PUBLIC R&D AND SPILLOVERS: EVIDENCE FROM THE SPACE RACE

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Geopolitical rivalry during the 1960s Space Race drove the world's two superpowers to make massive investments in spaceflight related technologies. This paper examines the impact of NASA's research and development efforts on the quantity and quality of space-related innovation. Combining the known universe of patent records with information on their federal reliance, along with a difference in differences design, I estimate that NASA-exposed fields increased their patenting relative to non-exposed fields, and that these patents were more impactful by citation metrics. These results are robust to removing NASA-related fields strongly related to concurrent defense spending. To explicitly account for the fact that technologies might have been selected by reasons other than achieving a Moon landing, I also produce estimates only using spaceflight-essential classes. To study the degree to which these results are driven by the reallocation of scientists and engineers, I use the inventor information in the patent documents to show that NASA-affiliated inventors obtained their first ever patents after joining NASA or obtaining a NASA contract, and not before.

I. INTRODUCTION

Technological innovation is one of the main drivers of increasing living standards and productivity growth. However, economic theory predicts that innovation will be undersupplied in a free market. A common policy lever to ensure the optimal supply of research and development (R&D) is government funding (Arrow, 1962). Despite this, there are few empirical studies of large public investments in R&D, especially in applied research (Gross and Sampat, 2022; Kantor and Whalley, 2022). A particularly understudied area about the impacts of these investments is their spillover potential in technology space. Despite not having ex-ante broad applicability, applied R&D investments in risky or untested fields can lead to novel uses of incipient technologies or create new influential fields altogether.

In this paper, I study one of the largest examples of government R&D funding and measure the extent to which it also generates externalities in technology space. In particular, I answer the following question: Did the creation of the National Aeronautics and Space Administration (NASA) increase the quantity, and more importantly, the quality of inventive output of the fields it was involved with?

I leverage the creation of NASA and its sizeable R&D funding during the Space Race—0.7% of GDP in 1966 and 35.9% of all federal R&D outlays (Office of Management and

Budget, 2021)—as a source of variation. Using a combination of administrative patent records and a novel historical patent dataset (Berkes, 2018), which includes the full text content of each patent, I compare changes in the quantity and quality of patenting in NASA-involved technology classes with changes in non NASA-involved technology classes, before and after NASA's creation. Relative to other government-funded fields, I find that NASA led to a 59.90% increase in spaceflight-related patenting, citations to these fields experienced a relative increase in citations of 72.27%, and that this impact extended beyond to non-spaceflight related fields.

Estimating the spillover effects of applied public R&D presents a causal identification challenge. A social planner will optimally invest in technologies that will yield the largest welfare returns, and can typically provide much larger funding than a specific private entity can.[1] The former will lead to selection bias, because treated fields are higher quality on average than control technologies. The latter will also bias estimates, because even within selected fields, higher R&D funding will typically yield a higher quantity and quality of patents.[2]

To circumvent these identification issues, I use a difference in differences design at the technology subclass level, where I compare NASA funded technologies to other government funded technologies. This setting and design have several desirable properties for identification. First, the timing of this funding was driven by the USSR's successful launch of Sputnik 1 in 1957, and the timing and decision for funding the Moonshot was largely a response to Yuri Gagarin's successful Earth orbit flight in 1961. Second, the selection of technologies invested in by NASA as the Mercury, Gemini, and Apollo programs developed was mission-driven, not driven by economic or spillover concerns. In essence, I argue that all comparison classes have ex-ante government interest, which is correlated with many sources of selection bias, except that treated classes experience a large excess funding that is driven by external geopolitical factors. To the degree that NASA invested in non-spaceflight related technologies, I also produce estimates using only fields that were ex-ante known to be directly related to achieving the Moon landing and find similar event study results. Due to the overlap between spaceflight technology and contemporaneous Department of Defense investments in rocketry, I show that my results are qualitatively similar when omitting ordnance and rocket related classes.

To understand the degree to which these effects are driven by the reallocation of inventive human capital, I use the inventor information in the patents to create an inventor-level panel dataset to observe NASA-affiliated scientists and engineers. Using this data, I observe whether they had generated patents before joining NASA or not, along with any changes in their pre and post-NASA fields of work. I find that the majority of NASA-affiliated engineers and scientists obtained their first patent after joining NASA, and not before,

[1] Despite the fact that corporate patents, foreign and domestic, have represented the largest share of US patents since the mid 1930s until today (Nicholas, 2010), at least 25% of US patents granted each year since 2005 have used some form of federal funding, with a peak of 30% in 2011. Corporate entities represent the majority of assignees in these federally funded patents (Fleming et al., 2019).

[2] This discussion omits a third source of bias: governments differentially over invest in basic science, which by definition has larger spillovers (Williams & Bryan, 2021). Therefore any estimate of public versus non-public innovation will overstate the difference. My main specifications only use publicly funded innovation, and given NASA's strong emphasis on applied science during Apollo, my estimates will, if anything, be attenuated by this bias.

which is congruent with the idea that the growth in spaceflight innovation during Apollo was not driven by the reallocation of existing inventors from other fields.

This article contributes to several strands of the innovation economics literature. First, it contributes to the broad literature on the drivers of technological innovation, with an emphasis on government investment as a policy lever (Arrow, 1962; Williams and Bryan, 2021). I contribute to a growing body of empirical case studies on government R&D programs using causal inference methods (Jacob and Lefgren, 2011; Howell, 2017; Azoulay et al., 2018; Gross and Sampat, 2022; Kantor and Whalley, 2022; Moretti et al., forthcoming) by studying one of the largest and most sudden government drives in technological spending in American history. While previous work has mostly focused on the effects of investing in basic science, this article adds to our understanding of how applied innovations can also create spillovers across technological space, even when their application is narrowly targeted.

By looking at non-NASA increases in patenting and subsequent citation patterns from non-government patents, this paper adds to the literature on private-sector responses to the government funding of innovation. Whether public R&D is a complement or a substitute to private R&D has been a longstanding empirical question in the economics of innovation literature (David et al., 2000). Theoretically, firm responses to public innovation efforts are ambiguous. On the one hand, firms can contract their supply of innovation, i.e., a crowding out effect. This could be the case if public demand exerts upwards pressure on the prices of R&D inputs (e.g., scientists and engineers, specialized facilities). In this instance, I find the opposite: government interest in spaceflight technologies resulted in further private sector innovation, a crowding in effect.

This result is congruent with recent work—Slavtchev and Wiederhold (2016) show that theoretically, a public demand shift towards technologically advanced goods increases private R&D by increasing the returns to innovation for the whole economy. Empirically, recent studies find that different forms of government investment in R&D spur further innovation from the private sector. Azoulay et al. (2018) link privately generated patents to scientific publications funded by the National Institutes of Health, and find that basic science funding leads to increased private patenting. Howell (2017) and Myers and Lanahan (2022) study Department of Energy research grants to small firms and conclude that the funding leads to increased patenting by grantees, and that these patents induce further downstream patenting by other firms. I complement this body of knowledge by showing that these crowding in effects also occur when the government invests in applied science, that they occur when the government specifies and directs the research agenda entirely, and that noticeably larger public R&D initiatives still exhibit these positive spillovers.

In related work, Gross and Sampat 2022 show that World War II government R&D investments in military technology through the Office of Scientific Research and Development helped shape the post-war direction and geographic distribution of innovation. By showing Space Race innovation effects persist even when omitting explicitly military classes, this article expands our understanding of the effects of these large innovation pushes beyond investments in military purposes (Moretti et al., forthcoming). Another advantage of the setting I study is that military inventions typically face high disclosure restrictions, which limit their spillover potential. As the civilian branch of the space effort, NASA's technology fields, while correlated with those of the Department of Defense, would have faced less restrictions and provide a setting where spillovers are allowed to develop naturally.

This paper complements previous and contemporaneous work on the effects of NASA on innovation and the economy more broadly. First, this paper is most similar, and can be seen as a direct successor to Jaffe et al. (1998), who look at federal agency patenting patterns through the years with an emphasis on NASA. They describe the spillovers of public R&D by looking at NASA's patenting behavior and the citations NASA patents have received over the decades. This paper builds on this conceptual question by exploiting the comprehensiveness, scope, and quality of patent data achieved in recent years due to computational advances, along with the development of causal inference methods in econometrics. In particular, their sample only allows for the study of patents assigned directly to NASA, and not those developed under contracts from NASA. Second, they can only observe these assignments starting in 1969, the year the Moon landing happened. The available data at the time only allowed researchers to observe citations made after 1977, the starting year for computerized records at the National Bureau of Economic Research (Hall et al., 2001), and well after the decline of NASA's budget post-Apollo. By combining datasets that leverage modern optical character recognition to identify citations and federal reliance for all years, along with a difference in differences design, this article can provide causal answers to the question Jaffe et al. posed two decades ago.

My work also complements Kantor and Whalley (2022), who study the geographic manufacturing growth effects of the Moonshot. Using Census of Manufactures data, they create a continuous measure of county-level spaceflight specialization and produce difference in differences estimates of manufacturing value added, employment, and other outcomes on local specialization. Using a market access approach derived from Donaldson and Hornbeck's (2016) county to county trade model, they argue that NASA also produced market-wide effects on manufacturing outcomes during the Space Race. They posit that local productivity spillovers are a possible driver of positive market-wide effects. By looking directly at innovation outcomes and looking at comparisons in technological as opposed to geographic space, the present article allows us to dissect one channel through which spillovers of the Space Race happened in ways beyond localized effects—through knowledge production directly.

Section II discusses the timeline of the Space Race, NASA's creation and funding, technology selection, and its contracting and patenting policies. Section III details data sources and key variables, Section IV discusses the empirical framework and identification. Section V discusses the results and Section VI concludes.

II. CONTEXT

II.A. Towards a Moon Landing

On October 4th 1957, the Soviet Union successfully launched the first artificial satellite, Sputnik I. A month later on November 3rd, the USSR launched Sputnik II, delivering a satellite weighing a hundred times more[3] than Sputnik I and containing the first living being in orbit, the dog Laika. In an attempt to respond, the United States launched the Vanguard TV-3 satellite, which immediately failed and exploded. These events over perceived American technological inferiority triggered the Sputnik Crisis, and led to the Eisenhower administration to create the National Aeronautics and Space Administration in 1958 (U.S. House of Representatives, 1958).

As early as 1959, discussions around achieving a lunar landing were taking place at various NASA facilities, particularly within the Research Steering Committee on Manned Space Flight, also known as the Goett Committee. Tasked with conceptualizing NASA's long term mission plans, members Maxime Faget from the Langley Research Center's Space Task Group[4] and George M. Low from the Lewis Research Center[5] urged the committee to conclude that a Moon landing should be the agency's post-Mercury goal. However, predicting that the political support for such vast spending wouldn't be there,[6] Abe Silverstein, Chief of Space Flight Programs, and T. Keith Glennan, NASA Administrator, concluded that NASA could not commit to any long term plans beyond Mercury (Brooks et al., 1979; Murray and Cox, 2004). Eventually, the Apollo program was announced in July 1960, with a reduced goal of a manned flight around the moon.

By late 1960, Low recommended the creation of a committee at the Lewis Research Center that would carry out preliminary feasibility studies for Apollo, with a particular goal of devising the requirements and options for achieving a lunar landing.[7] The resulting Manned Lunar Landing Task Group (or Low Committee) concluded in a February 7th, 1961 report that, given the required financial support, the agency had the technical capacity to achieve an Earth orbital flight by 1965, lunar orbit by 1967, and a Moon landing between 1968 and 1971 (Low, 1961; Low, 1999; Arrighi, 2019). These technical assessments aligned with opinions surveyed by the House Select Committee on Astronautics and Space Exploration in 1959, whose interviewed experts, including Wernher von Braun, predicted that circumlunar flights would be technically possible by the end of the next decade, with manned landings "a few years thereafter" (U.S. House of Representatives, 1959, p.4).

[3]Sputnik I weighed 184 pounds, while Sputnik II weighed around 17,200 pounds. Vanguard TV-3 weighed 3.3 pounds (Murray & Cox, 2004).

[4]NASA Langley, located in Hampton, Virginia, was the home of NASA's precursor agency, the National Advisory Committee for Aeronautics (N.A.C.A.) and the headquarters of the manned space program until November of 1961, when the Manned Spacecraft Center (MSC, now the Johnson Space Center) was established in Houston, Texas (Uri, 2021). The Space Task Group at Langley was in charge of managing the manned spaceflight program, starting with Project Mercury. Faget is credited with designing the Mercury capsule (US Patents 3,001,739; 3,093,346; and 3,270,908). He served as Director of Engineering and Development at the Manned Spacecraft Center from 1962 to 1981 (Allen, 2017).

[5]Lewis, in Brook Park, Ohio, now known was the John H. Glenn Research Center at Lewis Field, was another inherited facility from the N.A.C.A. (Keeter, 2017). Low was an aeronautical engineer at Lewis, Deputy Center Director at the MSC, and then NASA Deputy and Acting Administrator (Arrighi, 2019).

[6]"At 10:00 o'clock, I talked with Dr. Kistiakowsky about our budget. I found him resigned to the inevitable - that President Eisenhower is going to balance the budget, come hell or high water." (Glennan, 1993, Chapter 12).

[7]"This group will endeavor to establish ground rules for manned lunar landing missions, to determine reasonable spacecraft weights, to specify launch vehicle requirements, and to prepare an integrated development plan including the spacecraft, lunar landing and take-off systems, and launch vehicles. This plan should include a time phasing and funding picture and should identify areas requiring early studies by field organizations." - Memorandum for Director of Space Flight Programs Subject: Manned Lunar Landing Program, George M. Low (Low, 1999, Chapter 13).

President John F. Kennedy, who had been inaugurated a week before the Low Committee's report was presented, commissioned an advisory committee led by Jerome B. Wiesner[8] to assess the space program. The resulting report suggested a potential cancellation of Project Mercury, or at a minimum, to cease advertising Mercury as the United States' major space objective, as any failures would be blamed on the incoming administration, and to focus on unmanned space activities (Wiesner Committee, 1961). The resulting appointment of Wiesner as President Kennedy's Special Assistant for Science and Technology cast doubt on the administration's overall stance regarding the manned space program.

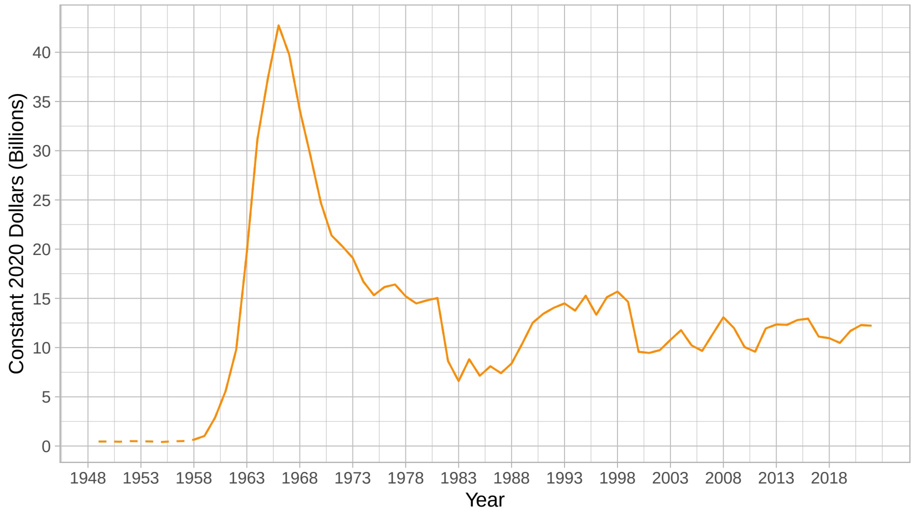
On Wednesday, April 12, 1961, the Soviet Union achieved its second major milestone over the American space program by placing cosmonaut Yuri Alekseyevich Gagarin in orbit. Gagarin's approximately two hour flight launched from the Baikonur Cosmodrome in Kazakhstan, passed over Kamchatka, Russia, the Pacific Ocean north of Hawaii, southeast over the tip of South America, the Atlantic, then entered Africa over Angola and left above Egypt, finally landing near the city of Engels, Saratov Oblast, Russia (European Space Agency, 2011).[9] Two days later, Kennedy, along with speechwriter and adviser Theodore Sorensen, summoned Jerome Wiesner, NASA Administrator James Webb, Deputy Administrator Hugh Dryden, and Director of the Office of Management and Budget David E. Bell, to discuss where could the United States achieve a "first" in space. By NASA's projections, the USSR would be first in crewed orbital flights, orbital space stations, and circumlunar flights. Given Low's previous feasibility studies, Dryden remarked that manned lunar landings would require further technology developments that could potentially achieved first, but it would take a scientific and funding effort akin to the Manhattan Project. After the meeting, Sorensen confided off the record to Life Magazine correspondent Hugh Sidey, who was present, that they were going to the Moon (Sidey, 1994, Murray and Cox, 2004).

Soon after, President Kennedy addressed a Joint Session of Congress, publicly stating that "this nation should commit itself to achieving the goal, before this decade is out, of landing a man on the Moon and returning him safely to the Earth" (Kennedy, 1961). What followed was a sharp increase in NASA's total budget and R&D outlays (Figure 1), and a rapid expansion in planning, contracting, and facility construction. Detailed hardware specifications and requests for contractor proposals had been completed by July (Murray & Cox, 2004). The first contract, for the design and prototyping of the Apollo Guidance Computer, was issued to the Instrumentation Laboratory at M.I.T. on August 9th, 1961 (Brooks et al., 1979). By September, land acquisition and planning for the Kennedy Space Center at Merritt Island, Florida, the Michoud Assembly Facility in Michoud, Louisiana, and the Manned Spacecraft Center in Houston (Dunbar, 2017; Mohon, 2008; Uri, 2021) were underway. By the mid-1960s, NASA's R&D outlays represented 35.9% of all federal R&D expenditure (Figure 2).

[8] Wiesner was the head of the Department of Electrical Engineering at the Massachusetts Institute of Technology (M.I.T.) and a member of the President's Science Advisory Committee during the Eisenhower administration (M.I.T. Libraries, 2005).

[9] The United States achieved its first orbital flight on the Mercury-Atlas 6 mission nearly a year later on February 20th, 1962, where astronaut John H. Glenn completed three orbits in under five hours. During his three passes on Friendship 7, Glenn flew over most of Africa, Australia, Hawaii, northern Mexico, the southern United States, and landed near the Bahamas (Uri, 2022; NASA, 1962).

Figure 1: NASA R&D Outlays, 1960-2022



Source: Calculated from the Office of Management and Budget's (2021) Historical Tables and deflated using the CPI-U (Bureau of Labor Statistics, 2023). Dashed pre-1958 values represent the N.A.C.A. budget.

II.B. NASA's Contracting and Patenting Policy

In order to obtain the necessary ingredients for a Moon landing within the decade, a key aspect of NASA's approach was to leverage private research and development and manufacturing capacity where possible. For example, the Saturn V rocket involved contracts with North American Aviation and its Rocketdyne division, Douglas Aviation, Boeing, and International Business Machines (IBM).[10]

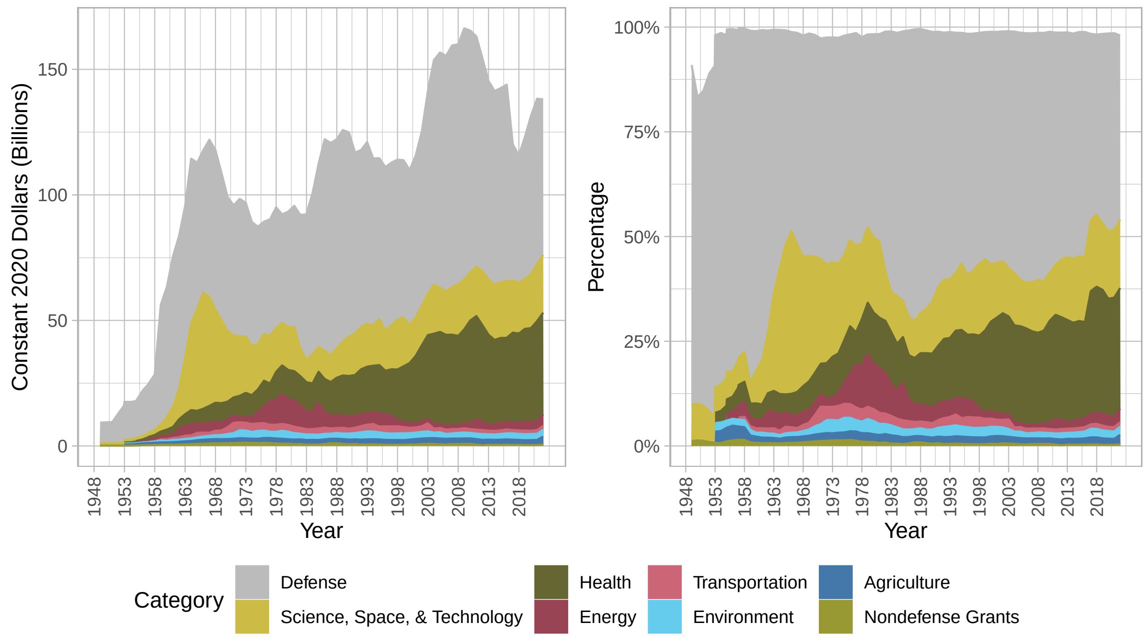
This public-private relationship in procurement and contracting for R&D has roots in the Department of Defense's (DOD) source evaluation procedure, which NASA adopted and modified, initially working with cost-plus-fixed-fee contracts and fixed-cost contracts post-1963 (Rosholt, 1966). Unlike the DOD, however, Section 305[11] of the Space Act allowed NASA to take title to all inventions produced while performing an R&D contract.[12] This right could be waived by the NASA Administrator and the Inventions and Contributions Board, leaving the contractor as the assignee of the resulting patents and giving the U.S.

[10]For a listing of major system contractors for Project Mercury, see Grimwood (1963), Appendix 9. For Project Gemini, see Grimwood et al. (1968), Appendix 7. For the Apollo program, see Ertel and Morse (1969), Appendix 3 for principal contractors from August 1961 to November 1962, Morse and Bays (1973), Appendix 3 for contractors from November 1962 to September 1964, Brooks and Ertel (1973), Appendix 3 from October 1964 to January 1966, and Ertel et al. (1978), Appendix 2 for those from January 1966 to July 1974. These listings do not account for subcontracts or smaller direct contracts.

[11]For a detailed legislative history of NASA patent policy and debates over Space Act sections relating to patenting (i.e., Section 203, Section 305, and Section 306), see Watson and Holman (1966) with an emphasis on Appendix A (written by Aaronson, 1966), Rosholt (1966), and Kraemer (1999).

[12]Department of Defense contracts followed this second policy, while Section 305 was modeled after Atomic Energy Commission policy since NASA was deemed to be more similar in nature to the AEC than the DOD. However, in practice the NACA's patent policies were more similar to the DOD's and NASA had a larger contractor and technological overlap with the DOD (Rosholt, 1966).

Figure 2: Federal R&D Outlays, 1948-2022



Source: Calculated from the Office of Management and Budget's (2021) Historical Tables. Outlays under "Other" category not plotted. The following lists the agencies included in each category by the Office of Management and Budget. Defense: Department of Defense & Other; Health: Science, Space and Technology: NASA, NSF, AEC General Science; Health: NIH & Other; Energy: DOE; Transportation: NASA Transportation, DOT; Environment, Agriculture and Nondefense Grants not specified.

Government a royalty-free license to use the invention.[13] Watson and Holman (1966) look at all NASA contractor waiver applications up to December of 1965 and estimate that 88% of waiver applications were granted. Even when not waived, industrial contractors typically had royalty-free, non-exclusive licenses upon coming up with an invention, conditional on bringing the invention to market (Kraemer, 1999).

These title (NASA owned) and waiver (contractor owned) patent policies did not preclude third parties from leveraging these technologies commercially. NASA owned patents can be licensed from its technology transfer programs for private sector use, and if waiver patent owners have not used their invention commercially, NASA can use its march-in rights[14] to force patent owners to license an agency-funded technology (Watson & Holman, 1966).

[13] Inventions from NASA employees follow a similar policy, where the U.S. Government by default claims title to all of their inventions, but employees can request title to their inventions (Watson & Holman, 1966).

[14] March-in rights allow the government to require the patent owning contractors to grant licenses to third parties, even when the current patent assignee refuses. NASA already had march-in rights to its funded inventions held by contractors, but the Bayh-Dole Act of 1980 extended this power to all federal agencies (Thomas, 2016).

Given the cutting edge nature of NASA's mission—Apollo represented some of the earliest applications of integrated circuits and electronic and digital fly-by-wire systems—, and the sizable funding it received during the Apollo era, quantifying the spillovers of this technology has been an open question since the agency's inception (Watson and Holman, 1966; Ginzberg et al., 1976; Jaffe et al., 1998). Since 1976, the Technology Utilization Office has published a yearly report detailing commercially licensed products that have spunoff from NASA-funded technologies. In earlier reports, NASA claimed successful spillovers in diverse fields including satellite weather forecasting and communications, integrated circuits and computing, water purification, medical imaging, food processing, and materials such as memory foam and blow rubber molding[15] (Ruzic, 1976).

Of note is NASA's co-occurrence with the birth of the integrated circuit. The Apollo Guidance Computer (AGC), developed at M.I.T.'s Instrumentation Lab, was one of the first real life, high stakes applications of integrated circuits at a time transistors were the main computational technology.[16] In the early 1960s, aerospace hardware ranging from navigation electronics to military radar was mainly analog. While the AGC is archaic by modern standards, "the exclusive use of integrated circuits in the processor ushered in a new era of computing, the novel memory design stored large amounts of data in a small space, and the human interface allowed real-time interaction with software" (O'Brien, 2010, p.xiii)—all features familiar to the modern computer user.

Ginzberg et al. (1976) argue that one of the drivers of the growth in integrated circuits and semiconductors was assured demand from the government, as space and defense accounted for between 25% to 48% of their production between 1955 and 1968. Between 1954 and 1963, this sector also consumed between 32% to 100% of US computer and computer service production. Given the emphasis on performance over cost in NASA and Department of Defense requests for integrated circuits and their derivatives, this assured demand is argued to have not only decreased production costs but also increased the reliability of these unproven components over time. Table 1 shows the total production and average prices of integrated circuits throughout the 1960s.

The 1960s growth in computing is also reflected in educational supply and human capital decisions. The first computer science department in the United States was created at Purdue University in 1962, and enrollments in computer science departments soon grew thereafter as shown in Figure 3.

[15] Marion Franklin Rudy, who worked on NASA projects for Lockheed and Rockwell International in the 1960s, adapted this technology to create small air membranes in shoe soles (US Patent Nos. 4,183,156 and 4,219,945). He partnered with Nike to commercialize it, creating the Nike Air shoe.

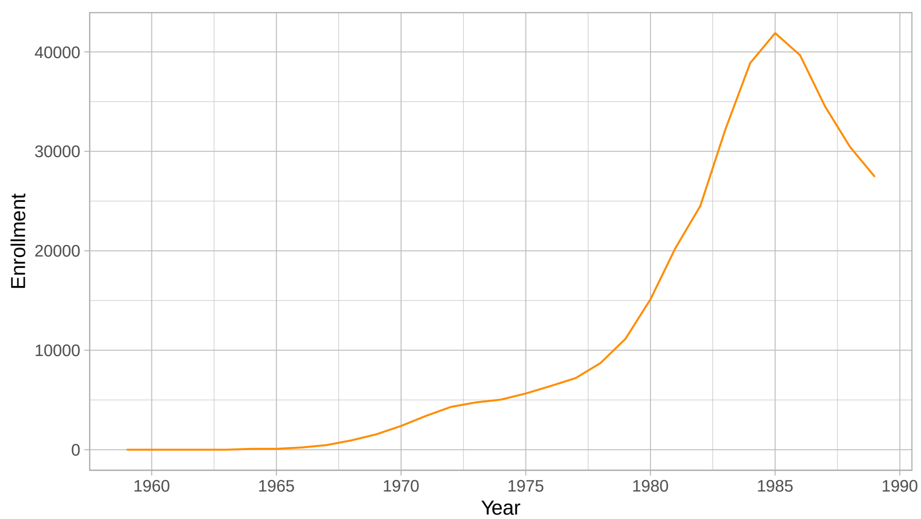
[16] For a painstaking walkthrough of the inner workings of the AGC and its development history from a computer science perspective, see O'Brien (2010).

Table 1: US Integrated Circuit Production and Prices

Year	Production (Millions of Dollars)	Avg. Price per IC (Dollars)
1962	4	50.00
1963	16	31.00
1964	41	18.50
1965	79	8.33
1966	148	5.05
1967	228	3.32
1968	312	2.33

Note: Reproduced from Ginzberg et al. (1976), Table 2-3, p.59.

Figure 3: US Computer Science Bachelor's Enrollments, 1959-1990



Note: Data from Snyder (1993).

III. DATA

This study draws data from several sources. First, I use the United States Patent and Trademark Office's (USPTO) administrative file on the universe of recorded patents (Marco et al., 2015). This dataset contains identifiers for all registered patents from 1836 onwards, along with technology classes and associated dates. Because this dataset does not contain many other variables one would require to study patenting behavior, I also use the Comprehensive Universe of U.S. Patents dataset (CUSP), a novel and private dataset constructed by Berkes (2018) which is currently considered to be the gold standard historical patent dataset in terms of scope of variables included and completeness (Andrews, 2021). These records are constructed from high quality, optical character recognized scans of the patents themselves, from which key variables such as inventor, assignee, location, previous patents cited, and more are drawn from. The dataset also contains the full text of each patent's claims. Figure

4 shows an example patent, along with the information that can be gleaned from this file.

To identify NASA-involved inventions, I combine this information with federal agency reliance data from Fleming et al. (2019), who also use the patent full text to infer the degree of federal agency involvement in the production of all patents from 1926 to 2017. Specifically, they define two sources of direct federal reliance. If the patent was produced by a NASA employee, the patent would be assigned to NASA[17] (see Figure 4 for an example). Further, if work from a NASA contract resulted in a patent, the patent's claims would start with a reference to said contract work, even if assigned to a private firm (Figure 5). The data further identifies patents that indirectly rely on NASA funding by determining whether the patent cites non-patent literature (e.g., scientific journal articles) that was funded by NASA. For purposes of this paper, a patent's NASA reliance is defined by being produced directly by NASA or originating from a NASA contract.[18]

Figure 4: Example U.S. Patent

United States Patent [19]
Shepard et al.

[11] **3,751,727**
[45] **Aug. 14, 1973**

[54] **SPACE SUIT**

[75] Inventors: **Leonard F. Shepard; George P. Durney; Melvin C. Case; A. J. Kenneway, III; Robert C. Wise; Dixie Rinehart,** all of Dover; **Ronald J. Bessette,** Wyoming; **Richard C. Pulling,** Dover, all of Del.

[73] Assignee: **Granted to The United States National Aeronautics and Space Administration Under The Provisions of 42 U.S.C. 2457,** Washington, D.C.

[22] Filed: **Aug. 5, 1968**

[21] Appl. No.: **750,031**

[52] **U.S. Cl.** .... **2/2.1 A, 2/81, 128/1 A**
[51] **Int. Cl.** **A62b 17/00**
[58] **Field of Search** .... 2/2, 2.1, 2.1 A, 2/6, 3, 81; 128/2.06, 2.05, 2.1, 283, 1.01, 142, 2.95, 285, 1 A

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Primary Examiner—Jordan Franklin
Assistant Examiner—George H. Krizmanich
Attorney—Leonard Rawicz, Neil B. Siegel and Marvin F. Matthews

[57] **ABSTRACT**

Disclosed is a pressure suit for high altitude flights and particularly space missions. The suit is designed for astronauts in the Apollo Space Program and may be worn both inside and outside a space vehicle, as well as on the lunar surface. It comprises an integrated assembly of inner comfort liner, intermediate pressure garment, and outer thermal protective garment with removable helmet and gloves. The pressure garment comprises an inner convoluted sealing bladder and outer fabric restraint to which are attached a plurality of cable restraint assemblies. It provides versitility in combination with improved sealing and increased mobility for internal pressures suitable for life support in the near vacuum of outer space.

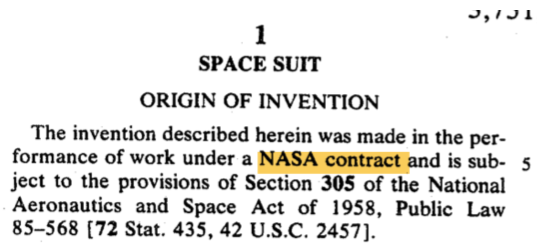
11 Claims, 25 Drawing Figures

The main unit of most analyses in this paper is the USPC technology subclass. The

[17] Patents always have inventors, who are individuals (35 U.S.C. 100(f), 2021), but they can also have assignees, which can be companies or other organizations, to whom ownership of the patent is transferred.

[18] To verify the extent of mistaken NASA attribution in the Fleming et al. (2019) data, I hand inspect the original patent scans for 200 randomly drawn patents and find they are all funded by NASA.

Figure 5: NASA Contract Mention in Patent Text



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SPACE SUIT

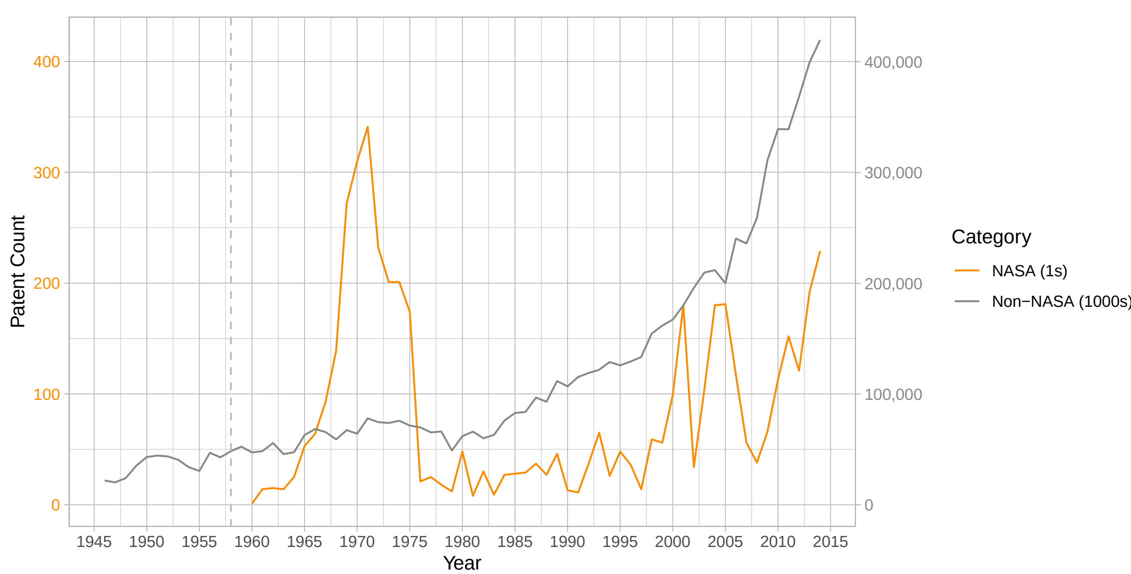
ORIGIN OF INVENTION

The invention described herein was made in the performance of work under a NASA contract and is subject to the provisions of Section 305 of the National Aeronautics and Space Act of 1958, Public Law 85–568 [72 Stat. 435, 42 U.S.C. 2457].

USPC classification scheme[19] is one of many systems used for patent classification. It has a hierarchical construction, with around 500 classes at the broadest level and 150,000 narrow classes or subclasses. For the purposes of this paper, "broad class" will refer to the former, while "narrow class" or "subclass" will refer to the latter[20]. A patent can have several classes, however, the first code is chosen to capture the main contribution of the invention. Figure 4, for example, shows Patent 3,751,727 as being in class 2, subclass 2.1 A, class 2 subclass 81, and class 128 subclass 1 A, with 2/2.1 representing "Apparel; astronaut's body cover", while 2/81 represents "Apparel; heat resistant". Classes are assigned by the patent examiner, who is a domain expert at the USPTO, and patents are reassigned as new classes are created. This implies that class and subclass assignments are internally consistent for all patents for data queried from internal USPTO records at a given point in time.

Figure 6 shows NASA and non-NASA patent counts at the individual patent level, where the non-NASA counts have been scaled. NASA patents increased sharply from its inception through the Mercury, Gemini, and Apollo eras, largely mimicking the budget shares in Figure 1 in that early period.

Figure 6: NASA and Non-NASA Patent Counts, 1960-2019



[19]USPC codes are constructed similarly to Journal of Economic Literature codes. There are other patent classification schemes, such as the Cooperative Patent Classification (CPC).

[20]"Class" will be used more generally, or where the distinction between broad and narrow class does not affect interpretation.

As expected, NASA's technology portfolio largely consists of patents in spaceflight-related fields. Among broad classes, measuring and testing and aeronautics and astronautics are the main fields of invention (Figure 7), while at the narrow class level five out of NASA's top subclasses are related to spacecraft or aerodynamics (Figure 8).

Figure 7: Top NASA Broad Classes

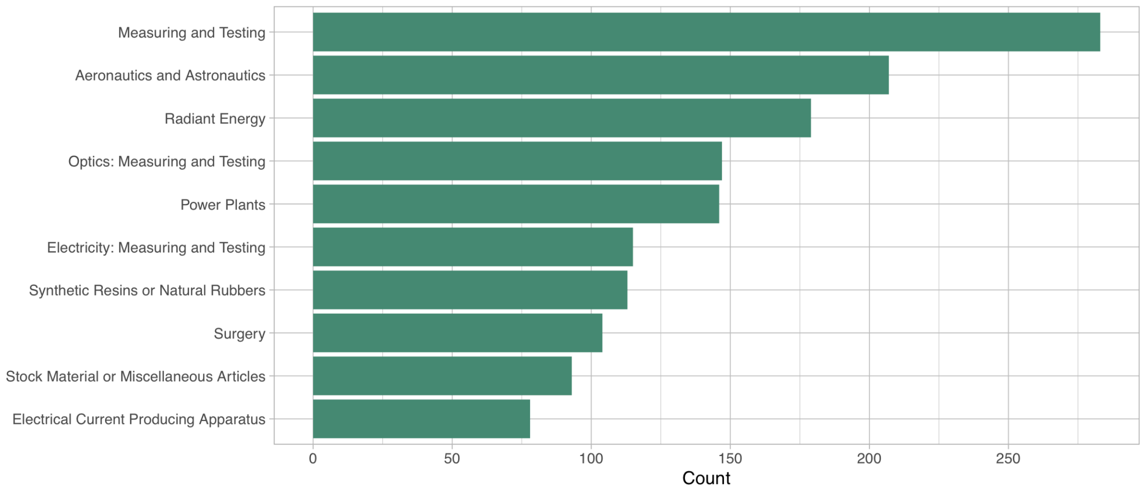
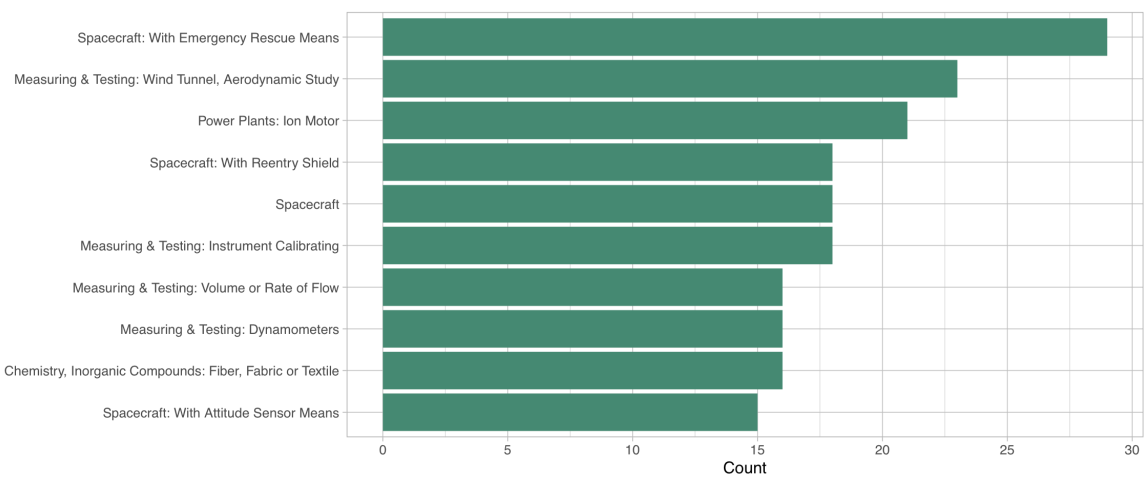


Figure 8: Top NASA Narrow Classes



The main empirical analysis focuses on a subclass-by-year panel dataset from 1948, starting ten years prior to NASA's creation and after World War II,[21] and ending in 1980, around a decade after the end of the Apollo program. The main outcomes of interest are patent counts and patent citations at the subclass-year level. Citations to a class can be measured in different ways, which merits discussion. Broadly, they can be construed as a measure of impact or influence, much like academic article citations. First, prior art citations are furnished by the inventor and their attorney at the moment of application to the USPTO. Afterwards, the patent examiner will observe the list and assign further prior patents deemed necessary.

[21]The post-war period appears to be a natural point to start the analysis, given the existence of both wartime disruptions and accelerations of innovation (Gross & Sampat, 2022).

Patent forward citations[22] have been found to correlate strongly to alternative measures of novelty, both scientific and economic. For the former, patents correlate strongly to natural language processing-based metrics where the full text of a patent's claims is compared to patents past and patents future. In this framework, patents are defined to be breakthroughs when they have a large text dissimilarity with previous patents and a large text similarity with future patents (Kelly et al., 2021). For the latter, (Kogan et al., 2017) develop a novel measure of stock market responses for publicly traded firms that receive new patents and find that this measure correlates with that patent's forward citations as well.

Using the citation network embedded in the patent-level data, I construct different measures of citations that reflect different aspects of a given subclass' future impact. First, I define a measure of yearly citations received, which I refer to as "citations per year". This is the number of citations made towards a given subclass in each year. Second, I define the sum of all citations made to patents issued in a given subclass in a specific year as "lifetime citations". Broadly, the former reflects overall interest in a given subclass in a given year. If citations per year are high for a subclass-year combination, it implies that inventive activity in that year expressed reliance on that given subclass. Lifetime citations on the other hand reflect the fact that inventions generated in some years are disproportionately influential.

Additionally, I create leave-one-out measures of these metrics by omitting citations made from one subclass to the same subclass to observe broader impact of a technology, and omit NASA patent to NASA patent citations to account for self-citing behavior.

Because the number of citations to a subclass is correlated with both the age and number of patents in it, and patenting behavior changes over the years, I also create versions of these measures where I only count citations within a fixed 20-year window of time, and I use time fixed effects throughout my estimations.

To set a baseline comparison, Table 2 shows a difference in means between NASA and non-NASA patents' lifetime citations for all patents issued after 1958. While the average post-1958 non-NASA patent has 10.816 citations over their lifetime, NASA patents have around 3.946 more lifetime citations. This holds when controlling for technology subclass and issue year fixed effects—the former adjusting for the fact that some technology classes have higher impact regardless of year, and the latter for the fact that citation behavior changes over time for all classes.

[22] For a given pair of patents A and B where B cites A, we can define the forward citation as A having a forward citation from B. Alternatively, B backwardly cites A.

Table 2: Difference in Lifetime Citations, NASA & Non-NASA Patents

	Lifetime Citations		
	(1)	(2)	(3)
$\mathbb{I}$(NASA)	4.650***	3.891***	3.946***
	(0.359)	(0.343)	(0.329)
Constant	10.816***		
	(0.011)		
Technology FE	N	Y	Y
Issue Year FE	N	N	Y
NASA/Non-NASA Obs.	6,770 / 7,489,012	6,770 / 7,489,012	6,770 / 7,489,012
Note:	Robust s.e. in parentheses. *p<0.1; **p<0.05; ***p<0.01		

However, even within the same technology class, NASA funded patents plausibly receive higher funding than non-NASA funding, confounding the true estimated effect of publicly funded innovation on citations. Given this potential selection bias, we proceed to detail our empirical design.

IV. EMPIRICAL FRAMEWORK

The main empirical analysis estimates changes in NASA-exposed technology subclasses, against changes in non-exposed technology subclasses, relative to a base year of 1957. The analysis is carried out at the subclass level instead of the patent-level for one main reason—patents are not observed until they are produced. Therefore, treated patents are always treated. On the other hand, one can observe outcomes for technology classes over time, and can estimate how these outcomes vary before and after NASA's creation. The main outcomes of interest are patent counts and patent citations at the subclass-year level.

Formally, the outcome y_{ct} in a given subclass c in a given year t is regressed on a treatment indicator that takes a value of 1 when the year is 1958 or later and the subclass is treated, along with its leads and lags, a subclass fixed effect γ_c, a year fixed effect δ_t, and an error term ε_{ct}. This dynamic two-way fixed effects estimator allows us to obtain difference in differences estimates for each pre-treatment and post-treatment year minus the base year of 1957, and provides for a test of parallel pre-treatment trends in the same estimation.[23]

$$y_{ct} = \sum_{\tau=-10\backslash\{-1\}}^{22} \beta_\tau(\mathbb{I}\{t - 1958 = \tau\} \times\ T_c) + \gamma_c + \delta_t + \varepsilon_{ct} \tag{1}$$

These estimates will also be summarized with a static two-way fixed effects specification without leads and lags as follows:

$$y_{ct} = \beta(\mathbb{I}\{t \geq 1958\} \times\ T_c) + \gamma_c + \delta_t + \varepsilon_{ct} \tag{2}$$

In this setting, I define treated subclasses T_c as narrow classes in which NASA-exposed patents were produced during the Apollo era, and untreated subclasses as those in which NASA did not. Appendix Tables A1 and A2 show the treatment and control classes with the most patents in the sample period. Because the difference in differences estimator requires pre-treatment and post-treatment observations, I do not utilize subclasses that only exist in the post-period. One concern is that if NASA is seeding many subclasses by creating entirely new technologies, this research design would not capture their influence. Using the USPTO administrative records, I find that only 34 out of all NASA patents were the first in their subclass, although 25 of these originated in the Apollo years.[24]

The identifying assumption in such a research design is that absent NASA's creation and funding, the quantity and quality of treated technologies would have evolved similarly to those NASA did not work on. Given the large possible number of control subclasses, it is hard to think ex-ante that they are as a whole a valid comparison group to NASA-exposed technologies. For my main specification, I will instead use subclasses that other federal agencies worked on before 1958 as a comparison group. In Appendix VII.H, I show however that results using both a) all untreated subclasses as controls, and b) only untreated subclasses within broad classes that were treated, yield qualitatively similar results to the main specification.

Standard errors are clustered at the subclass level to adjust for heteroskedasticity and subclass serial correlation throughout. Event study estimates also include sup-t confidence bands to account for multiple hypothesis testing (Callaway and Sant'Anna, 2021; Freyaldenhoven et al., forthcoming).

V. RESULTS

Table 3 shows summary statistics of the main outcomes in the baseline year, 1957, for both treatment and control subclasses. On average, treatment classes in the baseline year had

[23] This design avoids some of the concerns highlighted by recent literature on two-way fixed effects estimation: treatment is defined as starting at the same time for all treated units, avoiding using earlier treatments as controls for later ones (Goodman-Bacon, 2021). However, concerns regarding treatment effect heterogeneity are still valid in this context (de Chaisemartin & D'Haultfœuille, 2020), therefore I produce estimates using Callaway and Sant'Anna's (2021) methodology in Appendix VII.G and find nearly identical event study estimates.

[24] These subclass seed patents are in a number of different classes including aeronautics, nuclear measurement, fuel cells, medical diagnostics equipment, semiconductor manufacturing, optics, television signal processing, and arithmetic and calculation methods using electrical computers.

about double the number of patents issued, those patents were cited about twice as much over their lifetime, and those classes were themselves cited twice as much in 1957. These imbalances further motivate using a differences in differences design as opposed to the naive comparison of treated and control outcomes.

Table 3: Summary Statistics, 1957

Covariate	Control Mean	Treat. Mean	Diff. in Means	p-value
Patents Issued	1.094	2.032	0.938	0.000
Citations	4.731	8.751	4.021	0.000
Citations (Leave-one-out)	3.777	6.196	2.419	0.000
Lifetime Citations	7.953	15.634	7.682	0.000
Lifetime Citations (LOO)	6.157	11.142	4.985	0.000
Narrow USPC Count	6,468	869		

V.A. Baseline Difference in Differences Results

Figure 9 reports the estimated coefficients from the main equation. During the Apollo years and the following decade, patenting in spaceflight related subclasses increased by a statistically significant 0.974 per year on average over other subclasses, with a peak of 1.922 in 1971. Figure 10 only counts non-NASA funded patents.

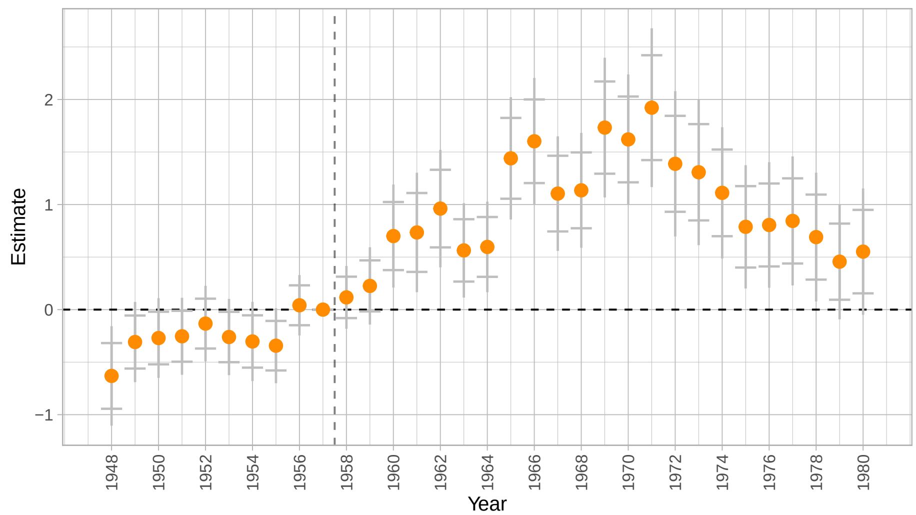
Table 4 summarizes these results using the static two-way fixed effects specification, with similar results. On average, patent counts increase by a statistically significant 1.217 within each subclass per year, and do so by 1.152 after excluding NASA-owned or contracted patents.

Table 4: Difference in Differences Estimates, Patent Counts

	Patent Issues	Patent Issues (Excl. NASA)
	(1)	(2)
$\mathbb{I}$(NASA)	1.217***	1.152***
	(0.154)	(0.153)
Subclass FE	Y	Y
Year FE	Y	Y
Observations	249,803	249,803
Note:	Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01	

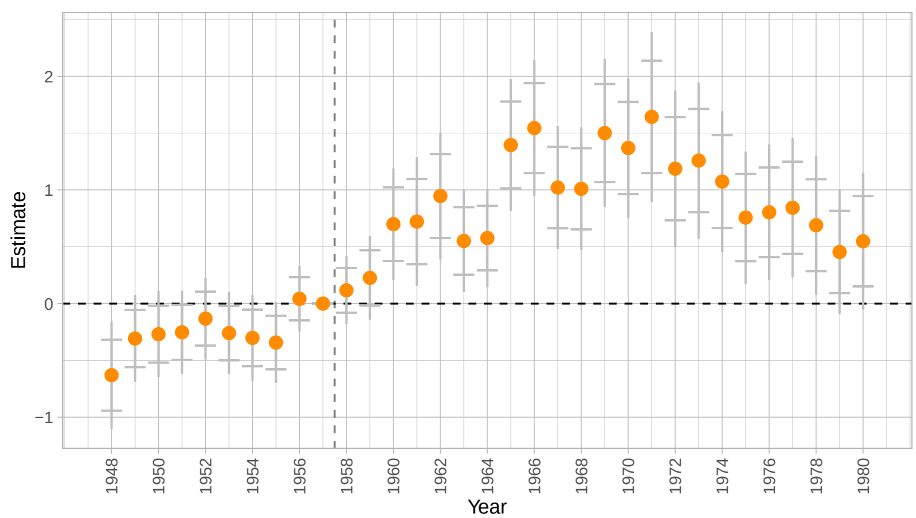
Taking the event study and static difference in differences estimates at face value, the estimates are largely unchanged when excluding NASA patents, hinting that these increases are not mostly driven by NASA's direct efforts, but rather by spillovers from other related inventions. However, another potential explanation is that NASA funding was underreported in the original patent documents,[25] or that the text analysis carried out by Fleming et al. (2019) was not able to identify all NASA reliant patents, resulting in false negatives. To address the second point, I manually inspect the original documents for a sample of two hundred post-1958 patents in treated subclasses that appear to have no NASA funding in the data, and only find two NASA funded patents.

Figure 9: Patent Issue DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure 10: Patent Issue DID Estimates, Excluding NASA Patents



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

[25] Empirically demonstrating this would require knowledge on all 1960s NASA contract specifications, and identifying all possible patents issued to contractors originating from the contracted work. However, there is anecdotal evidence that there was an underreporting of contractor inventions to NASA (Kraemer, 1999).

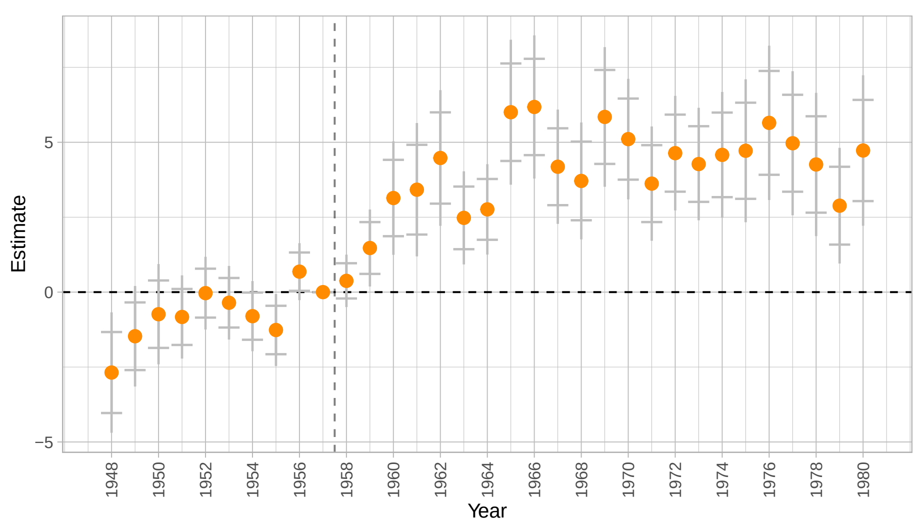
Table 5: Difference in Differences Estimates, Patent Citations

	Yearly	Yearly (Excl. NASA)	Lifetime	Lifetime (Excl. NASA)
	(1)	(2)	(3)	(4)
$\mathbb{I}$(NASA)	4.778***	4.771***	11.614***	11.604***
	(0.624)	(0.624)	(1.560)	(1.560)
Subclass FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	249,803	249,803	249,803	249,803

Note: Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01

Figures 11 and 12 show the estimates on citations by year and lifetime citations.[26] Citations per year increased by an average of 4.064 each year, and lifetime citations for patents issued in the Apollo years were 10.258 higher, similar to the static estimates in Table 5. These estimates imply increases in patenting and in-year citations of around 59.90% and 54.60%, and an increase in lifetime citations of around 72.27% over the 1957 treatment group mean. While patenting decreased over the years after Apollo and subsequent reductions in NASA funding, citation behavior and the lifetime citations towards treated classes remained constant in the decade after.

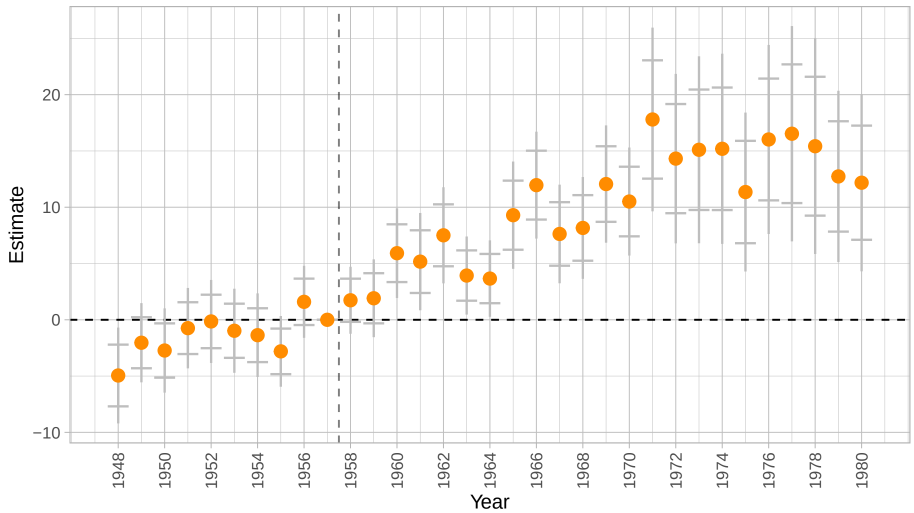
Figure 11: Citations by Year DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

[26]Estimates using only a fixed window of time instead of lifetime citations can be found in Appendix Table A3 and Figures A1-A3.

Figure 12: Lifetime Citation DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

V.B. Citation Breadth and Length

Increased patenting activity within a set of technologies can drive increases in citations to those technologies due to self-citations—many gradual improvements over the same base technology, or high idiosyncratic citation rates can both drive citation counts among treated subclasses.

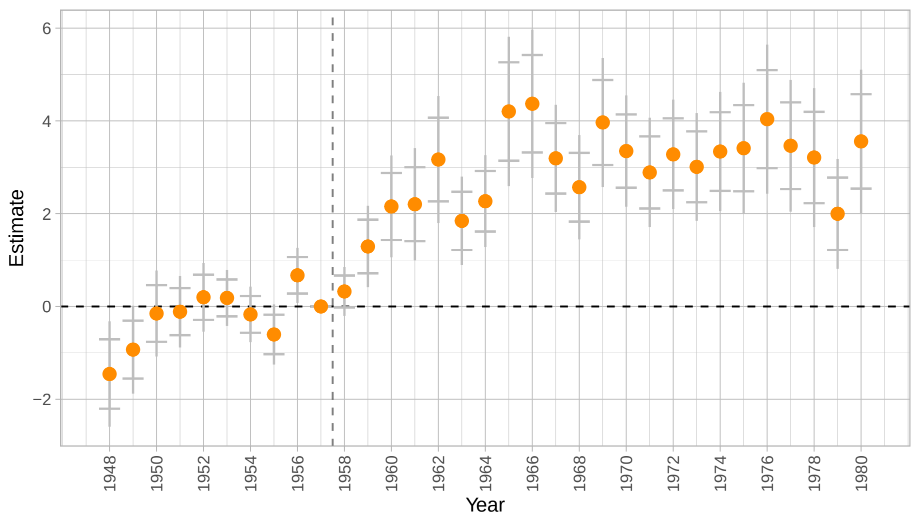
To study if the results are driven by either phenomenon as opposed to these classes having broader impact, I estimate the main regressions using leave-one-out citation outcomes as the number of citations originating from subclasses other than the subclass of interest (Table 6 and Figures A26 & A27) and find the results are qualitatively unchanged—most citations to these subclasses originate from other subclasses. I repeat this estimation using only citations from patents in entirely different broad classes (Columns (2) and (4) of Table 6, and Appendix Figures A28 and A29) and find diminished but statistically significant spillovers, implying this effect is not mostly driven by technology subclasses that are narrowly related, but rather, by classes that are in entirely different fields of invention.

Table 6: Difference in Differences Estimates, Leave-One-Out Citations

	Yearly	Yearly, Broad	Lifetime	Lifetime, Broad
	(1)	(2)	(3)	(4)
$\mathbb{I}$(NASA)	3.134***	2.055***	8.014***	5.860***
	(0.377)	(0.267)	(0.978)	(0.771)
Subclass FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	249,803	249,803	249,803	249,803

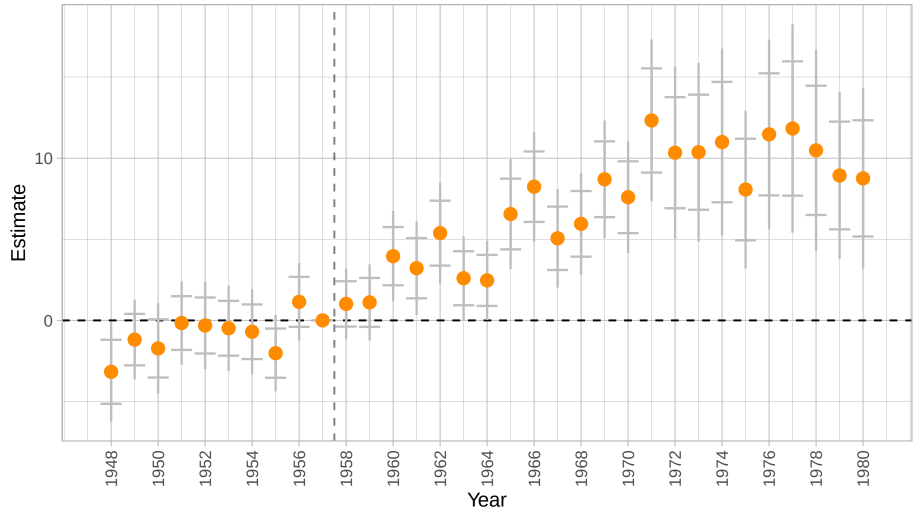
Note: Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01. Columns (1) and (3) exclude within-narrow subclass citations, while (2) and (4) exclude within-broad class citations. All columns exclude NASA to NASA citations.

Figure 13: Citations by Year (Leave-One-Out) DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure 14: Lifetime Citation (Leave-One-Out) DID Estimates, 1948-1980

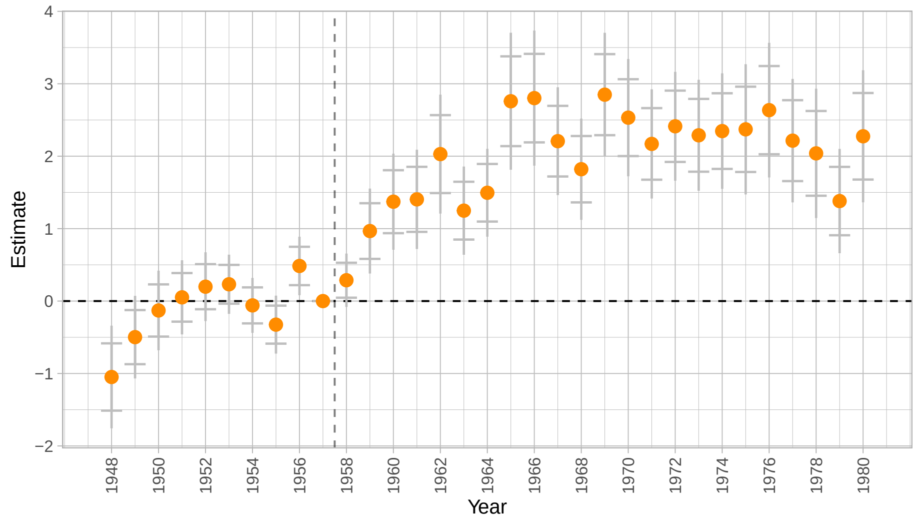


Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

To provide alternative measures of a technology's spillover breadth and length, I follow the literature on general purpose technologies (Moser and Nicholas, 2004; Rosenberg and Trajtenberg, 2004; Jovanovic and Rousseau, 2005), and calculate alternative measures of a patent class' generality and longevity as outcomes.

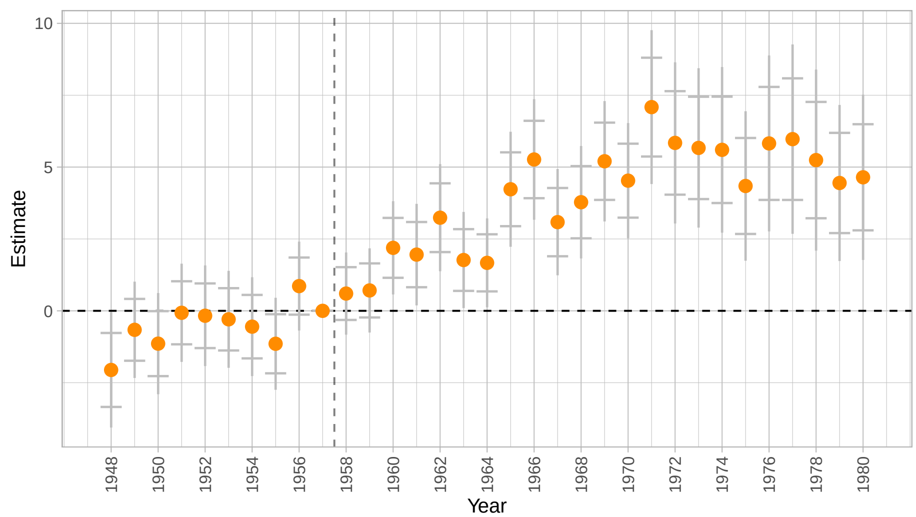
First, I estimate my main event study using a count of narrow classes that cite the treated class. While the previous set of regressions estimate the number of citations coming from other fields, this count abstracts from citation volume to calculate whether NASA's involvement changed the broadness of the impact of these technologies (Figures 15 and 16 and static estimates in Appendix Table A4). On average, the number of citing subclasses differentially increased for treated technology fields after treatment, with between 2.090 to 4.536 more classes citing treated classes over the control group.

Figure 15: Number of Citing Classes, Yearly Citations, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure 16: Number of Citing Classes, Lifetime Citations, 1948-1980



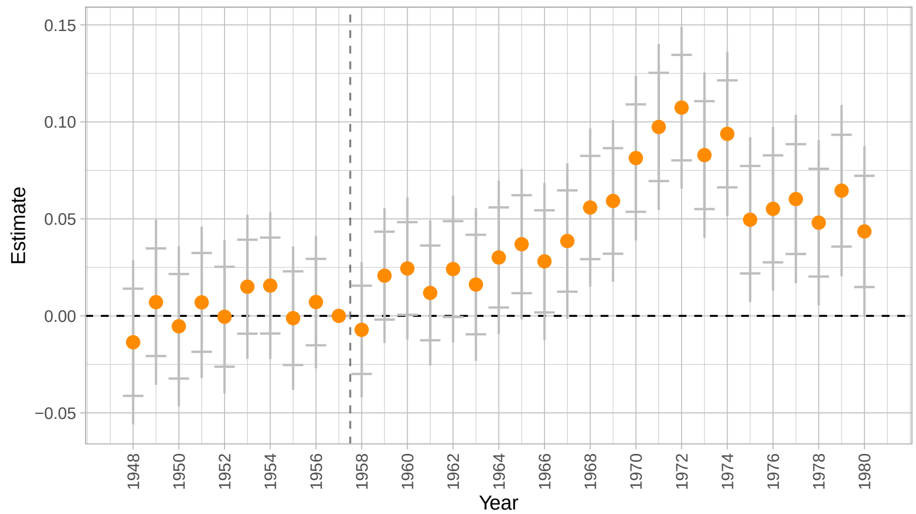
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

I also follow Moser and Nicholas (2004) and calculate a generality measure based on a Herfindahl-Hirschman index (HHI) for a given class and year's citations over all other J classes, defined as:

$$1 - \sum_{j=1}^{J} \left(\frac{C_j}{C} \right)^2 \tag{3}$$

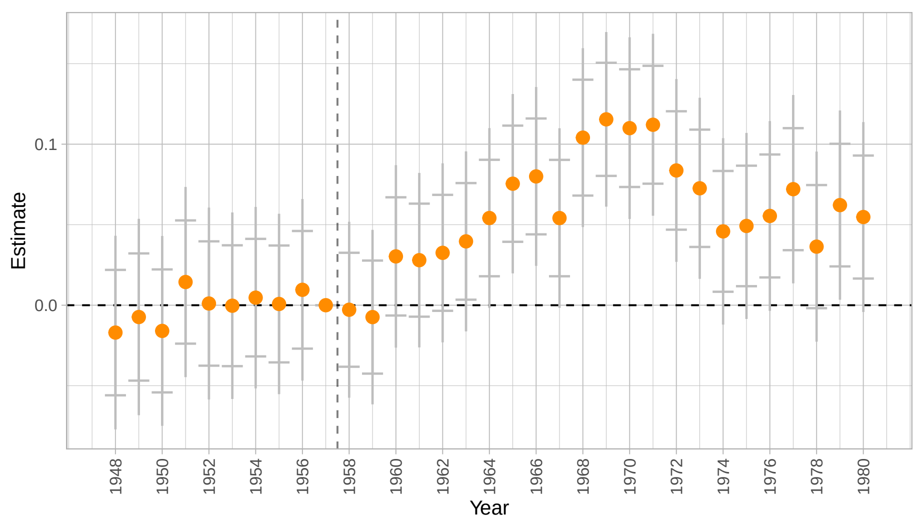
As the second term measures the concentration of a given class' citations, one minus the concentration term implies that for a value of one, a subclass-year's citations are spread over many classes, while a value of zero implies that all citations were concentrated in one technology field. The estimates in Figures 17 and 18, while noisier than the simple counts of citing classes, are mostly positive and statistically significant. Static two-way fixed effects estimates are presented in Appendix Table A5. On average, the HHI is higher by 0.046 to 0.060 for treated subclasses, and it is statistically significant to the 1% level.

Figure 17: Herfindahl-Hirschman Based Generality, Yearly Citations, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure 18: Herfindahl-Hirschman Based Generality, Lifetime Citations, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

To complement the estimates on breadth, Appendix Figures A6 and A7 estimate measures of longevity, that is, the speed of obsolescence for the inventions in a subclass-year cell. For patents issued in each subclass-year, I look at the mean and maximum lags in citations—the time difference between the original patent and the typical patent that cites it, and the gap between the original patent and the newest patent that cites it. Given that this measure was originally devised to estimate longevity in a cross-section of patents issued in the same time period (Moser & Nicholas, 2004), careful adjustments need to be applied in a panel data setting. First, as all other estimations, I use issue-year fixed effects, which accounts for the fact that older patents can mechanically have more citations on average. Note: this does not account for the fact that variance is also different. I am currently devising a new measure for this issue that I will implement for the final revision of this paper.

While the dynamic difference in differences specifications have noisier estimates, Appendix Table A6 shows that on average, treated subclasses have a longer citation lag of between 0.976 and 1.737 years, and this is statistically significant at the 1% level.

V.C. Blockbuster Patenting

The preceding sections indicate that knowledge spillovers stemming from treated subclasses increased on average. However, they do not specify if these fields generated individual patents that were particularly influential. In this following section, I devise a measure of breakthrough or blockbuster patenting based on the distribution of citation counts at the patent level.

First, I partial out subclass and year fixed effects from each individual patent's (i) lifetime citation count using equation 4 to obtain a citation count adjusted for the fact that different fields and years receive varying amounts of citations.

$$y_{ict} = \gamma_c + \delta_t + \varepsilon_{ict} \tag{4}$$

Then, I define blockbuster patents as those that are above the 90th, 95th, and 99th percentiles of the residual citation distribution. Next, I re-estimate the static and dynamic two-way effects regressions at the subclass-year, where the outcome is an indicator that takes the value of one if the subclass-year contains at least one blockbuster patent. Difference in differences results are shown in Table 7 and Appendix Figures A8 through A10. On average, treated classes increased their 90th percentile blockbuster patenting by 0.041 percentage points, over a treated base year average of 0.127. At the 99th percentile, there was a statistically significant increase of 0.012 percentage points over a base year treated average of 0.0104.

V.D. Space-Essential Classes

Treated and control subclasses appear to display mostly parallel pre-treatment trends in the decade before NASA's creation, which appears to support the argument that NASA's technology portfolio was mostly mission-driven. However, to the degree that selection of technologies deviated from NASA's mandate, I re-estimate my main regressions using technologies that were ex-ante known to be essential to winning the Space Race: spacecraft capable of withstanding travel in the vacuum of space and re-entry into Earth, heavy-lift rockets able to carry said spacecraft beyond Earth orbit, and life support systems that

Table 7: Difference in Differences Estimates, Blockbuster Patents

	90th Percentile	95th Percentile	99th Percentile
	(1)	(2)	(3)
$\mathbb{I}$(NASA)	0.041***	0.031***	0.012***
	(0.006)	(0.005)	(0.002)
Subclass FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	249,803	249,803	249,803
Note:	Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01		

can ensure the survival of humans under the stresses of space, such as heavy radiation and extreme temperatures.

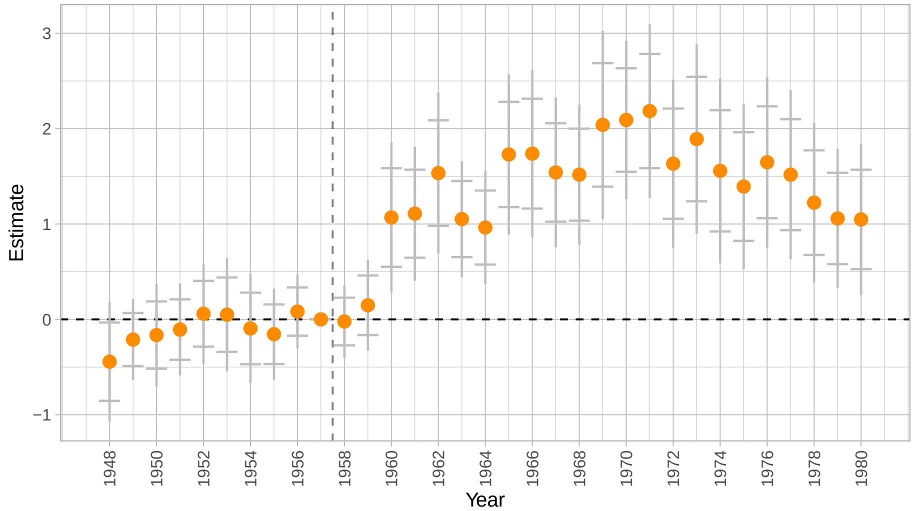
As evidenced in its first fiscal year budget, NASA had already commenced testing and development on all of these categories, ranging from life-support and restraint systems for manned spaceflight, heat and shock-resistant metals and ceramics for capsules, advanced digital guidance, control, and communications technologies, solid and liquid fuel rockets, solar cells, and batteries (U.S. House of Representatives. Committee on Appropriations, 1960).[27]

The following figures show event study estimates of this redefined treatment, following Equation 1, where treated subclasses are those in technology classes matching patent broad classes in rocketry, aeronautics and aerospace, batteries, digital communications, radiant energy, advanced alloys and coatings, and computer-aided calculation. These estimates are on average similar to the estimates in Figures 9-A27, with larger standard errors and flatter pre-treatment estimates.

Leave-one-out estimates are added to the Appendix (Figures A11 & A14) for brevity, but are significant and smaller than the non leave-one-out essential class estimates, much like the baseline event study estimates in Section V.

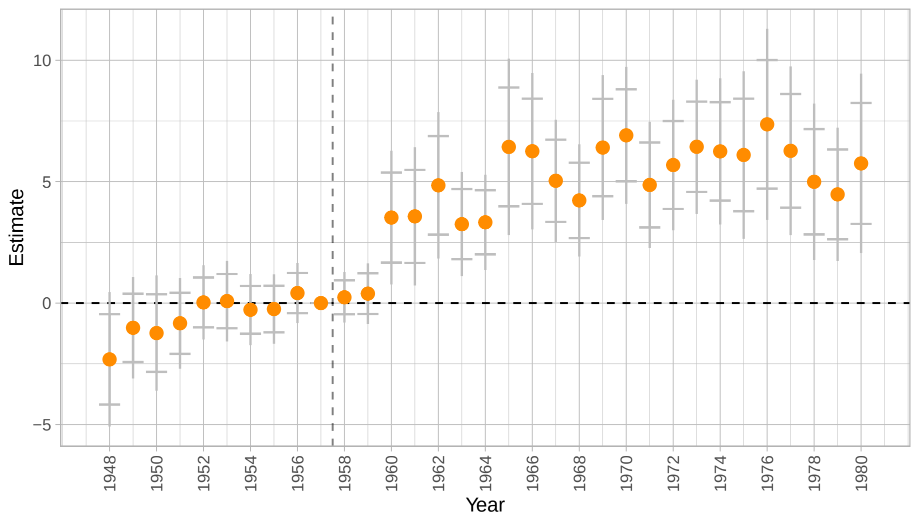
[27] This is evidenced in several other points early in NASA's history. President John F. Kennedy mentions some of these necessary advances in his first speeches advocating for a Moon landing: the Address to the Joint Session of Congress on May 25, 1961, where he first proposed a landing before the end of the decade, and his Address at Rice University on the Nation's Space Effort on September 12, 1962, colloquially known as his "We choose to go to the Moon" speech. Despite lack of political and budgetary support for a Moon landing prior to this, NASA had already formed 12 committees dedicated to feasibility and planning for the lunar landing, starting as early as February 1959 (Brooks et al., 1979; Hansen, 1995).

Figure 19: Patent Issue Estimates, Space-Essential Classes



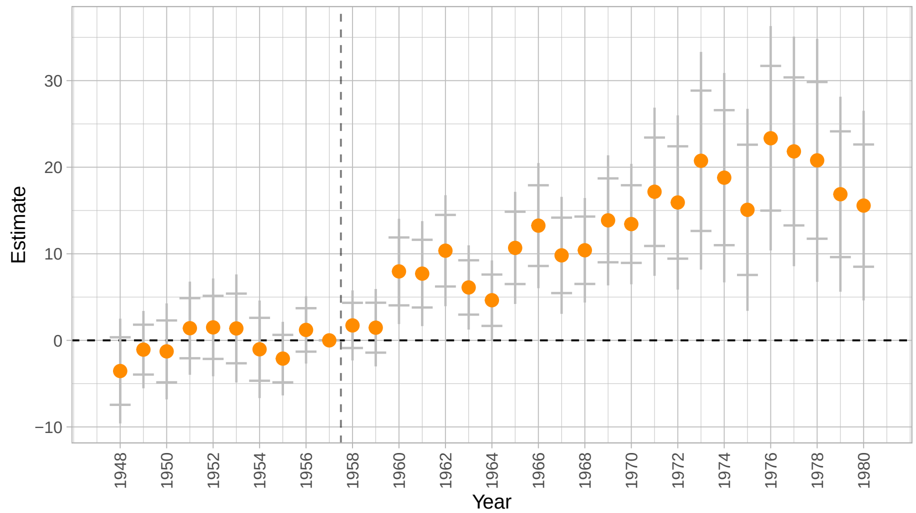
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure 20: Citations by Year Estimates, Space-Essential Classes



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

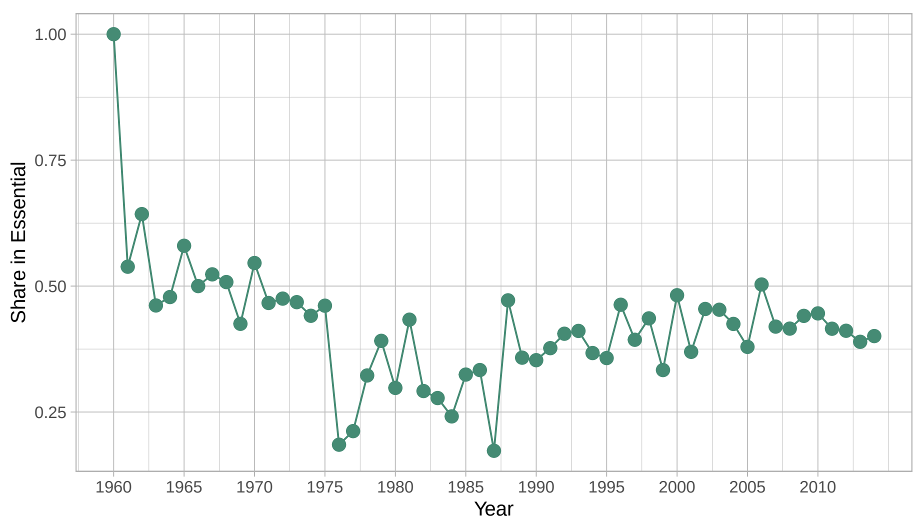
Figure 21: Lifetime Citations Estimates, Space-Essential Classes



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

To assess the degree to which NASA deviated from these space-essential classes throughout the years, I plot the share of treated classes within this essential subset for each year in the post-treatment sample in Figure 22. Over the Apollo years, this share averaged 53.692%, while over the whole sample this averaged to 42.053%.

Figure 22: Share of Essential Classes in Realized NASA Classes, 1958-2014



Note: First year in sample contains one single patent.

V.E. Non-Disclosure and Military Spending

Given that NASA was born of Cold War geopolitical competition, there are two natural questions to raise about NASA-involved inventions. First, were they affected by non-disclosure? That is, the government would have restricted their publication and potential to influence other downstream innovations. Second, are estimates of treated technologies simply capturing the effect of concurrent military spending on NASA-related technologies, such as innovations on intercontinental ballistic missiles (ICBMs)?

NASA innovations could have feasibly been affected by non-disclosure. However, given NASA's origins as the civilian branch of the United States' space effort, these inventions would have been subject to less restrictions than military efforts such as those from the Department of Defense. To the degree that non-disclosure affected NASA related technologies, it is likely that they would also be more restricted than untreated technologies, therefore restricting the potential influence of the treatment group. Given that previous results show a positive knowledge spillover from treated technologies, non-disclosure would make these estimates lower bounds on the average treatment effect on the treated.

To analyze the degree to which the effects are being driven by concurrent military spending, I re-estimate my baseline results after omitting highly-overlapping technology categories, such as ordnance and rocket-related classes[28] in Appendix Figures A15-A21. I find my main results largely unchanged. While defense spending has consistently taken the largest share of federal R&D across the years (Figure 2), the redirection of government technology efforts in the Apollo years coincided with some of the lowest of these shares in defense R&D spending in US history.

V.F. Inventor-level Reallocation

I investigate the extent to which the above results are plausibly driven by a relative reallocation of patenting as opposed to a shift in aggregate patenting. Using the inventor names in the patents, I identify all engineers and inventors that were ever issued a NASA-affiliated patent and manually match them to all other patents they held before joining NASA as employees or as contractors.[29]

NASA-affiliated inventors typically received their first patent after joining NASA, and not before. From 1940 to 1980, out of 2,276 affiliated inventors, only 27.46% held a patent before their first NASA patent. This would tentatively imply that NASA-affiliated inventive output was not mostly driven by the reallocation of existing scientists or engineers. This is not to say that NASA-affiliated inventors would not have counterfactually issued patents had they not joined NASA, but that the bulk of NASA inventors were not already producing patents elsewhere. This could however also be a result of heterogeneous patenting propensity across fields.[30] Given the discussion of non-disclosure above, however, one would expect patenting propensity to be lowest in treated fields and not in control fields.

However, conditional on holding a patent in the pre-treatment period, only 25.60% of

[28]Specifically, I omit subclasses within ordnance, ammunition and explosives, ammunition and explosive making, firearms, mechanical guns and projectors, and explosive and thermic compositions.

[29]The matching procedure is discussed in Appendix VII.I.

[30]Consider an engineer who works in non-NASA field A, which has a low propensity to patent. In the post-treatment period, she joins NASA and begins working in NASA field B, which has a high propensity to patent. Then, even though her movement implied a reallocation of inventive capital from field A to B, the patent data is less likely to show that she was already inventing in the pre-period.

inventors were working in at least one of their post-treatment fields in their pre-NASA patents. This implies that there was some degree of reallocation between fields for approximately 7.03% of NASA affiliated inventors.

VI. CONCLUSION

There is growing evidence that public research and development efforts can crowd in private sector innovation efforts, and that large scale government research programs affect the direction of future research. I estimate that NASA's creation and sizable funding during the Space Race of the 1960s increased the innovation output of spaceflight related fields, and that this increase in innovation did not originate entirely from patents that NASA originated or contracted. The patents that originated from this innovation rush had larger impact on future innovation by various citation metrics, and these impacts extended to technology fields beyond their own.

These results are robust to measuring citations and their breadth in multiple ways, to removing technology fields that are explicitly defense related, and when only looking at ex-ante spaceflight relevant technology classes.

To assess the degree to which this innovation came from reallocating scientists and engineers from other fields to spaceflight technologies, I match inventors in patent records over time, and find that most engineers that ever held a NASA patent had not received patents beforehand.

These empirical results altogether support the literature that large public R&D efforts can shape the direction and intensity of technological growth, and do so not only through their direct output, but through the crowding in of private sector innovation efforts. They also suggest that unlike commonly theorized, these causal effects are not only driven through the public sector's basic science efforts, but also through its applied innovation.

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VII. APPENDIX

VII.A. Treatment and Control Classes

The following tables show the top 10 treatment and control classes by patent count. Columns include total patents and accrued lifetime citations for 1948-1980 patents.

Table A1: Top 10 Treated Classes, by Patent Count, 1948-1980

USPC Subclass	Patents	Citations
Fluid Handling, Multiway Valve Unit	2,356	23,258
Power Plants, Combustion Products Used as Motive Fluid	2,296	21,362
Electricity: Circuit Makers and Breakers, Incubator	2,056	13,025
Measuring and Testing, Volume or Rate of Flow	1,746	17,385
Measuring and Testing, Dynamometers	1,391	10,771
Machine Element or Mechanism, Gyroscopes	1,348	6,215
Ordnance	1,331	10,193
Communications: Electrical, Continuously Variable Indicating	1,108	12,635
Compositions, Organic Luminescent Material	1,051	6,672
Metal Working, Catalytic Device Making	993	8,800

Table A2: Top 10 Control Classes, by Patent Count, 1948-1980

USPC Subclass	Patents	Citations
Fishing, Trapping, Vermin Destroying, Artificial Bait	1,540	12,347
Electric Lamp/Discharge Devices, Cathode Ray Tube Circuit	1,020	6,828
Electric Lamp/Discharge Devices, with Transmission Line	985	5,229
Internal Combustion Engines, Reversible	963	7,079
Printing, Bed and Platen Machines	939	6,750
Chemistry: Electrical and Wave Energy, Treating Materials	914	4,489
Land Vehicles, Suspension Arrangement	891	7,314
Brushing, Scrubbing, Cleaning, Implements	862	8,295
Specialized Metallurgical Processes, Electrothermic	835	5,368
Lubrication, Systems	687	5,150

VII.B. Fixed Window Citations

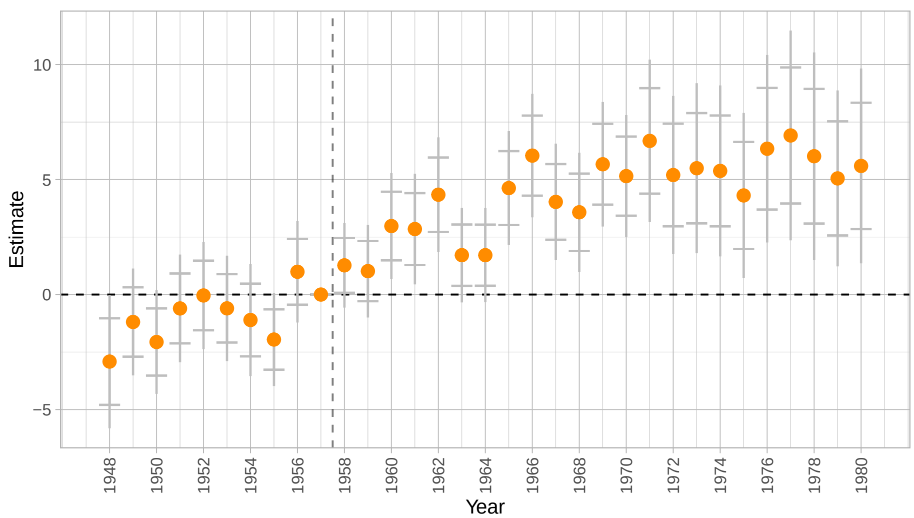
The following table and figures show results for the baseline difference in differences estimates using a fixed window of forward citations within 20 years of issuance instead of lifetime citations.

Table A3: Difference in Differences Estimates, 20-Year Window Citations

	Citations	Excl. NASA	Leave-One-Out, Narrow	LOO, Broad
	(1)	(2)	(3)	(4)
$\mathbb{I}$(NASA)	5.337***	5.330***	3.704***	2.567***
	(0.789)	(0.789)	(0.489)	(0.364)
Subclass FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	249,803	249,803	249,803	249,803

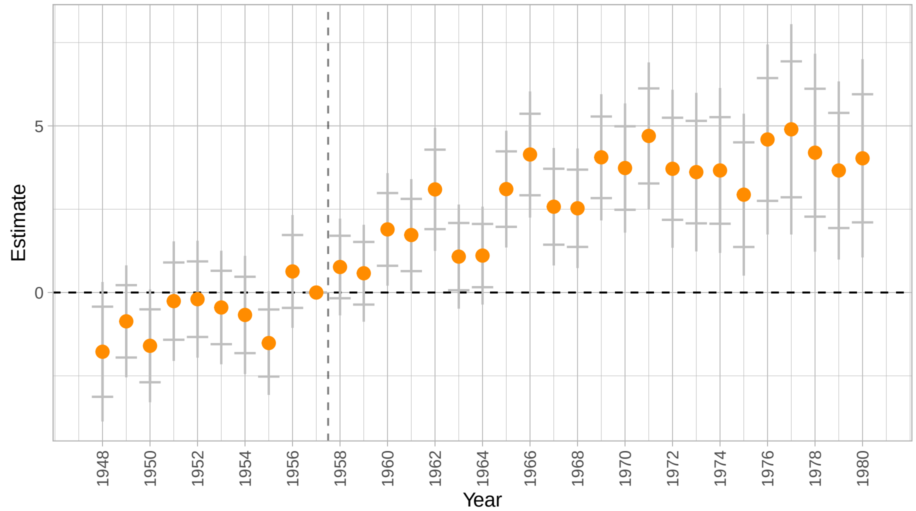
Note: Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01

Figure A1: 20-Year Window Citation DID Estimates, 1948-1980



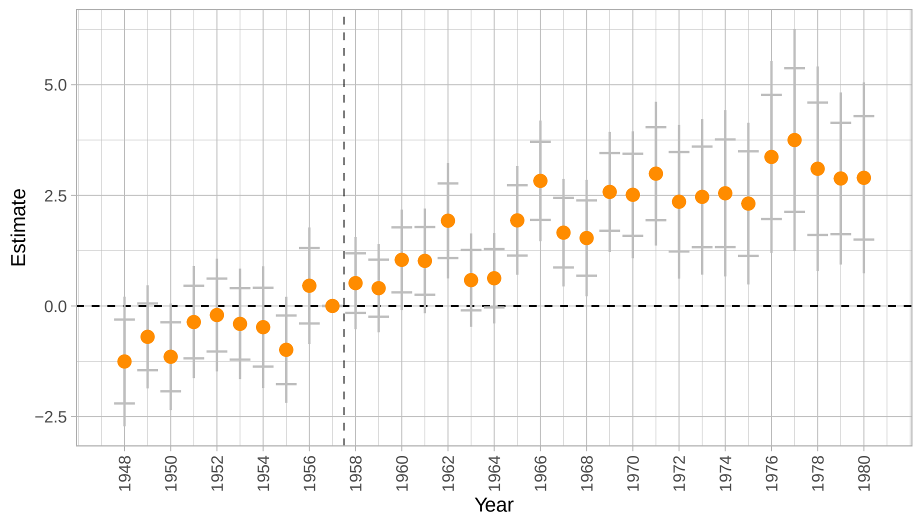
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A2: 20-Year Window Citation (Leave-One-Out) DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

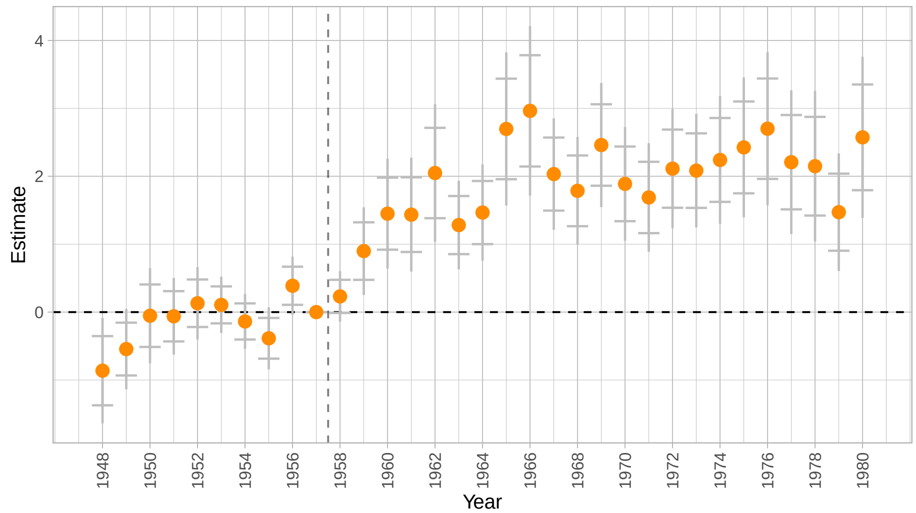
Figure A3: 20-Year Window Citation (Broad Leave-One-Out) DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

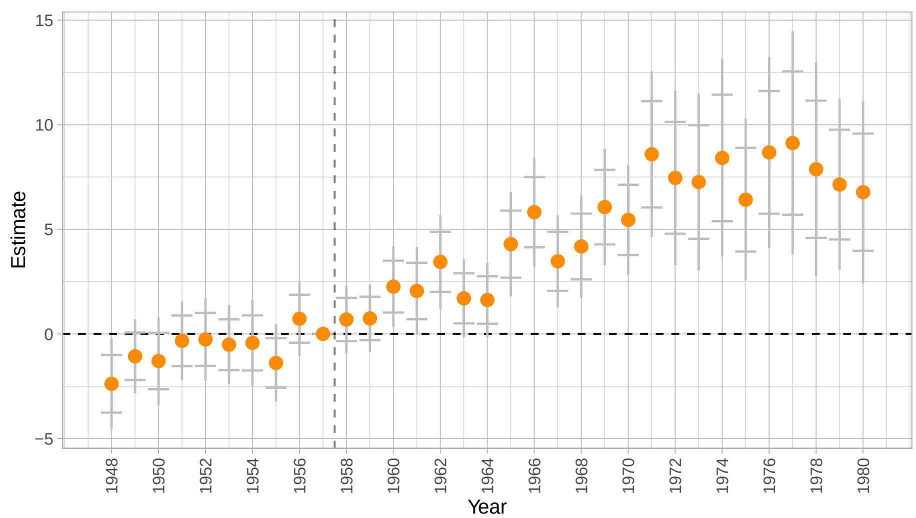
VII.C. Additional Difference in Differences Estimates for Citation Breadth and Length

Figure A4: Citations by Year (Broad Leave-One-Out) DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A5: Lifetime Citation (Broad Leave-One-Out) DID Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

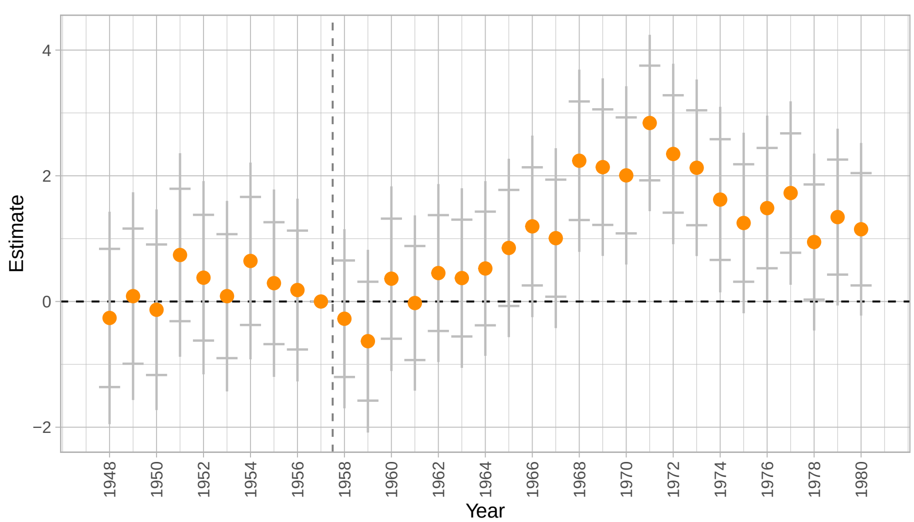
Table A4: Difference in Differences Estimates, Number of Citing Classes

	No. Citing Classes, Yearly	No. Citing Classes, Lifetime
	(1)	(2)
$\mathbb{I}$(NASA)	2.090***	4.536***
	(0.223)	(0.534)
Subclass FE	Y	Y
Year FE	Y	Y
Observations	249,803	249,803
Note:	Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01	

Table A5: Difference in Differences Estimates, Citation HHI

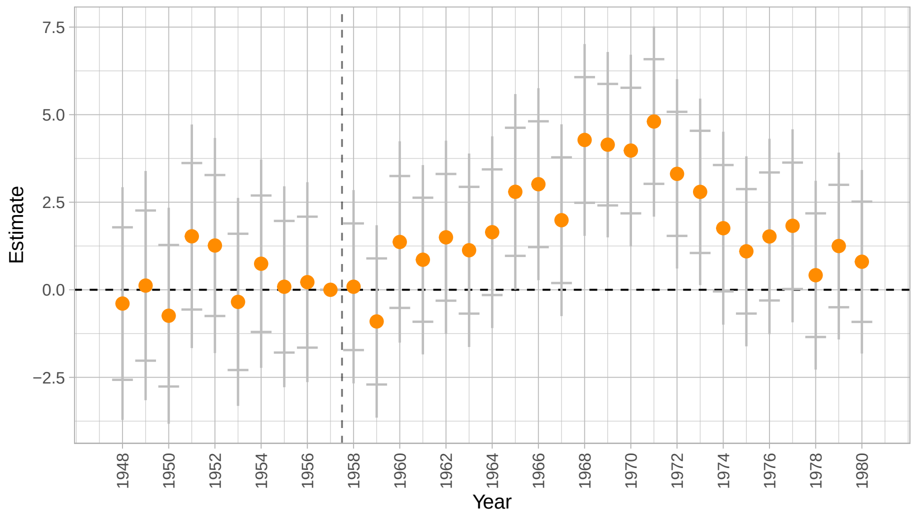
	HHI, Yearly	HHI, Lifetime
	(1)	(2)
$\mathbb{I}$(NASA)	0.046***	0.060***
	(0.008)	(0.008)
Subclass FE	Y	Y
Year FE	Y	Y
Observations	249,803	249,803
Note:	Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01	

Figure A6: Mean Lag in Citations, 1948-1980



Note: S.E. clustered at subclass level, I: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A7: Maximum Lag in Citations, 1948-1980



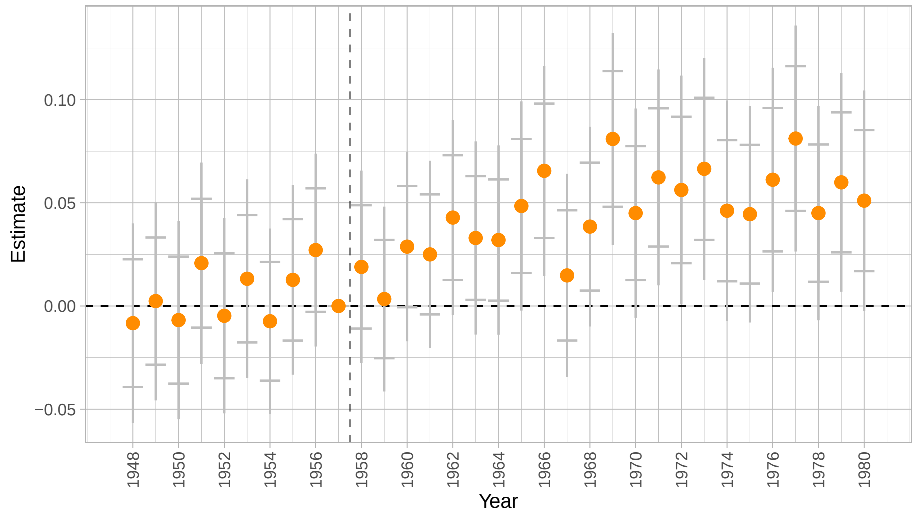
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Table A6: Difference in Differences Estimates, Mean and Maximum Citation Lag

	Mean Citation Lag	Maximum Citation Lag
	(1)	(2)
$\mathbb{I}$(NASA)	0.976***	1.737***
	(0.175)	(0.404)
Subclass FE	Y	Y
Year FE	Y	Y
Observations	249,803	249,803
Note:	Subclass clustered s.e. *p<0.1; **p<0.05; ***p<0.01	

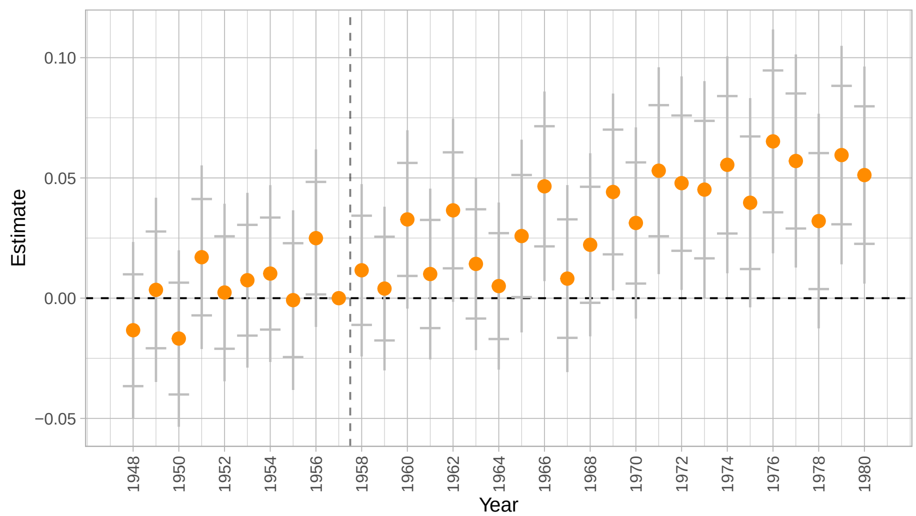
VII.D. Additional Blockbuster Patenting Event Studies

Figure A8: Blockbuster Patenting, 90th Percentile, 1948-1980



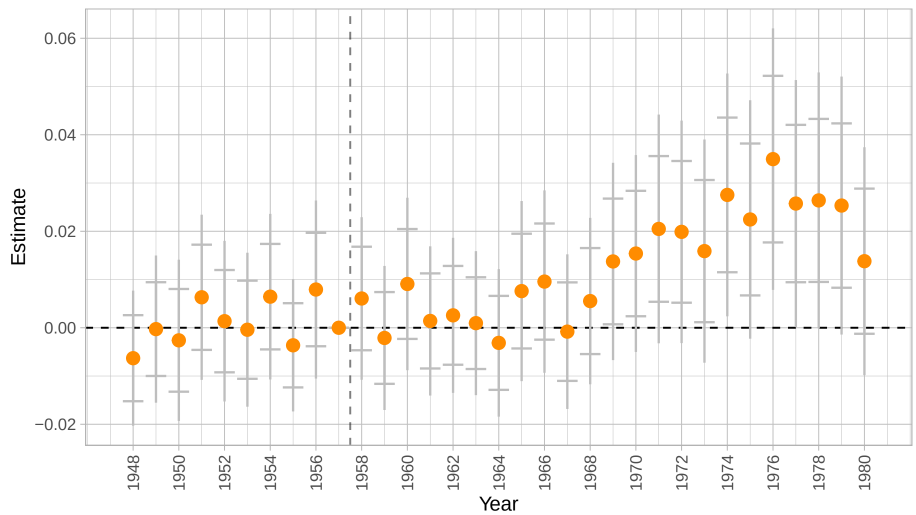
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A9: Blockbuster Patenting, 95th Percentile, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

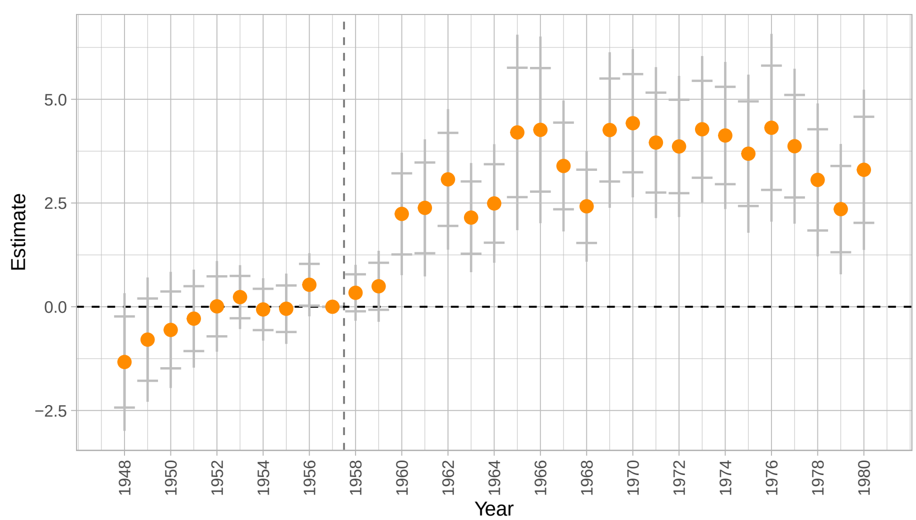
Figure A10: Blockbuster Patenting, 99th Percentile, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

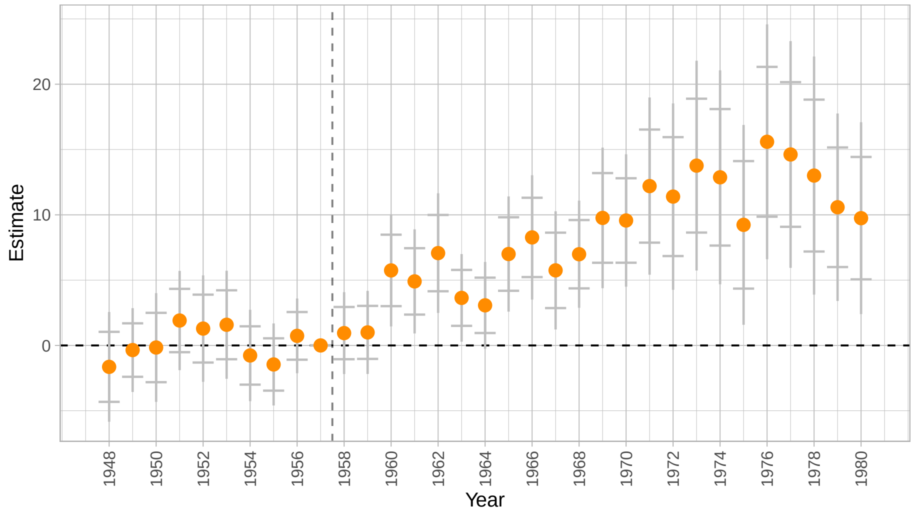
VII.E. *Additional Space Essential Class Event Studies*

Figure A11: Citations by Year Leave-One-Out Estimates, 1948-1980



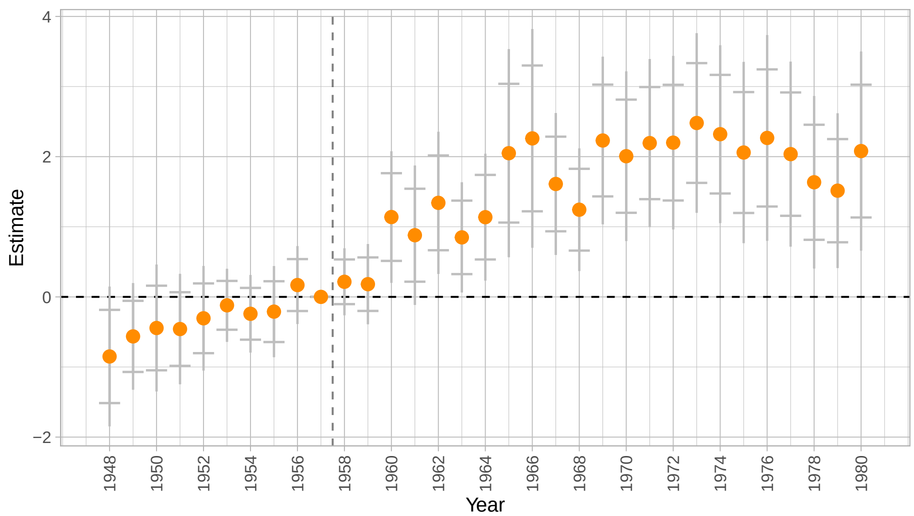
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A12: Lifetime Citations Leave-One-Out Estimates, 1948-1980



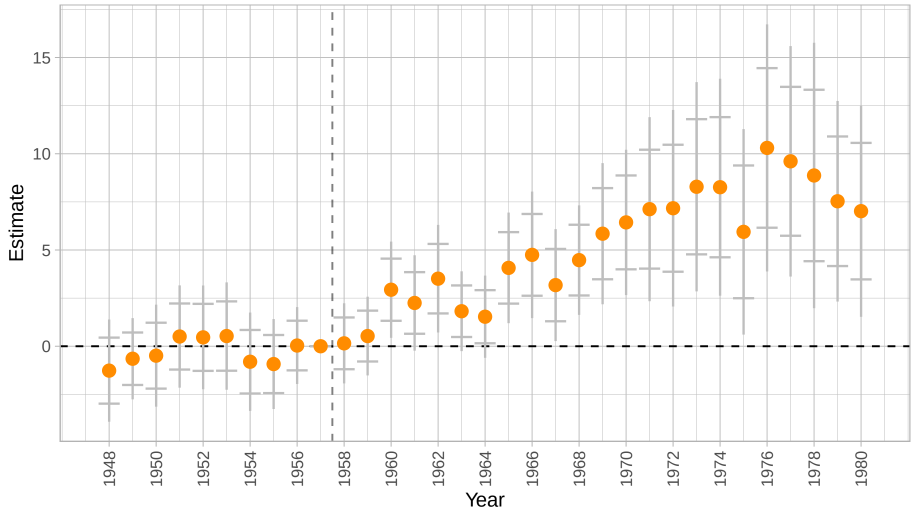
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A13: Citations by Year Leave-One-Out Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

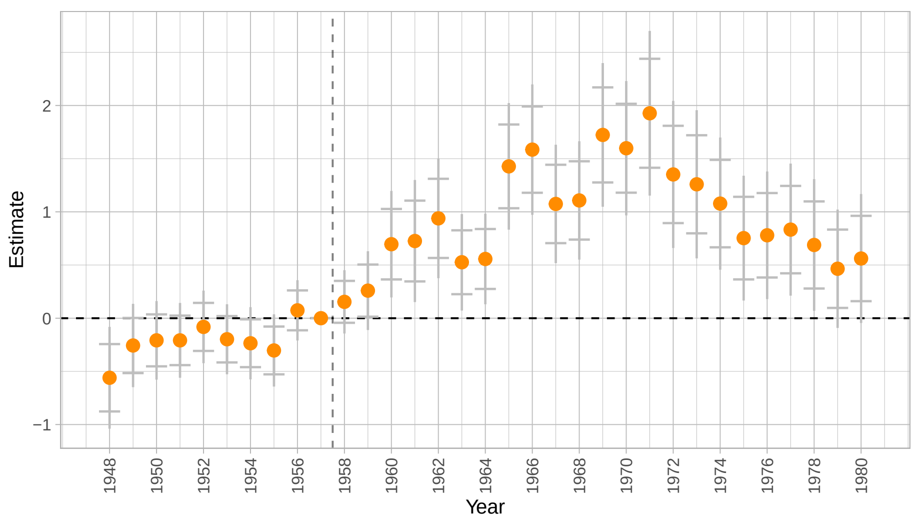
Figure A14: Lifetime Citations Leave-One-Out Estimates, 1948-1980



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

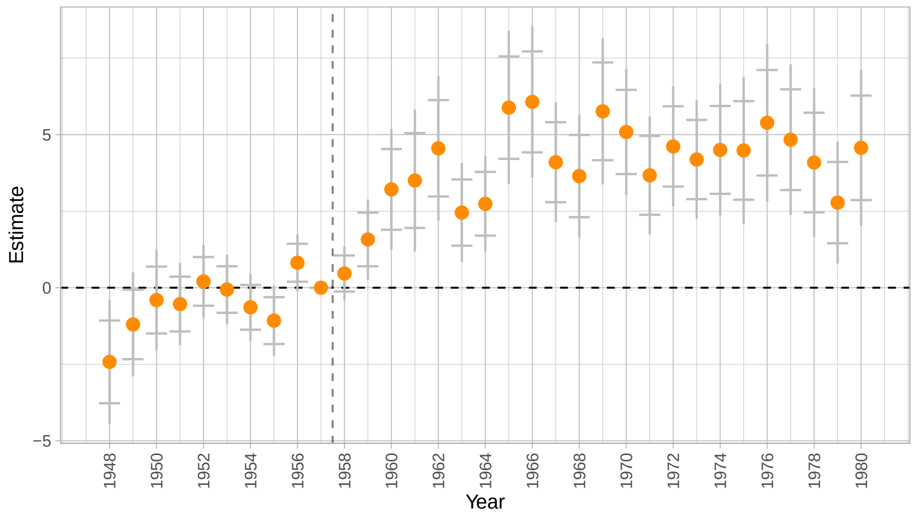
VII.F. Estimates Excluding Military-Related Classes

Figure A15: Patent Issue DID Estimates, Excluding Military Classes



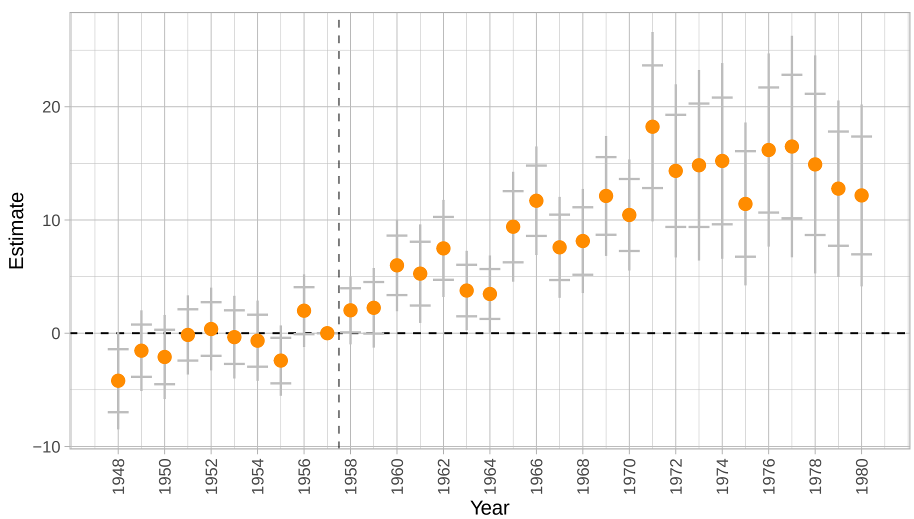
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A16: Citations by Year DID Estimates, Excluding Military Classes



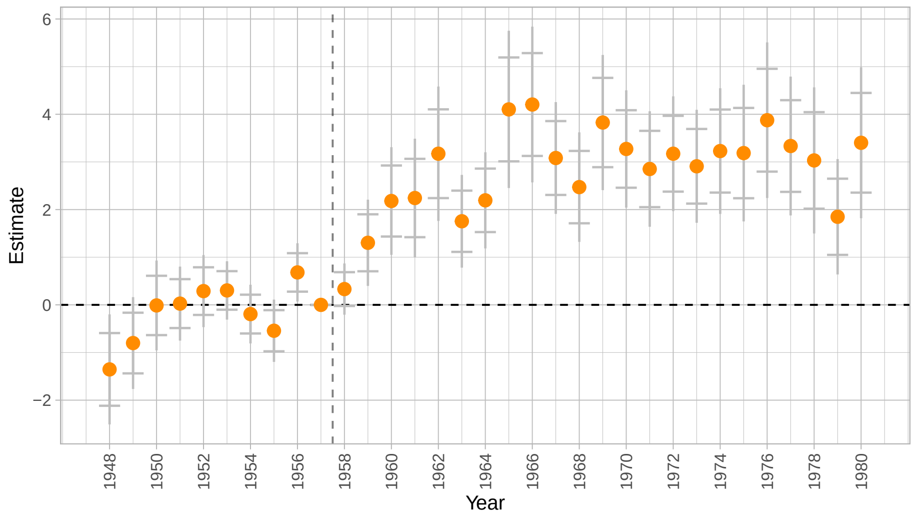
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A17: Lifetime Citations DID Estimates, Excluding Military Classes



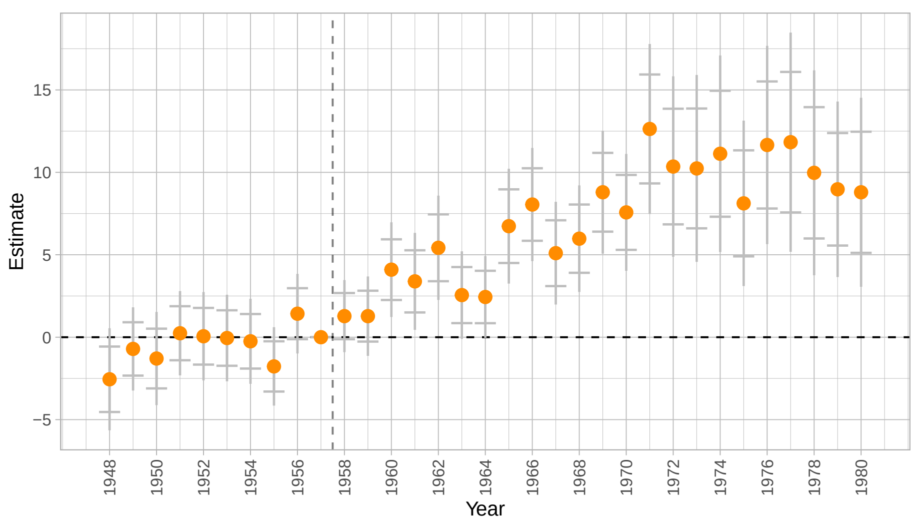
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A18: Citations by Year (Leave-One-Out) DID Estimates, Excluding Military Classes



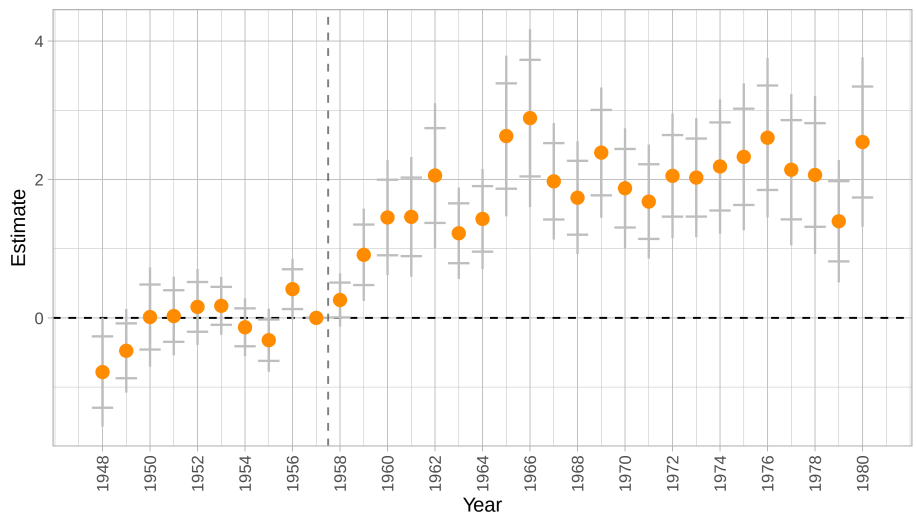
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A19: Lifetime Citations (Leave-One-Out) DID Estimates, Excluding Military Classes



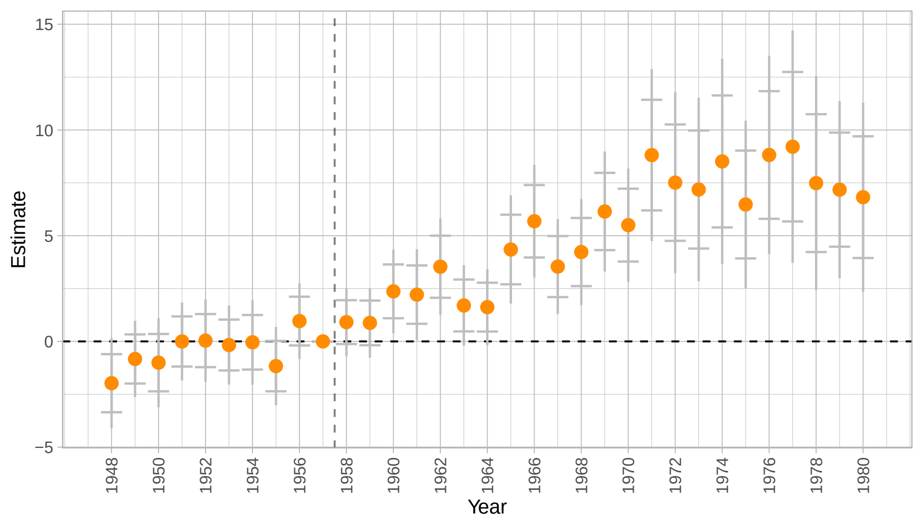
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A20: Citations by Year (Broad Leave-One-Out) DID Estimates, Excluding Military Classes



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A21: Lifetime Citations (Broad Leave-One-Out) DID Estimates, Excluding Military Classes

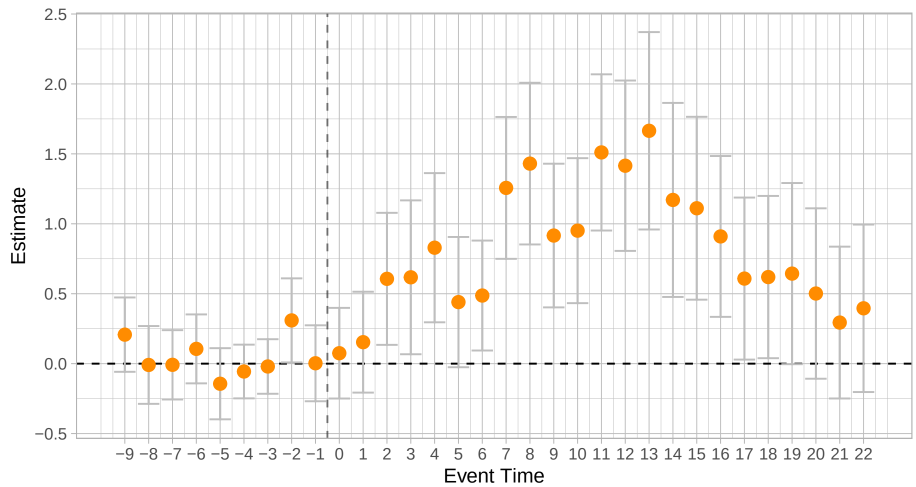


Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

VII.G. Alternate Event Study Estimation Methods

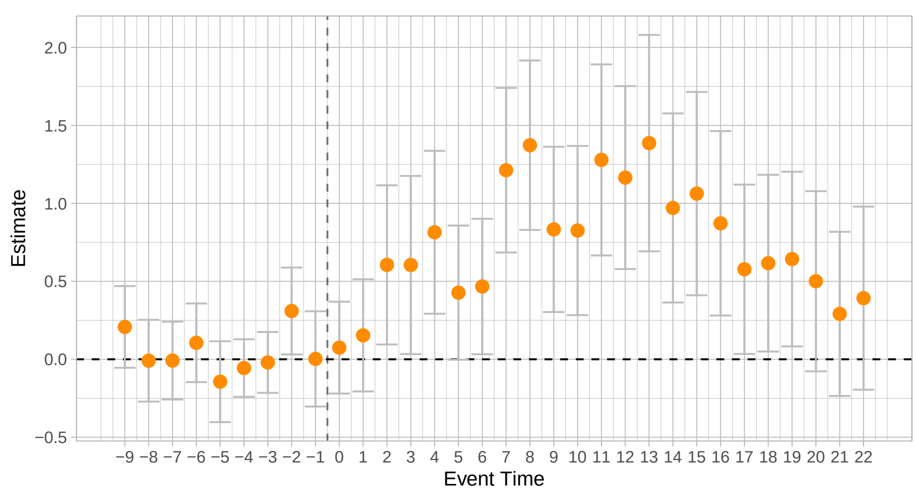
A recent strand of the econometrics literature has focused on the potential pitfalls of estimating static and dynamic two-way fixed effects regressions. In particular, bias can arise when treatments are staggered over time, when there is treatment effect heterogeneity, or when dynamic regressions are not fully saturated (de Chaisemartin and D'Haultfœuille, 2020, Goodman-Bacon, 2021, Callaway and Sant'Anna, 2021, Sun and Abraham, 2021). While my estimates have treatments happening at the same time, 1958, heterogeneous treatment effects are likely to exist in my setting, as certain technology subfields are likely higher impact on average, likelier to be treated, and have a potentially heterogenous response to different levels of R&D funding. Due to this, I re-estimate my main estimates using Callaway and Sant'Anna's (2021) method of estimating group-wise treatment effects individually and aggregating them via a group-size weighted average per year. The resulting event study estimates are mostly unchanged from my main estimates.

Figure A22: Patent Issue DID Estimates, Callaway-Sant'Anna



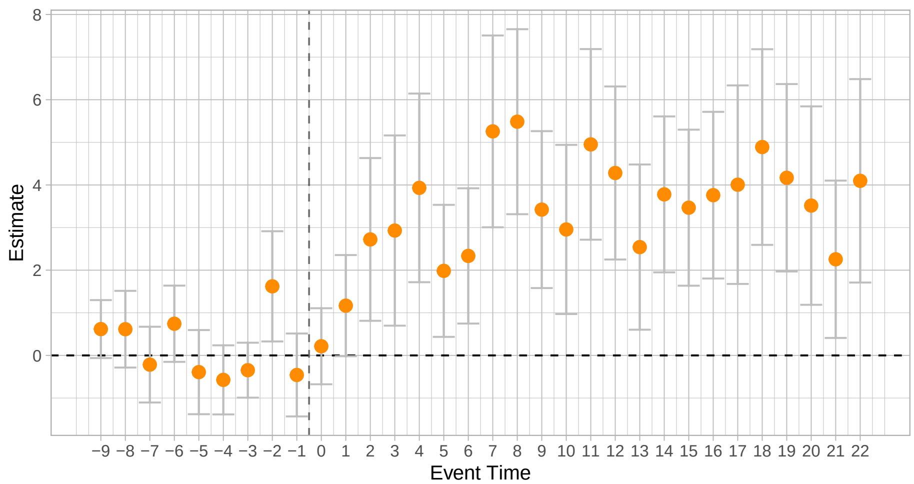
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A23: Patent Issue DID Estimates, Excl. NASA Patents, Callaway-Sant'Anna



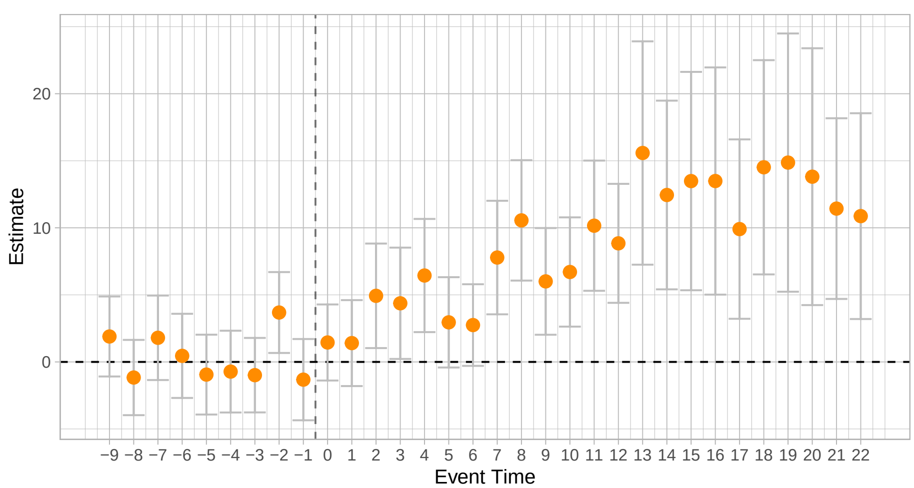
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A24: Citations by Year DID Estimates, Callaway-Sant'Anna



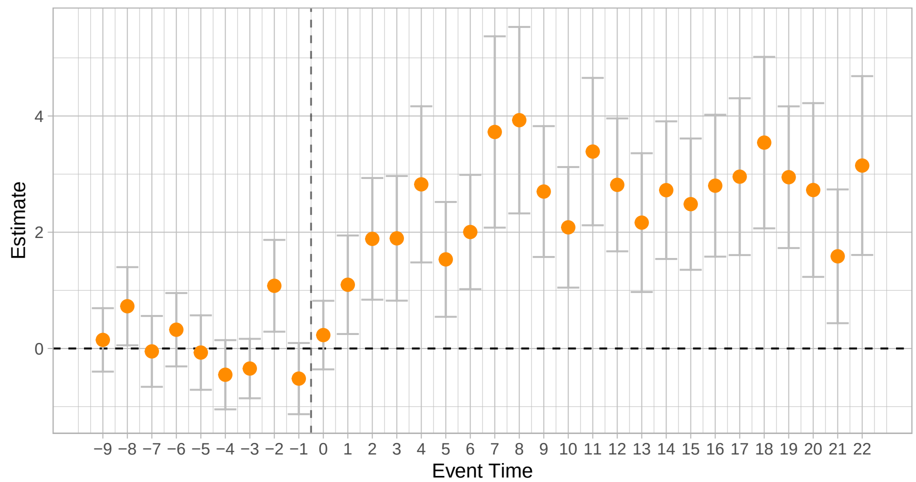
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A25: Lifetime Citation DID Estimates, Callaway-Sant'Anna



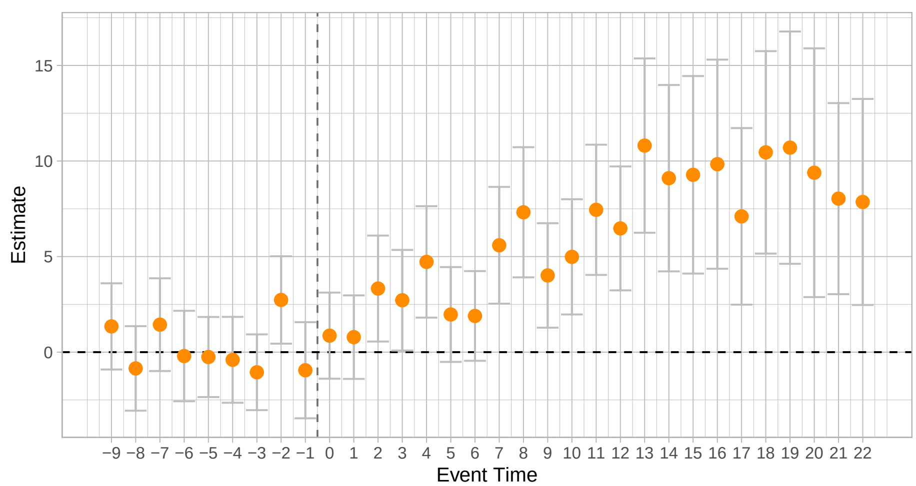
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A26: Citations by Year (LOO) DID Estimates, Callaway-Sant'Anna



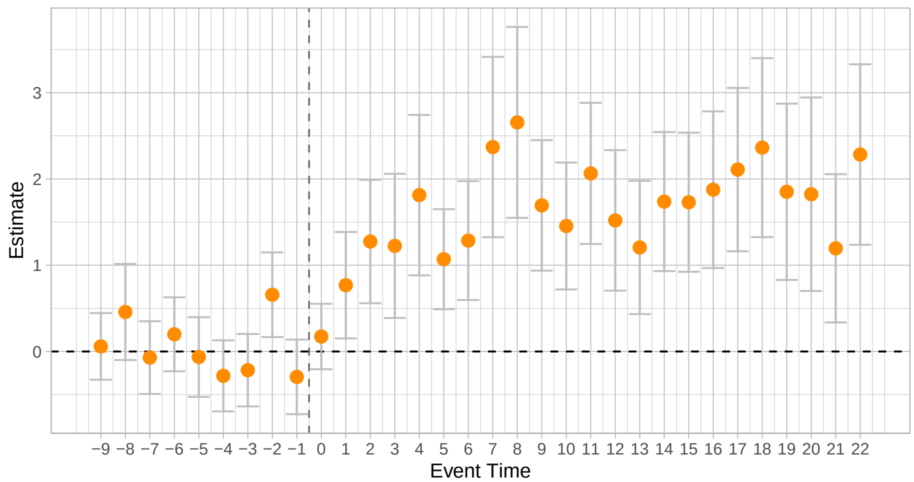
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A27: Lifetime Citation (LOO) DID Estimates, Callaway-Sant'Anna



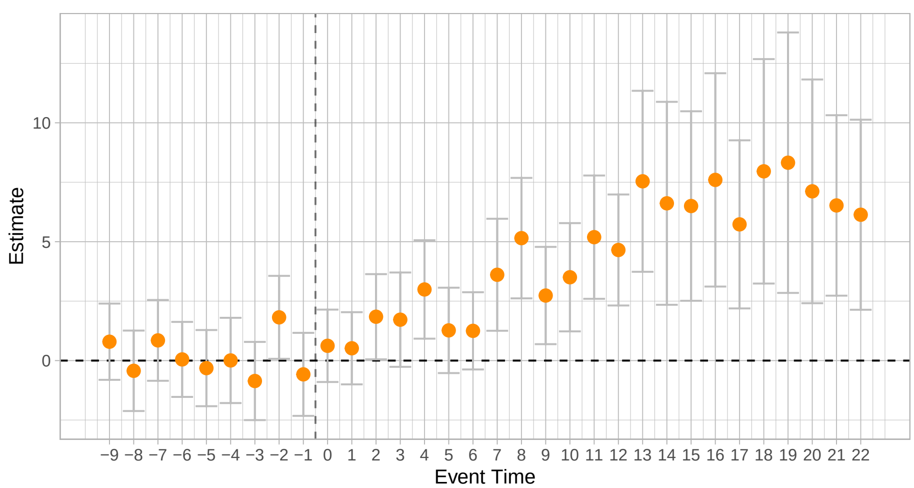
Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A28: Citations by Year (Broad LOO) DID Estimates, Callaway-Sant'Anna



Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

Figure A29: Lifetime Citation (Broad LOO) DID Estimates, Callaway-Sant'Anna



Note: S.E. clustered at subclass level, ⌶: sup-t 95% confidence band.

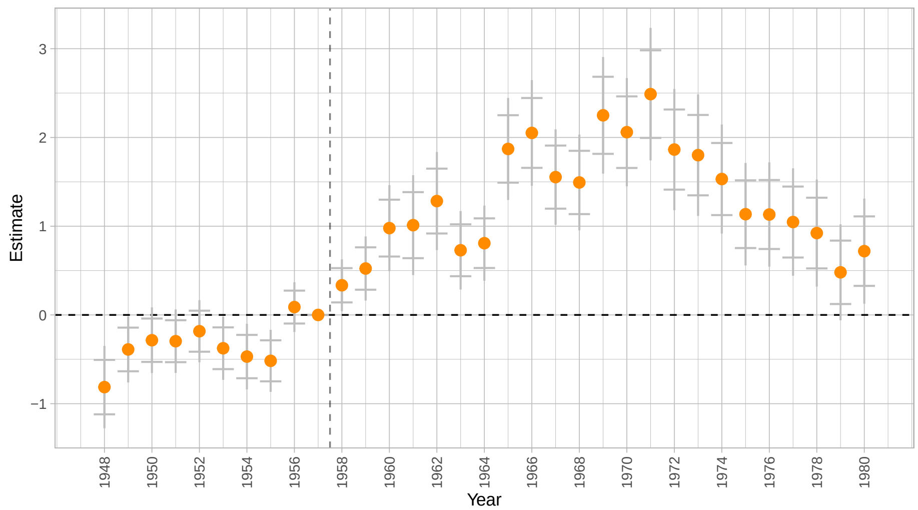
VII.H. Alternative Control Groups

This section re-estimates the baseline specification in Equation 1 using two alternative control groups instead of using other government related classes.

VII.H.1. All Classes

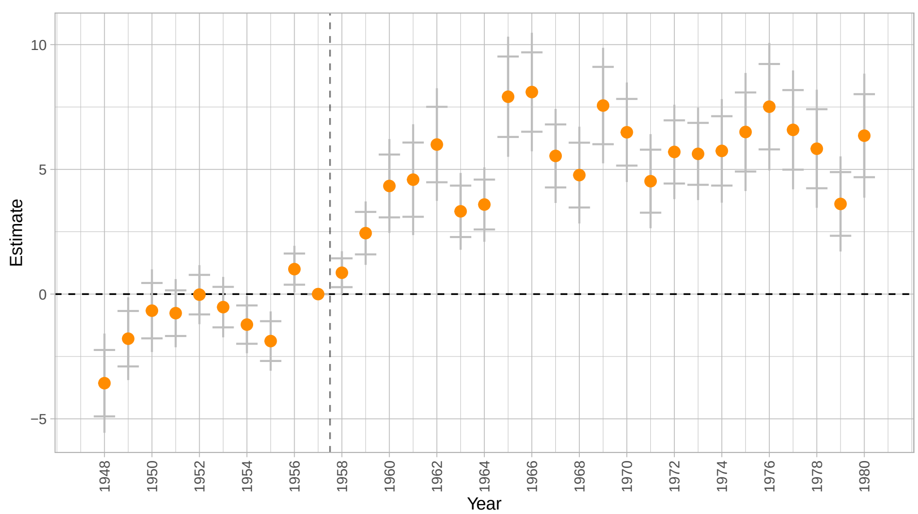
The first set of estimates uses all available technology subclasses that existed in the pre-treatment period.

Figure A30: Patent Issue DID Estimates, All Classes



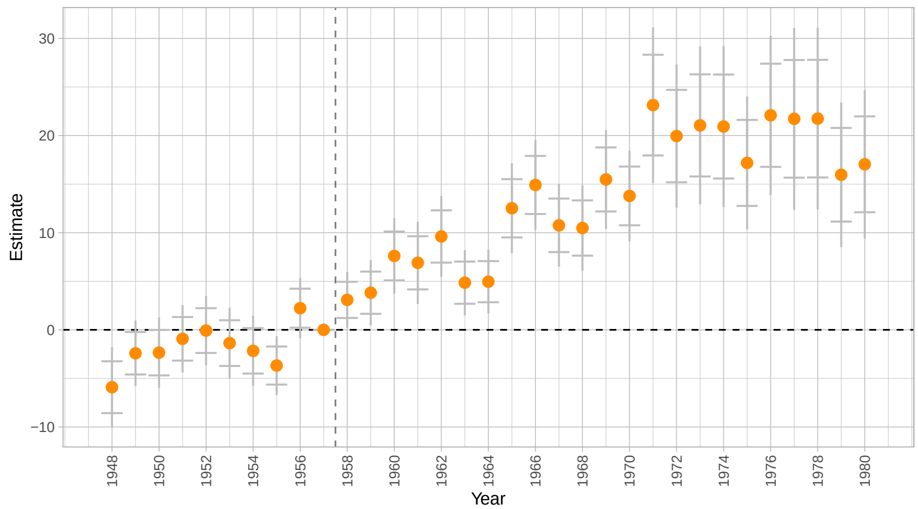
Note: S.E. clustered at subclass level, I: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A31: Citations by Year DID Estimates, All Classes



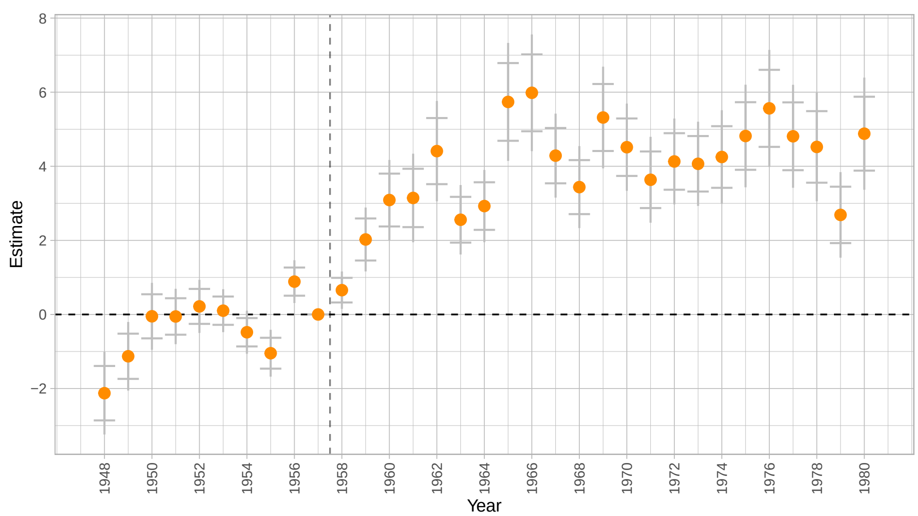
Note: S.E. clustered at subclass level, I: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A32: Lifetime Citations DID Estimates, All Classes



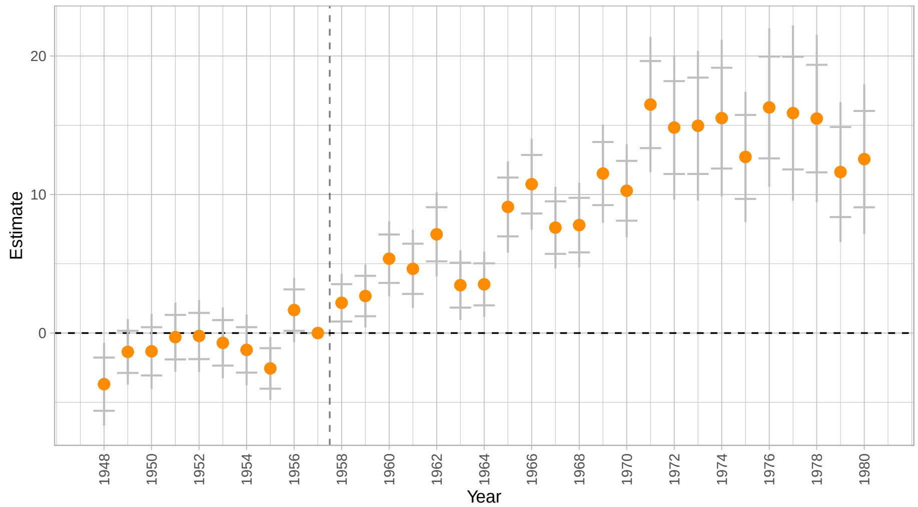
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A33: Citations by Year (Leave-One-Out) DID Estimates, All Classes



Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A34: Lifetime Citations (Leave-One-Out) DID Estimates, All Classes

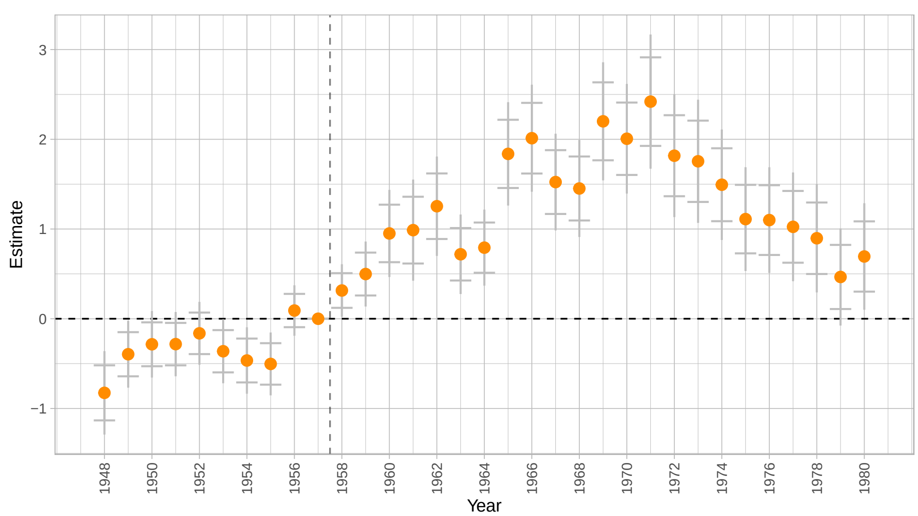


Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

VII.H.2. Treated Broad Classes

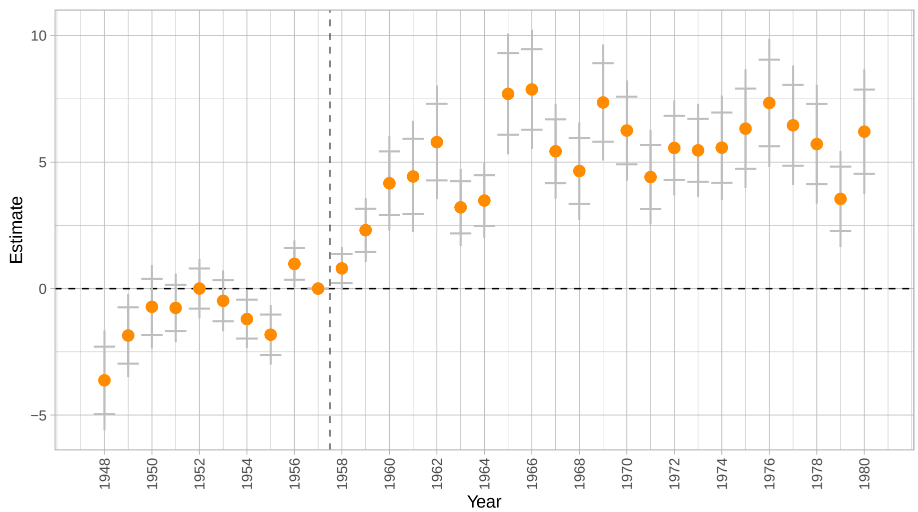
The following estimates use as controls the narrow classes that share a broad class with treated narrow classes.

Figure A35: Patent Issue DID Estimates, Same Broad Classes



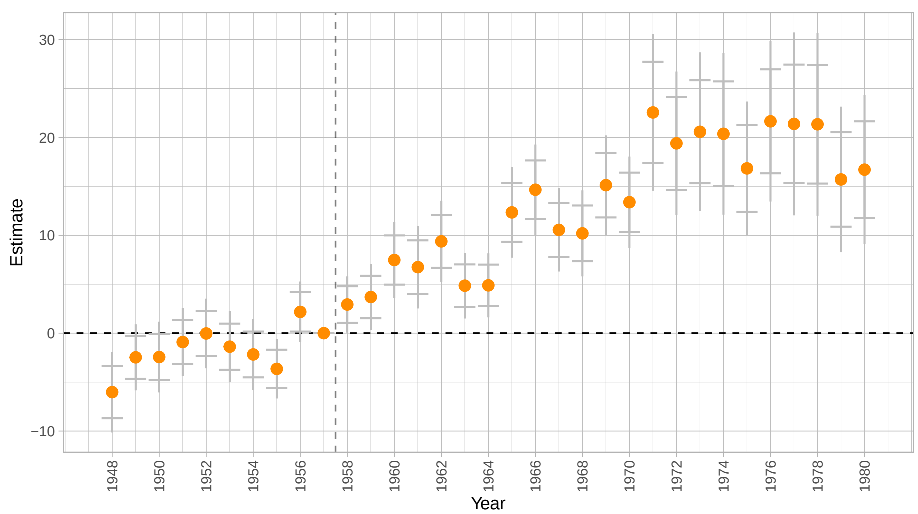
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A36: Citations by Year DID Estimates, Same Broad Classes



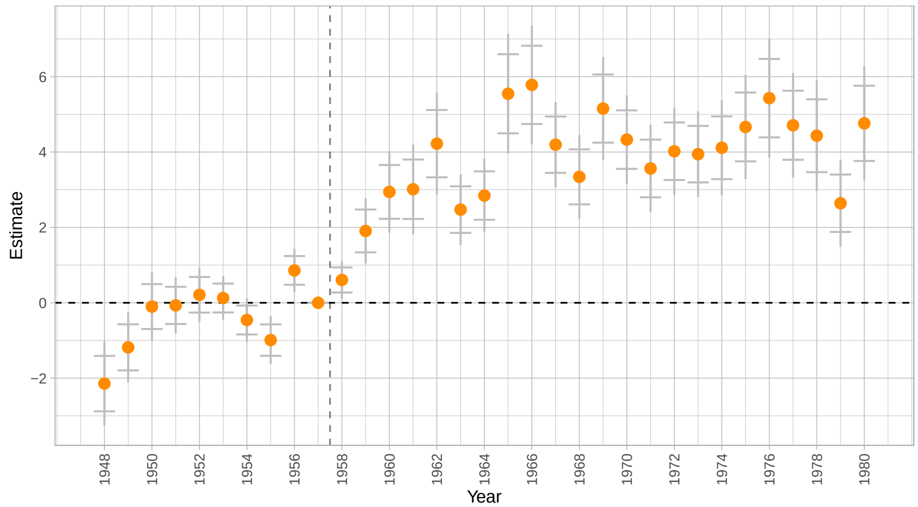
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A37: Lifetime Citations DID Estimates, Same Broad Classes



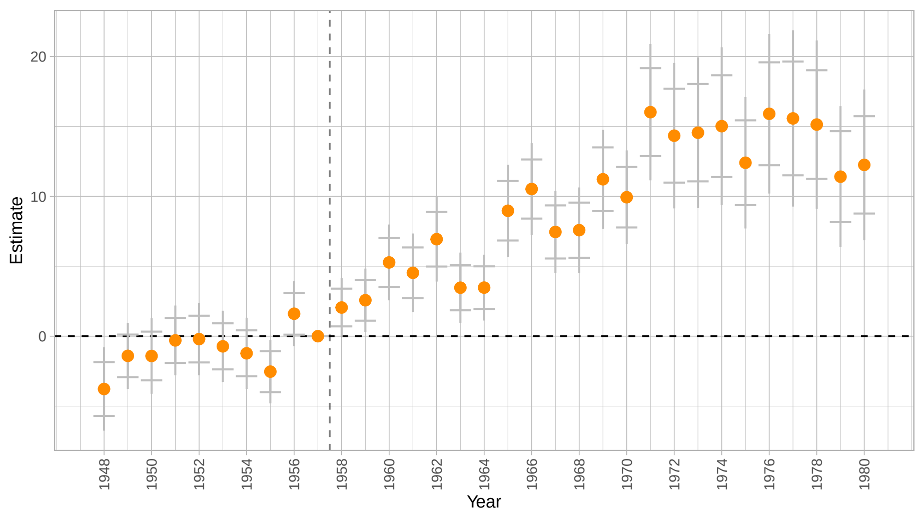
Note: S.E. clustered at subclass level, ⌶: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A38: Citations by Year (Leave-One-Out) DID Estimates, Same Broad Classes



Note: S.E. clustered at subclass level, I: point-wise 95% CI, |: sup-t 95% confidence band.

Figure A39: Lifetime Citations (Leave-One-Out) DID Estimates, Same Broad Classes



Note: S.E. clustered at subclass level, I: point-wise 95% CI, |: sup-t 95% confidence band.

VII.I. Linkage Procedure

This section details the procedure for matching NASA-affiliated inventors to their pre-NASA patents in Section V.F. First, I clean and standardize all inventor names in the data. Then, for each NASA patent's inventor (the target inventor), I produce a set of closest candidates by taking their Jaro-Winkler string distance (Winkler, 1990) and keeping the closest 5 names in all patents or all candidates with a distance under 0.1, whichever is lesser. Because inventors can possibly migrate over time, I do not utilize the location information in the patent in this first step. This first step yields 8,315 target-candidate pairs. It is worth noting that in this step, I am also allowing for NASA to NASA matches, to account for the fact that the same inventor might have naming variations.

This approach to find near matches using names is aided by two features that are not present in other common linkage applications, such as Census of Population linkages (Feigenbaum, 2016, Abramitzky et al., 2021). Two main sources of digitization error are at the input stage, that the original document contains typos or spelling errors, and at the digitization stage, that the transcription is incorrectly carried out. Because names have to be produced in patent applications by the inventor or a third party acting on behalf of them, one could expect higher accuracy at the time the original document was generated, relative to a Census enumerator taking someone's name for the Decennial Census. Second, because documents are consistently typed and then passed through optical character recognition, even though machine recognition will produce errors, it will produce consistent transcriptions. That is to say, two humans might transcribe the exact same text differently, even though one is correct. A program will always transcribe the same document the same way, even if it's incorrect. This second approach is more favorable for record linking.

Afterwards, I assess the match between each target inventor and their candidates. In the first pass, I only observe the name pairs to prune the list of possible candidates to those that have particularly similar names, resulting in 133 possible matches. Next, due to the lack of demographic information in the patents and the need to assess contextual information in each patent document, I manually study each scan for each inventor instead of relying on a probabilistic approach such as a supervised learning algorithm. As a non-random assessment of the optical character recognition in the CUSP dataset, I find that 66 of these potential matches where names are similar enough to look like matches but one appears to have a typo are in fact correctly transcribed as per the original patent document.

Due to the lack of identifying information, I rely on contextual clues in the patent scan such as employer and assignee information, proximity of target and candidate fields of invention, name consistency over time, and locations conditional on timing. Despite this, there is a subset of matches that have a close candidate but cannot be ruled as matches or non-matches with certainty. Specifically, there are 57 target-candidate pairs in this condition. However, none of these pairs changes the NASA or non-NASA status for all inventors' first patent in the data, thus the results are unchanged.