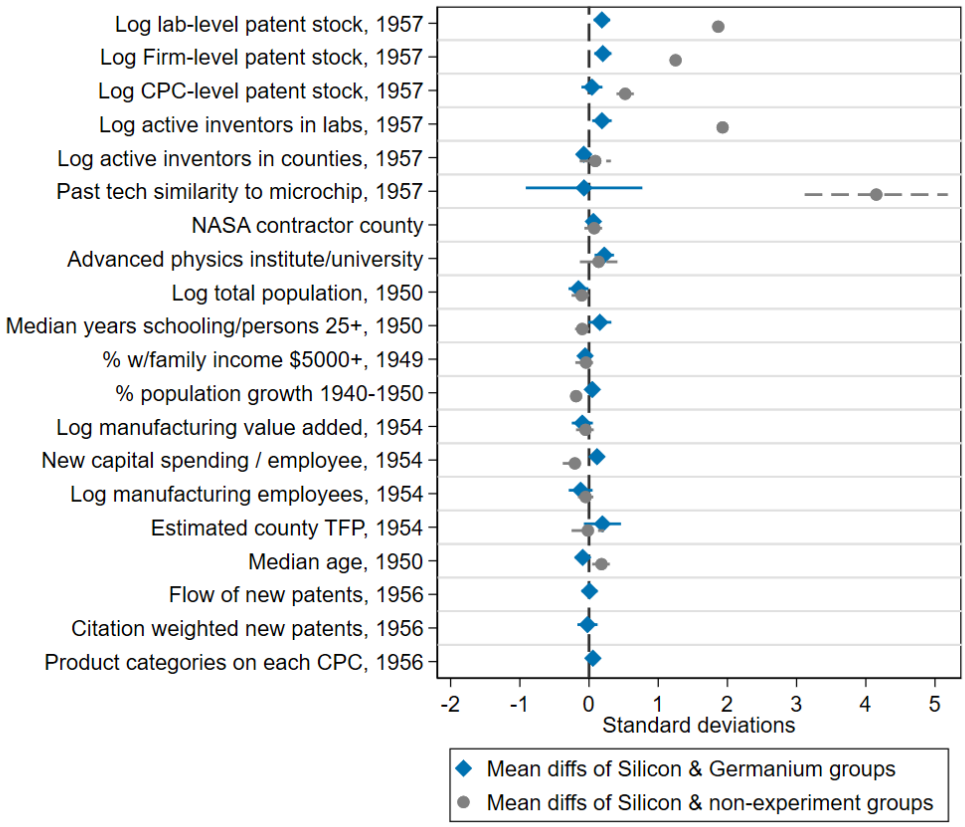
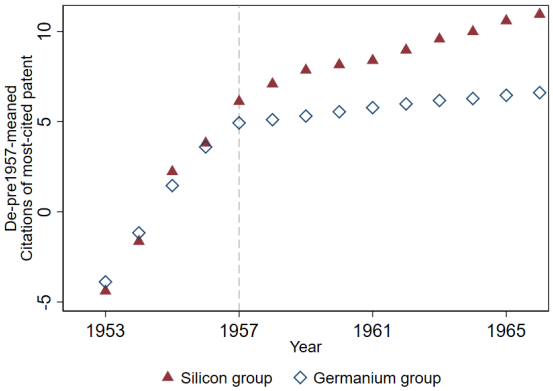
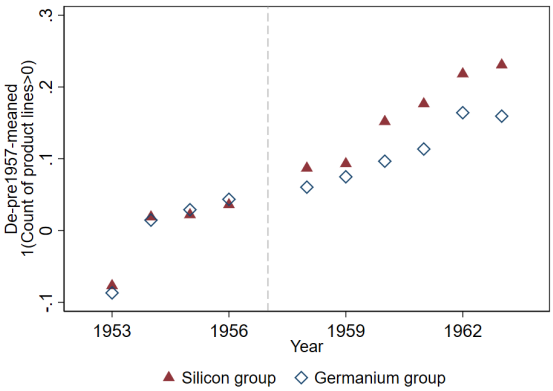


Figure 6: Balancing test

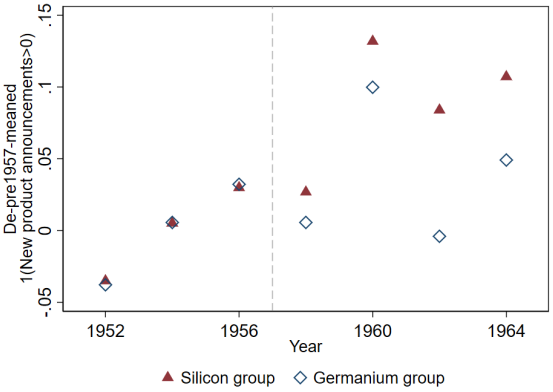
Note: Figure 6 reports the corporate lab×research field level t-tests for covariate mean differences. The year of each covariate is taken at the closest year before Fairchild Semiconductor emerged, depending on data availability. "Patent stock" is defined as cumulative count of all patents invented during 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.



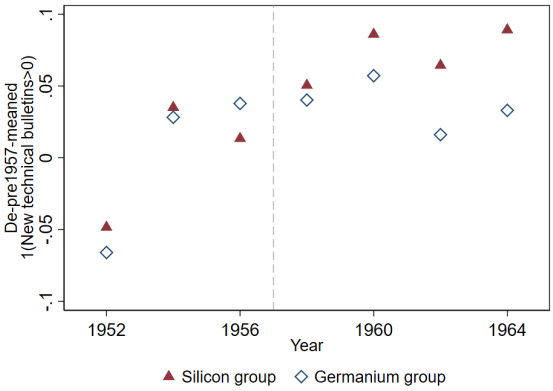
(a) Life-long citations of the most-cited patent



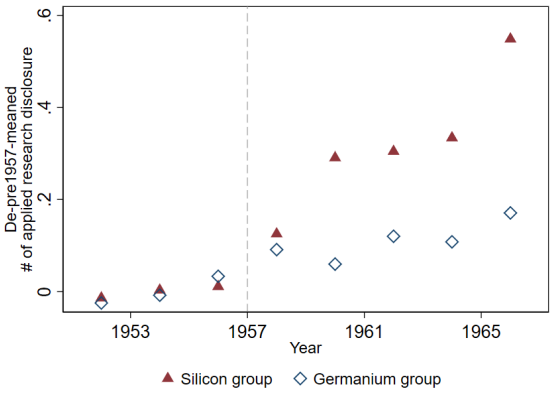
(b) Count of product lines



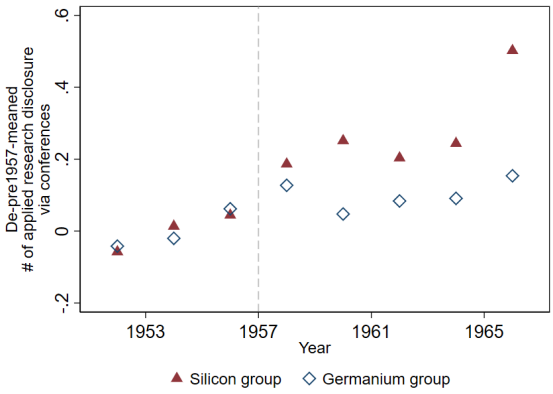
(c) New product announcements



(d) New technical bulletins



(e) Public disclosure of applied research



(f) Applied research disclosure via face-to-face

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.

7e and 7f). The evidence casts interesting question on the standard innovation models where the problem of market failure often leads to the classic incentive problem in private R&D spending.

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

3 The rise of early technology leaders

3.1 Silicon and early exposure to microchip breakthrough

After the Silicon microchip breakthrough, how significant is the head start of Silicon patent holders over their Germanium rivals in the same research field? I illustrate the extent of the head start by quantifying the timing of each lab's exposure to microchip within their respective research fields[12] (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[13] patent in year $t = T$ on research field f (Table 1 columns (1) - (3)). This binary variable is a proxy for whether lab v has introduced a combinatorial innovation with microchip in research field f by year T; 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

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

[13] 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.

41.3% increase in the stock of microchip-related patents by 1965, and a conservatively estimated[14] 3-year advantage in producing the first microchip related patent.

Are Silicon patent holders more likely to anticipate the arrival of Fairchild and the subsequent Silicon breakthrough? 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 Silicon breakthrough among the selected lab×research field pairs.

Table 1: Pre-Fairchild semiconductor choice and combinatorial innovations with microchip.

	(1) Microchip state t=1965	(2) Microchip state t=1957	(3) Microchip state t=1965	(4) IHS(Cuml. count) t=1965	(5) Microchip state 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 state variable indicating whether or not lab v has started a combinatorial innovation on microchip 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.

3.2 The rise of early technology leaders

In this section, I unveil to what extent the Fairchild Silicon microchip breakthrough shapes the market selection of early industrial leaders. Does the *ex ante* head start predict significant *ex post* leadership in the microchip industry? To illustrate this, I estimate equation (1) by first taking Life-long citations of the "best" patent at an outcome. I measure the local frontier of technology with the life-long citations of the cumulatively most-cited patent of lab v in research field f in each year. The measure provides a proxy for the maximum R&D capacity. Results show that the Silicon head

[14]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.

start leads to a persistent product differentiation in Silicon labs' leading research fields. On average, the effect is equivalent to an around 13.7% increase in the count of product lines for Silicon labs.

I then switch the outcome as new patent citations received from other firms. 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 the estimates in Table 2, columns (4-6). Results show 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: the effect on average amounts to 1.761 (approximately 32.4%) more citations. The finding suggests that after the breakthrough, patent profiles from Silicon labs are increasingly more demanded than that of Germanium labs in the market for ideas, conditional on the same research field.

Table 2: Baseline result: the rise of early technology leaders after the Silicon breakthrough.

	Life-long citations of most-cited pat.			New citations received		
	(1)	(2)	(3)	(4)	(5)	(6)
	Y_{vft}	Y_{vft}	IHS(Y_{vft})	Y_{vft}	Y_{vft}	IHS(Y_{vft})
Silicon × Post	3.589***	3.575***	0.198**	1.777***	1.761***	0.324***
	(0.555)	(0.554)	(0.079)	(0.368)	(0.352)	(0.053)
Research field×lab 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)	23.616	23.616	23.616	4.415	4.415	4.415
Obs.	17663	17663	17663	13507	13507	13507
R^2	0.934	0.934	0.826	0.770	0.774	0.757

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 cumulative most-cited patent up to year t in each lab×research field (columns (1) - (3)); new forward patent citations received from other firms for each year in each lab×research field (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.

Figure 8b checks if the advantage of Silicon labs in product market could reflect any other alternative explanations. For example, the pre-Fairchild choice of Silicon

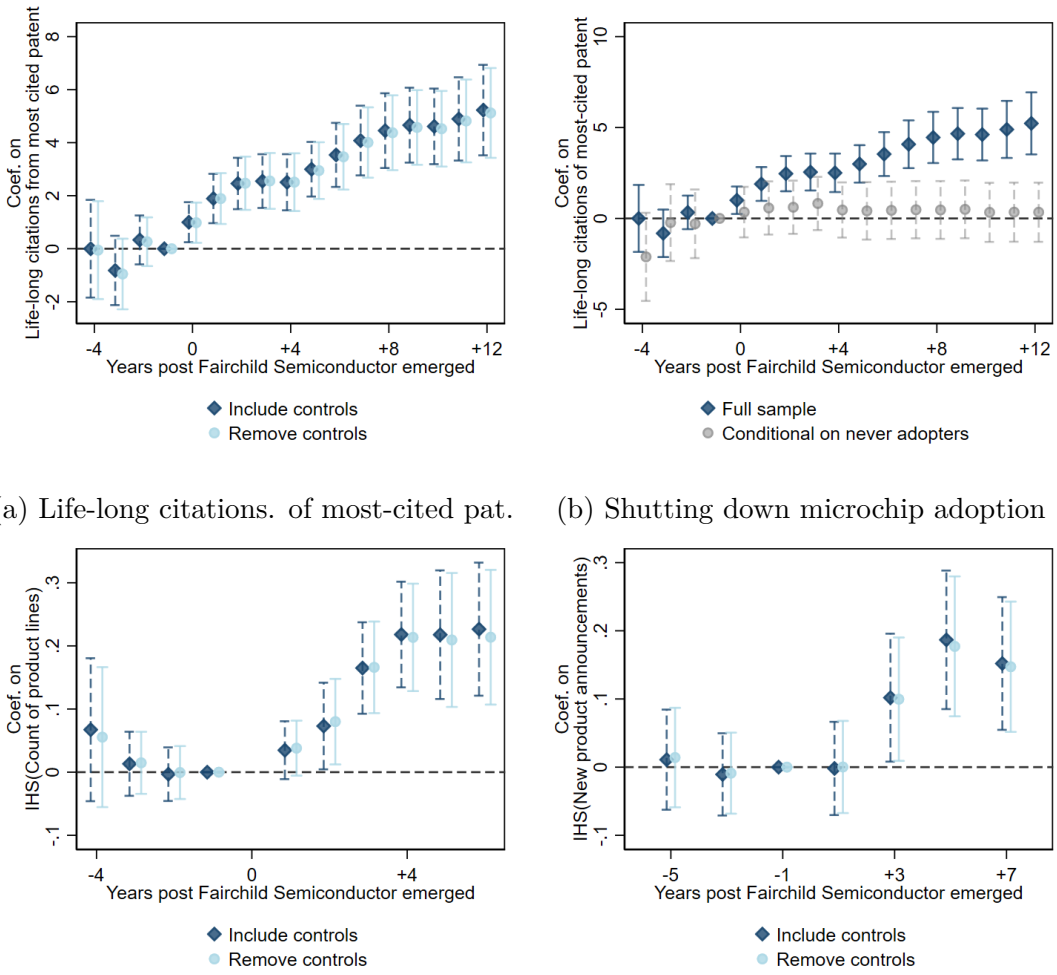
over Germanium may impact Silicon lab outcomes through other channels beyond the head start in microchip. I restrict the sample by including only labs that have never adopted microchip in the focal research field f, or any other closely related research fields in the same 4-digit CPC class of f. If any 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 8b displays the result 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 Silicon microchip breakthrough, but unlikely the other pre-Fairchild latent confounders.

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 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 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



(a) Life-long citations. of most-cited pat.

(b) Shutting down microchip adoption

(c) Count of product lines

(d) New product announcements

Figure 8: Corporate head start and the rise of early industrial leaders.

Note: Figures display the dynamic effects of the head start on corporate R&D outcomes. In Figure 8b, 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. Confidence intervals are displayed at the 95% level. Each observation is a corporate lab×research field×year unit.

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 8 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[15], 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.

[15]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).

4 Leader innovation and product differentiation

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 R&D expenditure from industrial leaders are still rising, recent work shows that a large proportion of leader 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 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 integrated circuit 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 innovation and commercialization 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 commercialize product innovations and consolidate their market position after they achieve technology leadership over their rivals? In the previous analysis, 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 using 1961 as the cutoff. Previous analysis looks at patents as the dependent variable. However, innovation may not be fully disclosed in patents, especially for the most radical ones. Firms may have incentives to protect critical innovations with trade secrecy rather than exposing them to patent office (Anton and Yao, 2004; Fadeev, 2023). To capture innovation with realized market value, I rely on several product market outcomes to trace newly commercialized innovations, including: 1) Count of product lines, which is a stock variable for lab v in research field f in each year; and 2) new product announcements released by lab v in research field f in each two-year period. The variables provide

both stock and flow measures of successfully commercialized innovations in market[16].

Table 3: Silicon head start and the product market performance.

	Count of product lines			New product announcements		
	(1)	(2)	(3)	(4)	(5)	(6)
	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})
Silicon × Post	0.137***			0.110***		
	(0.037)			(0.042)		
Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$		0.069***	0.064***		0.004	0.003
		(0.024)	(0.023)		(0.026)	(0.027)
Silicon × $\mathbb{1}\{1962 \leq t \leq T\}$		0.158***	0.168***		0.102**	0.105**
		(0.050)	(0.050)		(0.045)	(0.046)
Research field×lab FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	Y	N	Y	Y	N	Y
Obs.	10390	10390	10390	7273	7273	7273
R^2	0.885	0.881	0.885	0.863	0.859	0.862

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 product lines in year t in each lab×research field (columns (1) - (3)); new product announcements for each 2 years in each lab×research field (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.

In growth theory with heterogeneous firms and heterogeneous innovation, the large incumbents are often presumed to undertake less radical innovation that renders the old technology obsolete (Akcigit and Kerr, 2018). However, this does not seem to be the case during the early microchip breakthrough. Table 3 reports the static estimates and Figures 8c and 8d report the dynamic ones to test the pre-trends[17]. On average, the effect is equivalent to an around 13.7% increase in the count of product lines for Silicon labs compared with Germanium labs in the same research fields. Specified results (columns 2-3) show that for the first period before 1961, the Silicon head start predicts negligible product market advantage in Silicon labs' leading research fields. After 1962 when technology leadership is significantly detected, the head start expands the commercialized product lines to a significantly larger extent: for the second period after 1961, the increase of product lines rises to 16.8% for the Silicon labs. Figures 8c and 8d further plot out the dynamic effects. The evidence shows that early industrial

[16]Note that each of the above measures, when interpreted independently, is confronted with individual drawbacks. However, as I will argue in the following section, the measurement concern will be relieved when all empirical models based on these indicators show robust evidence of persistent early leader innovation.

[17]I attempt to keep at least four pre-Fairchild periods for all specifications. However, this number may shrink due to data availability. For the equation on life-long citations outcome, I further extend the post period to year + 12 to check for whether the technology advance from early leaders disappear in the long run.

leaders persistently expand product lines in their leading research fields. I further trace the early leaders' trajectories in commercializing new product innovations in Figure 8d. I display dynamic effects of the Silicon head start on the count of new product announcements. After 1962, the effect is equivalent to an around 10.5% increase in new product announcements for Silicon labs. All the above results suggest that by disproportionately announcing new products in market, the early industrial leaders significantly differentiate their new products away from conventional designs.

5 Voluntary knowledge sharing from early leaders

5.1 Theoretical framework (TBC)

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 such as by hiding crucial trade secrets from patents (Anton and Yao, 2004; 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, the leader firms could find it optimal to diffuse a certain amount of technical details about their designs toward potential users. The relative costs for potential downstream users to choose the given design could fall after the leader's voluntary disclosure of critical details. However, as the disclosed knowledge likely becomes quasi-public goods, rivals may also learn from the early leader's designs and refine their competing designs. Therefore, the diffusion from early leaders could rise until a certain point when the marginal loss 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 that builds complementary assets and downstream application sectors in the electric vehicle sector. For the context of early microchip industry, I first provide causal evidence to unveil a generic pattern of vertical voluntary knowledge diffusion from early technology leaders. Next, I introduce case studies of the two most advanced microchip designers, Fairchild and Texas Instruments, and demonstrate how the decision to diffuse may potentially ignite drastically diverse response from rivals.

5.2 Empirical evidence for knowledge sharing

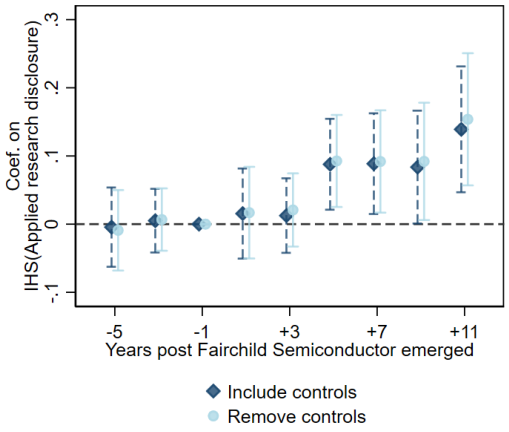
Figure 9 and Table 4 present evidence of such strategies: within the first 4 years when leader product market advantage is still uncertain, I detect no statistically significant rise of knowledge disclosure on fabrication techniques from Silicon labs. From year

5 onward, Silicon labs are significantly disclosing more new technical details regarding fabrication processes, either in the forms of applied research or technical manufacturing bulletins, than Germanium labs do on the same research field (Figure 9a and 9c). 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.

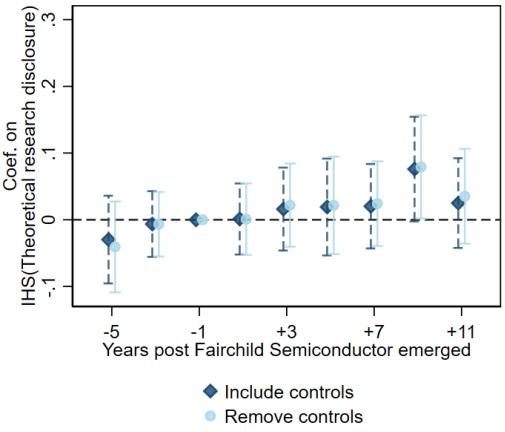
If the pattern of knowledge sharing follows the theoretical prediction, several features should be observed from data. Firstly, the leader labs are likely to selectively disclose applied research for downstream users, but not the types of knowledge that could benefit rivals that compete for the dominant design. To test for this prediction, I switch the outcome variable as the release of theoretical research in IEEE from lab v in research field f in year t. Results from Figure 9b and column (3), Table 4 confirms the prediction. Silicon labs indeed do not disproportionately disclose theoretical research 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 9e, 9f, and columns (10 - 12), Table 4. Results show that whether the leader lab disclose applied research to public is highly dependent on whether their parent firms have ex ante product lines on their leading research field before the breakthrough. When the early leaders fail to announce new products, or when their parent firms have limited *ex ante* productive capacities to compete for dominant design (Figure 9d), both the effects of Silicon head start on applied research disclosure and technical bulletins disclosure shrink to statistically near 0 (Figures 9e and 9f).

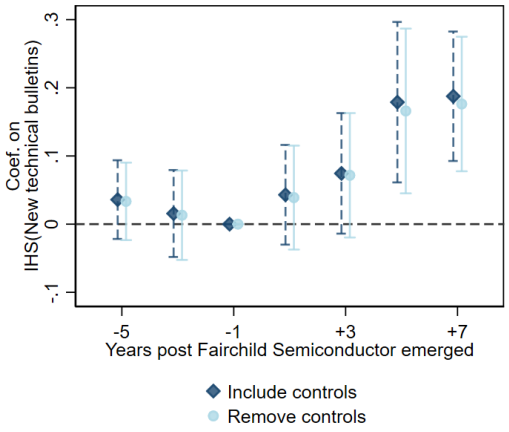
One concern may still remain: the risk of mis-measuring disclosure. When firms publish in conference/meeting paper publications on IEEE, the purpose may not be the disclosure of information, but instead it may be to leverage their publications as a ticket to attend the IEEE conferences. I check this 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.



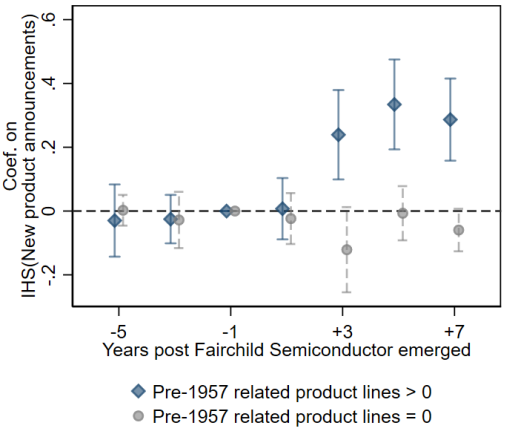
(a) Applied research disclosure



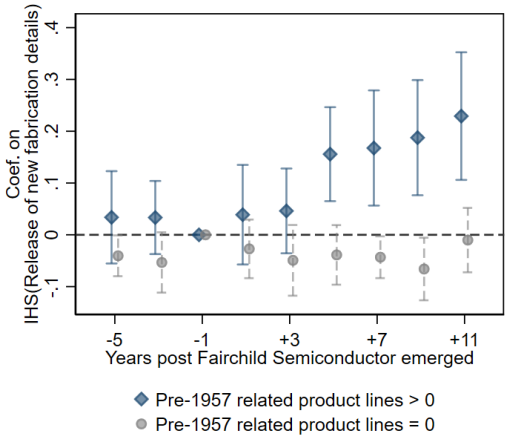
(b) Theoretical research disclosure



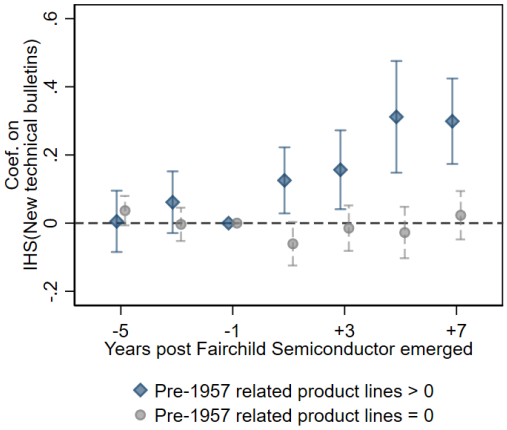
(c) Technical bulletins disclosure



(d) New products by prod. capacity



(e) "Applied" disclosure by prod. capacity



(f) Tech bulletins by prod. capacity

Figure 9: Public knowledge disclosure from leader firms.

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.

Table 4: Voluntary knowledge sharing: public knowledge disclosure in IEEE platforms.

	Applied research disclosure			Theoretical research disclosure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Y_{vft}	Y_{vft}	IHS(Y_{vft})	Y_{vft}	Y_{vft}	IHS(Y_{vft})
Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$	0.040	0.024	0.007	0.002	-0.007	-0.001
	(0.029)	(0.022)	(0.014)	(0.025)	(0.020)	(0.014)
Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.228***	0.201***	0.103***	0.033	0.021	0.020
	(0.076)	(0.057)	(0.028)	(0.029)	(0.018)	(0.013)
Research field×lab 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)	0.449	0.449	0.449	0.136	0.136	0.136
Obs.	9351	9351	9351	9351	9351	9351
R^2	0.656	0.718	0.729	0.507	0.596	0.559

	Release of fabric. (placebo)	Release via face-to-face	Release via. publications	Release of fabric.	Release of experim.	Release via face-to-face
	(7)	(8)	(9)	(10)	(11)	(12)
	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})	IHS(Y_{vft})
Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$	0.001	0.026***	-0.013	-0.007	-0.026*	-0.013
	(0.014)	(0.009)	(0.012)	(0.017)	(0.014)	(0.009)
Silicon × $\mathbb{1}\{1962 \leq t \leq T\}$	0.029	0.090***	0.049***	-0.009	-0.000	-0.002
	(0.017)	(0.022)	(0.018)	(0.015)	(0.013)	(0.010)
Pre-1957 product lines × Silicon				0.021	0.039	0.062***
× $\mathbb{1}\{1957 \leq t \leq 1961\}$				(0.028)	(0.029)	(0.017)
Pre-1957 product lines × Silicon				0.177***	0.031	0.145***
× $\mathbb{1}\{1962 \leq t \leq T\}$				(0.041)	(0.023)	(0.028)
Pre-1957 product lines×year FE	N	N	N	Y	Y	Y
Research field×lab FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	Y	N	Y	Y
Obs.	7878	9351	9351	9351	9351	9351
R^2	0.704	0.532	0.692	0.735	0.563	0.545

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.

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 persistent advance in the local technology frontier (column (2)) and sizable influx of citations (column (3)).

However, the absence of IEEE platform tends to shut down the channels for leader labs to achieve downstream product market advantage (column (4)): 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 (column (5)), conditional on the same 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[18], 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.

6 Face-to-face contacts and the rise of "Silicon Valleys"

How localized does the leaders' knowledge diffuse? 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 10a displays the result. In Figure 10b, I further displays the estimates when outcome switches to general publications in which no in-person meetings are needed. Findings

[18] 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).

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

	Sample: Research fields without IEEE coverage.					
	(1) "Applied" disclosure	(2) Life-long citations	(3) New citations received	(4) Count of product lines	(5) New product announ.	(6) New technical bulletins
Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$	-0.005	2.668***	0.571	0.144*	-0.113	-0.072
	(0.012)	(0.776)	(0.349)	(0.080)	(0.111)	(0.061)
Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.012	3.896***	1.470***	0.063	0.113	-0.005
	(0.011)	(1.028)	(0.542)	(0.164)	(0.110)	(0.061)
Research field×lab FE	Y	Y	Y	Y	Y	Y
Firm×year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Obs.	4797	9061	6929	5330	3731	2665
R^2	0.371	0.923	0.717	0.888	0.696	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 count of IEEE applied research publications for each 2 years in each lab×research field pair (column (1)), count of citations of the most-cited patent for each year in each lab×research field pair (column (2)), new citations received from different firms for each year in each lab×research field (columns (3)), count of product lines for each year in each lab×research field (column (4)), count of new product manuals for 2 years in each lab×research field (column (5)), and count of new technical bulletins 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.

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).

I conduct a county×research field level regression taking the form of equation (4):

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

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. Silicon_{cf} 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 10c displays the dynamic effects of equation (4). Evidence from Figure 10c 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 10d, 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 10c is reversed. The above evidence lends support to the hypothesis that early industrial leaders played a pivotal role in catalyzing early agglomeration spillovers.

7 Robustness: ruling out alternative explanations

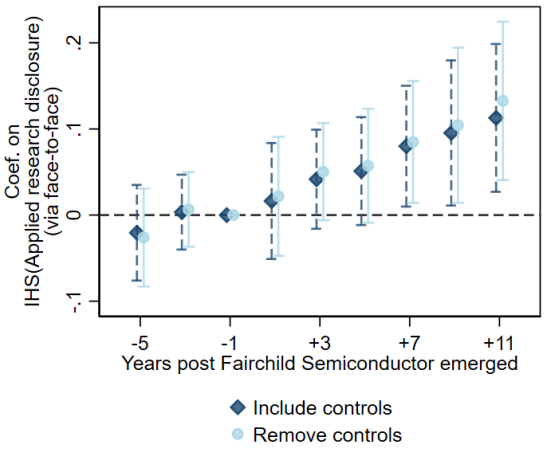
In previous sections, I have already shown that the observed effects from the head start is unlikely to be biased upward by the NASA Space Act, concerns of exclusion restriction, and mis-measurement of public knowledge disclosure. In this section, I further conduct a series of robustness checks to rule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

7.1 Specificity to California

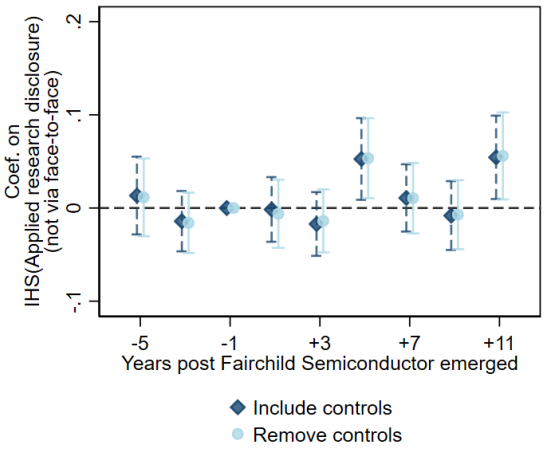
Is the effect specific to Silicon Valley, an agglomeration that has pioneered the global frontier ICT technologies ever since 1960s? To test for this channel, I rerun equation (1) and exclude all the labs from California and Texas (states where Fairchild and Texas Instruments were located) (Columns 3-4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

7.2 The triumph of large agglomerations?

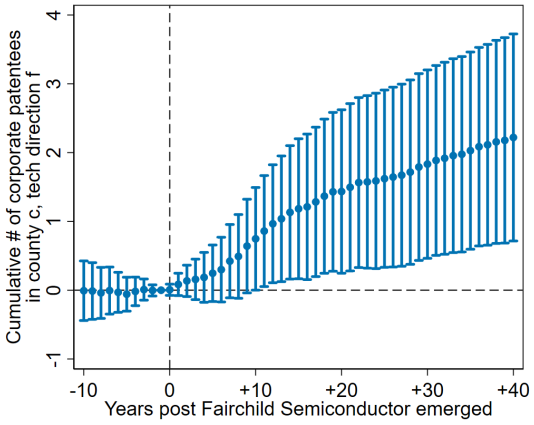
Another potential explanation is that prior military contracts (Gross and Sampat, 2022) could have explained the early formation of clusters, and then spur the early leaders in the microchip breakthrough. In Appendix section E.4, I test this view by first looking at the sorting bias of these early-movers. 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



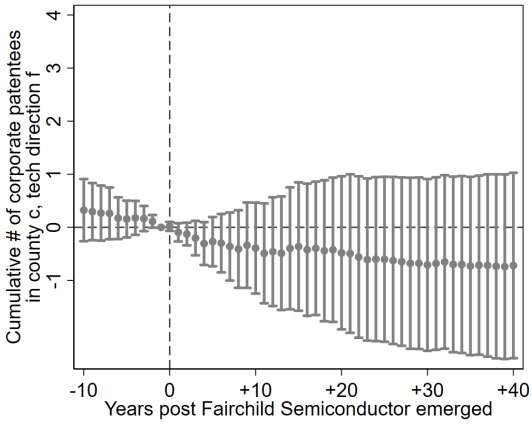
(a) Face-to-face "applied" disclosure



(b) Non face-to-face "applied" disclosure



(c) Full sample



(d) "Placebo early leader" counties.

Figure 10: The making of "Silicon Valley(s)".

Note: Each observation in Figures 10a and 10b is a county×research field pair. Each observation in Figures 10c and 10d is a county×research field pair. Confidence intervals are displayed at the 95% level. In figure 10d, only county×research field pairs in which the first microchip patent had not been started until 1962 are kept.

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 seeks to unveil the mechanics of knowledge diffusion during a revolutionary technological change. While the existing literature has demonstrated the significant role of knowledge diffusion in shaping new industries, clusters and business dynamism, the mechanics of knowledge diffusion process is still relatively unclear. I unveil that an approximately 3 years corporate head start quickly creates early leaders in the microchip industry, marked by persistent influx of citations and significant expansion of product lines. Moreover, new product varieties are not only introduced by new entrants, I find the incumbent early leaders also significantly increase the rate of new product designs after the leadership is achieved. More importantly, knowledge spillover is not simply "something in the air"; instead, the leaders disproportionately disclose technical details as public knowledge in professional associations. The voluntary knowledge diffusion is likely explained by a simple model in which early leaders would find it optimal to disclose crucial fabrication details as public knowledge to facilitate technology adoption from downstream users, until the marginal benefit of doing so is equated with marginal loss from benefiting horizontal product rivals. Empirical evidence suggests that the corporate labs indeed selectively disclose more fabrication techniques once they achieve product market advantage over their rivals. I also "shut down" the channels of knowledge disclosure and observe the response of corporate labs to the head start. I find that while the head start still leads to sizable innovation, the effects on production outcomes shrink to statistically near zero. The paper hence provides a likely framework to account for how early leaders in technology breakthrough facilitates vertical knowledge diffusion and rapid downstream product commercialization during the microchip breakthrough.

The findings call for a deeper examination of incumbent early leaders during technological revolution. The literature often suggests that industrial leaders find it sub-optimal to conduct radical innovation, because the pre-innovation rent often out-

weighs post-innovation rent (Arrow, 1962; Akcigit and Van Reenen, 2023). Therefore, innovation is mostly introduced by new entrants through a process of creative destruction (e.g., Arrow replacement effect). However, I demonstrate that breakthrough innovation could also induce forces of "creative construction", where incumbents with endowments favored by an revolutionary technological change can gain additional new post-innovation rent granted by the breakthrough. This creates an incentive for incumbents to engage in radical innovation. I find that early leaders indeed persistently create radical innovations and produce higher cited patents. The forces of creative construction warrant greater research focus, as they likely create "entrepreneurial incumbents" that persistently innovate even after they become the dominant design.

References

Acemoglu, D. and Akcigit, U. (2012). Intellectual Property Rights Policy, Competition and Innovation. *Journal of the European Economic Association*, 10(1):1–42.

Acemoglu, D., Akcigit, U., and Celik, M. A. (2022). Radical and incremental innovation: The roles of firms, managers, and innovators. *American Economic Journal: Macroeconomics*, 14(3):199–249.

Aghion, P., Harris, C., Howitt, P., and Vickers, J. (2001). Competition, Imitation and Growth with Step-by-Step Innovation. *The Review of Economic Studies*, 68(3):467–492.

Akcigit, U. and Ates, S. T. (2021). Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory. *American Economic Journal: Macroeconomics*, 13(1):257–98.

Akcigit, U. and Ates, S. T. (2023). What happened to US business dynamism? *Journal of Political Economy*, 131(8):2059–2124.

Akcigit, U. and Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy*, 126(4):1374–1443.

Akcigit, U. and Van Reenen, J. (2023). *The Economics of Creative Destruction*. Cambridge: Harvard University Press.[644].

Allen, R. C. (1983). Collective invention. *Journal of Economic Behavior Organization*, 4(1):1–24.

Anderson, P. and Tushman, M. L. (1990). Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative Science Quarterly*, 35(4):604–633.

Anton, J. J. and Yao, D. A. (2004). Little patents and big secrets: Managing intellectual property. *The RAND Journal of Economics*, 35(1):1–22.

Argente, D., Baslandze, S., Hanley, D., and Moreira, S. (2020). Patents to products: Product innovation and firm dynamics. *CEPR Discussion Paper No. DP14692*.

Arora, A., Belenzon, S., and Patacconi, A. (2021a). Knowledge sharing in alliances and alliance portfolios. *Management Science*, 67(3):1569–1585.

Arora, A., Belenzon, S., and Sheer, L. (2021b). Knowledge Spillovers and Corporate Investment in Scientific Research. *American Economic Review*, 111(3):871–98.

Arrow, K. J. (1962). The economic implications of learning by doing. *Review of Economic Studies*, 29(3):155–173.

Arrow, K. J. (1972). *Economic Welfare and the Allocation of Resources for Invention*. Springer.

Asheim, B. T. and Gertler, M. S. (2006). 291 The Geography of Innovation: Regional Innovation Systems. In *The Oxford Handbook of Innovation*. Oxford University Press.

Atkin, D., Chen, M. K., and Popov, A. (2022). The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley. *National Bureau of Economic Research Working Paper Series*, No. 30147.

Bergeaud, A. and Cyril, V. (2022). *PatentCity: A Dataset to Study the Location of Patents Since the 19th Century*.

Berkes, E. and Gaetani, R. (2021). The geography of unconventional innovation. *The Economic Journal*, 131(636):1466–1514.

Berlin, L. (2005). *The Man Behind the Microchip: Robert Noyce and the Invention of Silicon Valley*. Oxford University Press.

Berlingieri, G., De Ridder, M., Lashkari, D., and Rigo, D. (2024). Growth through innovation bursts.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81(4):1347–1393.

Bobtcheff, C., Bolte, J., and Mariotti, T. (2017). Researcher's Dilemma. *The Review of Economic Studies*, 84(3):969–1014.

Bryan, K. A. and Williams, H. L. (2021). Innovation: Market failures and public policies. Working Paper 29173, National Bureau of Economic Research.

Catalini, C., Fons-Rosen, C., and Gaulé, P. (2018). How Do Travel Costs Shape Collaboration? *National Bureau of Economic Research Working Paper Series*, No. 24780.

Cohen, W. M. and Klepper, S. (1996). Firm size and the nature of innovation within industries: The case of process and product r&d. *The Review of Economics and Statistics*, 78(2):232–243.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162.

Duranton, G. (2007). Urban Evolutions: The Fast, the Slow, and the Still. *American Economic Review*, 97(1):197–221.

Dyevre, A. (2023). Public R&D spillovers and productivity growth. *Working paper, London School of Economics*.

Fadeev, E. (2023). Creative construction: Knowledge sharing and cooperation between firms. *Working paper, Duke University Fuqua School of Business*.

Fudenberg, D., Gilbert, R., Stiglitz, J., and Tirole, J. (1983). Preemption, Leapfrogging and Competition in Patent Races. *European Economic Review*, 22(1):3–31.

Gans, J. S., Hsu, D. H., and Stern, S. (2000). When does start-up innovation spur the gale of creative destruction? Working Paper 7851, National Bureau of Economic Research.

Giorcelli, M. and Li, B. (2021). Technology Transfer and Early Industrial Development: Evidence from the Sino-Soviet Alliance. *National Bureau of Economic Research Working Paper Series*, No. 29455.

Glaeser, E. L. (1999). Learning in Cities. *Journal of Urban Economics*, 46(2):254–277.

Gordon, R. J. (2018). Why has economic growth slowed when innovation appears to be accelerating? Working Paper 24554, National Bureau of Economic Research.

Grinich, V. H. and Haas, I. (1959). P-n--n triode switching applications. *IRE Transactions on Electronic Computers*, EC-8(2):108–113.

Gross, D. P. and Sampat, B. N. (2022). America, Jump-started: World War II R&D and the Takeoff of the U.S. Innovation System. *National Bureau of Economic Research Working Paper Series*, No. 27375.

Haines, M. R. (2010). Historical, Demographic, Economic, and Social Data: The United States, 1790-2002.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Working Paper 8498, National Bureau of Economic Research.

Helpman, E. and Trajtenberg, M. (1994). A Time to Sow and a Time to Reap: Growth Based on General Purpose Technologies. *National Bureau of Economic Research Working Paper Series*, No. 4854.

Helpman, E. and Trajtenberg, M. (1996). Diffusion of General Purpose Technologies. *National Bureau of Economic Research Working Paper Series*, No. 5773.

Hill, R. and Stein, C. (2019). Scooped! Estimating Rewards for Priority in Science. Working Paper.

Institute of Radio Engineers (1963). *Year Book-Institute of Radio Engineers*. Institute of Radio Engineers.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3):577–598.

Kantor, S. and Whalley, A. (2022). Moonshot: Public R&D and Growth. *American Economic Review*.

Kerr, W. R. (2010). Breakthrough Inventions and Migrating Clusters of Innovation. *Journal of Urban Economics*, 67(1):46–60. Special Issue: Cities and Entrepreneurship.

Klepper, S. (1996). Entry, Exit, Growth, and Innovation over the Product Life Cycle. *The American Economic Review*, 86(3):562–583.

Klepper, S. (2002). Firm Survival and the Evolution of Oligopoly. *The RAND Journal of Economics*, 33(1):37–61.

Klepper, S. (2010). The Origin and Growth of Industry Clusters: The Making of Silicon Valley and Detroit. *Journal of Urban Economics*, 67(1):15–32.

Koh, Y., Li, J., and Xu, J. (2022). Subway, Collaborative Matching, and Innovation. *The Review of Economics and Statistics*, pages 1–45.

Kuhn, J., Younge, K., and Marco, A. (2023). Strategic citation: A reassessment. *Review of Economics and Statistics*, 105(2):458–466.

Lojek, B. (2007). *History of semiconductor engineering*. Springer.

Ma, S. (2021). Technological obsolescence. *National Bureau of Economic Research Working Paper Series*, No. 29504.

MacDonald, J. R. (1954). The calibration of amplitude modulation meters with a heterodyne signal. *Proceedings of the IRE*, 42(10):1515–1518.

Marx, M., Gans, J. S., and Hsu, D. H. (2014). Dynamic commercialization strategies for disruptive technologies: Evidence from the speech recognition industry. *Management Science*, 60(12):3103–3123.

Mokyr, J., Sarid, A., and van der Beek, K. (2022). The Wheels of Change: Technology Adoption, Millwrights and the Persistence in Britain's Industrialisation. *The Economic Journal*, 132(645):1894–1926.

Nimmen, J. V., Bruno, L. C., and l. Rosholt, R. (1976). NASA Historical Data Book. Volume I: NASA Resources 1958-1968. Technical report, Scientific and Technical Information Office, National Aeronautics and Space Administration.

Orton, J. W. (2009). *Semiconductors and the Information Revolution: Magic Crystals that Made IT Happen*. Academic Press.

Petralia, S., Balland, P.-A., and Rigby, D. L. (2016). Unveiling the geography of historical patents in the united states from 1836 to 1975. *Scientific Data*, 3(1):160074.

Reid, T. R. (2001). *The Chip: How Two Americans Invented the Microchip and Launched a Revolution*. Random House Trade Paperbacks.

Saxenian, A. (1994). *Regional Advantage*. Harvard University Press, Cambridge, MA.

Storper, M. and Venables, A. J. (2004). Buzz: Face-to-Face Contact and the Urban Economy. *Journal of Economic Geography*, 4(4):351–370.

Tushman, M. L. and Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 31(3):439–465.

United States Atomic Energy Commission (1970). *Corporate Author Headings Used by the US Atomic Energy Commission in Cataloging Reports*. United States Atomic Energy Commission, Division of Technical Information.

Williams, H. L. (2013). Intellectual Property Rights and Innovation: Evidence from the Human Genome. *Journal of Political Economy*, 121(1):1–27.

Ye, P. (2016). Switching channels. *IEEE Spectrum*, 53(12):40–45.

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.

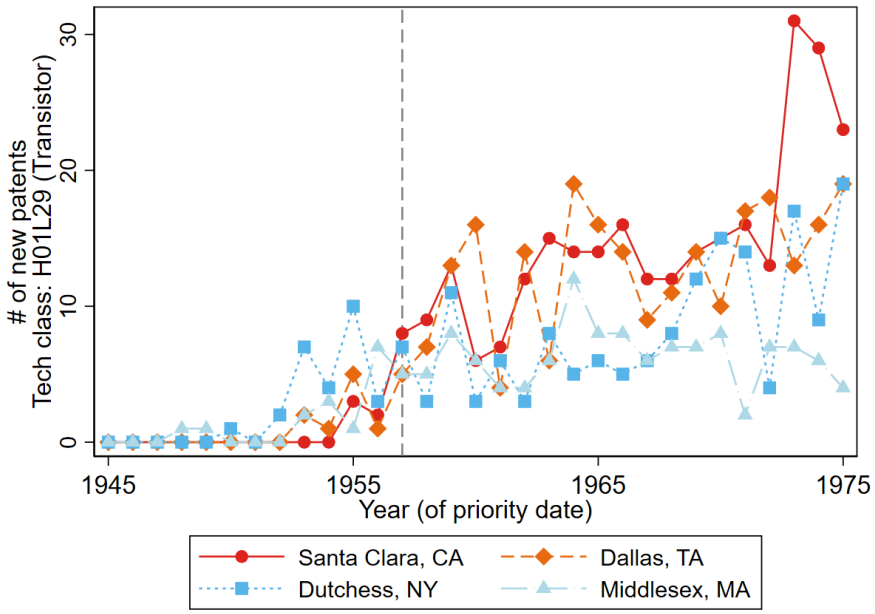
William Shockley, a Nobel laureate and a pioneer in solid-state physics, played a pivotal role in spawning the seed of future growth in Silicon Valley. In 1955, Shockley, along with a team of talented engineers, founded the Shockley Semiconductor division in Mountain View, California. His division attracted 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 coat 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

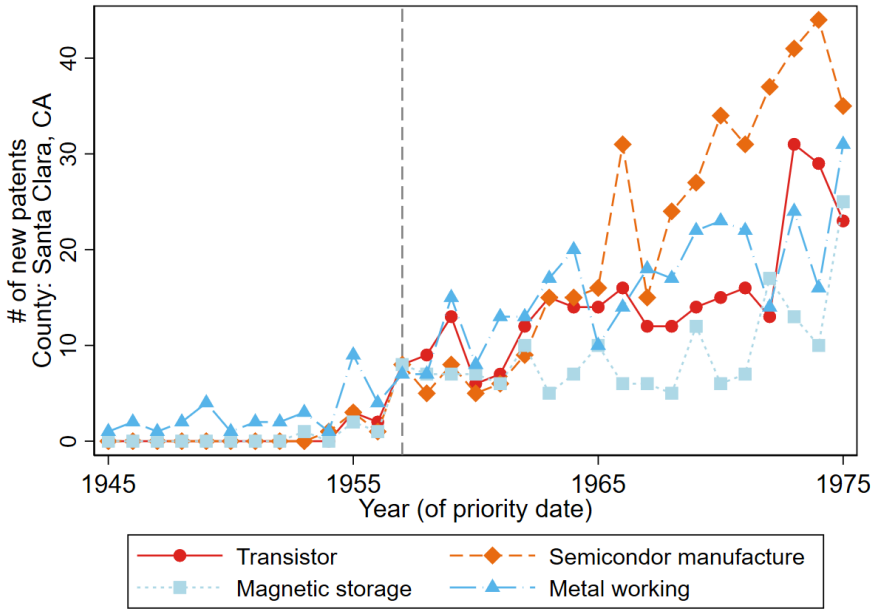
USPTO office and in July 1959, the breakthrough patent of microchip was filed by Robert Noyce (one of the eights) based on Hoerni's planar idea. The planar-microchip idea has been so pervasive in almost every segment of modern high-tech sectors ever since its invention to even today.

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 Proof for 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:

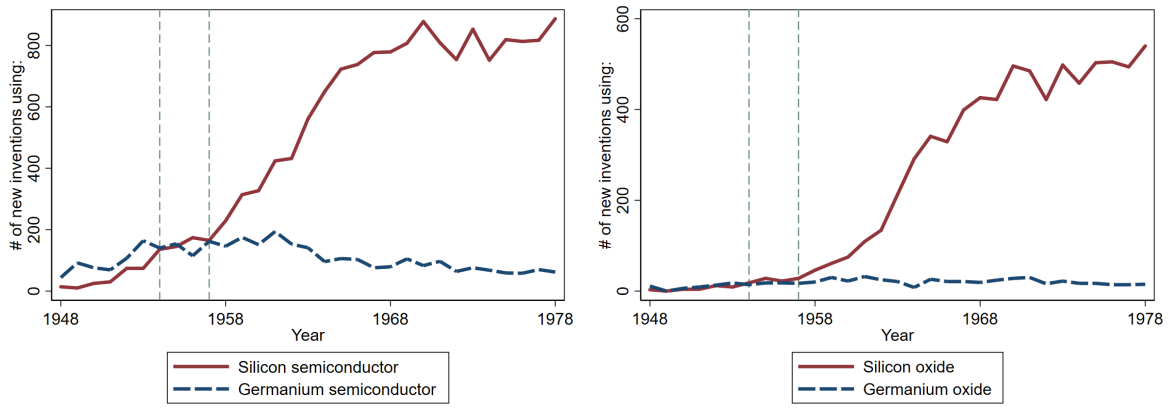
[1] Aerospace Navigation & Test [2] Amateur [3] Amplifiers [4] Antenna Accessories [5] Attenuators [6] Audio Frequency Test [7] Automatic Control [8] Batteries [9] Bio-Medical [10] Blowers & Cooling Fans [11] Bridges [12] Broadcast Receivers [13] Broadcast Transmitters [14] Cabinets, Consoles & Enclosures [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



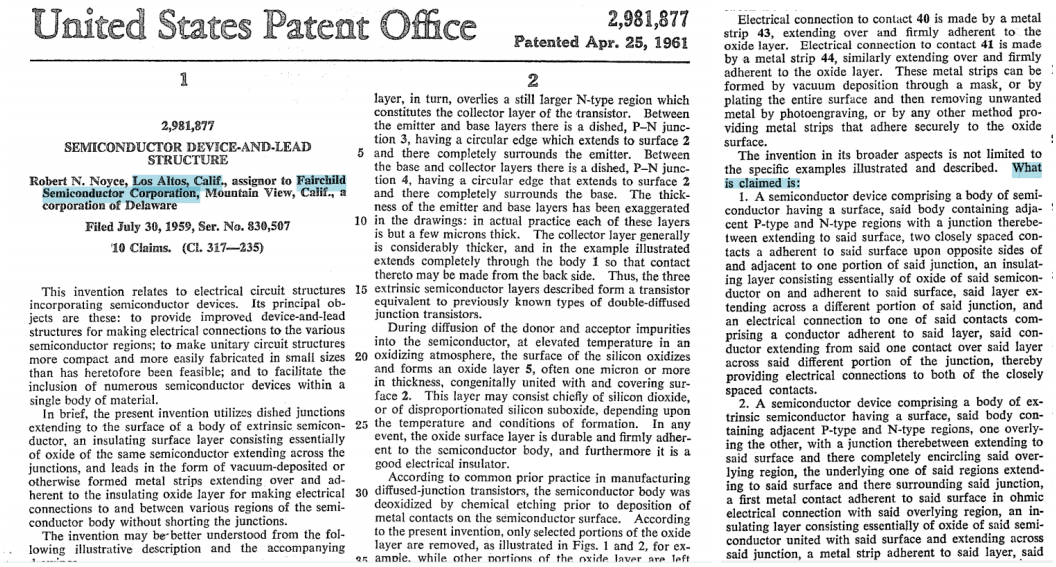
(a) Choice of Silicon v.s. Germanium (b) Oxide patents

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

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:

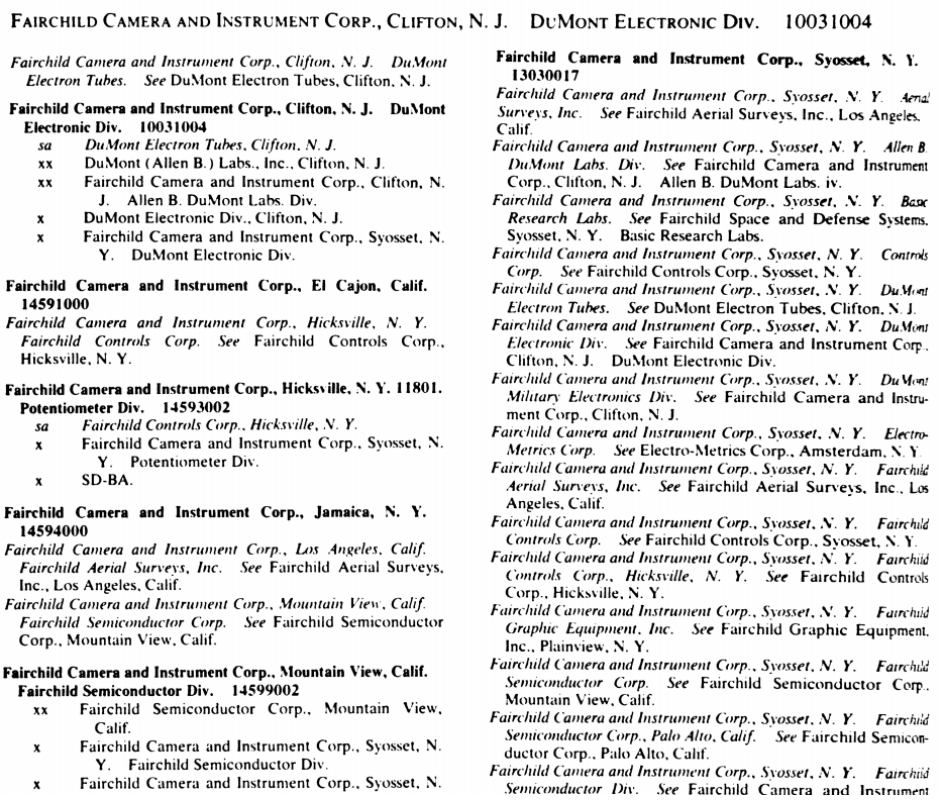
1. A semiconductor device comprising a body of semiconductor having a surface, said body containing adjacent P-type and N-type regions with a junction therebetween extending to said surface, two closely spaced contacts a adherent to said surface upon opposite sides of and adjacent to one portion of said 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

(a) Inventor location & assignee (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.

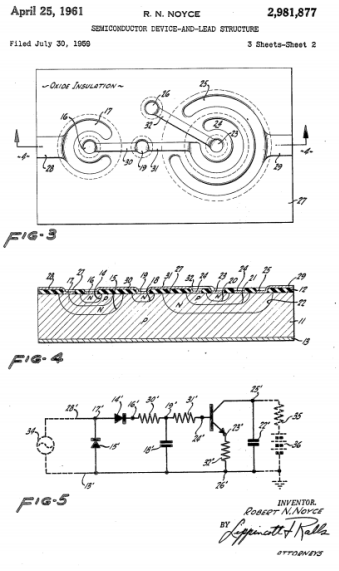
Fairchild Camera and Instrument Corp., Syosset, N. Y. 13030017
Fairchild Camera and Instrument Corp., Syosset, N. Y. Aerial Surveys, Inc. *See* Fairchild Aerial Surveys, Inc., Los Angeles, Calif.
Fairchild Camera and Instrument Corp., Syosset, N. Y. Allen B. DuMont Labs. Div. *See* Fairchild Camera and 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[19] 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

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-

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 herein-before 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.

[19]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.

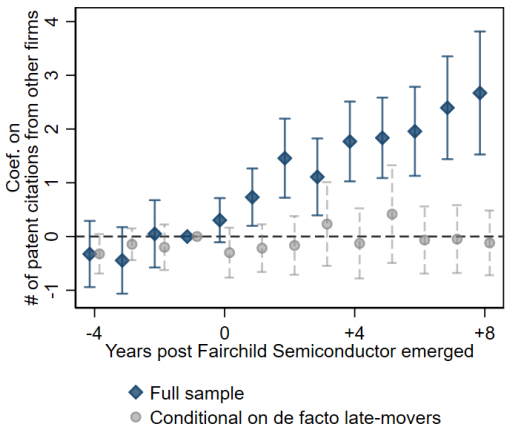
	Conditional on de facto late-movers in microchip:					
	(1) New patent flow	(2) Citation weighted new pat.	(3) Radical innovation	(4) Ordinary innovation	(5) Count of product lines	(6) New product manuals
Silicon × Post	0.057	0.998	0.067	-0.001	0.067	0.115
	(0.053)	(0.633)	(0.087)	(0.035)	(0.182)	(0.151)
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.

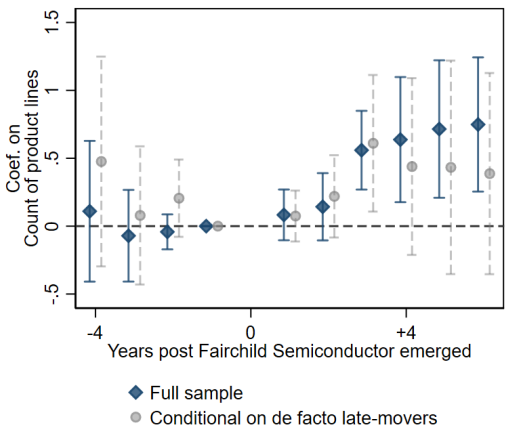
Table D.3: Falsification test on voluntary knowledge diffusion.

	Conditional on de facto late-movers in microchip:				
	(1) Release of fabric.	(2) Release of experim.	(3) Release of fabric. (residualized)	(4) Release of fabric. via face-to-face	(5) 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

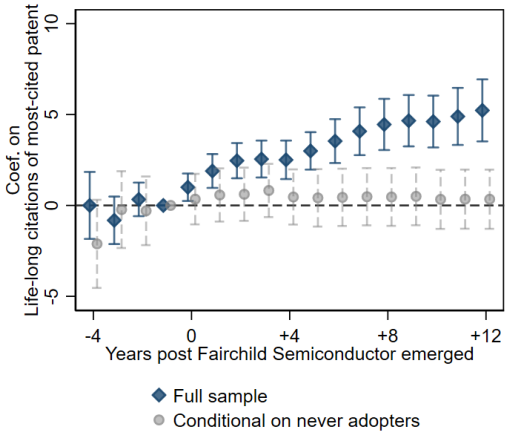
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. The sample consists only of "de facto late-mover" labs, defined as the labs which have never adopted microchip in the focal research field f, 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.



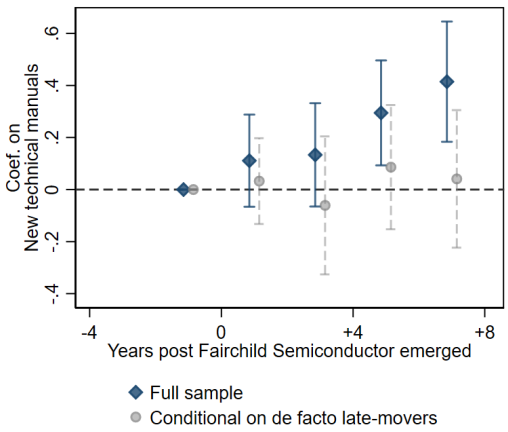
(a) New citations received



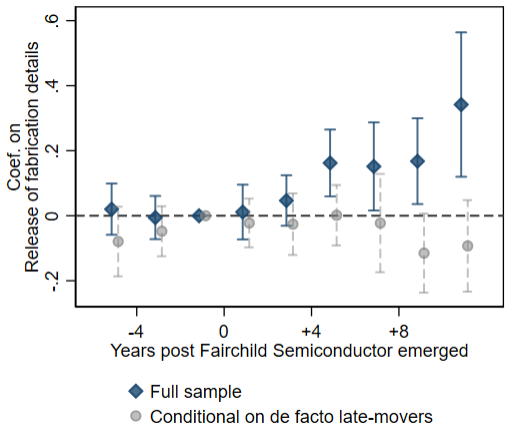
(b) Count of product lines



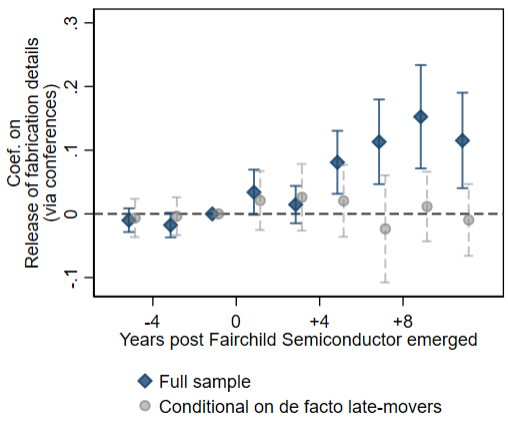
(c) Long-long citations of most cited patent



(d) New technical 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

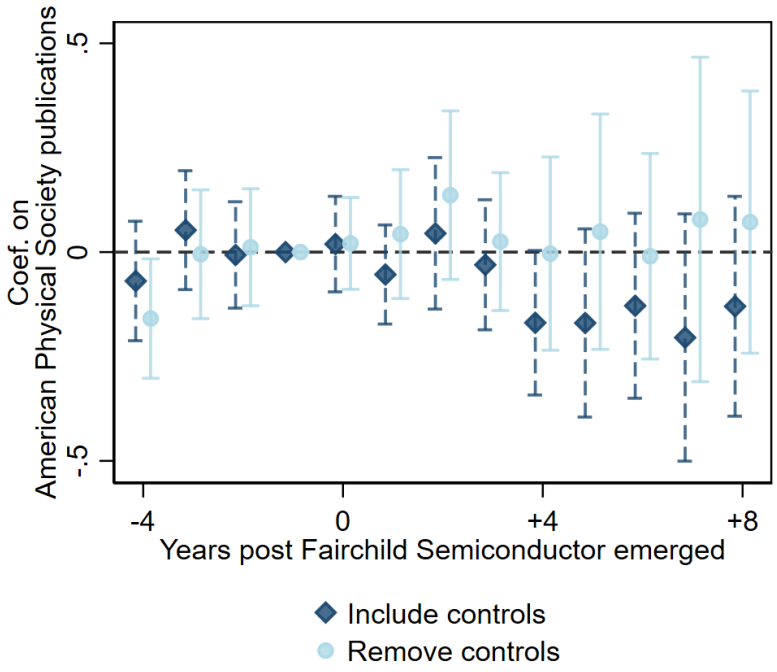
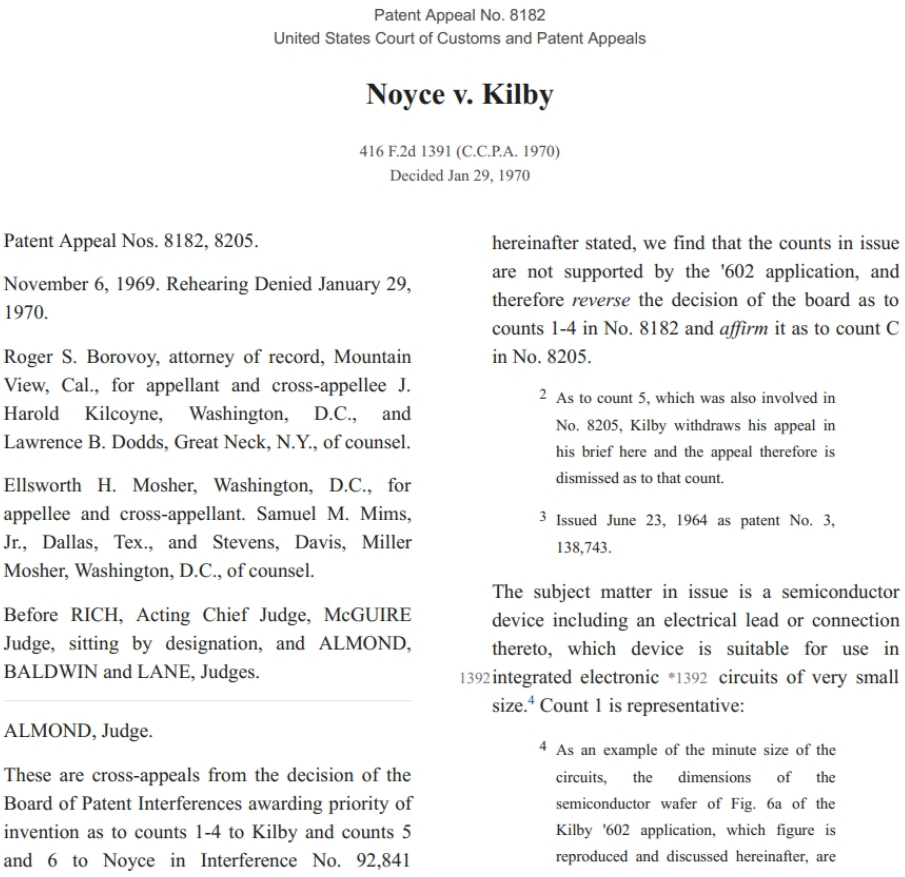


Figure D.2: Time-varying change of corporate basic research in Silicon and Germanium groups.

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.

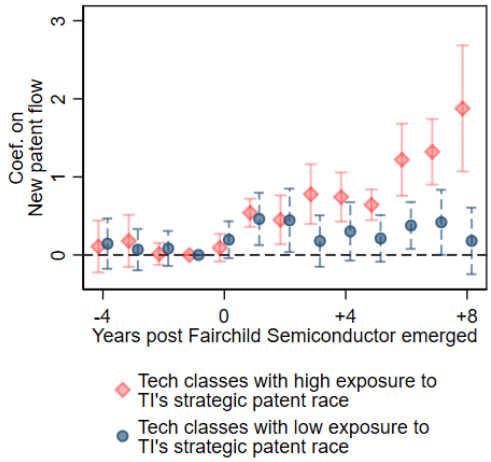
[3] Issued June 23, 1964 as patent No. 3, 138,743.

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:

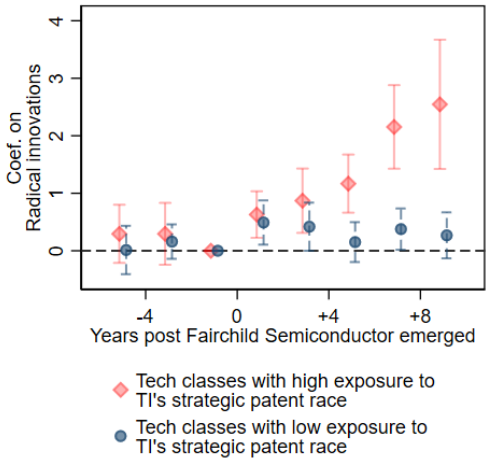
[4] As an example of the minute size of the circuits, the dimensions of the semiconductor wafer of Fig. 6a of the Kilby '602 application, which figure is reproduced and discussed hereinafter, are

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

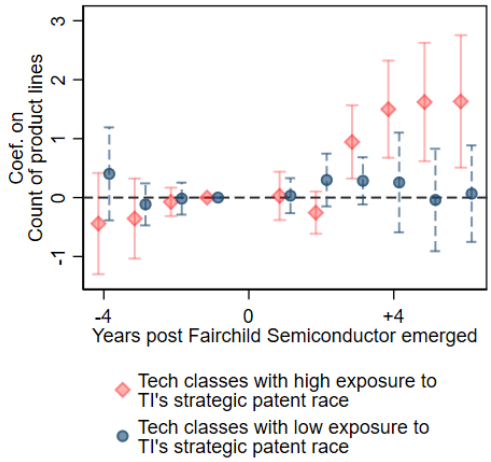
Note: Data source: Casetext.



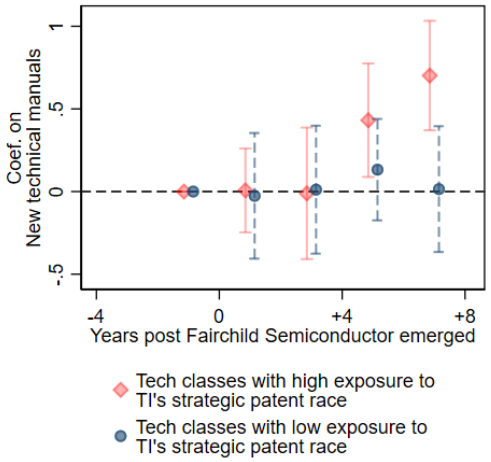
(a) New patent flow



(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.

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

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 × $\mathbb{1}\{1957 \leq \text{t} \leq 1961\}$	0.260**	0.306**	0.533*	-0.069
	(0.115)	(0.149)	(0.300)	(0.160)
Silicon × $\mathbb{1}\{1962 \leq \text{t} \leq 1965\}$	0.351**	0.442**	0.023	0.162
	(0.171)	(0.223)	(0.380)	(0.152)
Patent Race × Silicon × $\mathbb{1}\{1957 \leq \text{t} \leq 1961\}$	0.353***	0.332**	0.394**	0.210
	(0.085)	(0.136)	(0.165)	(0.155)
Patent Race × Silicon × $\mathbb{1}\{1962 \leq \text{t} \leq 1965\}$	1.210***	1.725***	1.261***	0.442**
	(0.189)	(0.275)	(0.448)	(0.201)
Patent Race×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×research field×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 × Silicon × Post, and Patent race × Year FE are included. Patent race × 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 (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.

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 × $\mathbb{1}\{1957 \leq t \leq 1961\}$	-0.033	0.010	0.192	-0.338***
	(0.114)	(0.039)	(0.243)	(0.124)
Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	0.046	0.011	-0.588*	-0.273**
	(0.225)	(0.051)	(0.301)	(0.124)
Litigation risk × Silicon × $\mathbb{1}\{1957 \leq t \leq 1961\}$	1.282***	0.202***	1.589***	1.470***
	(0.165)	(0.060)	(0.228)	(0.161)
Litigation risk × Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	3.592***	0.139**	4.084***	2.175***
	(0.422)	(0.057)	(0.726)	(0.236)
Litigation risk × 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 spillovers

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 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 2). "# 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

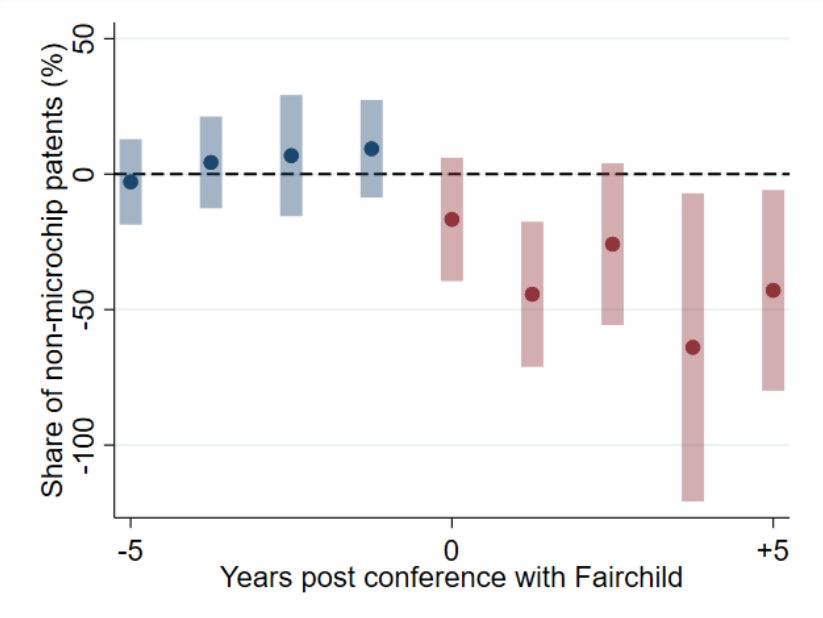


Figure D.5: Share of patents irrelevant to microchip after co-presenting work with Fairchild.

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. (re-sidualized)
Silicon × 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) New patent flow	(2) Radical innovation	(3) Count of product lines	(4) 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) New patent flow	(6) Radical innovation	(7) Count of product lines	(8) 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

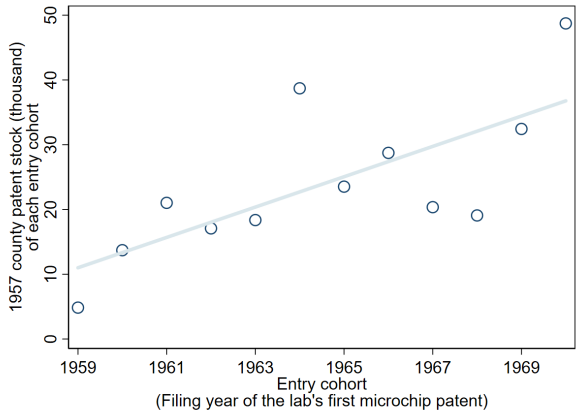
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Panel A checks if key estimates are sensitive to the exclusion of potential NASA (sub-)contractor labs from places with prime NASA contracts during 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

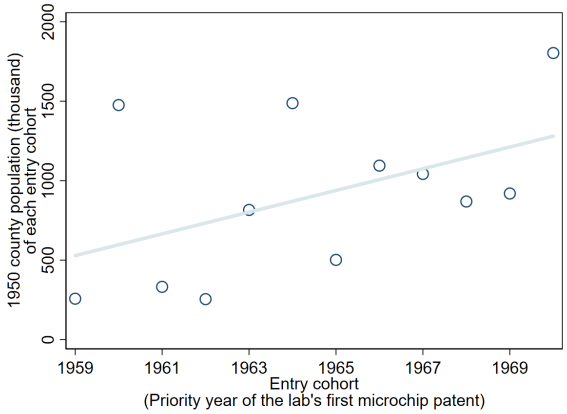
Table E.5: Heterogeneity to 1950 county population.

	(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

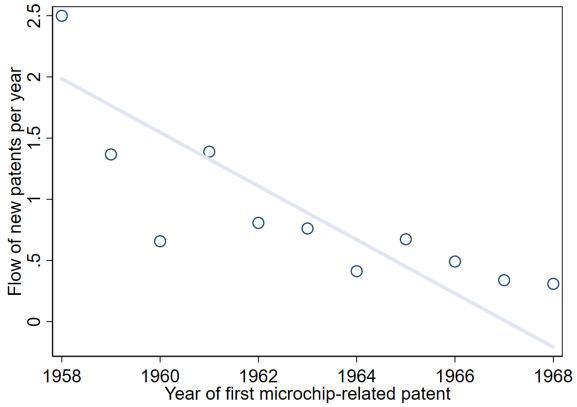
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the research field level. Each observation is a corporate lab×research field×year unit. Dependent variables are: count of new patents for each year in each lab×research field pair (columns (1) and (5)), count of radical innovations 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 × $\mathbb{1}\{1957 \leq t \leq 1961\}$	-0.015	-0.059	-0.011	-0.009
	(0.045)	(0.067)	(0.011)	(0.009)
Silicon × $\mathbb{1}\{1962 \leq t \leq 1965\}$	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.