Moonshot: Public R&D and Growth*

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Abstract

We estimate the long-term effect of public R&D on growth in manufacturing by analyzing new data from the Cold War era Space Race. We develop a novel empirical strategy that leverages US-Soviet rivalry in space technology to isolate windfall R&D spending. Our results demonstrate substantial effects of public R&D on economic growth - implying a social rate of return to public R&D above 20%. While migration responses were important, they were not sufficient to generate a wedge between local and national long-term effects. The iconic Moonshot R&D program had first order economic effects for both local and national economies.

JEL Classifications: H54, N12, O32, R11

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1 Introduction

Technological progress plays a central role in theories of economic growth (Solow 1957, Romer 1990, Aghion and Howitt 1992). Because social returns to research and development may be larger than private returns, firms may underinvest in innovation, thus reducing the rate of technological progress (Arrow 1962, Griliches 1992, Bloom, Schankerman, and Van Reenen 2013). Can government-funded R&D fill this gap and generate long-term growth? Despite the fact that governments expend significant resources on R&D every year – over $158 billion in the OECD in 2020 (OECD 2022) – the answer remains unclear.

In this paper we provide new evidence on the effects of public R&D on long-term economic growth by analyzing a unique episode in U.S. history – the race to beat the Soviet Union to the Moon during the 1960s. The shock of the Soviet launch of the first satellite Sputnik in 1957 led to a geopolitical crisis that initiated the creation of the National Aeronautics and Space Administration (NASA) in 1958 and launched the race to the Moon in 1961. Figure 1 shows that the ambitious mission to send (and return) a manned crew to (and from) the Moon led to a massive expansion of federal investment in R&D – NASA received over 0.7 percent of GDP in the mid-1960s (Weinzierl 2018) and employed over 400,000 workers at the peak of the Space Race.

We analyze the effects of this R&D windfall on growth in manufacturing in the short- and long-terms. Focusing on manufacturing growth is likely to capture the indirect effects of space R&D well because getting to the Moon not only required new ideas and technologies, but also the production of real products. Innovations of the Space Race era were embodied, for example, in spacecraft, satellites, thrusters, navigation and communications equipment, computer software and hardware, and launch infrastructure. In fact, manufacturing firms accounted for over 87% of NASA contractor spending during the Space Race. Thus, the spillover effects of the space program's R&D were likely manifest significantly in manufacturing.

To estimate our models we develop a novel empirical approach to isolate the exogenous variation in NASA R&D. The imperative to win the Space Race meant that NASA was compelled to rapidly allocate funding to producers already specialized in the technological building blocks needed to complete the mission. NASA did not invest in technologies randomly, but sought to harvest any promising space technologies that could be supplied by American firms to win the race to the Moon. We address technology harvesting in two steps.

We first utilize the CIA's declassified National Intelligence Estimates of Soviet Space Technology (NIE) from the post-Sputnik era to define the set of technologies demanded by the space mission. We then search for these technologies in U.S. patents before 1958 to determine which U.S. counties specialized in space-relevant technologies before the Space Race began. We term counties as "Space Places" if their pre-1958 technological specialization matched post-1958 space technology demand, as seen through the perspective of the Soviet space program not NASA's. Isolating variation in NASA R&D that is virtually independent of location-specific unobservables, our research design compares changes in outcomes between space places that benefited from the geopolitical windfall R&D relative to other counties.

To carry out our empirical analysis we construct a new panel dataset containing highly granular data on U.S. manufacturing and NASA activity for over 790 counties from 1947 to 1992. For each county we have digitized the amount that NASA contractors received and that NASA spent directly on its own operations. We then match this information to manufacturing value added, employment, and labor income from the Census of Manufactures at the county $\times$ 2-digit industry level to estimate our models. We also utilize newly-available data on NASA ownership and funding of patents from Fleming, et al. (2019).

A first suggestive look at state-level correlations in Figure 2 reveals that states with more NASA activity experienced larger increases in value added and employment. Our analysis that addresses potential endogenenity of NASA's spending decisions reveals five main results. First, we establish that the Space Race caused NASA activity to expand more in the counties that had already specialized in the building blocks of space technology before Sputnik. The amount of NASA spending and the number of NASA patents expanded significantly relative to other locations that were not already specialized in the rudiments of space technology. Both NASA spending and NASA patenting grew over time, so by the time that the iconic Space Race ended in 1972 at the conclusion of the successful Apollo 17, the differential between pre-existing space places and other counties was especially large.

Second, we show that the Space Race led manufacturing value added and employment to expand more in the space places that had already specialized in early space technology before Sputnik. Interestingly, the effects are strongest after the end of the race to the Moon in 1972. One possible concern is that NASA activity followed trends in manufacturing. We show that there were negligible differential trends in the space places before the Space Race began, thus ruling out that space activity simply followed local private sector trends. Our results are also robust to controlling for industry or state specific trends, military contracting, and skill.

Our main estimates of the growth impact of NASA R&D imply a social rate of return of over 20%. Because long-term output effects include technology diffusion delays and private sector adjustments, our estimates are informative about the social rate of return in equilibrium. One caveat to our approach is that our estimates are likely to be lower bounds as they do not account for international technology diffusion or effects outside of the manufacturing sector.

We also find that R&D spending on the Space Race had a larger impact than typical government expenditures. Our results imply a localized NASA fiscal multiplier of about 3.8 in the post-Space Race period, as measured by changes in manufacturing value added. This estimate is notably larger than the cross-sectional estimate of 1.8 in Chodorow-Reich (2019) and larger than the upper end of the range (2.0) of Ramey's (2011) time-series estimates.

Our third set of results test for local productivity spillovers from NASA R&D. We find meaningful long-term local effects on measured productivity, accounting for about a third of the output effects. The presence of productivity spillover effects may explain why fiscal multipliers for R&D spending are larger than other government spending programs and the magnitude of our estimated social rates of return.

Our estimated value added effects could be large because they represent local rather than national effects. Local estimates would overstate national effects if workers migrated toward space places from other locations. Thus, our fourth set of results explores migration responses and implications. Studying migration during the Space Race era is a challenge due to a lack of panel data on individual workers. Instead, we turn to patent data where we build on recent advances in identifying specific inventors (Akcigit, Grigsby, Nicholas, and Stantcheva 2022) to construct a patent-inventor-level panel dataset. Our analysis examines whether inventor migration toward space places increased after onset of the Space Race. The results reveal that inventors did in fact migrate toward these space locations, and the results are robust to typical county-to-county migration patterns and state tax policy.

While our migration responses would imply national effects are smaller than local effects, other positive spatial spillovers – demand and technology being two notable examples – can counteract them. We develop a spatial framework based on Donaldson and Hornbeck (2016) that allows for workers and firms to respond to local shocks through adjustments in migration, trade, and production. Our framework accounts for multiple sources of spatial spillovers from NASA R&D to obtain the net effect of non-local NASA activity. Applying this theoretical framework, our fifth set of results shows that in the medium term – during the Space Race – positive market effects amplified the aforementioned positive local effects.

We do not find market effects in the post-Space Race era, however. Including both local- and market-level effects, which better captures a national multiplier, our estimated implied multiplier of NASA expenditures in the post-race era is about 4.1. This estimate is virtually the same as the local multiplier.

We believe that our analysis of the Space Race makes important new contributions to the economics of innovation literature. A recent literature has sought to obtain causal estimates of the effect of public R&D on knowledge production (Azoulay, Graff Zivin, Li, and Sampat 2019, Gross and Sampat 2020, Lanahan and Myers 2021) and productivity (Moretti, Steinwender, and Van Reenen 2021).[1] Perhaps most closely related to our work here is Schweiger, Stepanov and Zacchia (2021) who show that Science Cities created in Soviet Russia for space and military purposes are more productive and innovative today. We contribute to this literature by providing causal estimates of the effect of public R&D on long-term economic growth and estimating implied social rates of return to the real economy.

Second, our analysis contributes to the literature on industrial policy. Recent work has emphasized that temporary management practice transfers (Giorcelli 2019, Bianchi and Giorcelli 2020), trade protection (Juhasz 2018), or university funding (Kantor and Whalley 2014 and 2019, Andrews 2020, Hausman 2022) can have long-term effects on directly targeted firms or regions. Direct causal evidence on the impacts of industrial policy in Criscuolo, Martin, Overman, and Van Reenen (2019) shows contemporaneous effects on employment for small firms, but has not examined long-term effects. Our analysis provides new empirical insights into the spatial and temporal lags associated with public R&D that directly engaged private firms.

Third, we add new insights to the literature on government spending multipliers. Few studies focus on heterogeneous fiscal spending multipliers.[2] Our findings complement Cox, Muller, Pasten, Schoenloe and Weber's (2021) analysis that documents heterogeneity in government spending multipliers across sectors. We provide a novel source of multiplier amplification - productivity spillovers that happen over time - rather than sector-specific price stickiness. Our findings complement Ramey's (2021) work on short- versus long-term effects of public infrastructure. We also contribute to the debate on whether local fiscal multipliers adequately reflect nationwide multipliers (Nakamura and Steinsson 2014, Chodorow-Reich 2019, Ramey 2019). Our estimates of individual migration responses to local Space Race activity builds on recent work using patent inventor panel data to understand migration

[1] There is a long standing literature that has sought to estimate social effects of R&D from case studies, regression analyses, and macroeconomic models. See Jones and Summers (2021) for a literature review.

[2] See Chodorow-Reich (2019) and Ramey (2011) for recent surveys.

responses to tax policy and their implications (Moretti and Wilson 2017, Akcigit, Grigsby, Nicholas, and Stantcheva 2022). We show that while individual patent inventors did migrate toward areas experiencing persistent fiscal shocks during the Cold War, migration effects were not sufficiently large to generate a wedge between local and national fiscal multipliers.

Modern commentators contend that Space Race research had particularly high returns because NASA's organization was highly effective at research coordination and the intrinsic geopolitical motivation encouraged scientists to exert high levels of effort (Mazzucato 2021). Those advocating for significant government spending to jump-start innovation and economic growth often call for a new "Sputnik Moment," harkening back to a time when the United States devoted significant treasure racing the Soviet Union to the Moon (Gruber and Johnson 2019).[3] Yet, surveys of space scientists shortly after the Space Race suggest that NASA's role in technological development was mostly incremental (Robbins, Kelly and Elliot 1972) and some economists since Fogel (1966) – who was writing in real-time during the Space Race – have expressed skepticism that commercially relevant technology would be developed from mission-oriented R&D.[4] While the intellectual roots of the economics of innovation draw on the proverbial "moonshot" (Nelson 1959), a measure of the effects of such large-scale public expenditures still remains elusive (Bloom, Van Reenen, and Williams 2019).[5] Our estimates imply iconic Moonshot R&D had first-order effects on economic growth.

2 Historical Background

The Origins of NASA and its Geography. The Space Race effectively began with the Soviet launch of Sputnik on October 4, 1957. The U.S. government had intelligence that a launch was imminent (Logsdon 1995, 329), but the high-profile failure of the U.S.'s initial satellite effort – Project Vanguard – on live TV on December 6, 1957, instilled public fear (Divine 1993). Perceived American technological inferiority brought immediate national

[3]For example, President Joe Biden initiated his Cancer Moonshot in February 2022, renewing the effort that President Barack Obama began in 2016. But the proverbial Moonshot ambition with regard to cancer is long-standing. In advocating for the National Cancer Act, President Richard Nixon argued in his 1971 State of the Union, "The time has come in America when the same kind of concentrated effort that split the atom and took man to the moon should be turned toward conquering this dread disease."

[4]Over 60 years ago, Nelson (1959, 297) laid bare in rather subdued language the challenge to economists to begin understanding the impacts and tradeoffs associated with national spending on scientific research: "Recently, orbiting evidence of un-American technological competition has focused attention on the role played by scientific research in our political economy. Since Sputnik it has become almost trite to argue that we are not spending as much on basic scientific research as we should . . . it seems useful to examine the simple economics of basic research. How much are we spending on basic research? How much should we be spending? Under what conditions will these figures tend to be different?"

[5]Business R&D appears to be shifting away from basic research (Arora, Belenzon, and Sheer 2021). In such an environment, the importance of public funding for basic research may be increasing.

security concerns, as Eisenhower emphasized in his 1958 State of the Union Address: "what makes the Soviet threat unique in history is its all-inclusiveness. Every human activity is pressed into service as a weapon of expansion. Trade, economic development, military power, arts, science, education, the whole world of ideas – all are harnessed to this same chariot of expansion. The Soviets are, in short, waging total cold war."

In response to the emerging geopolitical tension, the Eisenhower administration proposed the National Aeronautics and Space Administration (NASA) in 1958, which would bring space activities under civilian control, except as they related to weapons systems, military operations, and national defense.[6] Exploring space transcended the simple military imperative, for as McDougall (1985, 172) notes in his Pulitzer Prize-winning history of the Space Race era, "The purposes of space activities were the expansion of human knowledge, improvement of aircraft and space vehicles, development of craft to carry instruments and living organisms in space, preservation of the United States as a leader in space science and applications, cooperation with other nations, and optimal utilization of American scientific and engineering resource." The immediate need was to forcefully respond to Sputnik and to the national realization that the U.S. was slipping behind the Soviet Union technologically.

Given the time-sensitive importance of building out the U.S. space program quickly in the immediate aftermath of Sputnik, much of early NASA's locational choices were effectively predetermined, adopted whole-cloth from NASA's predecessor the National Advisory Committee for Aeronautics (NACA) or parts of the military.[7] NASA itself soon established a few of its own physical research centers and operational facilities to fulfill its mission. First, in 1959 NASA began construction of a new research center (to be named the Goddard Space Flight Center) in Beltsville, MD, a location chosen mostly for expediency (Rosenthal 1968, 28). Second, to facilitate the manufacturing, testing, launch, and control of space vehicles, NASA established a variety of centers within the so-called "Space Crescent" (i.e., the Gulf

[6] Military applications of space technology were to be developed by the Advanced Research Projects Agency, which was also established in 1958.

[7] With administrative headquarters in Washington, DC, NASA began operations on October 1, 1958, absorbing NACA intact, including its 8,000 employees, an annual budget of $100 million, three major research laboratories – Langley Aeronautical Laboratory (established in 1917 in Hampton, VA), Ames Aeronautical Laboratory (established in 1939 in Santa Clara County, CA), and Lewis Flight Propulsion Laboratory (established in 1942, renamed John H. Glenn Research Center in 1999, near Cleveland, OH) – and two smaller test facilities (established in 1945 on Wallops Island, VA; and established around 1946 at Edwards Air Force Base in Kern County, CA). In addition, NASA in short time incorporated three military research groups that were conducting early work to support space flight – specifically, the space science group of the Naval Research Laboratory in Washington, DC; the Army's Jet Propulsion Laboratory (JPL) near Pasadena, CA, managed by the California Institute of Technology; and the Army Ballistic Missile Agency (renamed Marshall Space Flight Center) in Huntsville, AL, where Wernher von Braun's team of engineers had been engaged in the development of increasingly powerful rockets since the end of World War II.

of Mexico region).[8] At least with regard to the new Manned Spacecraft Center that would serve as the hub of the Moon mission, NASA ultimately chose Houston because of a number of its desirable characteristics: access to water transportation sufficient for barges, moderate climate, all-weather commercial jet service, mature industrial complex and sufficient labor resources, and strong electric utility and water supply (Dethloff 1993, chapter 3).

Growth and Organization. While Eisenhower's early efforts may have "ensure[d] that the United States remain *a* leader, not *the* leader in space, [he] did not commit the nation to an all-out race" (McDougall 1985, 172; italics in original). President Kennedy, however, laid down a bold marker, announcing on May 25, 1961, shortly following Alan Shepard's successful suborbital space flight: "I believe 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 Earth." Of course, the U.S. was nowhere close to having the technological capability to immediately fulfill that mission, so Kennedy's proverbial Moonshot required a massive investment in space technology and hardware. NASA's budget grew accordingly, from roughly $7 billion (2021$, or about 0.9% of all federal spending at the time) in 1961 to a peak of about $51 billion (2021$, or 4.4% of the federal budget at the time) in 1966.[9]

The National Aeronautics and Space Act of 1958 gave NASA broad powers to develop, test, and operate space vehicles and to make contracts for its work with individuals, corporations, government agencies, and others (Rosholt 1966, 61). NASA, from its inception, made the decision to contract out much of the R&D work to private contractors. T. Keith Glennan, the first NASA Administrator, was an advocate for contracting-out not only because of his philosophical aversion to expanding the government payroll, but also because "by spreading its wealth to contractors, NASA would not just be putting together a national team to beat the Soviets in the space race but would also be invigorating the aerospace industry and strengthening the country's economy" (Hansen 1995, 82-83).[10] This emphasis

[8]Specifically, a new Manned Spacecraft Center was established in Houston in 1962 (renamed Johnson Space Center in 1973); Cape Canaveral in 1962 became the Launch Operations Center (renamed Kennedy Space Center in December 1963) and maintained one of the largest buildings in the world to facilitate the assembly of space vehicles; the largest rocket test facility (now Stennis Space Center) was built in southern Mississippi (Hancock County) on the Pearl River in 1961; and NASA took over the Michoud Assembly Facility in New Orleans in 1961 to produce rockets during the Space Race era and external fuel tanks during the Space Shuttle era.

[9]In nominal terms, NASA's budget was $744 million in 1961 and $5.933 billion in 1966. NASA's spending did decline after the landing on the Moon was successfully accomplished in 1969, but still accounted for 1.92% of federal spending in 1970. Subsequently, the level of spending fluctuated between 0.75% to 1% of the federal budget from 1975 until the end of the twentieth century. To provide some perspective on the magnitude of NASA's budget during the Space Race, consider that in 2020 the total of all non-defense federal R&D amounted to 1.5% of the federal budget.

[10]For further elaboration on Glennan's views see (Hunley 1993, 5) and (Dunar and Waring 1999, 64).

is reflected in the growth in personnel. While in-house NASA employees grew from 10,200 in 1960 to 34,300 in 1965, employment by NASA contractors increased from 30,500 in 1960 to a peak of 376,700 in 1965. This massive increase in space-related employment outside of NASA was concentrated in private sector contractors, which accounted for 90% of total NASA employment in 1965. Universities, on the other hand, accounted for only 1.7% of total NASA employment in 1965 (Van Nimmen and Bruno 1976, 106). By 1988 total NASA employment was only a fraction of its heyday, with a total workforce of 52,224, with 56 percent of them employed by contractors (Rumerman 2000, 468).

Selecting Contractors. While the space program required scientists and engineers to solve basic scientific questions, in practical terms winning the Space Race and achieving successes in subsequent space missions meant developing and engineering actual products. According to an input-output table constructed for NASA expenditures for fiscal year 1967, the top five manufacturing sectors accounted for about half of NASA expenditures (Schnee 1977, 65).[11] Similarly, relatively few firms were so-called prime NASA contractors. In 1965, for example, the top 10 contractors received nearly 70% of the contract spending. Leading technology companies receiving NASA projects included North American Aviation, Boeing, Grumman Aircraft Engineering, Douglas Aircraft, General Electric, McDonnell Aircraft, International Business Machines, and Radio Corporation of America (Van Nimmen and Bruno 1976, 197). Given that the vast majority of the work that NASA, and its contractors, actually conducted led to manufactured goods, NASA's impact on the real economy should manifest in manufacturing outcomes, not just patents or scientific publications.

Rosholt (1966, 272) notes in his administrative history of early NASA work that "The geographic distribution of NASA contracts was a touchy political problem. Congressmen were sensitive to the fact that most of NASA's procurement dollar was spent in a handful of states. NASA's answer was that the competence of a contractor rather than his location was the basis for awarding contracts." After all, excellence was demanded because, quite literally, lives were at stake. Dieter Grau, the Director of the Quality and Reliability Assurance Lab at Marshall, put the logic simply: "you cannot put a man on a [launch vehicle] and say 'if it fails, and if you get killed, take the next one.'" Marshall, therefore, demanded that contractors shift from their perhaps existing "mass production with acceptable errors" mentality to one where "craftsmanship-do it right the first time-with no error" was the imperative (Dunar and Waring 1999, 45). New monitoring systems, such as NASA's Performance, Evaluation

[11] The five SIC 3-digit industries with the largest share of NASA spending were: Aircraft and Parts (SIC=372), Electrical Equipment (SIC=361-366), Computer And Office Equipment (SIC=357), Industrial Inorganic Chemicals (SIC=281), and Instruments (including Professional and Scientific) for Measuring, Testing, Analyzing, and Controlling (SIC=381-387).

and Reporting Technique (PERT) (Bilstein 1996, 286), were established to ensure contractor compliance with engineering specifications and NASA scientists embedded themselves in the contractors' organizations to minimize informational friction (Sato 2005).

Technology Impacts. Winning the Space Race did not necessarily entail developing entirely new technologies as much as combining or speeding along the development of existing technologies (Robbins, Kelly and Elliot 1972). NASA's mission-oriented objective, especially during the race to the Moon, led to R&D breakthroughs that might cause the casual observer to wonder whether any broader economic impacts would even be expected. As examples, in Appendix Exhibit A1 we display several representative NASA patents of the Space Race, including patents on space capsule design, a navigation and guidance system, and a Moon-landing apparatus. Yet the Space Race did produce and escalate innovative breakthroughs in a number of areas, such as cryogenics, integrated circuits, digital communications, and computer simulation, that had the potential to spillover more broadly (see, e.g., Bilstein 1996). In Appendix Exhibit A2 we show several examples of burgeoning technologies in which NASA participated in enough fashion that the agency considered them spin-offs. Such technologies include magnetic resonance imaging, remote sensing, a gas analyzer, and a circuit connector.

Astronauts lamented that they were merely "spam in a can" when it came to flying spacecraft because the vehicles and systems were so highly automated. Today we dream of fully autonomous vehicles, but in fact NASA created one during the 1960s and it landed on the Moon. To achieve such stunning technological successes during the 1960s, especially, and into the 1970s, NASA rapidly developed novel computer hardware and software systems; data management systems (e.g., on-board processing, data compression, data archival); digital communications (i.e., an early-form "internet"); man-machine systems that combined human sensory, cognitive, language, and motor-control systems with machine intelligence; sensors that could be used for mapping and meteorology; and robots. Many of the ideas that NASA pursued, especially in the post-Space Race era, might have seemed like science fiction at the time and some only recently have begun to achieve widespread commercial application. The so-called Sagan Report (NASA Study Group 1980) describes NASA's spearheading work and developments in "machine intelligence and robotics." Therefore, the main point we emphasize here is that NASA's very early work and technological successes were intensely focused on accomplishing the Moon mission, but the groundwork was laid for many subsequent innovations that had the potential to contribute to tangible advancements in real economic activity, especially in manufacturing.

3 Data Construction and Descriptive Statistics

This paper uses newly-constructed datasets on technological specialization, space sector activity, and manufacturing during the Cold War era. Our measurement relies on three components: (i) declassified CIA intelligence documents detailing Soviet space capabilities, which are then matched to pre-Sputnik U.S. patents, thus enabling us to define space places based on technological similarity; (ii) county-level NASA patents and spending that are used to measure space sector activity; and (iii) county-industry-level manufacturing census data used to measure outcomes in the real economy. In this section, we describe the construction of these components and some data limitations. Detailed discussions of the construction of each variable, as well as the data sources, are available in the online appendix sections 1 and 2.

Space Technologies and Space Places. Our research design compares changes in outcomes between counties that specialized in research forming the building blocks of spaceflight technology before the Space Race to those that did not. We first need to measure which technologies were the building blocks of spaceflight technology. At first glance, using observed NASA technology choices might seem a promising approach. However, NASA technological choices reflect both mission requirements and opportunities provided by U.S. leadership in specific technologies that could help win the race to the Moon. Locations that specialized in technologies where the U.S. had technological superiority – and selected by NASA for that reason – may have been poised for growth regardless of the space program. Integrated circuits is a case in point. While NASA was one of the first large-scale customers for microchips, locations specializing in microchip research likely would have grown even without NASA largess. Because NASA may have simply harvested technological potential, rather than having developed technological breakthroughs to solve emergent challenges, a correlation between NASA activity and growth may not reflect a causal effect.

To address this issue we define the building blocks of spaceflight technology from Soviet technology choices. Soviet choices did not necessarily reflect the scientific areas where the U.S. had technological superiority, as a lack of U.S.-Soviet trade or knowledge sharing made them irrelevant. Instead, Soviet technological choices reflected mission requirements as well as opportunities provided by Soviet leadership in specific technologies. We obtain these technologies by digitizing the CIA's declassified National Intelligence Estimates of Soviet Space Capabilities (NIE) from 1947 to 1991.[12]

[12]The titles and dates of the NIE documents are provided in online appendix table A1.

We obtain the locations of pre-Space Race spaceflight technology in the United States by searching for post-Sputnik Soviet spaceflight technologies in the U.S. patent record. Using text similarity to connect units in technology-space has been shown to quantify economically meaningful concepts (see, e.g., Azoulay, Graff Zivin, Li, and Sampat 2019, Myers 2020, and Meyers and Lanahan 2021). We discuss our approach in detail in online appendix section 2.2, but provide a brief summary here. To connect NIE space intelligence documents to patents, we first require a corpus of scientific terms for which we search in both documents. We use the Science Direct (SD) technology term corpus that is used to index specific technologies in all of their scientific publications.[13] This corpus of technology terms covers a much broader range of technologies than other commonly used approaches that are domain specific (e.g., Medical Subject Headings (MeSH)). To estimate a numerical similarity score between each NIE document and each U.S. patent we use term frequency cosine similarity.[14] Finally, we compute the county-level median of the similarity between technologies in the pre-1958 patents and the post-1958 NIE Soviet space technology intelligence reports, which we term the *space score*. To visually illustrate our approach, two examples of pages from NIE documents and patents containing relevant SD technology terms that contribute to textual similarity are highlighted in Appendix Exhibit A3. The frequency of similar terms in the patents and NIE pages leads them to be highly similar and have a high space score value. We define those counties with above-median values of the space score as *space places*.

Our textual similarity measure captures spaceflight technological similarity regardless of how patents were classified by the Patent Office. Examples of patents that are highly similar to a specific NIE document are shown in Figure 3. We see patents dealing with pop-up fins, orbital devices, and satellites.[15] While the majority of frequent technology terms in our examples are closely connected to spaceflight, they do suggest one potential limitation of our measure. NIE intelligence and U.S. patent documents may be textually similar because of matching non-spaceflight technologies. For instance, military technology

[13]We obtain this corpus as the set of all scientific terms here: https://www.sciencedirect.com/topics/index, accessed on September 7, 2021.

[14]The set of SD technological terms we use excludes those that appear in a very high fraction of patents - the top 1% most frequently occurring terms - and those appearing in no patents. We also drop stop words and stem the SD terms, as discussed in the data appendix and as frequently applied in the literature on using text as data (Gentzkow, Kelly and Taddy 2019). We present details of these choices and robustness results in the online appendix section 2.2.

[15]Examples of SD technology terms most frequent in patents owned or funded by NASA, shown in appendix table A2, include “Aircraft,” “Antennae,” and “Propellant.” Examples of SD technology terms most frequent in NIE space technology intelligence reports, shown in appendix table A3, include “Missiles,” “Satellites,” and “Orbitals.” Appendix table A4 reports the SD terms occurring frequently in *both* NIE and patent documents. Such terms as “Aircraft,” “Spacecraft,” and “Satellites” are frequently found in both types of documents.

terms such as “Warhead” or “Missile” – even though they were commonly used to describe rocket technology at the time – could lead to a high similarity score even if their space-relevance might be low. In appendix table A5 we show that our patent-level space score based on textual similarity between the patent and NIE technologies strongly predicts NASA ownership or funding of a patent, conditional on military funding, technological area, and county fixed effects.[16] We further address this concern by showing that our main results below are robust to a broad range of controls for military research and spending (Table 4) and point out here that the spatial correlation between military and NASA R&D activity is small (appendix table A6).

Map 1 shows the spatial distribution of space scores. The map shows that many space places – i.e., those with a high space score – were distributed throughout the country without a cluster in a single state or region. In Section 4 below we show econometrically that our measure of pre-Sputnik space-related research in a county performs well in explaining subsequent NASA spending and patenting.

NASA Activity. We measure NASA activity using expenditures and patents. We collect and digitize new data on NASA primary contractors from NASA's historical databooks. These data include the company names, amount of primary contracts, and place of performance (in addition to location of company headquarters) for the top 100 contractors from 1963 to 1992.[17] NASA primary contracts, in practice, flowed to a small number of large firms so that the top 100 firms accounted for between 87% to 92% of total contractor spending. In addition to contractor spending, we also include NASA spending on its own R&D centers.[18]

A second source we use to measure NASA activity is patents owned or funded by the agency. For patents prior to 1976, this information is drawn from Fleming et al. (2019) who

[16] The regression results reported in online appendix table A5 are patent level and are specified as:

$$NASA_l = \omega_1 + \omega_2 \text{Space Score}_l + \gamma_t + \nu_l, \quad (1)$$

where $NASA_l$ takes a value of 1 if the patent is a NASA patent and zero otherwise. $SpaceScore_l$ measures the cosign similarity between patent l and all NIE documents, as discussed above. We expect ω_2 to be positive if our measure captures technological similarity to NASA demands. We report versions of this model that also control for NBER technology subcategory fixed effects, other government involvement in the patent, and county fixed effects.

[17] Companies receiving the largest amount of NASA contracts include Boeing, Ford, General Motors, General Electric, Grumman, IBM, McDonnell Douglas, North American Aviation. Prominent metro areas containing counties having high levels of NASA spending include Los Angeles (Los Angeles County, CA), New York City (Nassau County, NY), and Cincinnati (Hamilton County, OH).

[18] To avoid double counting funds that might have been contracted out by NASA R&D centers, we multiply NASA centers' R&D spending by NASA's national fraction of in-house spending (25%) to obtain totals of NASA-specific R&D within the county where the center is located.

have scraped assignee and government funding information from the full text of USPTO patents. After 1976 the information is directly reported by the USPTO. We next allocate granted patents to locations. We utilize a few sources to obtain a county for each patent. For the data before 1975 we use the HISTPAT database that has scraped the full text of the patent to assign each patent to the most appropriate county (Petralia, Balland and Rigby 2016). For the post-1975 data we use the USPTO Patentsview data that has the exact address for each inventor. We use the address of the first inventor to assign a patent to a county.[19] Map A1 in the online appendix shows which counties had a patent or any spending from 1947 to 1992. Appendix table A6 shows that NASA spending and NASA patenting variables are highly spatially correlated.

Figure 1 plots the times-series of NASA activity from 1947 to 1992. In Panel A we see that real NASA spending increased substantially after 1958. Spending peaked in 1965 at the height of the Space Race before declining more than 50% by the mid-1970s. While spending steadily increased thereafter, it did not return to the Space Race peak. In panel B we see that NASA patents were very low before NASA was founded in 1958.[20] During the Space Race the number of patents granted per year increased from 21 in 1961 to 256 in 1969. From 1967 until today the number of patents per year has fluctuated in the 150 to 300 range. In the postwar period the total number of patents and total number of government patents increased much more slowly and gradually than NASA's. Both NASA spending and patenting show a sharp increase in activity after the launch of the Space Race. Differing trends after the end of the Moon missions in December 1972 may reflect a tilt of NASA activity toward basic research in the post-Space Race era.

Manufacturing Data. The primary data we use to estimate the impact of NASA research and development on value added, employment, and labor income is from the Census of Manufactures. We digitize data at the county-industry level from the censuses of 1947, 1954, 1958, 1963, 1967, 1972, and combine them with existing digital sources from 1977, 1982, 1987, and 1992.[21] We obtain data on total value added, total employment, total annual wages, and total plant and equipment additions for each county-industry cell. We

[19]We build a cross-walk between fips counties and state-city name text fields from the USPTO patent technology team database (https://bulkdata.uspto.gov/data/patent/ptmtdvd/). This database assigns each address on a patent from 1969 to 2014 to a fips county. Most city-state text fields are assigned to a unique location. For the few that are not we assign the city-state text to the largest county listed.

[20]The few patents from before 1958 are likely from patents under NASA's precursor the National Advisory Committee for Aeronautics. The patents were later reassigned to NASA (Ferguson 2013).

[21]Manufacturing census data are available at the county-industry level after 1992; however, the data are reported at the NAICS instead of SIC level from 1997 onward. For this reason and given our focus on the Space Race prior to the end of the Cold War, we do not examine later years of data.

use 2-digit SIC industries (1972 definition) in the county as the unit of analysis.[22]

Additional Data. We also employ data on local measures of skill from the population census, number of research scientists from the National Register of Scientific and Technical Personnel, the number of IBM mainframes installed in various locations, defense spending, and transportation cost data. Details of the construction and source of each variable are described in the Appendix.

Sample Selection and Descriptive Statistics. The sample of counties and industries represented in our analysis is based on those reported in the Census of Manufactures, with the caveat that we exclude the few counties that had no patents between 1945 and 1958.[23] Effectively, our sample captures the major urban labor markets that had innovative activity prior to 1958. Entry and exit of specific manufacturing sectors in a county leads to an unbalanced panel. Data may also be unreported because the number of establishments was below the threshold for confidentiality. We require that a county-industry cell report in at least three censuses to address issues with a highly unbalanced sample. Additional sample restrictions include a requirement that both value added and employment were reported and that the reported number of total workers (i.e., production plus non-production) was greater than the number of reported production workers in a given year. We also drop the 30 observations that appear in ND, SD or WY because only a single county in each state reported manufacturing data. Our analysis sample contains 26,862 county-industry observations from 791 counties and 20 two-digit SIC industries from 1947 to 1992.

Table 1 provides a first look at summary statistics of relevant measures in 1958, the first year immediately after Sputnik was launched. Column (1) presents the means and standard deviations of key variables for the full sample. We stratify counties based on whether they had already specialized in the technological areas that the Space Race with the Soviets would later demand. In columns (2) and (3) we stratify based on whether a county was considered a space place or not, as defined above. Column (4) reports the p-value for differences in the baseline variables for the full sample. In columns (5)-(8) we conduct the same analysis on a limited sample that excludes the upper 25th and lower 25th percentile of places based on their total number of patents before 1958.

Columns (1) to (4) show that firms that would later be more exposed to the Space Race

[22] The census manufacturing data are also available at the 3- and 4-digit SIC × county level. We choose the 2-digit level, however, because the masking of cells with few establishments results in extensive missing data if we were to use disaggregated data. Using 2-digit level data results in fewer non-reported observations.

[23] We exclude these counties without pre-1958 patents because we are unable to compute a space score for them.

were already quite different in 1958. In columns (2) and (3) we see that those locations that were eventually more heavily exposed to the Space Race generally had larger firms, had more patenting, and were more populous with their citizens more likely to have greater human capital. The results in columns (5) to (8) contrast with this set of findings. In this limited sample we see similar levels of manufacturing activity, patenting, population, and upper tail human capital.

Throughout our analysis, we account for differences between areas with high and low exposure to the Space Race using a number of approaches. First, all regressions include a full set of county fixed effects that control for permanent differences across counties. Hence, our identification strategy does not require that counties were similar in 1958. We assume only that manufacturing activity in counties with pre-1958 technology more similar to Space Race Soviet technology would have evolved in parallel to other less similar counties had the Space Race not occurred. We present evidence in support of this assumption below. Because manufacturers in certain industries may have been more exposed to the Space Race regardless of local technological specialization, we add industry fixed effects so that we are only considering within-industry changes. Moreover, we control for potential shocks to counties with different characteristics by using a wide range of control variables interacted with time fixed effects.

To further strengthen our identification strategy, we also examine how our results change when we use the limited sample in columns (5)-(8). When we exclude counties with high or low levels of pre-1958 patenting, baseline characteristics in 1958 were quite balanced between high and low space score counties. We consistently find that the effects of interest do not differ in this subsample.

4 Local Effects of Public R&D

This section presents our main results. We analyze how the launch of the Space Race in 1958 affected a variety of activities in space places – that is, places that had, prior to Sputnik, specialized in technologies that would later prove useful for winning the Space Race. For this analysis we use data on NASA expenditures and patenting and manufacturing outcomes in the census years of 1947, 1954, 1958, 1963, 1967, 1972, 1977, 1982, 1988, and 1992.

NASA Activity. We first test whether NASA activity was disproportionately allocated to locations that specialized in the early building blocks of space research before the Space

Race even began. We estimate the following equation:

$$\begin{aligned}\text{arsinh}(NASA_{it}) =& \alpha_1 + \alpha_2 \text{Space Place}_{i,<1958} \times \text{Space Race}_t + \\ & \alpha_3 \text{Space Place}_{i,<1958} \times \text{Post-Space Race}_t + \delta_i + \gamma_t + \nu_{it}.\end{aligned} \tag{2}$$

The outcome variable is the inverse hyperbolic sine of a certain NASA activity measure, such as the amount of NASA spending or number of NASA patents, in county i in year t.[24] Space Place$_{i,<1958}$ is a binary variable that takes a value of one when the text similarity between technologies mentioned in pre-1958 patents in county i and those mentioned in the post-1958 National Intelligence Estimates of Soviet space capabilities is above median. Space Race$_t$ is a dummy variable that takes a value of one during the Space Race (i.e., 1959 to 1972, inclusive) and zero otherwise. Post-Space Race$_t$ is a dummy variable that takes a value of one after the Space Race (i.e., 1973 to 1992, inclusive) and zero otherwise. δ_i is a full set of county fixed effects and γ_t is a full set of year effects. As areas with pre-1958 space specialization might have had unobserved time-invariant characteristics that drove space activity before, during, and after the Space Race, we include county fixed effects in our analysis. To account for potential correlation of shocks within counties across time, we cluster standard errors at the county level.

In addition, areas specializing in space technology before 1958 may have been more innovative overall and subject to different trends regardless of the Space Race. In some models we add Total Pre-1958 Patents$_i$ $\times$ γ_t controls to account for these trends. In these models our identification is from variation in the composition of pre-1958 innovation across counties, not the level. Finally, we include State$_i \times \gamma_t$ to flexibly control for state level trends in some models.

We expect α_2 and α_3 to be positive as places that were specialized in space-relevant technologies before 1958 were likely to experience more NASA activity after 1958, once the Space Race began. If NASA spending became more tightly connected to pre-Sputnik research specializations, as basic research intensity rose, we might expect effects to have grown over time.

Our research design is based on the idea that locations that specialized in scientific research before 1958, which ultimately became important space technology areas after 1958, did not experience higher levels of NASA activity until after the Space Race began. We regard this assumption as plausible given that the decision to go to the Moon was only made

[24]We use the inverse hyperbolic sine transformation $\text{arsinh}(x) = ln(1 + \sqrt{x^2 + 1})$. This approximation to the log transformation retains zero values of the NASA activity in our estimation sample.

after the launch of Sputnik in 1957. As NASA did not even exist until 1958, we cannot examine pre-Space Race trends with these data. We do, however, examine the possibility that NASA may have allocated space funding in response to pre-existing trends in the local manufacturing sector in later analyses.

The results of estimating equation (1) are reported in Table 2. In columns (1), (2), and (3) we see that NASA spending was larger in space places during (1958-1972) and after (1973-1992) the Space Race.[25] Our preferred estimates in column (3) imply that NASA spent \$2.6 million (\$1958) more during and \$4.2 million (\$1958) more after the Space Race in locations with a prior history in space-related research. We use these magnitudes to estimate local fiscal multiplier effects below.

In columns (4) through (6) we see similar results when we use patents owned or funded by NASA as the outcome variable. The results differ in magnitude from the expenditures, perhaps reflecting that Space Race activity was more focused on refining and applying existing technologies than developing new ones. Across all columns we obtain larger point estimates for the post-Space Race era than for the time period when the race to the Moon was taking place. This finding may indicate that NASA spending became more focused on basic research in the post-Space Race era.

Manufacturing. We use the same empirical strategy to examine manufacturing outcomes. We estimate:

$$\begin{aligned}\log(Y_{ijt}) =& \beta_1 + \beta_2 \text{Space Place}_{i,<1958} \times \text{Space Race}_t + \beta_3 \text{Space Place}_{i,<1958} \times \text{Post-Space Race}_t + \\ & \delta_i + \gamma_t + \text{Pre-1958 Patents}_i \times \gamma_t + \nu_{ijt}.\end{aligned} \tag{3}$$

Here the outcome variables are the log of a manufacturing outcome, such as value added or employment, in county i, industry j, and year t. All models include a full set of county fixed effects (δ_i), a full set of year effects (γ_t), and Pre-1958 Patents$_i \times \gamma_t$ controls to account for differential trends based on pre-existing patenting in a county. In other versions of the models we include State$_i \times \gamma_t$ to flexibly control for state-level trends. Finally, we also extend the model to include θ_j and $\theta_j \times$Year$_t$ fixed effects to account for time invariant differences across industries and industry specific flexible time trends. To account for potential correlation of shocks within county-industry cells across time, we cluster standard errors at the county-industry level.[26] Again, we expect β_2 and β_3 to be positive as places that were specialized in

[25]In Appendix table A7 shows the results are very similar using the limited sample described in Table 1.

[26]We examine alternative inference procedures - clustering on county, county $\times$ industry, state-industry and using a spatial HAC approach - in online appendix table A8.

space-relevant technologies before 1958 received more NASA activity once the Space Race commenced, which likely impacted manufacturing outcomes.

In Table 3 we report the main results. The results in columns (1) to (4) show that manufacturing value added grew faster in space places. The effects are more than double (and more precise) after the race to the Moon had ended after 1972. Growing space place effects could reflect NASA's shift toward basic research over time, which may have produced larger local spillovers.[27] It could reflect manufacturing productivity taking time to respond due to lags in technology diffusion, thus implying that gains from public R&D take time to manifest.[28] Growing space place effects could also reflect lags in the responses of private sector firms and workers. Crowding-in of physical capital investment or follow-on innovation could take time and amplify the direct effects of NASA activity. Alternatively, increasing effects could reflect spatial reallocation that takes time to manifest, as migration, for example, may be more responsive to a persistent demand shock.

In columns (5) to (8) we see a similar pattern of results for employment. Again, the effects are larger and more precise after the Moon landing phase of the Space Race had ended. The magnitudes of the employment and value added effects are quite similar.

These manufacturing results are robust to controlling for state trends, industry fixed effects, and industry trends. They are also robust to dropping any single state or industry (online appendix figures A1 and A2, respectively). Moreover, in Table 1 column (4) we saw that space places differed from other locations in terms of their baseline levels on a number of outcomes in our main analysis sample. When we trim the sample to only include locations with pre-1958 patent counts near the median, the sample becomes much more balanced on initial outcomes (Table 1 column (8)). We present our main results for manufacturing employment using this limited sample in online appendix table A9 and find similar results.

Our conclusions are also robust to alternative inference procedures - clustering on county, county $\times$ industry, state-industry and implementing a spatial HAC approach (see online appendix table A8). Estimating similar models with the outcomes in levels (online appendix table A10) gives a similar pattern of results. Finally, our results are also robust to defining space places based on alternative approaches to measuring textual similarity between the

[27] Recent work by Akcigit, Hanley, and Serrano-Velarde (2021) argues that spillovers from basic research are broader than those from applied research.

[28] Jones and Summers (2020) survey the literature and conclude that delays of three to six years appear reasonable, 10 year delays are conservative, but basic research delays may be longer, up to 20 years. Similarly, in the context of agricultural research innovations, Kantor and Whalley (2019) find spatial diffusion delays in the United States after 1920 of about 10 years.

intelligence documents and patents (online appendix table A11).

We separately estimate own- and cross-industry exposure effects in appendix table A12 to see how concentrated the effects are in technology space. Columns (1) to (3) reveal that the effects of technologically distant R&D are almost 50% larger than own-industry R&D in our value added models. For employment we find that own- and other-industry effects are quite similar in columns (4) to (6).[29]

Prior Trends. A potential lingering concern with our estimates is that NASA activity may have been endogenous to local outcomes. It could be the case, for example, that NASA was harvesting technologies by responding to unobserved productivity shocks within an industry-county cell. While our reading of the historical evidence indicates that NASA did not follow trends in the productivity of manufacturing firms or of specific locations because of the imperative to win the race to the Moon, exploring prior trends is an important specification check.

We graphically present dynamic versions of our main econometric model with 1958 as the reference year in Figure 5 and report the coefficients in online appendix Table A13.[30] The results from this analysis reveal little evidence of prior trends. The coefficients of the 1947 and 1954 interactions are very close to zero and not statistically different from zero at any conventional confidence level. These results lend additional credibility to our research design.

Military Activity and Skills. The Cold War period in the United States featured dramatic expansions in military-sponsored research and skill accumulation. Both factors

[29]That our estimates indicate roughly a third to one half of the overall effects we estimate are attributable to cross-industry spillovers lines up closely with patent-based spillover effect estimates. Azoulay, Graff Zivin, Li, and Sampat (2019) find that spillover effects from NIH funding to non-targeted diseases account for about half the overall effects. Myers and Lanahan (2021) find that nearly two-thirds of net patent output is related to technologies that are not very similar to the original objectives as stipulated in the Department of Energy's Funding Opportunities Announcements. This similarity suggests that manufacturing outcomes can well capture both narrowly focused as well as broader cross-technology domain spillovers. Our main estimates in Table 3 account for both effects.

[30]The model we estimate is:

$$\begin{aligned}\log(Y_{ijt}) =& \alpha_1 + \sum_{k=1947,k\neq 1958}^{1992} \gamma_k \text{Space Place}_{i,<1958} \times \text{Year=k}_t + \\ & \delta_i + \gamma_t + \text{Total Pre-1958 Patents}_i \times \gamma_t + \nu_{ijt}.\end{aligned} \tag{4}$$

where $Year = k_t$ is a dummy variable that takes a value of one for manufacturing census year k and is zero otherwise. The excluded year is manufacturing census year 1958. Other variables are defined as in equation (3).

may have been important for the growth of manufacturing output and potentially correlated with the rise of NASA activity itself. A simple approach to address this concern is to control for these factors at the county or preferably county×industry level.

In panel A of Table 4 we add controls for military activity. We utilize newly-digitized data on government-sponsored patents in this period from Fleming et al. (2019) to measure Army and Navy patents at the county level. Controlling for these patents in columns (1) and (2) of Table 4-Panel A does little to alter our value added estimates.[31] Another important control to consider is county-level military spending.[32] Controlling for county-level military spending in column (3) also has little effect on our value added results. Our last model takes advantage of data on a cross section of research scientists in 1962 that include information on their location and whether they received military funding for their research. When we add controls for defense scientist×year fixed effects in column (4), our value added results again change little. The results for employment in columns (5) to (8) of Table 4-Panel A are similarly robust.

In panel B of Table 4 we add controls for worker skill. In column (1) we add controls for the fraction of manufacturing workers who were non-production workers and the value added results change little. This measure of skill has the advantage that it is measured at the same unit of observation as our outcome variable – county × industry × year. It has the disadvantage, however, that it likely captures occupational, as well as educational attainment, variation. The variable also likely captures little variation in upper-tail skill that may matter for growth (Squicciarini and Voigtländer 2015). In column (2) we add a control for the number of research scientists in 1962×year to capture differential trends in the upper-tail of human capital accumulation. Similarly, in column (3) we add a control for the number of IBM mainframes in 1961×year to capture differential trends based on the installation of advanced information technology in a location, which may reflect a highly skilled population. Finally, we add controls for high school graduate percentage in 1960×year. The value added results remain largely unchanged across these experiments. The results for employment in columns (5) to (8) of Panel B are similarly robust. In sum, our results appear highly robust to controls for military activity and local human capital characteristics.

Rates of Return. A strength of our approach is that we can recover estimates of the

[31] This result may be expected as the spatial correlation between military patents and NASA patents turns out to be quite small. See online appendix Table A6.

[32] A county-level measure is unavailable before 1966, so we create a county-level series back to 1940 using annual state-level defense spending allocated to counties based on their actual shares of contracting within their respective states in 1967 (see details in the data appendix).

marginal rate of return to NASA R&D spending from output (and productivity, below) estimates directly. We follow Jones and Summers (2020) in computing the internal rate of return to capture the social rate of return to R&D spending. As space spending and resulting effects on output had a specific time path of initially high costs with benefits coming later, we use the calculation in appendix section 3 rather than Summers and Jones's (2020) balanced growth path approach to compute these estimates.

Using our preferred estimates in column (3) of Table 3 we find an internal rate of return of 34% over our sample period. We regard our estimate to be a lower bound since it does not include international or even inter-regional spillovers. Myers and Lanahan (2021) find that local spillovers only account for just under half of total spillovers.[33] Our estimates also do not incorporate effects outside the manufacturing sector. While we expect these to be small based on the historical accounts and technologies where NASA was active, they are another unaccounted for impact. Lastly, common issues associated with measuring inflation, such as substitution bias, product improvement, and the introduction of new goods, can affect our ability to measure real output accurately simply using value added.[34]

In terms of putting our rate of return estimate into some perspective, one comparison would be the return on risky assets that could be an alternative investment option since the Moon mission was certainly risky. Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) find that the risky rate of return across many counties and time periods is about 7%. Our estimate of the social rate of return to research – despite being a lower bound – is over 4 times larger than this. Our estimated rate of return is comparable to much of the literature. Griliches (1992) summarizes estimated rates of return to public R&D in the agricultural sector at 20-67%. Bloom, Schankerman, and Van Reenen (2013) estimate a social return to private R&D at 55%. Our estimate is smaller than Myers and Lanahan (2021) who find marginal social returns to R&D about 100–300% of the marginal private returns, though they note their setting is likely to yield an upper bound.

Multipliers. To compare the effects of public R&D spending relative to government expenditures in general, we compute the contemporaneous fiscal multiplier.[35] We use the es-

[33] We incorporate inter-regional spillovers below by incorporating market level effects in our analysis. In a similar vein, Moretti, Steinwender and Van Reneen (2021) find meaningful international spillovers from R&D.

[34] Advances in product quality and the introduction of new goods have been estimated to lead inflation to be overstated by about 0.65% per year (Gordon 2000), for example.

[35] See Ramey (2021) for calibrations of long-term multiplier effects under alternative models as well as a summary of the multiplier literature with respect to public capital. Her work shows long-term multipliers are larger when the public investment has larger effects on productivity and the economy is initially below the socially optimal level of public investment. Public R&D may be expected to have a larger rate of return

timates in Table 3 column (3) to compute: *Space Race Output Effect* $= \hat{\beta}_2 \times \overline{\text{Value Added}_{ijt}} \times \overline{\text{Output-Value Added Ratio}_{ijt}}$ and analogously a *Post-Space Race Output Effect* $= \hat{\beta}_3 \times \overline{\text{Value Added}_{ijt}} \times \overline{\text{Output-Value Added Ratio}_{ijt}}$. In other words, this measure computes the local value added effect for space places from Table 3 times the sample mean of value added scaled up by the output/value added ratio. We do not have total output in manufacturing before 1967, so we scale our value added estimates up by this fraction to find an implied total manufacturing output effect. We also compute *Space Race Spending Effect* $= \hat{\alpha}_2 \times \overline{\text{NASA Spending}_{ijt}}$ and *Post-Space Race Spending Effect* $= \hat{\alpha}_3 \times \overline{\text{NASA Spending}_{ijt}}$ using estimates in Table 2 column (3). Our local fiscal multiplier estimates are then *Local Space Race Multiplier* $= \frac{\text{Space Race Output Effect}}{\text{Space Race Spending Effect}}$ and *Local Post-Space Race Multiplier* $= \frac{\text{Post-Space Race Output Effect}}{\text{Post-Space Race Spending Effect}}$.

We obtain an implied local fiscal multiplier for public R&D of 2.4 during the Space Race (i.e., 1958 to 1972, inclusive) and 3.8 after the Space Race (i.e., after 1972). We focus on the post-Space Race multiplier as that statistical evidence is stronger. Our post-Space Race multiplier is notably larger than the cross-sectional estimates in the literature. A recent survey (Chodorow-Reich 2019) indicates that the literature supports a local fiscal multiplier of 1.8. Our estimates are also larger than time-series based national multiplier estimates. Ramey (2011) finds that time-series evidence supports estimates ranging from 0.5 or 2.0.

Our contemporaneous local multiplier estimates are subject to many caveats. First, by comparing within-era expenditures to within-era manufacturing output we are not accounting for the potential dynamic effects of Space Race-era research and development on later economic outcomes. Such an issue could be dissatisfying if productivity, follow-on innovation, or capital investment responded to public R&D with a lag as we might expect, assuming of course that these responses generated increases in value added. Second, our calculation does not account for the effect of NASA research on output in other sectors or locations, or how the expenditure was financed. Third, our estimates could be state dependent. The 1960s was generally a decade of economic growth, so our estimated effects could be relatively smaller than those that would have otherwise been generated in the late 1970s and 1980s when growth was slower. While keeping these caveats in mind our local fiscal multiplier estimates are notably larger than the fiscal multiplier estimates in the literature.

One possible reason that our local fiscal multipliers are larger than estimates in the literature is that public R&D may have had a range of multiplier-augmenting responses not present for other types of government spending. Public R&D related to spaceflight may have

than other types of public spending as these conditions are more likely to be met in the public R&D case.

generated new technologies that made local firms involved in the research and development more productive, thus increasing their output. Such targeted R&D may have produced discoveries that were augmented by local private sector firms, thus also increasing output. We turn to examining these possible local productivity spillover effects next.

Measured Productivity. In Table 5 we test for local spillover effects from public R&D onto measured productivity. We measure total factor revenue based productivity by estimating the production function $Y_{ijt} = A_{ijt} K_{ijt}^{\beta_{1j}} L_{ijt}^{\beta_{2j}}$ allowing factor shares to be industry specific to recover manufacturing revenue total factor productivity at the industry-county-year level, A_{ijt}. A limitation of our approach is that because we only have a few years of data before the launch of Sputnik and our panel is unbalanced, we are unable to address the concern that firms chose inputs in response to unobserved productivity shocks. For this limitation to be an important source of bias for our analysis it would need to be the case that unobserved productivity shocks unrelated to the Space Race were correlated with NASA activity. Based on our results above and the historical evidence, we view this concern to be unlikely.

In columns (1) to (4) of Table 5 we find that space places experienced larger increases in productivity during and after the Space Race. These effects are statistically significant with the exception of column (4), which includes industry $\times$ year fixed effects.

Conducting a similar internal rate of return calculation using the productivity impacts reported in Table 5 column (3) gives an estimate of 22%. Calculating internal rates of return using productivity, rather than output, effects could be preferred; however, there are important limitations with our productivity measure to note. Because we measure revenue productivity rather than physical productivity our estimates may pick up changes in markups or product quality as well as physical productivity. This concern is likely to be salient in the short term as the Space Race was an important demand shock that likely affected prices in an industry with significant barriers to entry. Thus, our measure of TFP would increase even if physical productivity did not change. We address the problem of industry specific price changes by including year$\times$industry fixed effects. Output price effects of NASA activity may still remain a problem for our local estimates if demand is spatially concentrated. We would not expect these local price effects to persist, however, as firms entered high markup markets over the longer term. The fact that our post-Space Race productivity effects are larger suggests that they were not primarily driven by price effects. A second issue is that because we do not have a balanced panel we cannot address the potential biases in productivity estimation from firms' endogenous choices of inputs in response to unobserved productivity shocks.

5 Spatial Spillovers of Public R&D

Our estimated value added effects could be large because they represent local rather than national effects. Local estimates would overstate national effects if, for example, labor was supplied elastically and workers migrated toward space places from other locations. Such an increase in employment in space locations would come at the cost of reduced employment elsewhere.[36] Such worker mobility would be consistent with historical accounts and the fact that adjustment through migration can take substantial time (Blanchard and Katz 1992).[37] Alternatively, local estimates can understate national effects if there are positive demand or technology spillovers across areas.[38] How spatial spillovers may have generated a wedge between local and national effects is an empirical question.

Inventor Migration. A central challenge with measuring migration responses during the time period under consideration is lack of individual panel data.[39] We attempt to overcome these data shortcomings by using a disambiguated panel of patent inventors that tracks their locations, following the procedures in Akcigit, Grigsby, Nicholas, and Stantcheva (2022). We create an individual identifier for each U.S. inventor, using patent data covering 1945 to 1992. See online appendix section 2.3 for more details. Our analysis follows Moretti and Wilson's (2017) empirical approach with two differences.[40] First, we study county-to-county migration flows and construct the data at the county $\times$ patent application year level.[41] Second, we include time-invariant measures of space technology scores interacted

[36]That migration can lead to different local versus national multipliers is discussed in Ramey (2019) and Chodorow-Reich (2019); however, most evidence to date has focused on less persistent spending shocks and does not find a substantial migration response. Our context may be more likely to lead to migration given the persistence of the shock to local spending from NASA's founding and continued operations as its missions evolved in the Cold War era.

[37]For example, while almost all of the technical and clerical workers for the Manned Spacecraft Center in Houston could be hired locally, only 10 percent of the 6,000 scientists, engineers, and administrators were from the Houston area (Holman and Konkel 1968, 31-32). Similarly, within five years of opening the center, over 125 technological firms that had a presence in the space field opened offices in Houston, including some of the most prominent such as General Electric, Honeywell, IBM, North American Aviation, Lockheed, Raytheon, Texas Instruments, and TRW (Brady 2007, 455).

[38]Myers and Lanahan (2021) find positive technological spillovers across space, and positive demand spillovers are at the heart of the market access approach developed in Donaldson and Hornbeck (2016).

[39]The 1940s to 1960s is too recent for linked population Census data to be available and too early for modern panel datasets, such as the PSID, that track an individual's location.

[40]We choose to follow Moretti and Wilson (2017) instead of Akcigit, Grigsby, Nicholas, and Stantcheva (2022) as the latter's approach has a significant computational burden at the state level and we are using even more fine-grained county-level data.

[41]In this context patent application year is preferred over patent grant year that we use above as it is closer to the time period of innovation. We thus obtain a measure of location with less measurement error

with space era dummies into our migration model.

Moretti and Wilson (2017) show that the equilibrium number of inventors who migrate into a county as a function of location-based factors can be estimated as:

$$\begin{aligned}\log\left(\frac{P_{odt}}{P_{oot}}\right) &= \eta_1\left([\log(\text{Space Score}_d) - \log(\text{Space Score}_o)] \times \text{Space Race}_t\right)\\ &+ \eta_2\left([\log(\text{Space Score}_d) - \log(\text{Space Score}_o)] \times \text{Post-Space Race Era}_t\right)\\ &+ \eta_3[\log(1-I_{dt}) - \log(1-I_{ot})] + \eta_4[\log(1-C_{dt}) - \log(1-C_{ot})]\\ &+ \eta_5[\log(1+R_{dt}) - \log(1+R_{ot})] + \gamma_t + \gamma_o + \gamma_d +\\ &+ \gamma_{od} + \text{Pre-1958 Patents}_0 \times \gamma_t + \text{Pre-1958 Patents}_d \times \gamma_t + u_{odt}.\end{aligned} \tag{5}$$

We denote origin locations o and destination locations d. The number of inventors who move from o to d is P_{odt} and the number of inventors who begin in o and do not move is P_{oot}, so that $\log\left(\frac{P_{odt}}{P_{oot}}\right)$ is the log odds ratio for inventor out-migration. We examine how the odds of moving depend on the differences in space scores, $(\log(\text{Space Score}_d) - \log(\text{Space Score}_o))$, interacted with indicator variables for the Space Race era and post-race periods (Space Race Era_t and Post-Space Race Era_t, respectively). We control for origin-destination differentials in personal income tax rates, $([\log(1-I_{dt}) - \log(1-I_{ot})])$, corporate income tax rates, $([\log(1-C_{dt}) - \log(1-C_{ot})])$, and R&D tax credits, $([\log(1+R_{dt}) - \log(1+R_{ot})])$. Finally, we control for county origin (γ_o) and destination (γ_d) fixed effects, year of patent application (γ_t) fixed effects, as well as pair fixed effects (γ_{od}) to capture time invariant pair specific features such as distance or travel costs.[42] To account for trends by initial innovation intensity, as in our analysis above, we also control both origin and destination pre-1958 patents times year fixed effects (Pre-1958 $\text{Patents}_o \times \gamma_t$ and Pre-1958 $\text{Patents}_d \times \gamma_t$, respectively). We consider a few variants of this specification - with and without tax rates and including state × year fixed effects - in our analysis.

The coefficient estimates η_1 and η_2 capture how the relationship between space score differentials between origin and destination places affected migration during and after the Space Race relative to the pre-NASA era. If NASA spending caused inventors to migrate toward space places, then we would expect η_1 and η_2 to be positive. Time invariant factors that affected wages or amenities in the origin and destination locations, as well as typical

by using application year instead of grant year.

[42]For this analysis, we follow Moretti and Wilson (2017) in showing standard errors that allow for three-way clustering by origin county × year, destination county × year, and origin-destination pair. This clustering addresses the issues that errors could be correlated across origin (destination) counties within a year because they share the same level of space technology similarity in all observations involving that origin (destination) county in a year. In addition, standard errors may be correlated over time within the panel.

migration patterns, are controlled using origin, γ_o, and destination, γ_d, and pairwise γ_{od} fixed effects. A potential threat to our approach is that changes in wages or amenities were correlated with differentials in space place likelihood during and after the Space Race. Based on our results above and historical accounts, we do not expect this to be likely.

Table 6 reports the results of estimating alternative versions of our migration model. In column (1) we see that inventors moved toward areas with higher space scores in the post-Space Race period. Adding controls for personal tax rates, corporate tax rates, and R&D tax credits in column (2) does little to alter these results. Finally, column (3) adds origin state × application year and destination state × application year fixed effects.[43] Across all of these specifications our results change little and the robust conclusion is that Space Race spending led to inventors' migration toward opportunity.

Including Market Effects. How might migration, demand and technology spillovers combine to affect the national return to R&D spending? To address this question we incorporate market level effects of R&D that reflect a wedge between local and national effects driven by R&D spending in other counties. These market level effects are derived in an extension to the simple county-to-county trade model from Donaldson and Hornbeck (2016) in online appendix section 4.[44] We use our model to obtain the estimating equation:

$$\begin{aligned}\log(Y_{ijt}) =& \beta_1 + \beta_2 \text{Space Place}_{i,<1958} \times \text{ Space Race}_t + \beta_3 \text{Space Place}_{i,<1958} \times \text{post-Space Race}_t + \\ & \beta_4 \text{High Space Market}_{i,<1958} \times \text{Space Race}_t + \beta_5 \text{High Space Market}_{i,<1958} \times \text{Post-Space Race}_t \\ & + \delta_i + \gamma_t + \text{Total Pre-1958 Patents}_i \times \gamma_t + S_i \times \gamma_t + \nu_{ijt}.\end{aligned} \tag{6}$$

We define High Space Market$_{i,<1958}$ as a binary variable where counties with above median values of our space-score-based market measure receive a value 1, and other counties receive a zero. For details of how this variable is constructed see online appendix section 4.2. Our goal is to estimate β_4 and β_5 which will capture the market-level effects of Space Race activity elsewhere during and after the race to the Moon. With these estimates in hand we can get a sense of how spatial spillovers may affect our estimates of the fiscal multiplier and

[43]Migration elasticities may be heterogeneous. Our focus on the same sample of inventors - in the top 5% of lifetime patent inventors - follows Moretti and Wilson (2017) as locations may be better measured for persistent patent authors. However, using the top 5% to construct the sample of inventors is arbitrary, but we present results for top 25% and top 50% lifetime inventors in the appendix tables A14 and A15. The results are largely consistent regardless of the sample construction.

[44]This approach allows us to quantify national effects, while maintaining research design credibility typically found in reduced-form studies. We differ from Donaldson and Hornbeck (2016), however, in that we focus on the impact of public R&D spending, holding transportation infrastructure fixed and introducing market-level consumption externalities.

implied rate of return reported above. For these models that use both local and market level variation to estimate the effects of space activity, we cluster the standard errors at the state-industry level.

In Table 7 we report the results of estimating equation (6). In column (1) we report our baseline value added local effects model for reference (i.e., drawn from Table 3, column (3)). In column (2) we report value added market effects only; and column (3) combines both. Here we see positive market effects during the Space Race, which would be expected with cross-county demand or productivity spillovers. In the post-Space Race era we find no market effects. A lack of market effects in the longer term would be consistent with the worker mobility toward space places described above, which seem to have outweighed any market-level demand or technology spillover effects. Similar results are present for employment in columns (3)-(5).

The results in Table 7 indicate that positive market effects seem to amplify the positive local effects related to NASA R&D during the Space Race era, but the market effects seem to attenuate in the longer term. Using the estimates in column (3) of the table and applying the output to value added adjustment noted above, we re-calculate the implied Space Race multiplier for a county to be 4.3 and the post-Space Race multiplier to be 4.1 when market effects are included.[45] Our post-space race national multipliers are again larger than the literature. Our internal rate of return estimate is larger that those above because the positive and statistically significant market effects during the Space Race expands the number of time periods with a positive effect.[46] Our results suggest that incorporating spatial spillovers does not lower the estimated impact of NASA R&D spending.

6 Conclusion

Landing on the Moon in 1969 represented a critical moment for boosting American technological capabilities and leadership. Looking to this iconic Moonshot event, our paper

[45]We obtain the national multiplier implied for county i using the estimates in Table 7 to compute: $\mathit{SpaceRaceOutputEffect} = (\hat{\beta}_2 \times \overline{\text{Value Added}_{ijt}} + \hat{\beta}_4 \times \overline{\Delta SpaceMarket_{ijt}}) \times \overline{\text{Output-Value Added Ratio}_{ijt}}$ where $\overline{\Delta SpaceMarket_{ijt}}$ is the sample average difference in $SpaceMarket_o \approx \sum_d \tau_{od}^{-\theta_d} \mathit{SpaceSpending}_d^{\theta}$ between space place and non-space place counties. Analogously, $Post - \mathit{SpaceRaceOutputEffect} = (\hat{\beta}_3 \times \overline{\text{Value Added}_{ijt}} + \hat{\beta}_5 \times \overline{\Delta SpaceMarket_{ijt}}) \times \overline{\text{Output-Value Added Ratio}_{ijt}}$. We divide the output effect by the relevant spending effect to obtain the implied multiplier.

[46]Using these estimates accounting for market effects, we obtain an internal rate of return estimate of 191% over our sample period. This estimate is comparable to the results in Myers and Lanahan (2021). Important caveats to our spatial spillover approach include: (1) an approximated market access term; (2) obtaining nationwide effects from a representative county; (3) defining markets regionally; and (4) not including follow-on innovation or international spillovers.

seeks to address fundamental questions about the role of public R&D in facilitating economic growth. Despite its focal point as a shining example of American R&D investment and accomplishment, there is no credible empirical estimate of the space mission's contribution to economic growth. Using newly-collected data and a novel identification strategy that takes advantage of the geopolitical tensions of the historic moment, we uncover relatively large, stable, and precisely estimated effects of public R&D on long-term manufacturing growth. The implied rate of return to public R&D spending related to space exploration was over 20% – significantly larger than typical costs of financing. In terms of fiscal multipliers, our estimates are double those found from most types of government spending.

Economists have long sought to untangle the multiple factors that contribute to economic growth. The roles of public and private sector R&D, human and physical capital investment, transportation and communications infrastructure, culture, geography, political and legal institutions, and even luck have been carefully explored and debated. Our analysis of the Space Race and its aftermath indicates an important role for public policy and public R&D in generating economic growth. Today the U.S. government invests a tiny fraction in non-military R&D relative to the heights of the Cold War. The economic impacts of the politically-charged Space Race Era provides some credence to some policymakers and advisors' calls for a new Sputnik Moment to seed a new era of U.S. economic growth and international leadership.

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TABLE 1: Descriptive Statistics of Pre-Space Race Era

Sample:	Full				Trimmed – Drop < 25th and > 75th Percentile of Pre 1958 Patents			
		Space Place Score$_{i,<1958}$				Space Place Score$_{i,<1958}$		
	All	>=Median	<Median	Difference	All	>=Median	<Median	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Manufacturing Census Data								
Value Added ($1958 Million)	34	43	23	0.010	23	23	24	0.735
	(92)	(117)	(40)		(32)	(31)	(33)	
Employment (1958)	3,779	4,712	2,617	0.010	2,559	2,509	2,606	0.716
	(9,430)	(12,072)	(3,988)		(3,077)	(2,955)	(3,192)	
Labor Income ($1958)	4,390	4,448	4,303	0.032	4,629	4,643	4,615	0.755
	(1,057)	(1,050)	(1,061)		(908)	(895)	(920)	
Capital Investment ($1958 '000's)	1,821	2,078	1,502	0.184	1,399	1,155	1,634	0.065
	(5,796)	(5,734)	(5,854)		(4,090)	(2,086)	(5,345)	
Panel B: Annual Patent Data								
Total Patents (1958)	43	60	26	0.012	37	38	36	0.622
	(191)	(257)	(80)		(41)	(46)	(36)	
Navy Patents (1958)	0.03	0.04	0.01	0.013	0.04	0.04	0.03	0.509
	(0.16)	(0.20)	(0.10)		(0.18)	(0.20)	(0.16)	
Army Patents (1958)	0.02	0.02	0.01	0.431	0.01	0.01	0.01	0.984
	(0.16)	(0.19)	(0.11)		(0.12)	(0.13)	(0.10)	
Panel C:Population Census and Other County Data								
Population (1960)	169,372	213,654	124,979	0.001	217,071	223,647	210,332	0.575
	(379,436)	(501,211)	(181,323)		(185,365)	(193,187)	(177,541)	
High School Graduate Percent (1960)	46	40	53	0.370	43	44	42	0.013
	(209)	(10)	(295)		(7)	(8)	(6)	
Research Scientists (1962)	741	965	517	0.011	1,331	1,446	1,222	0.584
	(2,485)	(2,991)	(1,819)		(3,105)	(3,294)	(2,909)	
IBM Mainframe Computers (1961)	0.43	0.57	0.28	0.011	0.67	0.75	0.58	0.488
	(1.62)	(1.89)	(1,29)		(1.93)	(1.97)	(1.89)	
No. of Counties	791	396	395		245	124	121	

Notes: Data are drawn from National Intelligence Estimates, Census of Manufacturers, Census of Population, United States Patent and Trademark Office, National Roster of Scientific and Technical Personnel and IBM mainframe data, as described in the data appendix. The Space Place Score is the $\tilde{\rho}_c$ as discussed in section 2.2 of the appendix. The unit of observation is county × 2-digit SIC industry in panel A and county in panels B and C. In columns (1),(2),(3),(5),(6), and (7) the main entries are means for the variables indicated with standard deviations in parentheses. Column (4) reports the p-value for the hypothesis test that the values in (2) and (3) are different. Column (8) reports the p-value for the hypothesis test that the values in (6) and (7) are different. Columns (1)-(4) are for the full sample for 1958. Columns (5)-(8) are for the trimmed sample that drops locations with more than 75th percentile level of pre-1958 patents and less than the 25th percentile of pre-1958 patents.

TABLE 2: Space Places, NASA Spending, and NASA patents

Dependent Variable =	Arsinh(NASA Spending)			Arsinh(NASA Patents)		
	(1)	(2)	(3)	(4)	(5)	(6)
Space Place$_{i,<1958}$ × Space Race$_t$	0.75	0.39	0.43	0.04	0.02	0.03
	(0.28)	(0.24)	(0.23)	(0.01)	(0.01)	(0.01)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.81	0.57	0.66	0.06	0.04	0.04
	(0.26)	(0.23)	(0.23)	(0.02)	(0.01)	(0.01)
County Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects		Y	Y		Y	Y
State × Year Fixed Effects			Y			Y
R^2	0.48	0.52	0.56	0.44	0.51	0.56

Notes: Data are drawn from National Intelligence Estimate, NASA Historical Data Book, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (1) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992 (the Space Score), as described in the text and the appendix. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is county × year. The models in columns (1) and (4) includes county and year fixed effects, the models in columns (2) and (5) also include the count of pre-1958 patents in a county × year fixed effects, and the models in columns (3) and (5) also include state × year fixed effects. Dependent variables are transformed using the inverse hyperbolic sine: $arsinh(x) = \ln\left(x + \sqrt{x^2+1}\right)$. Standard errors are clustered at the county level. All models have 7,910 county-year observations and 791 county observations.

TABLE 3: Space Places, Value Added, and Employment

Dependent Variable =	Log(Value Added)				Log(Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	0.06	0.07	0.06	0.05	0.07	0.07	0.06	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.12	0.14	0.14	0.14	0.13	0.13	0.13	0.13
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects		Y	Y	Y		Y	Y	Y
Industry Fixed Effects			Y	Y			Y	Y
Industry × Year Fixed Effects				Y				Y
R^2	0.36	0.37	0.50	0.52	0.34	0.35	0.46	0.48

Notes: Data are drawn from National Intelligence Estimate, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in its pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. The models in columns (1) and (5) includes county and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in columns (2) and (6) also include state × year fixed effects; columns (3) and (7) also include industry fixed effects; and the models in columns (4) and (8) further include industry × year fixed effects. Standard errors are clustered at the 2-digit SIC industry-county level. All models have 26,862 2-digit SIC industry × county × year observations, 20 2-digit SIC industries, and 791 county observations.

TABLE 4: Space Places, Value Added, and Employment: Military and Skill Controls

Dependent Variable =	Log(Value Added)				Log(Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Military Controls								
Space Place$_{i,<1958}$ × Space Race$_t$	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.12
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Additional Controls:								
Army Patents	Y	Y	Y	Y	Y	Y	Y	Y
Navy Patents		Y	Y	Y		Y	Y	Y
Military Spending			Y	Y			Y	Y
1962 Defense Scientist × Year Fixed Effects				Y				Y
R^2	0.50	0.50	0.50	0.50	0.46	0.46	0.46	0.46
Panel B: Skill Controls								
Space Place$_{i,<1958}$ × Space Race$_t$	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.13	0.13	0.13	0.12	0.13	0.12	0.12	0.11
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Additional Controls:								
Non-Production Worker Share	Y	Y	Y	Y	Y	Y	Y	Y
1962 Research Scientist × Year Fixed Effects		Y	Y	Y		Y	Y	Y
1961 IBM Mainframes × Year Fixed Effects			Y	Y			Y	Y
1960 High School Graduate × Year FEs				Y				Y
R^2	0.51	0.51	0.51	0.51	0.47	0.47	0.47	0.48

Notes: Data are drawn from National Intelligence Estimates, Censuses of Manufactures and Population, United States Patent and Trademark data from 1947 to 1992, United States Department of Defense, National Roster of Scientific and Technical Personnel, and IBM mainframe data, as described in the data appendix. Each column in a panel reports the results from estimating one version of equation (2) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in its pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post-Space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. In panel A the models columns (1) and (5) includes county and year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and Army patents; the models in columns (2) and (6) also include Navy patents; the models in columns (3) and (7) also include military spending; and the models in columns (4) and (8) further include the 1962 count of defense funded research scientists × year fixed effects. In panel B the models columns (1) and (5) includes county and year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and non-production worker share; the models in columns (2) and (6) also include the 1962 count of research scientists × year fixed effects; the models in columns (3) and (7) also include count of number of 1961 IBM mainframes × year fixed effects; and the models in columns (4) and (8) further include the percentage of the population in 1960 with a terminal high school education × year fixed effects. Standard errors are clustered at the 2-digit SIC industry-county level. All models have 26,862 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 791 county observations.

TABLE 5: Space Places and Measured Productivity

Sample =	Full				Trimmed			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	0.04	0.04	0.03	0.01	0.09	0.09	0.08	0.06
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.05	0.05	0.05	0.03	0.08	0.08	0.06	0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects		Y	Y	Y		Y	Y	Y
Industry Fixed Effects			Y	Y			Y	Y
Industry × Year Fixed Effects				Y				Y
R^2	0.76	0.77	0.78	0.81	0.76	0.78	0.78	0.81

Notes: Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. The outcome variable is Measured Productivity computed as total factor productivity estimated using a Cobb-Douglas model with industry specific factor shares as described in the online appendix section 1.1. Space Place$_{i,<1958}$ is an indicator variable reflecting a county being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is 2 digit SIC industry × county × year. The models in columns (1) and (5) includes county, year fixed effects, and the count of pre-1958 patents in a county × year fixed effects, the models in columns (2) and (6) also include state × year fixed effects, the models in columns (4) and (7) also include industry fixed effects, and the models in columns (4) and (8) also include industry × year fixed effects. Standard errors are clustered at the 2 digit SIC industry-county level. Models in columns (1) to (4) has 26,607 2-digit SIC industry × county × year observations, 20 2 digit SIC industry, and 791 county observations and models in columns (5) to (8) has 13,301 2 digit SIC industry × county × year observations, 20 2 digit SIC industry, and 244 county observations.

TABLE 6: Space Places and Patent Inventor Migration

Dependent Variable =	Log(Out Migration Ratio)		
	(1)	(2)	(3)
Space Score Difference$_{od,<1958}$× Space Race$_t$	0.09	0.10	0.17
	(0.05)	(0.05)	(0.05)
Space Score Difference$_{od,<1958}$× Post-Space Race$_t$	0.27	0.28	0.31
	(0.07)	(0.07)	(0.08)
Corporate Income Tax Rate (1-CIT)$_{odt}$		0.37	
		(0.23)	
Personal Average Income Tax Rate, 90th percentile (1-ATR)$_{odt}$		0.92	
		(0.18)	
R&D Credit (1+credit)$_{odt}$		0.00	
		(0.02)	
Origin County Fixed Effects	Y	Y	Y
Destination County Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Origin Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Destination Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Origin County × Destination County Fixed Effects	Y	Y	Y
Origin State × Year Fixed Effects			Y
Destination State × Year Fixed Effects			Y
R^2	0.89	0.89	0.91

Source: Data are drawn from National Intelligence Estimate, United States Patent and Trademark and Akcigit, Grigsby, Nicholas, and Stantcheva (2022) data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (4) in the text. Space Score Difference$_{ij,<1958}$=Log(Space Score$_d$)-Log(Space Score$_o$) is the difference in space scores between the origin and destination counties, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is origin county × destination county × application year. The models in all columns includes county, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and include industry fixed effects. The model in column (3) also includes origin state × year fixed effects and destination state × year fixed effects Standard errors in parentheses, with three-way clustering by origin county × year, destination county × year, and county-pair. All models have 57,551 origin-county × destination-county × application year observations and 480 county observations.

TABLE 7: Space Places, Value Added and Employment: Local Versus Market Effects

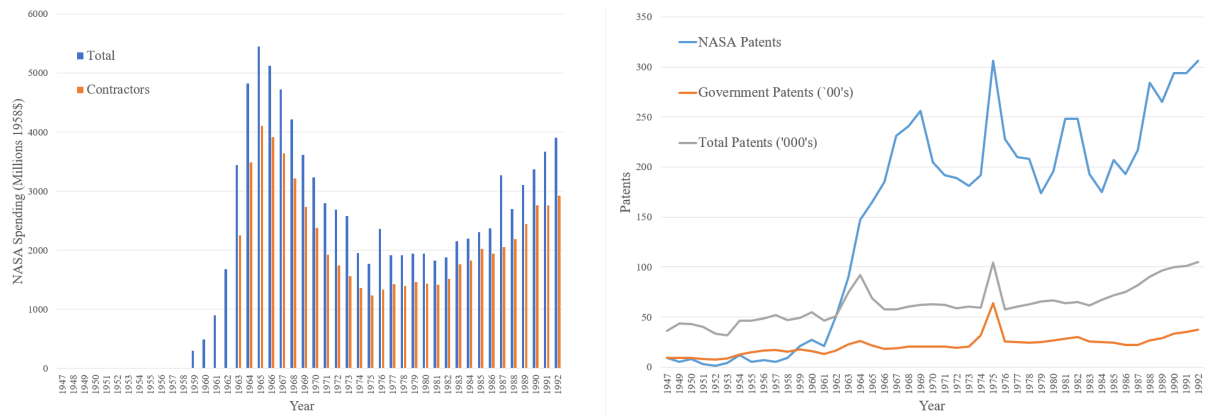
Dependent Variable =	Log(Value Added)			Log(Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Space Place$_{i,<1958}$ × Space Race$_t$	0.06		0.06	0.06		0.06
	(0.03)		(0.03)	(0.03)		(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.14		0.14	0.13		0.13
	(0.04)		(0.04)	(0.04)		(0.04)
High Space Market$_{i,<1958}$ × Space Race$_t$		0.13	0.13		0.10	0.10
		(0.04)	(0.04)		(0.03)	(0.03)
High Space Market$_{i,<1958}$ × Post-Space Race$_t$		0.03	0.03		-0.02	-0.03
		(0.07)	(0.07)		(0.06)	(0.06)
County Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Industry × Year Fixed Effects						
R^2	0.50	0.50	0.50	0.46	0.46	0.46

Notes: Data are drawn from National Intelligence Estimate, Census of Manufacturers, United States Patent and Trademark, and Jaworski and Kitchens (2019) data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (5) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992 (the Space Score), as described in the text and appendix. High Space Market$_{i,<1958}$ takes a value of one in counties with above median space spending in their market during the era indicated, as described in section 1.2 of the online appendix. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is 2 digit-SIC industry × county × year. The models in all columns includes county, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and include industry fixed effects. Standard errors are clustered at the 2 digit SIC industry - state level. All models have 26,862 2 digit SIC industry × county × year observations, 20 2 digit SIC industry, and 791 county observations.

Figure 1: NASA Spending and Patenting, 1947-1992

Panel A: NASA Spending

Panel B: Patenting

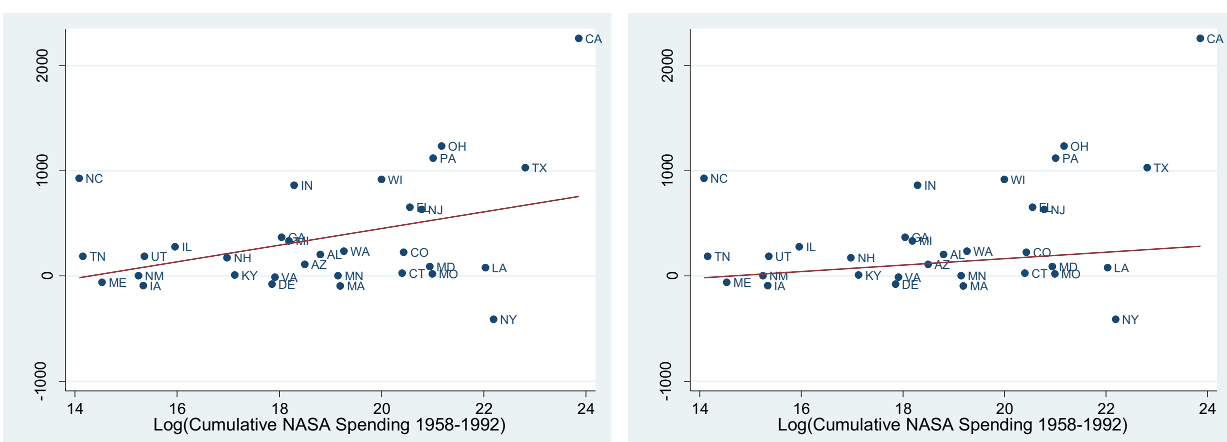


Notes: Data are drawn from United States Patent and Trademark Office, and Flemming et al. (2019) and NASA Historical Data Books. Reported NASA spending in fiscal year 1963 include both 1963 and earlier years. NASA Spending is measured in 1958$. NASA patents include patents assigned to or funded by NASA.

Figure 2: State NASA Spending, and Changes in Value Added and Employment, 1958-1992

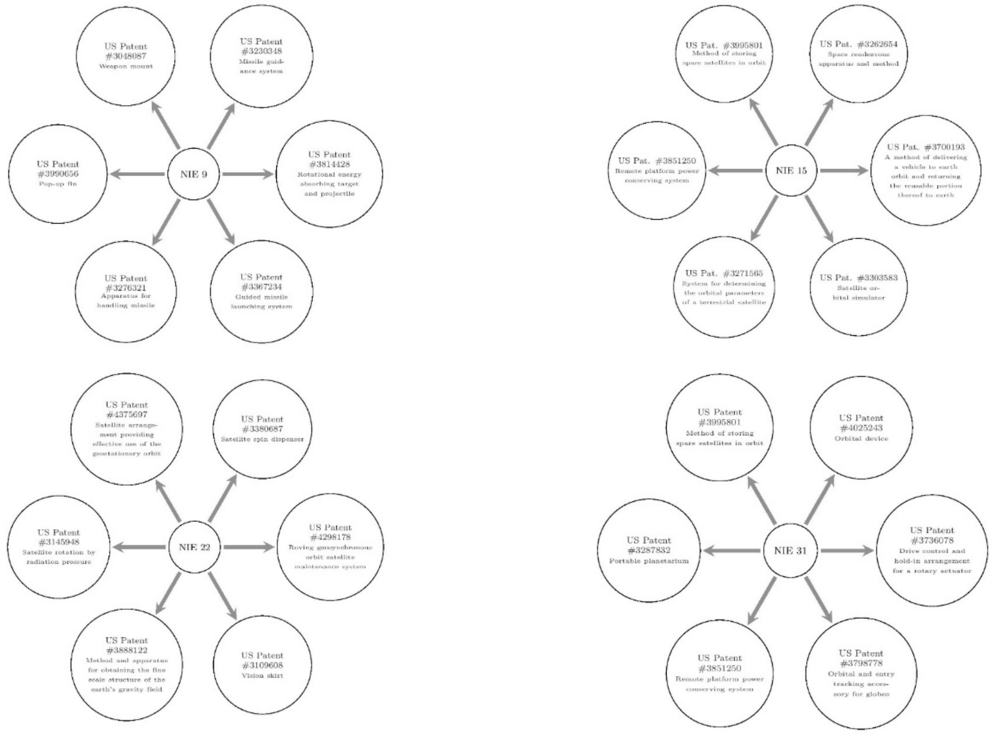
Panel A: Value Added

Panel B: Employment



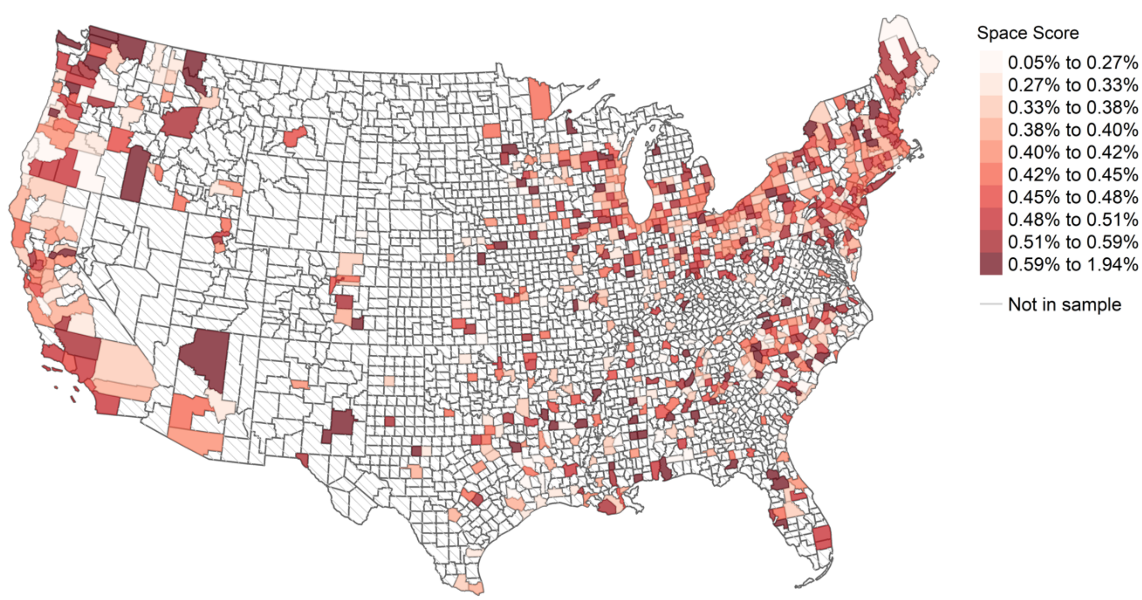
Notes: Data are drawn from the Census of Manufacturers and NASA Historical Data Books. See the data appendix for details.

Figure 3: Patents Highly Similar to National Intelligence Soviet Space Capabilities Estimates



Source: Authors' calculations using National Intelligence Soviet Space Capabilities Estimate data from 1958 to 1992 and United States Patent and Trademark data from 1945 to 1958. Each panel list the patents with technologies most similar to the indicated NIE document.

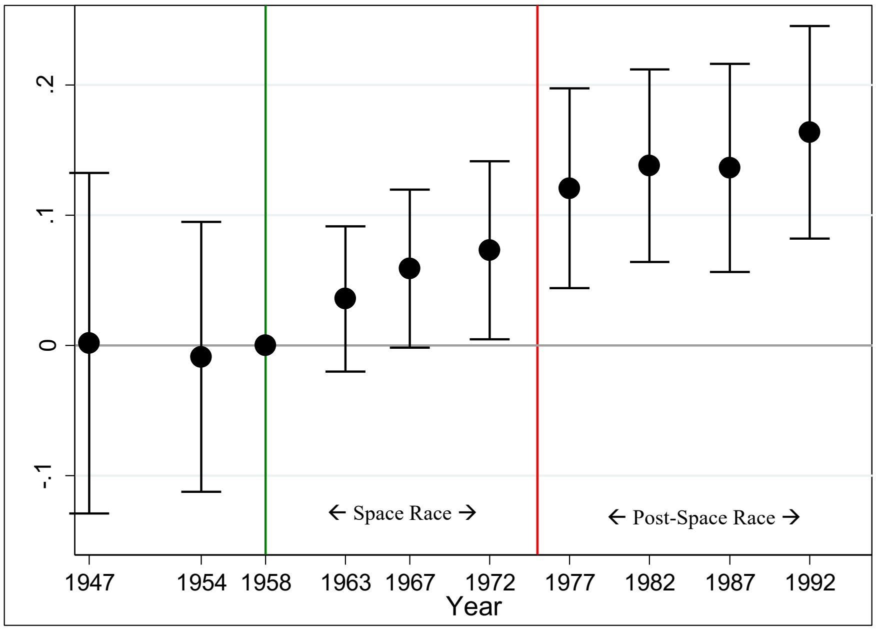
Map 1: Map of Space Scores



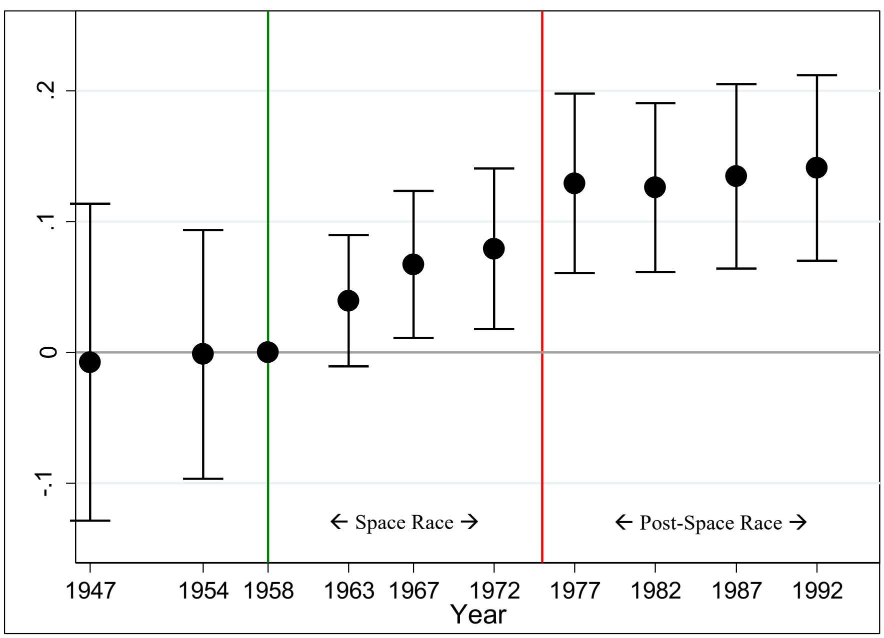
Source: Authors' calculations using National Intelligence Estimate data from 1958 to 1992 and United States Patent and Trademark data from 1945 to 1958. The space score is the $\widehat{\rho_i^c}$ as discussed in section 2.2 of the appendix.

Figure 5: Value Added and Employment Effect Dynamics

Panel A: Log (Value Added)



Panel B: Log(Employment)



Notes: Source: Authors' Calculation from National Intelligence Estimate, Manufacturing Census Data, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each panel in the table displays the results from estimating one version of equation (4) in the text for the outcome indicated. High Space Intel Tech$_{i,<1958}$ is an indicator variable reflecting a county being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text. The points plot the year by year coefficient estimates on for High Space Intel Tech$_{i,<1958}$ with the 95% confidence intervals indicated by the range with 1958 is the omitted year, as indicates in the equation (4) in the text. Space race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2 digit SIC industry × county × year. The models in all columns includes county, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and include industry fixed effects. Standard errors are clustered at the 2 digit SIC industry × county level.

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"Moonshot: Public R&D and Growth" Appendix

Shawn Kantor & Alexander Whalley

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Contents

1 Variable Definitions and Sources

1.1 Manufacturing

Value Added: Total difference between value of shipments and expenditure on materials in the county-industry-year unit, 1958 $.

Employment: Total employment in the county-industry-year unit.

Labor Income: Average annual labor income in the county-industry-year unit, 1958 $.

Non-Production Worker Share: Ratio of non-production to production workers in the county-industry-year unit.

Capital Investment: Total investment in by manufacturing firms in the county-industry-year unit, 1958 $.

Capital: Measured by the capital stock in the industry-county-year unit. We construct our capital stock measure from the reported investment series using the perpetual inventory method. We follow Bloom, Shankerman, and Van Reenen (2013) and choose the baseline value of the capital stock in 1958: $k_{ij1958} = i_{ij1958} 0.08 + g_{kij1958}$, where $g_{kij1958}$ is the growth rate of investment between 1954 and 1958 in the county-industry cell. We follow Bloom, Bond and Van Reenen (2007) in assuming a 8% depreciation rate. Our capital stock measure in years other than 1958 is given by $k_{ijt} = i_{ijt} + (1 - 0.08)^{2.5} k_{ijt-1}$. We assume that investment occurs at the mid-point between the five year differences in manufacturing census years. If investment is missing we assume it is zero, and depreciate the prior capital. If the lagged capital stock is missing, use the SIC2 capital-employment ratio and observed employment in the industry-county cell to impute lagged capital stock. Measured in nominal dollars.

TFPR, Solow: Estimated total factor revenue productivity using a Cobb-Douglas value added production function with capital and labor as inputs, nominal $. We estimate the production function $Y_{ijt} = A_{ijt} K_{ijt}^{\beta_{1j}} L_{ijt}^{\beta_{2j}}$ allowing factor shares to be industry specific to recover manufacturing revenue productivity at the industry-county-year level, A_{ijt}. We estimated this using OLS and consider other estimation methods below.

Unit of measurement for all variables: County $\times$ SIC 2 digit $\times$ year.

Sources for all manufacturing variables: U.S. Census Bureau, Census of Manufactures (various years).

1.2 Space Places

Space Score: The county median cosign similarity between full-text pre-1958 patent texts and post-1958 CIA National Intelligence Estimates of Soviet Space Capabilities texts. The *space score* ($\tilde{\rho^C}_i$) is the median value of $\tilde{\rho}_{p<1958}$ across all pre-1958 patents in county i, as describe in appendix section 2.2. This variable is defined at the county level.

Space Place: "Space Places" are counties with above median values of the space score variable, as describe in appendix section 2.2. This indicator variable is defined at the county level.

High Own-Industry Space Score: High Own-Industry Space are county-industries with above median values of the own-industry space score variable. The calculation is similar to that described in appendix section 2.2, however, $\tilde{\rho^C}_{ij}$ is computed for each industry(j)-county (i) cell rather than county cell. This indicator variable is defined at the county-industry level.

High Other-Industry Space Score: High Other-Industry Space are county-industries with above median values of the other-industry space score variable. Own industry patents are excluded from this calculation. The calculation is similar to that described in appendix section 2.2, however, $\tilde{\rho^C}_{i-j}$ is computed for each set of other industries($-j$)-county (i) cell rather than county cell. This indicator variable is defined at the county-industry level.

High Space Market: High Space Market are counties above median in terms of our space market measure $SpaceMarket_o \approx \sum_d \tau_{od}^{-\theta_d} \text{S}paceSpending_d^{\theta}$, and zero otherwise. $\theta = 6.74$. See appendix section 3 for the derivation and discussion of this measure. This indicator variable is defined at the county-era level.

Space Place, Unstemmed: Space places are counties with above median values of the space score variable, as describe in appendix section 2.2. We compute the *space score* as the median of $\tilde{\rho}^{nostem}_{p<1958,i}$ for each county i using all the patents in the county, as describe in appendix section 2.2. This version calculates the cosign similarity using unstemmed versions of the science direct terms ($\tilde{\rho}^{nostem}_{p<1958,i}$). This indicator variable is defined at the county level.

Space Place, All: Space places are counties with above median values of the space score variable, as describe in appendix section 2.2. We compute the *space score* as the median of $\tilde{\rho}^{all}_{p<1958,i}$ for each county i using all the patents in the county, as describe in appendix section 2.2. This version uses the full of NIE documents that cover space technology to compute the median as indicated in appendix Table A1 column 'All'. This indicator variable is defined at the county level.

Space Place, Mean: Space places are counties with above median values of the space score variable, as describe in appendix section 2.2. We compute the *space score* as the *mean* of $\tilde{\rho}_{p<1958,i}$ for each county i using all the patents in the county, as describe in appendix section 2.2. This indicator variable is defined at the county level.

Space Place, Exclusive: Space places are counties with above median values of the space score variable, as describe in appendix section 2.2. We compute the *space score* as the median of $\tilde{\rho}^{exclusive}_{p<1958,i}$ for each county i using all the patents in the county, as describe in appendix section 2.2. This version only uses the subset of NIE documents that cover space technology exclusively to compute the median as indicated in appendix Table A1 column 'Exclusive'. This indicator variable is defined at the county level.

All space place variables are derived from the authors' calculations using the full text of patent documents, the full text of CIA National Intelligence Estimates of Soviet Space Capabilities, and the Science Direct Technology Corpus of terms. More details on the creation of the variables is provided in appendix section 2.2 below.

1.3 Patents

Total Patents: Total patents in a year at county-year unit level. Patents with authors from more than one county are assigned fractionally to multiple counties based on county authorship share.

Pre-1958 Patents: Total patents between 1947 and 1958 at the county-year unit.

NASA Patents: Total NASA patents in the county-year unit. NASA patents are those in which NASA is either the assignee or listed as a funder on the patent. Patents with authors from more than one county are assigned fractionally to multiple counties based on county authorship share.

Army Patents: Total Army patents in the county-year unit. Army patents are those in which the Army is either the assignee or listed as a funder on the patent. Patents with authors from more than one county are assigned fractionally to multiple counties based on county authorship share.

Navy Patents: Total Navy patents in the county-year unit. Navy patents are those in which the Navy is either the assignee or listed as a funder on the patent. Patents with authors from more than one county are assigned fractionally to multiple counties based on county authorship share.

Non-NASA Patents: Total Non-NASA patents in the county-year unit. These patents include those for which NASA is neither an assignee nor listed as a funder on the patent. Patents with authors from more than one county are assigned fractionally to multiple counties based on county authorship share.

Unit of measurement for all variables (unless stated otherwise): County $\times$ SIC 2 digit $\times$ year.

Sources for all patent variables: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO (2020); and authors' calculations. Information on assignment or funding of patents is drawn from Fleming, Greene, Li, Marx, and Yao (2019) for patents before 1976 and from USPTO PatentsView for those 1976 and after.

1.4 Population

Population: Total population in the county-year unit.

High School Graduate Percentage: Percentage of adults age 25+ who are high school graduates in the county-year unit. In other words, the high school diploma is the terminal degree.

Unit of measurement for all variables: County $\times$ year.

Source for all variables: Haines (2010).

1.5 NASA and Military Spending

NASA Spending (1958$): The sum of contractor and NASA R&D center spending in a county since the prior manufacturing census year. NASA contractor spending is obtained from summing up the amount spent by the top 100 NASA contractors from 1963 to 1992 in a county in 1958 dollars. Locations of contractor activity, not corporate headquarters, are utilized. The top 100 contractors account for the vast majority of NASA prime contractor spending. The maximum share of NASA contractor spending occurring at the top 100 is 92.86% and the minimum share is 87.17%. Because NASA R&D center spending includes contractor spending we multiply each NASA center's reported spending by the fraction of NASA spending that was not contracted out. This fraction is 25%. NASA contractor data drawn from Van Nimmen and Bruno (1976, 191-208) and Gawdiak (1994, 184-99). NASA R&D data is from Rumerman (1999) and Rumerman (2012).

Military Spending: Total military contract spending in the county-year unit. The 1947-1966 data are based on state-level data, but allocated using 1967 SIC2-county weights applied to each location and industry. The 1967 to 1992 data are based on totals on individual contracts over $10,000 at the SIC2-county level. The earliest year for the state data is 1951. The data we use for 1947 is based on reported values in 1951. The post-1967 contract data only have industry in a few years. We use the federal supply codes for equipment cross-walked to SIC2 industries to get the industry level data. Unit of measurement: County × SIC 2 digit × year. Sources: USDOD(1975); USDOD(1981); USDOD(2007); authors' calculations.

1.6 Patent Inventor Migration

County In-Migration of Patent Inventors: We denote origin locations o and destination locations d. The number of inventors who move from o to d is P_{odt} and the number of inventors who begin in o and do not move, P_{oot}, so that $\log\left(\frac{P_{odt}}{P_{oot}}\right)$ is the log odds ratio for inventor migration. This variable is measured at the origin-destination county pair level for the 1945 to 1992 patent application years. Source: Authors' calculation using patent inventor panel data as described in section 2.3 of the appendix.

Corporate Income Tax Rate: The additional tax burden accruing to a firm in the top tax bracket in state s for an additional one dollar of revenue if all of its operations were in s.

Measured at the state-year level. Source: Akcigit, Grigsby, Nicholas, and Stantcheva (2022).

Personal Average Income Tax Rate, 90^{th} Percentile: The total tax burden for an individual at the 90^{th} percentile of the national income distribution divided by that individual's total income. Calculated using the tax calculator by Bakija (2006). Measured at the state-year level. Source: Akcigit, Grigsby, Nicholas, and Stantcheva (2022).

R&D Credit: Statutory credit rate adjusted for recapture and type of credit for a given state-year. Source: Akcigit, Grigsby, Nicholas, and Stantcheva (2022)

1.7 Transportation Costs and Other Variables

Transportation Costs (τ_{ij}): County-to-county transportation costs in 1960. This measure is based on the 1959 Rand McNally Road Atlas highway network to compute the travel costs between all county pairs in the contiguous United States in each year. Transportation costs are computed by measuring the road surface, using historical sources for travel speed by road surface type and legislated speeds. Monetary travel costs are obtained by using the per mile wage of a truck driver multiplied by the travel time plus the per mile fuel cost times the distance. See Jaworski and Kitchens (2019) for more details. Unit of measurement: County. Sources: Jaworski and Kitchens (2019); authors' calculations.

Defense Scientist (1962): Number of research scientists who have received funding from a defense agency before 1962 in the county. Source: National Register of Scientific and Technical Personnel (NSF, 1962).

Research Scientist (1962): Number of research scientists in 1962 in the county. Source: National Register of Scientific and Technical Personnel (NSF, 1962).

IBM Mainframe Computers (1961): Number of IBM mainframes installed before 1961. Unit of measurement: County. Source: IBM (1962).

2 Data Construction

2.1 Manufacturing Census Panel

We obtain data from the Censuses of Manufactures of 1947, 1954, 1958, 1963, 1967, 1972, 1977, 1982, 1987, and 1992. These census data provide reporting at the county and MSA levels. We standardize the reporting to measure consistent quantities and monetary values across data years for SIC 2-digit industries. Some large metro counties do not report separately from the MSA in 1963, 1967, 1972, and 1977. We apportion these MSA values to counties using the share of employment in an industry-county cell in a MSA-industry cell. We take the average of this apportionment factor in 1958 and 1982 to apportion the 1963-1977 MSA-industry data to county-industry cells.

We drop observations that report: (1) missing value added or employment in a year; (2) the reported number of total workers (i.e., production plus non-production) was less than the number of reported production workers in a given year; (3) less than three times during the sample; and (4) no pre-1958 patents. These restrictions lead to a loss of 2,597 observations. We further drop 30 observations that are state singletons (from SD, ND, and WY) so that we utilize the same sample throughout our analysis when we include state $\times$ year fixed effects in our models. Our main analysis sample contains 26,862 county-industry observations from 791 counties and 20 two-digit SIC industries from 1947 to 1992.

2.2 Space Places: Patent and Soviet Space Intelligence Text

Corpus of Technology Concepts: To compute the similarity between full-text USPTO patent documents and CIA National Intelligence Estimates of Soviet Space Capabilities documents we employ three sources. First, we obtain the Science Direct (SD) corpus of Technology Terms.[1] The SD corpus of technology concepts consists of 193,715 expressions comprising Science Direct (SD) Topics. Similar to the well-known Medical Subject Headings (MeSH) terms, the vocabulary in the SD Topics indexes articles in SD in order to improve information retrieval for researchers. Unlike the medical focus of MeSH terms, the SD Topics cover all scientific disciplines represented in SD.

Full Patent Text: Two sources are used for extracting full patent texts for the time period

[1] The list is available here: https://www.sciencedirect.com/topics/index.

from January 1940 to December 1991, inclusive. Full patent text since 1976 is available in the US Patent and Trademark Office's Patent Full-Text and Image Database (PatFT)[2]. For the time period of 1940-1975, description and claims text was extracted using the Google Patents Public Datasets on BigQuery.[3]

National Intelligence Estimates (NIEs): The CIA's now-declassified NIEs are authoritative intelligence assessments related to the Soviet Union's capabilities with regard to space flight, among a number of other geopolitically sensitive areas.[4] During the period of 1946-1991, these documents provide estimates of Soviet scientific and technical capabilities in space. Some of the documents also focus on military technology. We exclude the documents that primarily focus on military technology from our baseline analysis. We compute an additional patent text similarity measure using only documents with an exclusive space focus as a robustness exercise. The documents we use are listed in appendix Table A1.

Data Pre-Processing: English stop words were removed, and Porter stemming was applied to the SD Topics corpus, as well as to the full patent and NIE texts.[5] To reduce the dimension of the SD Topics, we then dropped stemmed topics appearing less than 1,000 times over the full set of patent texts, and then dropped the top 1% most frequently occurring terms. The most frequently occurring terms that were dropped include "Copper," "Dye," "Gridding," and "Duct," for example. SD Topics containing more than four words are also dropped. The combination of stop word removal, stemming, dropping infrequent and too frequent terms, and dropping Topics comprising more than four words result in a dictionary of 25,767 technology concepts.

Text Similarity: We first compute the text similarity between each patent and each NIE document in appendix table A1 using a cosine similarity measure. This process is implemented by following the steps:

[2] Available at https://bulkdata.uspto.gov/. Search for links under Patent Grant Full Text Data (No Images) (JAN 1976 - PRESENT).

[3] Available at https://cloud.google.com/blog/topics/public-datasets/google-patents-public-datasets-connecting-public-paid-and-private-patent-data. Follow directions to Google Patents Public Data. Data set ID: "patents-public-data:patents".

[4] Documents were sourced from http://www.astronautix.com/r/russiawhatddidtheyknowit.html. More information regarding these records is available at https://www.cia.gov/readingroom/collection/declassified-national-intelligence-estimates-soviet-union-and-international-communism.

[5] Both the English stop words removal and the Porter2 stemming were achieved using the SnowballStemmer function from the Natural Language Toolkit (NLTK) Python module.

1. Construct a document term matrix containing frequency counts for each SD Topic in this representative NIE document (after data cleaning);
2. Construct document term matrices for each U.S. patent (after data cleaning);
3. For each patent document term matrix, compute the cosine similarity against the representative NIE:

$$\rho_{p<1958,n>1958} = \frac{\sum_{i=1}^{n} TF_{i,n>1958} TF_{i,p<1958}}{\sqrt{\sum_{i=1}^{n} TF_{i,n>1958}^2}\sqrt{\sum_{i=1}^{n} TF_{i,p<1958}^2}} \tag{A1}$$

where $\rho_{p<1958,n>1958}$ is cosine similarity between a patent document issued before 1958 ($p < 1958$) and an NIE document issued after 1958 ($n > 1958$). $TF_{i,n>1958}$ is the term frequency for SD term i in NIE document $n > 1958$, and $TF_{i,p<1958}$ is the term frequency for SD term i in patent document $p < 1958$. Exhibit 3 in the online appendix provides a visual example of highly similar pages in an NIE document and patent document captured by this approach with the SD technology terms highlighted.

Space Places: We aggregate patent level NIE similarities to the county level to determine space places. We first compute median of $\rho_{p<1958,n>1958}$ at the patent level across all NIE documents after 1958 to obtain $\tilde{\rho}_{p<1958}$. The *space score* ($\tilde{\rho^C}_i$) is the median value of $\tilde{\rho}_{p<1958}$ across all pre-1958 patents in county i. Counties with high values of $\tilde{\rho_i^C}$ (high space place score) have pre-Sputnik technologies represented in the county, as evidenced through their patent records, similar to the space technologies that the Sovets possessed after 1958. Counties with low values of $\tilde{\rho_i^C}$ (low space place score) had pre-Sputnik technologies within the county that were not similar to later Soviet space technologies. Our *space place* variable takes a value of 1 for counties with above median values of $\tilde{\rho_i^C}$, and a value of zero otherwise.

2.3 Patent Inventor Panel

We build a panel of inventors by disambiguating the inventors listed on all USPTO patents from 1947 to 1992. We follow the disambiguation procedure of Li et al. (2014) to determine if a pair of patent-inventor records belongs to a single individual. This task is a clustering problem which is addressed using an Authority machine learning approach (see Torvik and Smalheiser 2009). Given a training data set of disambiguated inventors, we cluster inventors in our historical patent data based on a similarity profile. Following Akcigit, Grigsby, Nicholas and Stantcheva (2018), we measure similarity across a pair of inventors using combinations of inventor-level features – inventor name and location – and patent-level features

– patent assignee, technology class, and coauthor network. Intuitively, the algorithm assigns a higher probability of two patent-inventor records belonging to the same individual when the two patents are technologically similar, or share the same assignees, trace back to geographically close locations, etc.

The ideal implementation of the disambiguation algorithm considers the similarity across all pairs of inventors in the historical patent records available through Google Patents (GP). With over 3.8 million patent-inventor records during our period of analysis (1920-1980), this translates to over 14.4 trillion inventor pairs. To reduce the computational burden of the ideal implementation, we adopt the iterative blocking approach from Akcigit, Grigsby, Nicholas and Stantcheva (2018). The starting point is to compare only record pairs within a block of inventors sharing an exact first and last name. Later iterations allow for increasingly larger blocks by comparing, for example, inventors with a same first initial and exact last name. The purpose of the iterative blocking approach is to (1) reduce the computational cost of the algorithm, and (2) allow for different feature sets when constructing the similarity of a pair of patent-inventors. The exact implementation of our disambiguation algorithm is described below.

2.3.1 Feature set and similarity profiles

Feature set. We compare two records by constructing pairwise similarity profiles $\mathbf{x}$ using a set of features $x_1, ..., x_k$. Each available feature x_i is encoded as follows.

- Middle name: middle names (and first and last names as well) are constructed from the inventor full name field. Once constructed, we compare the middle name feature for a pair of records and assign one of of the following alternatives.
  (a) The middle names match exactly (e.g. "JAMES" and "JAMES");
  (b) One record has a full middle name (with length greater than a single letter). The other record has only a middle initial which matches the initial of the other record (e.g. "JAMES" and "J");
  (c) Both records have missing middle name;
  (d) One of the two records have a missing middle name (e.g. "JAMES" and " ");
  (e) Otherwise (e.g. "JAMES" and "EDWARD").

- Location: we geolocate patent-inventors by linking patent numbers and inventor names with latitude and longitude information available at the Comprehensive Universe of U.S. Patents data. [6] Once each patent-inventor record is geolocated, we measure geodesic distance for a pair of records and assign one of the following alternatives:

  (a) The two inventors are located less than 1 mile apart;

  (b) The two inventors are located from 1 to under 10 miles apart;

  (c) The two inventors are located from 10 to under 25 miles apart;

  (d) The two inventors are located from 25 to under 50 miles apart;

  (e) Either the two inventors are located 50 or more miles apart, or at least one record has a missing location).

- Patent technology classes: this feature uses the first reported U.S. Patent Class (USPC) code of a patent record. Comparison across a pair of records yields the following assignment:

  (a) The USPC codes are identical;

  (b) The USPC codes are not identical.

- Assignee: the assignee feature is constructed from the harmonized_assignee field in the Google Patents Big Query data base. We retain only the first assignee listed in the patent record. Comparison of a pair of records yields the following assignment:

  (a) The two patent records yield a Jaro-Winkler (JW)-based similarity metric of at least 0.9;

  (b) $0.8 \leq \text{JW} < 0.9$;

  (c) $0.7 \leq \text{JW} < 0.8$;

  (d) One of the two patent records have a missing assignee;

  (e) Otherwise.

- Coauthor network: we construct the coauthor network feature by assigning, to each patent, a list of all the patent's inventors. The list is alphabetically sorted, and uses each inventor's first and last name. We compare coauthor networks between two patent-inventor records and assign:

[6] The data set was compiled by Enrico Berkes. Data inquiries should be directed to `enrico.berkes@gmail.com`.

(a) The patent coauthors list is identical between the pair of records;

(b) Otherwise.

Similarity profile. We construct pairwise similarity profiles using the features above. For example, in an iteration where similarity is defined using the middle name and location features, the similarity profile for two records with middle names "JAMES" and "J" geolocated within a mile from one another is the vector $\mathbf{x} =< b, a >$.

Treating the disambiguated inventor data from Li at al. (2014) as a "ground truth" training set, we compute the probability that each profile $\mathbf{x}$ belongs to the same inventor. We construct this probability from the count of records with profile X that belong to the same inventor versus the count that belong to different inventors. Let M denote the event that a patent-inventor pair is a match (i.e., belong to the same individual) and N the event that it is a non-match. Using Bayes rule, the probability of a match M given an observed similarity profile X is:

$$P(M \mid \mathbf{x}) = \frac{P(\mathbf{x} \mid M)P(M)}{P(\mathbf{x} \mid M)P(M) + P(\mathbf{x} \mid N)(1 - P(M))}. \tag{A2}$$

The posterior probability $P(M \mid X)$ has a one-to-one relationship with the posterior odds of a match, defined as:

$$\frac{P(M \mid \mathbf{x})}{1 - P(M \mid \mathbf{x})} = \frac{P(M)}{1 - P(M)} \frac{P(\mathbf{x} \mid M)}{P(\mathbf{x} \mid N)}. \tag{A3}$$

Eq A3 can be converted back to *Eq A*2, and defining the likelihood ratio $r(\mathbf{x}) = \frac{P(\mathbf{x}|M)}{P(\mathbf{x}|N)}$, we get:

$$P(M \mid \mathbf{x}) = \frac{1}{1 + (\frac{1-P(M)}{P(M)})(\frac{1}{r(\mathbf{x})})}. \tag{A4}$$

From Eq A4, two components are needed to determine the posterior probability of a match given an observed similarity profile: the matching prior and the likelihood ratio. The prior match probability $P(M)$ at each iteration of the algorithm is the ratio of within-cluster matched pairs in a block over the total number of pairs in the block. The likelihood ratio $r(\mathbf{x})$ is determined directly from the training set by taking the ratio of times the similarity profile $\mathbf{x}$ lead to matched events M versus non-matched events N. The training set consists of disambiguated data from Li at al. (2014)[7], which we use to compute posterior match

[7]Available at the Harvard Dataverse Network at `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5F1RRI`. Use the compressed file "invpat_final.zip"

probabilities for each similarity profile at each blocking algorithm. This data set contains over 9 million patent-inventor instances from over 4 million patents issued between 1975-1999. The underlying assumptions from using this data for our disambiguation task are that the inventor identifiers are accurately assigned in the training data, and also that there would be no systematic differences in the posterior match probabilities for patents in our historical records of 1920-1980 and patents in the training set years of 1975-1999.

2.3.2 Disambiguation blocks

After each iteration, we say that two records originate from the same inventor if the computed posterior match probability exceeds 0.85. The blocking iterations are described below:

Iteration 1. Block inventors based on exact first and last name. Construct similarity profiles based on middle name and location.

Iteration 2. Same as Iteration 1.

Iteration 3. Same as Iteration 1.

Iteration 4. Block inventors based on exact first and last name. Construct similarity profiles based on assignee, patent technology class, coauthor network, and middle name.

Iteration 5. Block inventors based on first five letters of first name and exact last name. Construct similarity profiles based on assignee, patent technology class, coauthor network, and middle name.

Iteration 6. Block inventors based on first three letters of first name and exact last name. Construct similarity profiles based on assignee, patent technology class, coauthor network, and middle name.

Iteration 7. Block inventors based on initial of first name and exact last name. Construct similarity profiles based on assignee, patent technology class, coauthor network, and middle name.

Iteration 8. Block inventors based on initial of first name and exact last name. Construct similarity profiles based on middle name and location.

2.3.3 Algorithm performance

For the purposes of measuring algorithm performance and optimizing the cutoff parameter c of the posterior match probability, we subset a random sample 73,562 patent-inventor instances from 67,443 patent records from the Li et al. (2014) data. We refer to this subset of the data as the held-out test set. Upon computing the posterior match probabilities in the training set (while holding out the test set), we ran the disambiguation iterations described above on this hold-out test data. We varied the cutoff parameter c in the set $\{0.8, 0.85, 0.9, 0.95, 0.99\}$ and computed splitting (S) and lumping (L) performance statistics, defined as:

$$S = \frac{\sum_i \{\mathbf{x} \mid \mathbf{x} \in U_i, \mathbf{x} \notin V_i\}}{\sum_i |U_i|}, \tag{A5}$$

$$L = \frac{\sum_i \{\mathbf{x} \mid \mathbf{x} \in V_i, \mathbf{x} \notin U_i\}}{\sum_i |V_i|}. \tag{A6}$$

In Eqs A5 and A6, U_i denotes the set of patents for inventor i on the ground truth disambiguation of the Li at al. (2014) data, while V_i denotes the largest set of patents for inventor i based on our disambiguation algorithm. The splitting and lumping statistics using the held-out test set in the searched range are shown below. For our disambiguation of historical patent records, we chose the cutoff $c = 0.85$ which minimizes the sum of splitting and lumping in the held-out test set.

2.3.4 Analysis Dataset

Our disambiguation identifies 882,072 U.S. inventors who were jointly granted 2.4 million patents for our sample period 1945 to 1992. Our main analysis in Table 7 uses a subsample of inventors in the top 25% of lifetime inventors, who have at least 13 lifetime patents. This subsample has 25,684 U.S. inventors who were jointly granted 626,705 patents. Our analysis in Appendix tables in A13 utilizes a subsample consisting of the top 5% of lifetime inventors, those with at least 51 lifetime patents. This subsample has 1,481 U.S. inventors who were jointly granted 119,436 patents. Our analysis in Appendix tables in A14 utilizes subsamples consisting of the top 50% of lifetime inventors. This subsample has 105,458 U.S. inventors who were jointly granted over 1.1 million patents.

Splitting and lumping statistics in held-out test set using different cutoffs of the posterior match probability

Cutoff	.80	.85	.90	.95	.99
Splitting	.01504	.02069	.03636	.15756	.43979
Lumping	.08360	.07626	.06326	.03212	.01447
Splitting + Lumping	.09864	.09696	.09961	.18969	.45426

3 Calculating the Internal Rate of Return

The internal rate of return (IRR) is the interest rate that makes the net present value of a project zero. This calculation includes both the benefits and costs. In our setting the benefits are expanded output and the costs are expenditures on Space R&D.

We compute the internal rate of return from the perspective of a 1958 investor in the project. They take account of the costs and benefits of the space spending in each period and compute the discount rate required to provide a zero net present value.

The IRR is defined as the solution to this equation,

$$0 = NPV = \sum_{t=1958}^{1992} \frac{Y_{impact,t} - S_{impact,t}}{(1 + IRR)^t} \tag{A7}$$

To implement our calculation we use our preferred estimates on the differential NASA spending in space place counties in the post-space race era in Table 2 column (3) and the space place differential in the post-space rage output in Table 3 column (3) (or Table 6 column (3) for the productivity variant). Multiplying NASA spending impact estimates times the nationwide total of NASA spending in a year gives us an implied nationwide spending impact in each year ($S_{impact,t}$). Similarly, multiplying the output or productivity impact estimates times the nationwide manufacturing output in 1958 gives us an implied nationwide output effect in each period ($Y_{impact,t}$). We then compute the IRR by setting the net present value of this stream of annual project benefit (in terms of output or productivity) minus annual project costs (in terms of NASA spending) equal to zero.

4 Modelling Nationwide Effects of Public R&D

In this section we describe our approach to estimate the effect of public R&D on nationwide economic outcomes. We use a simple county to county trade model based on Donaldson and Hornbeck (2016) and for ease of exposition we follow their notation and presentation closely. We differ from their model, however, in that we focus on the impact of public R&D spending, holding transportation infrastructure fixed and introducing market-level consumption externalities.

4.1 Set Up

We index counties by o if they are origin of trade and d if they are destinations. Consumers have CES preferences over a continuum of differentiated product varieties, where the elasticity of substitution across varieties is given by σ. Producers in each county combine a fixed factor land (L_o), and mobile factors labor (N_o) and capital (K_o) using a Cobb-Douglas technology to produce varieties. Public R&D reduces unit costs for firms in location o. The marginal cost of each variety is given by:

$$MC_o(j) = \frac{s_o^{-1} q_o^{\alpha} w_o^{\gamma} r^{1-\alpha-\gamma}}{z_o(j)} \tag{A8}$$

where s_o captures the unit cost effect of public R&D, q_o is the land rental rate, w_o is the wage, r is the interest rate, and $z_o(j)$ is the local productivity shifter drawn from a Frechet distribution with a CDF $F_o(z) = e^{-A_o z^{-\theta}}$. A_o captures the local knowledge stock, and θ captures the standard deviation of the knowledge stock.

Trade costs between o and d are iceberg: for each unit shipped from o to d, $\tau_{od} \geq 1$ is the cost to ship. That is, if a variety is produced and sold in the same county the price is $p_{oo}(j)$, while the same variety sold in a different county has price $p_{od}(j) = \tau_{od} p_{oo}(j)$.

Production and Prices. By assuming perfect competition, unit costs (including marginal and trade costs, as well as public R&D effects) are equal, letting consumers buy from the cheapest origin county. Using the assumption that $r_c = r$, Donaldson and Hornbeck (2016) note that the price index in destination d is defined by

$$(P_d)^{-\theta} = \kappa_1 \sum_o A_o (s_o^{-1} q_o^{\alpha} w_o^{\gamma})^{-\theta} \tau_{od}^{-\theta} = CMA_d \tag{A9}$$

where $\kappa_1 = \left[\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right]^{\frac{1}{1-\sigma}-\theta} r^{(1-\alpha-\gamma)\theta}$. The price index in county d will fall with an increase in public R&D in any origin market, with a weight that is declining in trading costs. Bilateral trade between counties then implies that location specific public R&D may affect prices in other markets, where the size of the cross-market effect depends on the cost of trading. The inverse transformation of the price index reflecting customer access to cheap products is commonly termed Consumer Market Access and denoted CMA_d.

Workers and Amenities. Turning to workers, we assume that they are perfectly mobile across space as our goal is to understand spatial equilibrium implications. We depart from Donaldson and Hornbeck (2016), however, by including both consumer market access as a positive amenity of a location and an exogenous fixed utility level ($\bar{u}$) that is common across locations. As a result of workers' endogenous location choice, workers' utility levels are equalized across counties in equilibrium and, hence, real wages satisfy:

$$\frac{w_o}{P_0} = \bar{u} CMA_o^{\epsilon} \tag{A10}$$

We include a consumer city amenity where access to a larger set of varieties (Glaeser, Kolko and Saiz, 2001) increases utility where the spatial scope for agglomeration amenities is beyond just a county of residence. For example, a worker in Princeton, NJ obtains amenities not just from the variety of products available in Princeton, NJ, but also those accessible in New York City. The strength of the market access amenity is captured by the parameter ϵ.

Output. We obtain output in a county by summing up exports to all other locations. Eaton and Kortum (2002) give the following gravity equation for exports from o to d.

$$X_{od} = A_o (s_o^{-1} q_o^{\alpha} w_o^{\gamma})^{-\theta} \tau_{od}^{-\theta} \kappa_1 CMA_d^{-1} Y_d \tag{A11}$$

Total output in county o is the summation of exports to all other counties, so that

$$Y_o = \sum_d X_{od} = \kappa_1 A_o (s_o^{-1} q_o^{\alpha} w_o^{\gamma})^{-\theta} \sum_d \tau_{od}^{-\theta} CMA_d^{-1} Y_d \tag{A12}$$

Multilateral market access for the origin county, termed Firm Market Access, is defined as:

$$FMA_o = \sum_d \tau_{od}^{-\theta} CMA_d^{-1} Y_d \tag{A13}$$

Thus, output in county o is given by

$$Y_o = \kappa_1 A_o (s_o^{-1} q_o^{\alpha} w_o^{\gamma})^{-\theta} FMA_o \tag{A14}$$

This expression suggests intuitively that output in increasing in location specific productivity, A_o, cost reductions from public R&D, s_o, and firm market access, FMA_o. Output is falling in local factor prices for labor, w_o, and land, q_o.

Solving the Model. We solve the model for equilibrium output to obtain our estimation equation. First, we solve for the county labor supply relationship in (A10) in terms of nominal wages to substitute into equation (A14) and obtain

$$Y_o = \kappa_2 A_o s_o^{\theta} q_o^{-\theta\alpha} CMA_o^{\frac{\gamma-\epsilon\gamma\theta}{\theta}} FMA_o \tag{A15}$$

where $\kappa_2 = \kappa_1 \bar{u}$.

Next, we express CMA_d in terms of FMA_o. We can use equation (A14) to solve for $(\kappa_1 A_0 s_o^{-1} q_o^{\alpha} w_o^{\gamma})$ and substitute into (A9) to get:

$$CMA_d = \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \tag{A16}$$

Under symmetric trade costs (i.e., $\tau_{od} = \tau_{od}$), equation (A16) and the definition of FMA_o implies there exists a constant ρ such that $FMA_o = \rho CMA_o$.[8] We further define $MA_0 \equiv FMA_o = \rho CMA_o$. Substituting for $FMA_o = MA_o$ and $CMA_0 = \frac{MA_o}{\rho}$ into equation (A15) and rearranging we obtain,

$$Y_o = \kappa_3 A_o s_o^{\theta} q_o^{-\theta\alpha} MA_o^{1+\frac{\gamma-\epsilon\gamma\theta}{\theta}} \tag{A17}$$

where $\kappa_3 = \kappa_2 \rho^{(\epsilon\gamma\theta-\gamma)}$.

Market Effects of Public R&D. Finally, we express MA_0 as a function of s_d so that market effects can incorporate public R&D unit cost shocks. Solving for market access $MA_o \equiv FMA_o = \sum_d \tau_{od}^{-\theta} CMA_d^{-1} Y_d$, $CMA_d = \left(\frac{MA_d}{\rho}\right)$, and $\mathrm{Y}_d = \kappa_3 A_d s_d^{\theta} q_d^{-\theta\alpha} MA_d^{1+\frac{\gamma-\epsilon\gamma\theta}{\theta}}$ from equation (A14), we obtain

$$MA_o = \kappa_3 \rho \sum_d \tau_{od}^{-\theta} A_d s_d^{\theta} q_d MA_d^{1+\frac{\gamma-\epsilon\gamma\theta}{\theta}} \tag{A18}$$

Market access in county o increases in response to a distance-weighted sum of county d's productivity (A_d), public R&D (s_d), land values (q_d), and multilateral market access (MA_d). These supply side fundamentals affect the income level in county d and thus take the place of county d's output in Donaldson and Hornbeck (2016)'s market access formulation.

[8] See Appendix section 3 for the proof of this proposition. Donaldson and Hornbeck (2016) and Allen and Arkolakis (2014) make use of a similar relationship.

Estimation Equation. We can obtain an estimation equation by taking logs of equation (A15) which leads to:

$$\log(Y_o) = \psi_Y + \theta\log(s_0) + \left(1 + \frac{\gamma - \epsilon\gamma\theta}{\theta}\right)\log(MA_o) - \theta\gamma\log(q_o) + \log(A_o) \tag{A19}$$

where $\psi_Y = \log(\kappa_3)$ is a constant. The local effect of public R&D cost shocks in the same county is captured by θ, the trade elasticity. The local public R&D effect is positive.

The market effect of public R&D cost shocks – that is, $\left(1 + \frac{\gamma - \epsilon\gamma\theta}{\theta}\right)$ – can be either positive or negative, depending on two key factors. A first force is that public R&D in location d increases location d's income, which, in turn, increases exports of goods from location o, which results in an increase in output by firms in the origin county. A positive market access effect is standard in this class of models. A second mitigating force is migration. Public R&D in locations near d increase amenities that may induce workers in county o to move. With a sufficiently strong amenity effect the negative effects of migration away from o can outweigh the positive effects of increasing income in location d so that market-level public R&D results in a reduction in output. Thus, the sign of the market effect of public R&D is an empirical question.[9]

4.2 Empirical Implementation

Our goal is to use an econometric model to estimate the national manufacturing effects of NASA activity. To do so we add market effects from the spatial model into our baseline

[9] We can also derive an expression for employment in county o using equation (10) and $W_o N_0 = Y_o\gamma$ to obtain

$$N_o = \kappa_4 A_o s_o^{\theta} q_o^{-\theta\alpha} MA_o^{\frac{1+\theta-\gamma-\epsilon\gamma\theta-\epsilon\gamma}{\theta}} \tag{A20}$$

where $\kappa_4 = \kappa_3 \frac{\gamma}{\bar{u}}$. Taking logs we obtain an estimation equation for employment as,

$$\log(N_o) = \psi + \theta\log(s_o) + \left(\frac{1 + \theta - \gamma - \epsilon\gamma\theta - \epsilon\gamma}{\theta}\right)\log(\sum_d \tau_{od}^{-\theta} s_d^{\theta}) - \theta\gamma\log(q_o) + \log(A_o) \tag{A21}$$

where $\psi_Y = \log(\kappa_4)$ is a constant. Again, local public R&D has a positive effect on employment. Market level public R&D has an ambiguous effect on employment depending on the parameter values.

econometric model using using specification,

$$\begin{aligned}\log(Y_{ijt}) =&\beta_1 + \beta_2 \text{Space Place}_{i,<1958} \times \text{ Space Race}_t + \beta_3 \text{Space Place}_{i,<1958} \times \text{post-Space Race}_t + \\ &\beta_4 \text{High Space Market}_{i,<1958} \times \text{Space Race}_t + \beta_5 \text{High Space Market}_{i,<1958} \times \text{Post-Space Race}_t \\ &+ \delta_i + \gamma_t + \text{Total Pre-1958 Patents}_i \times \gamma_t + S_i \times \gamma_t + \nu_{ijt}.\end{aligned} \tag{A22}$$

Here the outcome variables are the log of a manufacturing outcome in county i, industry j and year t, such as value added or employment. Again, we expect β_2 and β_3 to be positive as places that were specialized in Space Race-relevant technologies before it began in 1958 were likely to experience more NASA activity after 1958.

Market effects of public R&D are captured by β_4 and β_5. Market effects may be positive implying national effects would be larger than local effects due to strong cross-county demand or productivity effects. Alternative, market effects may be negative implying national effects are smaller than local effects due to strong cross-county migration effects. The sign and magnitude of market effects are an empirical question.

Our empirical implementation in (A22) differs from our model-derived estimation equations in (A19) for a number of reasons. First, our market access measures build on our research design using the same source of variation as our main analysis. We follow Donaldson and Hornbeck (2016) in applying further assumptions to make our market access term empirically tractable.

First, we assume that our space score measure indexes the unit cost effect of space R&D in our model (s_d) and that we can approximate space-driven market access in equation (A19) in county o with

$$SpaceMarket_o \approx \sum_{d \neq o} \tau_{od}^{-\theta} \text{Space}Score_d^{\theta} \tag{A23}$$

Our approximation for space market access for county o in era e focuses on a distance-weighted average of space scores across destination locations. It allows us to obtain a market access measure when land value (q_d) and productivity (A_d) are not reported in manufacturing census years. It does not include differences across regions in terms of multilateral effects (MA_d since we treat the market access from county d as part of the constant term). It does not include income in county d unlike Donaldson and Hornbeck (2016) because our supply side fundamentals take the place of income in our formulation.

We do not include origin county space scores in the market activity measure to separately identify only market-level effects. All variation in market activity comes from shocks in space scores elsewhere that are likely exogenous to county-level outcomes. For this reason we do not seek instruments for space market activity.

Second, construction of our market-level activity measure, $SpaceMarket_i$, requires θ values. We use $\theta = 8.28$, the preferred estimate from the meta analysis in Head and Meyer (2014).

Lastly, we retain the median contrast in our main specification for estimation of market effects. The variable $HighSpaceMarket_i$ takes a value of 1 for counties with above median $SpaceMarket_i$ and zero otherwise.

4.3 Proof ρ is Constant

Define key equations

$$FMA_o = \sum_d \tau_{od}^{-\theta} CMA_d^{-1} Y_d \tag{A24}$$

$$CMA_d = \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \tag{A25}$$

and

$$FMA_o = \sum_d \tau_{od}^{-\theta} \left(FMA_d\right)^{-1} Y_d \tag{A26}$$

and

$$FMA_o = \rho_o CMA_o \tag{A27}$$

Step 1: Rearrange (A27) for CMA_0, change index from o to be d to substitute into (A24) for CMA_d so that:

$$FMA_o = \sum_d \tau_{od}^{-\theta} \left(\frac{FMA_d}{\rho_d}\right)^{-1} Y_d \tag{A25}$$

and

$$FMA_o = \sum_d \rho_d \tau_{od}^{-\theta} \left(FMA_d\right)^{-1} Y_d \tag{A26}$$

Step 2: Substitute in for CMA_d into (A25) so that:

$$\frac{FMA_d}{\rho_d} = \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \tag{A27}$$

then

$$FMA_d = \rho_d \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \tag{A28}$$

Changing indexes we get

$$FMA_o = \rho_o \sum_d \tau_{od}^{-\theta} FMA_d^{-1} Y_d \tag{A29}$$

Noting that (A26) and (A29) are both expressions for FMA_o, we can see that only $\rho_o = \rho_d = \rho$ can be a solution to this system of equations.

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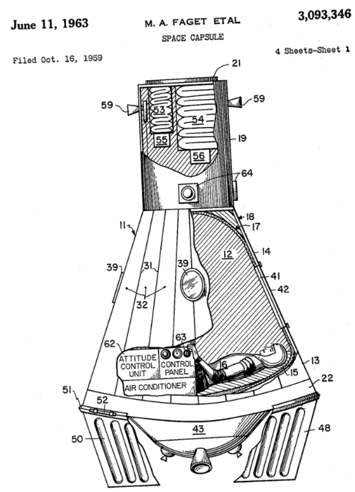
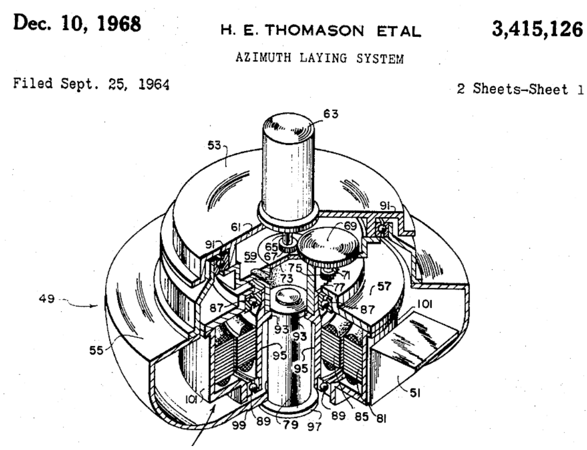
Exhibit A1: NASA Space Race Patent Examples

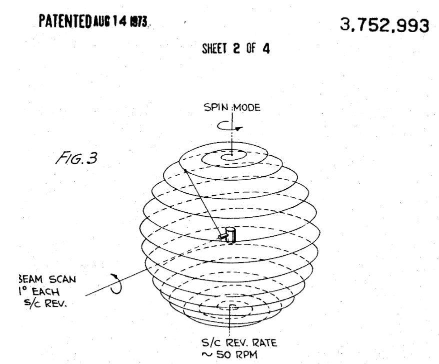
A. Space Capsule



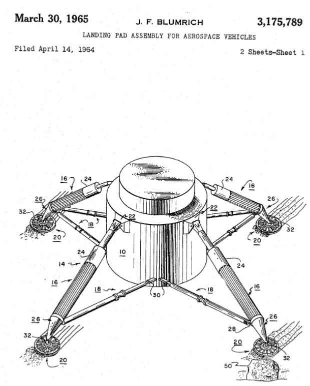
B. Navigation and Guidance System



C. High Altitude Sensor



D. Moon Landing Pad Apparatus

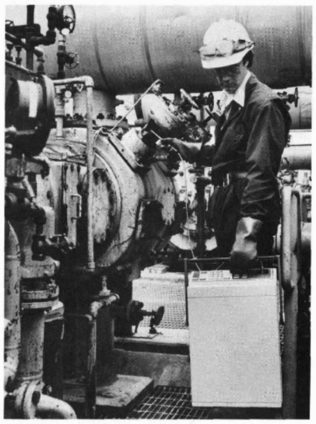


Source: USPTO Patents.

Exhibit A2: NASA Spinoff Examples

A. Gas Analyzer:

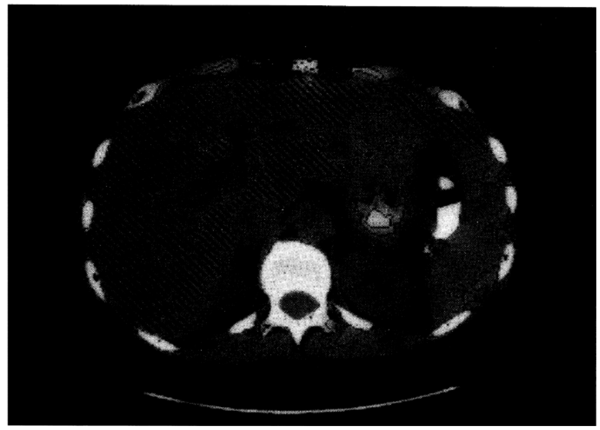
1983: Mircosensor Technology, California



Source: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20030001721.pdf

B. Magnetic Resonance Imaging (MRI):

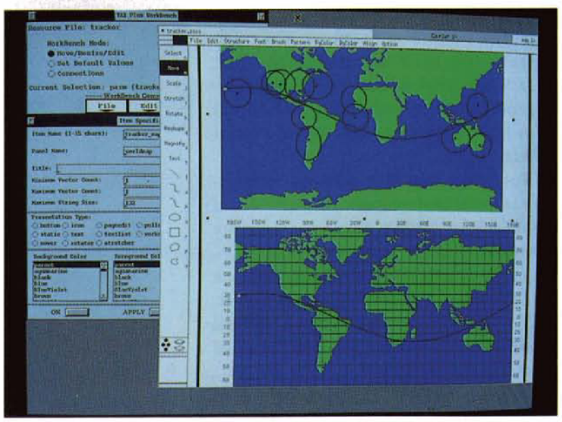
1990: University of Michigan, Michigan



Source: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20020087015.pdf

A. Remote Sensing

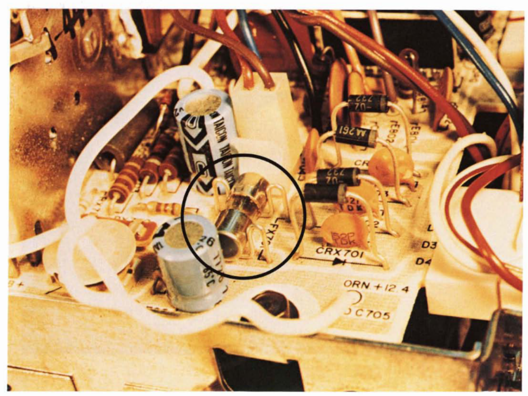
1989: NASA, District of Columbia



Source: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20020087609.pdf

B. Circuit Connectors

1979: Components Corporation, New Jersey



Source: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20070019747.pdf

Exhibit A3: Science Direct Technology Terms and Intelligence-Patents Similarity Examples

A. Intelligence Document (NIE13, p27)

TABLE 3

OTHER POSSIBLE SOVIET SPACE MISSIONS

We have estimated that the chances are better than even that the Soviets will attempt a manned lunar landing ahead of or in close competition with the US. In addition, the Soviets will probably undertake other programs including scientific satellites, military support satellites, and interplanetary probes. This table lists space missions estimated to be within Soviet capabilities, but we do not believe that all these missions could be accomplished within the time periods indicated. If the Soviets are not committed to a lunar race with the US, other programs will probably receive greater emphasis.

PROGRAMS	POSSIBLE DATE
UNMANNED SATELLITES	
Space Science Operations [a]	
(1) Magnetic measurement	
(2) Radiation measurement	
(3) Study of electromagnetic propagation	
(4) Study of upper atmosphere	1962 on
(5) Study of meteorites	
(6) Orbital astronomical observatory	
Military Systems	
(1) Early warning satellite	1962 on
(2) Reconnaissance satellite	1962 on
(3) Defensive space weapons systems [b]	
(i) Inspection of single nonmaneuvering satellite	1964
(ii) More sophisticated satellite with inspection, neutralization, and damage assessment capability	Later in decade
(4) Offensive space weapons systems	
(i) Demonstration of orbital bombardment satellite [c]	1962 on
(ii) Developmental system of limited effectiveness	1965
Commercial or Military Application	
(1) Meteorological satellites	
(2) Communications satellites	1962–1963
(3) Geodetic satellites	
(4) Navigation satellites	
MAN-IN-SPACE	
Manned Earth Orbital Flights	
(1) Orbit of multimanned spacecraft	1962–1963
(2) Rendezvous and docking	1962–1963
(3) Demonstration of 10-day life support system	1962–1963
(4) Transfer of man from one space vehicle to another	1963–1964
Large Manned Space Station	1965–1966 [d]
Manned Lunar Flights	
(1) Circumlunar	1965–1966 [d]
(2) Lunar satellite	1966–1967
UNMANNED LUNAR AND PLANETARY EXPLORATION	
Circumlunar, Lunar Satellite, Lunar Soft Landing	1962 on
Probes to Mars and Venus	1962 on
Probes to More Distant Planets	1963 [c]
Solar Probe	1963
Ejection of Vehicle from Solar System	1963 [c]

B. Similar Patent (3907225)

1

SPACECRAFT FOR DEPLOYING OBJECTS INTO SELECTED FLIGHT PATHS

BACKGROUND OF THE INVENTION

1. Field of the Invention

This invention relates generally to the space field and more particularly to a spacecraft for deploying objects into selected multiple space flight paths.

2. Prior Art

Spacecraft of the class to which this invention pertains are launched into space carrying a number of objects which are deployed at intervals from the spacecraft in a manner such that each object is inserted into a selected space flight path. The flight paths into which the objects are inserted may be either orbital paths, outer space paths, or ballistic trajectories. The invention will be described in the context of launching objects into ballistic trajectories.

According to a typical ballistic trajectory deployment sequence, the spacecraft is launched into an initial flight path and any of the objects which are to follow this path are then deployed from the spacecraft. Insertion of objects into other flight paths is accomplished by propelling the spacecraft along the local range insensitive axis, i.e., an axis passing through the spacecraft and the center of the earth, and across the desired flight paths and deploying the objects along these paths. Such deployment may be accomplished either passively or actively. Passive deployment of an object is accomplished by releasing the object for separation from the spacecraft and backing the spacecraft away from the object. Active deployment involves forcible ejection of the object from the spacecraft by spring action or the like.

Actual separation of the deployable objects from the spacecraft along the seleted flight paths may be only one of the requirements for proper insertion of the objects into these paths. Another deployment requirement may involve proper orientation of each object relative to its path at the time of separation from the spacecraft. Thus, objects which are deployed in the manner described herein generally have an axis, referred to as a reference axis, which must be oriented at a predetermined angle relative to the respective flight paths at the time of deployment.

My prior U.S. Pat. No. **3,652,042** discloses a spacecraft of the general class described. Another patent of interest with regard to such spacecraft is U.S. Pat. No. **3,547,375.**

SUMMARY OF THE INVENTION

This invention provides a novel spacecraft for deploying objects into selected multiple flight paths. The spacecraft comprises two separable, individually powered units, referred to herein as deployment vehicles, with unique interfitting configurations which permit assembly or mating of the vehicles into a compact unitary spacecraft structure. Each deployment vehicle has propulsion, braking and attitude control thrusters, an object mounting platform, fuel tanks, control systems, and the like. A number of objects to be deployed are mounted on the platform of each vehicle by either active or passive deployment means.

The two deployment vehicles are initially assembled in mating or interfitting relation to form a unitary spacecraft which is stowed within the nose section of a launch vehicle for launch of the spacecraft into a pre-

C. Intelligence Document (NIE16, p15)

43. There are several likely near term applications of the automatic rendezvous and docking system. When Soyuz 4 and 5 docked, the Soviets claimed that they had fulfilled the rendezvous techniques that would be used to assemble space stations in earth orbit; they would also be used for resupply of such stations and crew rotation. Moreover, the Soviets have indicated that rendezvous and docking would be used to assemble lunar and planetary spaceships in earth orbit.

44. The need for a cooperating target limits the use of the automatic rendezvous and docking technique in many applications such as rescue and in-orbit repair and maintenance. However, the Soyuz automatic rendezvous and docking system equipped with suitable sensors could be used by a maneuverable satellite for passive targets.

45. In the Soyuz and Zond programs the Soviets employed aerodynamic lift re-entry techniques similar to those used in the Gemini and Apollo missions. The Soyuz vehicle is designed to follow a preprogrammed deceleration profile, which is calculated to reduce re-entry "g" loadings during re-entry and to provide some control over the point of landing. The Zond re-entry is more complicated. The spacecraft normally re-enters over the Indian Ocean, and its lifting capability is used to move the landing point some five thousand miles north into the Soviet Union. The lifting re-entry techniques indicate a desire to recover manned lunar spacecraft in the Soviet Union rather than to rely regularly on a water recovery system. The ocean recovery capability is probably provided mainly as a backup.

46. The prime electric power source for the Soyuz and the Zond is solar energy. Solar power, however, is inadequate for some interplanetary missions and orbital missions having high continuous power requirements in excess of 50 kilowatts; nuclear powered systems will be required for such flights. The Soviets are actively engaged in R&D on various nuclear electric power systems. By the mid-1970's they could have a nuclear auxiliary power system generating a few kilowatts.

47. The Soviets have made significant strides in improving the reliability of their planetary spacecraft. They are using an improved thermal control system and also are equipping spacecraft with redundant component subsystems for backup in the event of failure. In their discussions of the Venus 4, the Soviets for the first time mentioned the use of a space simulator to check out the completed spacecraft before launch. These modifications should improve spacecraft and insure better success in the future.

D. Similar Patent (3232560)

3,232,560
RECOVERABLE SPACE VEHICLE
John C. Moise, Carmichael, and John Eut Tileston, Sacramento, Calif., assignors to Aerojet-General Corporation, Azusa, Calif., a corporation of Ohio
Filed Feb. 25, 1963, Ser. No. 260,355
3 Claims. (Cl. 244—1)

This invention relates in general to space vehicles and more particularly to a space tanker or freighter which may be recovered and reused.

It is expected that within the next decade space stations will be in use either for military or for scientific purposes or for both. Such space stations will be set up for purposes of refueling space craft, effecting transfer of personnel from one mission to another and for other such uses. It is seen, then, that a vehicle capable of placing these stations in orbit and keeping them supplied, at a minimum total operating cost per pound of payload in orbit, is needed. It is to this latter requirement that the present invention is primarily directed.

Various means have been proposed for conveying large payloads to low orbit space stations, some including water recoverable vehicles and others winged vehicles such as an aerospace plane. However, in expected cost per pound of payload the present invention is greatly superior to any of the above.

The device of the present invention is fundamentally an aerodynamically configured grouping of liquid fuel and liquid oxidizer storage tanks plus propulsion means sufficient to permit vertical take-off, rendezvous and docking at a space station, payload transfer, retro-thrust and reentry at a shallow angle followed by a controlled glide landing.

Accordingly, it is an object of the present invention to provide a vehicle capable of carrying a significant payload to orbit at a minimum cost.

It is another object of the present invention to provide a vehicle which may be recovered and reused a considerable number of times.

It is a further object of the present invention to provide a vehicle which permits full recovery of the vehicle through a single recovery technique.

Other objects and many of the attendant advantages of this invention will be readily appreciated as the same becomes better understood by reference to the following detailed description when considered in connection with the accompanying drawings, wherein:

FIG. 1 is a plan view of one embodiment of the invention.

FIG. 2 is a sectional view along line **2—2** of the embodiment of FIG. 1.

FIG. 3 is a side elevation of the embodiment of FIG. 1.

FIG. 4 is a sectional view along the line **4—4** of the embodiment of FIG. 1.

FIG. 5 is an alternate configuration for the section of FIG. 4.

FIG. 6 is an alternate configuration for the section of FIG. 4.

FIG. 7 is an alternate configuration for the section of FIG. 4.

FIG. 8 is an alternate configuration for the section of FIG. 4.

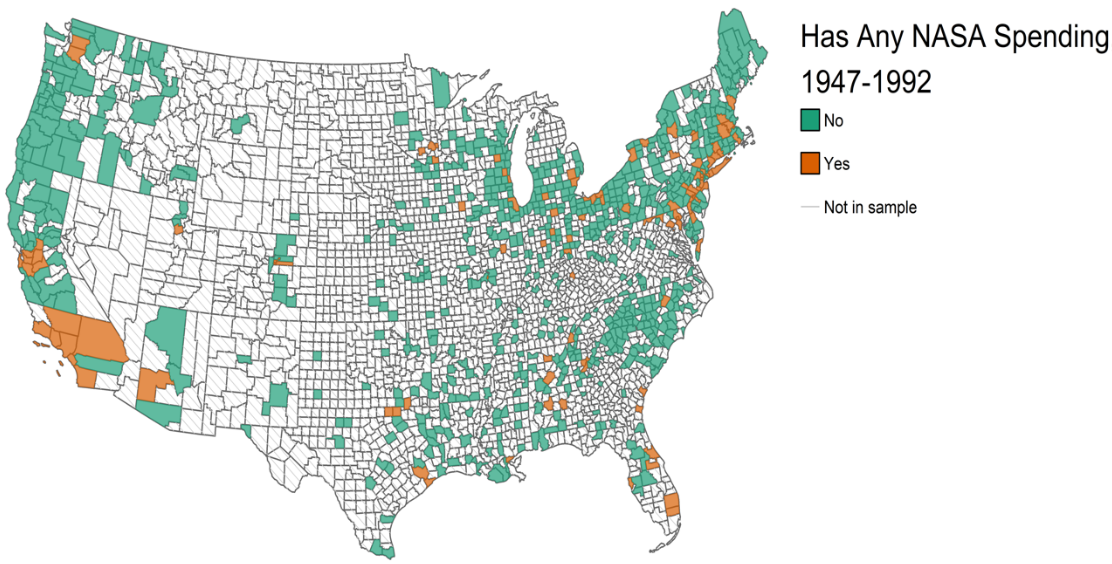
The space freighter or tanker of the present invention is primarily seen to be a series of aerodynamically configured tanks capable of generating sufficient lift during re-entry to enable the vehicle to return safely to the earth's surface, and, further, having means for propulsion and attitude control providing the capability of delivering an exceedingly high percentage of its total weight as payload to a space station.

Referring now to FIG. 1, space vehicle **11** is shown

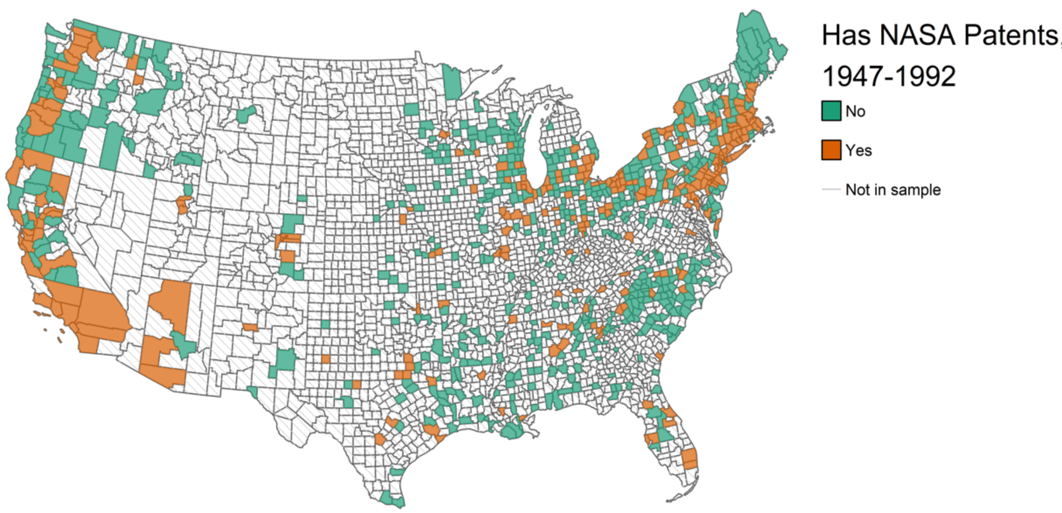
Notes: The highlighted words are Science Direct Technology Terms used to compute document similarity. The NIA document displayed in panel A would be considered similar to the patent in panel B. The NIE document in panel C is similar to the patent in panel D.

Map A1: NASA Locations, 1947-1992

A. NASA Spending



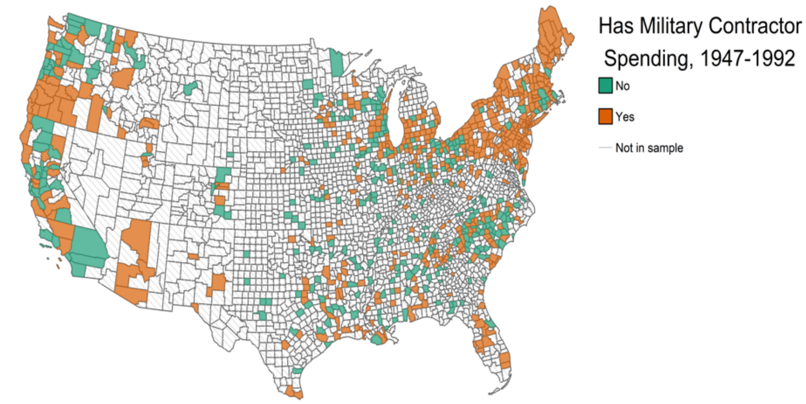
B. NASA Patents



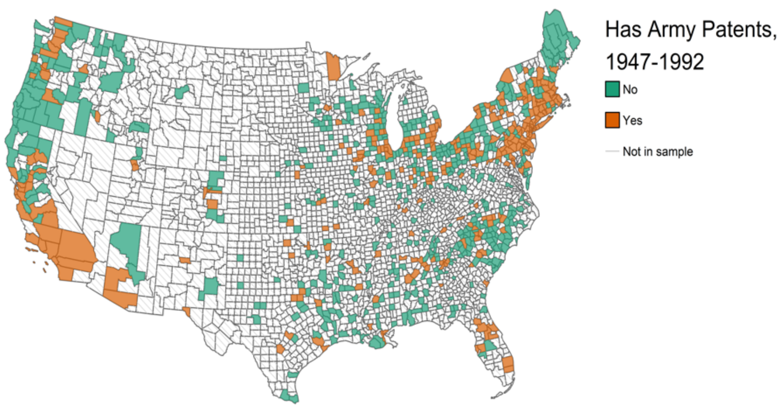
Sources: See the data appendix under NASA spending and NASA patents.

Map A2: Military Locations, 1947-1992

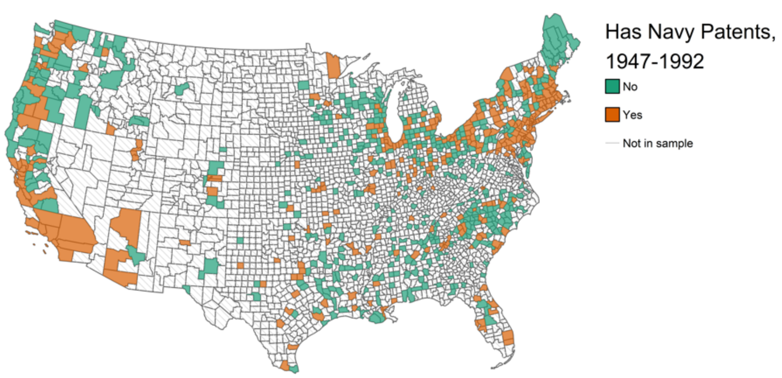
A. Military Contractor Spending



B. Army Patents



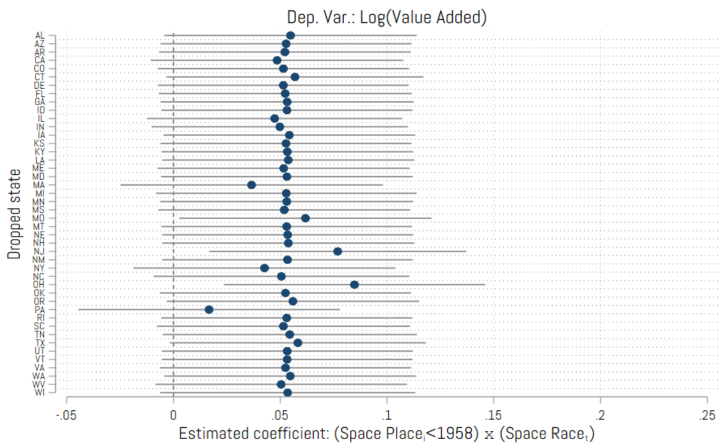
C. Navy Patents



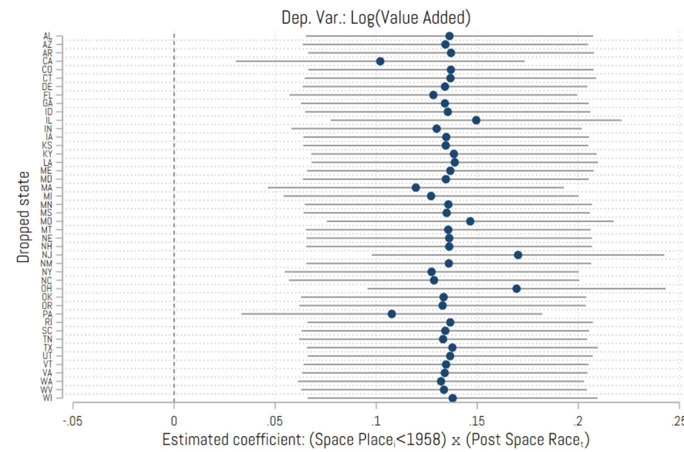
Sources: See the data appendix under military spending and Army and Navy patents.

Figure A1: Space Place Effects - Leave One State Out Estimates

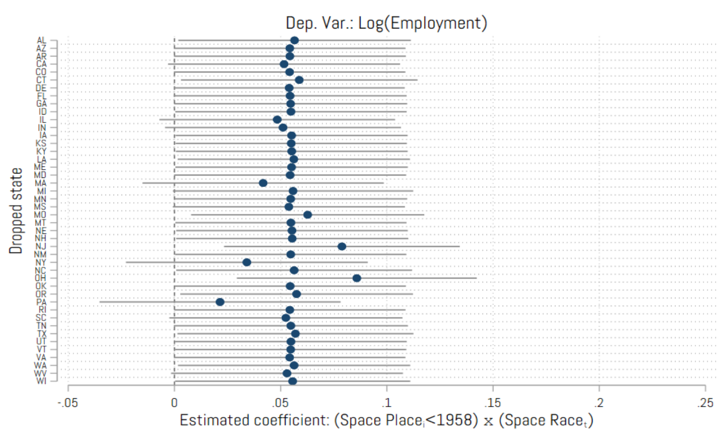
A. Log(Value Added) – Space Race Era Estimates



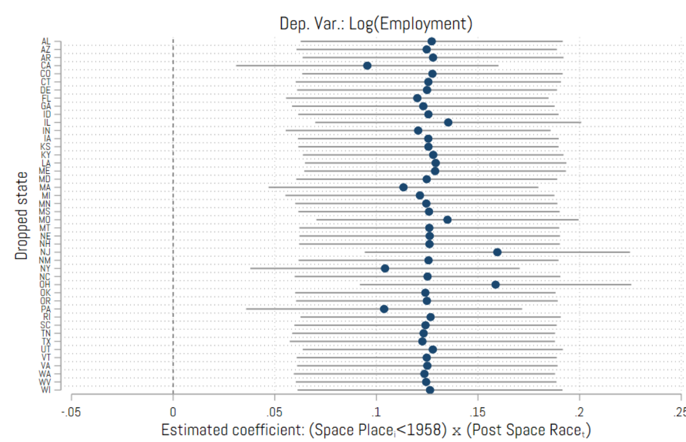
B. Log(Value Added) – Post Space Race Era Estimates



C. Log(Employment) – Space Race Era Estimates



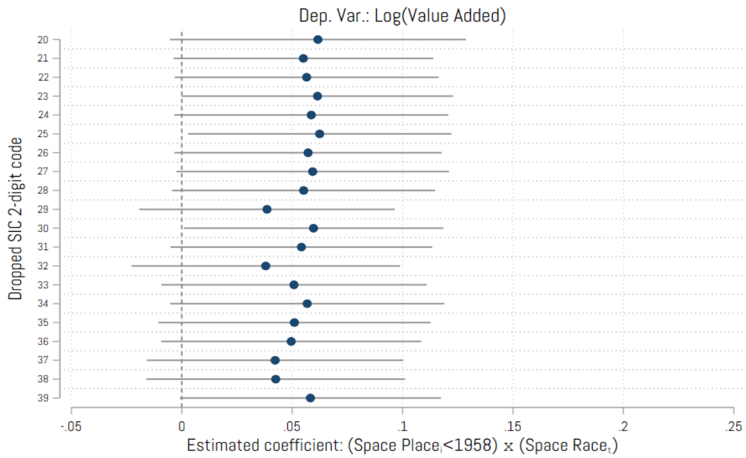
D. Log(Employment) – Post Space Race Era Estimates



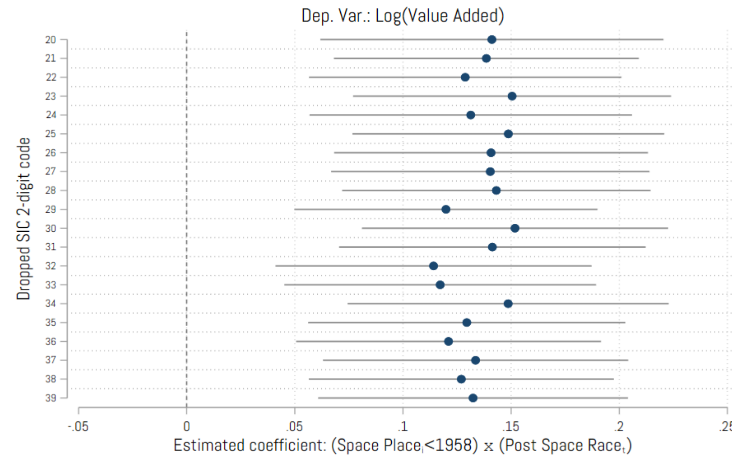
Notes: The estimates shown here graphically follow the regression estimation (equation (3)) presented in Table 3, column (3) in the main paper. Each panel in the table displays the coefficient from estimating one version of equation (3) in the text, but omitting one state at a time. Panels A and C display coefficients and 95% confidence intervals for Space $Place_{i,<1958}$ × Space $Race_t$ for value added and employment outcomes, respectively. Panels B and D display coefficients and 95% confidence intervals for Space $Place_{i,<1958}$ × Post-Space $Race_t$.for value added and employment, respectively.

Figure A2: Space Place Effects - Leave One Industry Out Estimates

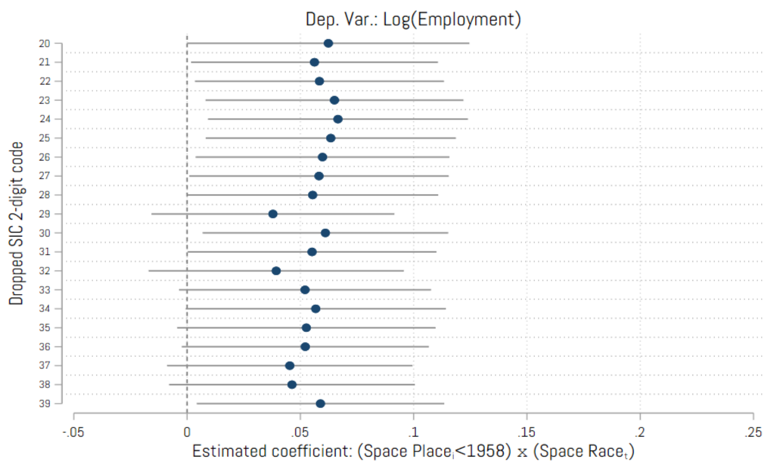
A. Log(Value Added) – Space Race Era Estimates



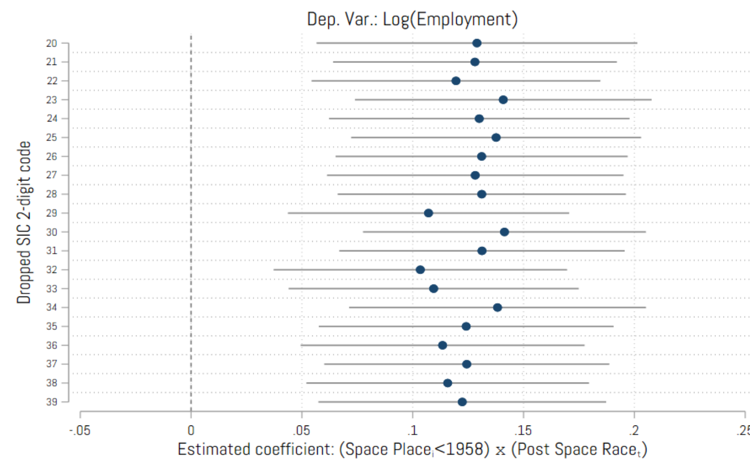
B. Log(Value Added) – Post Space Race Era Estimates



C. Log(Employment) – Space Race Era Estimates



D. Log(Employment) – Post Space Race Era Estimates



Notes: The estimates shown here graphically follow the regression estimation (equation (3)) presented in Table 3, column (3) in the main paper. Each panel in the table displays the coefficient from estimating one version of equation (3) in the text, but omitting one industry at a time. Panels A and C display coefficients and 95% confidence intervals for Space $\text{Place}_{i,<1958} \times \text{Space Race}_t$ for value added and employment outcomes, respectively. Panels B and D display coefficients and 95% confidence intervals for Space $\text{Place}_{i,<1958} \times \text{Post-Space Race}_t$.for value added and employment, respectively.

Table A1: National Intelligence Estimate of Soviet Space Capabilities Documents

Document	Date	Title	Baseline; Post-1958	All	Space Exclusive
NIE1	1946-10-31	Soviet Capabilities For The Development And Production Of Certain Types Of Weapons & Equipment		Included	
NIE2	1950-11-15	Soviet Capabilities And Intentions		Included	
NIE3	1951-09-15	Soviet Capabilities For A Surprise Attack On The Continental United States Before July 1952		Included	
NIE4	1953-03-05	Soviet Capabilities For Attack On The Us Through Mid-1955		Included	
NIE5	1953-06-16	Soviet Bloc Capabilities Through 1957		Included	
NIE6	1954-10-05	Soviet Capabilities And Probable Programs In The Guided Missile Field		Included	
NIE7	1955-12-20	Soviet Guided Missile Capabilities And Probable Programs		Included	
NIE8	1957-03-12	Soviet Capabilities And Probable Programs In The Guided Missile Field		Included	
NIE9	1958-08-19	Soviet Capabilities In Guided Missiles And Space Vehicles	Included	Included	
NIE10	1959-09-08	Soviet Capabilities In Guided Missiles And Space Vehicles	Included	Included	
NIE11	1959-11-03	Soviet Capabilities In Guided Missiles And Space Vehicles	Included	Included	
NIE12	1961-04-25	Soviet Technical Capabilities In Guided Missiles And Space Vehicles	Included	Included	
NIE13	1962-12-05	The Soviet Space Program	Included	Included	Included
NIE14	1965-01-27	The Soviet Space Program	Included	Included	Included
NIE15	1967-03-02	The Soviet Space Program	Included	Included	Included
NIE16	1969-06-19	The Soviet Space Program	Included	Included	Included
NIE17	1969-06-23	Soviet Strategic Attack Forces	Included	Included	
NIE18	1970-03-26	The Soviet Space Program	Included	Included	Included
NIE19	1971-07-01	The Soviet Space Program	Included	Included	Included
NIE20	1973-12-20	Soviet Space Programs	Included	Included	Included
NIE21	1974-10-15	A Soviet Land-Mobile ICBM: Evidence Of Development And Considerations Affecting A Decision On Deployment	Included	Included	
NIE22	1975-11-15	Soviet Dependence on Space Systems	Included	Included	Included
NIE23	1980-08-06	Soviet Military Capabilities And Intentions In Space	Included	Included	
NIE24	1982-10-15	The Technology Acquisition Efforts Of The Soviet Intelligence Services	Included	Included	
NIE25	1983-07-15	The Soviet Space Program	Included	Included	Included
NIE26	1984-11-15	Potential For The Transfer Of Space Technology To The Soviet Union	Included	Included	

NIE27	1984-12-15	Soviet Approach To Nuclear Winter	Included	Included	
NIE28	1985-12-15	Soviet Space Programs	Included	Included	Included
NIE29	1986-03-15	Soviet Military Production, 1974-85	Included	Included	
NIE30	1987-06-15	Soviet Military Production, 1975-86	Included	Included	
NIE31	1988-09-15	Soviet Reusable Space Systems Program: Implications for Space Operations in the 1990s	Included	Included	Included
NIE32	1991-08-08	Soviet Capabilities For Strategic Nuclear Conflict Through the Year 2000	Included	Included	

Notes: See data appendix section 2.2. This table lists the National Intelligence Estimates of Soviet Space Capabilities that are used in this paper. Our baseline measure of space places uses NIE documents #9 to #32 (i.e., those from 1958 and beyond). Our All-NIE space place measure uses all available relevant NIE documents #1 to #32. Our space-exclusive-NIE space place measure uses NIE documents indicated in the last column.

Table A2: 25 Most Frequent Science Direct Technology Topics in NASA Patent Documents

Unstemmed Term	Stemmed Term	Topic Rank in NASA Patents	Topic Rank in NIE Documents
Aircraft	aircraft	1	17
Antennae	antenna	2	99
Nationalism	nation	3	14
Transducer	transduc	4	13652.5
Amplitudes	amplitud	5	13652.5
Spacecraft	spacecraft	6	13
Specimen	specimen	7	649.5
Governance	govern	8	70.5
Modelers	model	9	78.5
Wavelength	wavelength	10	832.5
United States of America	unit state of america	11	1246.5
Instrumentalism	instrument	12	53.5
Propellant	propel	13	32.5
Reflectors	reflector	14	1246.5
Waveform	waveform	15	1246.5
Equator	equat	16	399.5
Provisioning	provis	17	155.5
Satellites	satellit	18	3
Emittance	emitt	19	649.5
Multiplication	multipl	20	73.5
Acceleration	acceler	21	399.5
Ceramer	ceram	22	13652.5
Factorization	factor	23	23
Minimality	minim	24	214
Actualization	actual	25	51

Notes: The first column reports the Science Direct Technology Topic in unstemmed form and the second column reports the stemmed form of the Science Direct topic. The third and fourth columns report the ranking of each term with respect to its appearance in NASA patent documents and in the CIA National Intelligence Estimates of Soviet Space Capabilities documents, respectively.

Table A3: 25 Most Frequent Science Direct Technology Topics in National Intelligence Estimates of Soviet Space Capabilities Documents

Unstemmed Term	Stemmed Term	Topic Rank in NASA Patents	Topic Rank in NIE Documents
Missiles	missil	762	1
USSR	ussr	16565	2
Satellites	satellit	18	3
Estimability	estim	138	4
Orbitals	orbit	34	5
Secretions	secret	8846	6
Intelligibility	intellig	1782.5	7
Defensiveness	defens	8115.5	8
Scientification	scientif	947.5	9
Warhead	warhead	18245.5	10
Directorate	director	2392	11
Payload	payload	165.5	12
Spacecraft	spacecraft	6	13
Nationalism	nation	3	14
Westernization	western	6151.5	15
Germanate	german	4295	16
Aircraft	aircraft	1	17
Mobilization	mobil	476	18
Altitude	altitud	198	19
Space Stations	space station	183	20
Reconnaissance	reconnaiss	13452.5	21
Lates	late	1745	22
Factorization	factor	23	23
Basicity	basic	81	24
Economics	econom	493	25

Notes: The first column reports the Science Direct Technology Topic in unstemmed form and the second column reports the stemmed form of the Science Direct topic. The third and fourth columns report the ranking of each term with respect to its appearance in NASA patent documents and in the CIA National Intelligence Estimates of Soviet Space Capabilities documents, respectively.

Table A4: 25 Most Frequent Science Direct Technology Topics Occurring in Top 0.5% of both NASA patents and NIE documents

Unstemmed Term	Stemmed Term	Topic Rank in NASA Patents	Topic Rank in NIE Documents
Nationalism	nation	3	14
Aircraft	aircraft	1	17
Spacecraft	spacecraft	6	13
Satellites	satellit	18	3
Orbitals	orbit	34	5
Propellant	propel	13	32.5
Factorization	factor	23	23
Instrumentalism	instrument	12	53.5
Actualization	actual	25	51
Governance	govern	8	70.5
Observability	observ	40	41.5
Modelers	model	9	78.5
Multiplication	multipl	20	73.5
Antennae	antenna	2	99
Basicity	basic	81	24
Publicity	public	73	46
Calibrator	calibr	52	91
Identifiability	identifi	95	50
Physicalism	physic	61	88.5
Criticality	critic	108	45
Pastes	past	130.5	27
Simulators	simul	54	106.5
Affectivity	affect	127	40
Interference	interfer	128	55.5
Commercialization	commerci	106	97.5

Notes: The first column reports the Science Direct Technology Topic in unstemmed form and the second column reports the stemmed form of the Science Direct topic. The third and fourth columns report the ranking of each term with respect to its appearance in NASA patent documents and in the CIA National Intelligence Estimates of Soviet Space Capabilities documents, respectively. The set of terms represented in this table are the top 25 terms in the intersection of the top 132 terms from the NASA patents and the top 132 terms in the NIE documents.

Table A5: Soviet Space Intelligence Similarity and NASA patents

Dependent Variable=	NASA Patent			
	(1)	(2)	(3)	(4)
Space Score	0.203	0.196	0.100	0.062
	(0.005)	(0.005)	(0.005)	(0.005)
Army Patent			-0.089	-0.085
			(0.007)	(0.007)
Navy Patent			-0.089	-0.100
			(0.008)	(0.001)
Government Patent			0.086	0.084
			(0.003)	(0.003)
Year Fixed Effect	Y	Y	Y	Y
NBER Technology Subcategory Fixed Effects		Y	Y	Y
County Fixed Effects				Y
R^2	0.004	0.005	0.087	0.142

Notes: Each column in the table reports the results from estimating one version of equation (1) in the text. The unit of observation is patent level. The space score variable measures the cosign similarity between the CIA National Intelligence Estimates of Soviet Space Capabilities texts between 1958 and 1992 and the text of the reference patent using the Science Direct technology terms corpus, as described in the text and data appendix. The model in column (1) includes year fixed effects, the model in columns (2) also includes NBER technology subcategory fixed effects, the model in column (3) further includes indicator variables for whether the Army, Navy, or other government agency was the owner or funder of the patent. Finally, column (4) further adds county fixed effects. All models have 900,822 patent observations.

TABLE A6: Correlation Between NASA and Military Measures

	Total NASA Spending	NASA Contractor Spending	NASA R&D Center Spending	Military Spending	NASA Patents	Army Patents	Navy Patents	Government Patents
Total NASA Spending	1							
NASA Contractor Spending	0.9974	1						
NASA R&D Center Spending	0.5992	0.5399	1					
Military Spending	0.0788	0.0796	0.0362	1				
NASA Patents	0.6673	0.6478	0.5972	0.0662	1			
Army Patents	0.055	0.0549	0.0335	0.0142	0.1662	1		
Navy Patents	0.1714	0.1694	0.1197	0.0143	0.293	0.244	1	
Government Patents	0.4778	0.4694	0.3653	0.0327	0.6051	0.3637	0.5663	1

Notes: Definitions and sources for the various spending and patent measures are in the data appendix.

TABLE A7: Space Places, NASA Spending, and NASA patents – Limited Sample

Dependent Variable =	Arsinh(NASA Spending)			Arsinh(NASA Patents)		
	(1)	(2)	(3)	(4)	(5)	(6)
Space Place$_{i,<1958}$ × Space Race$_t$	0.92	0.99	1.14	0.05	0.05	0.04
	(0.56)	(0.56)	(0.52)	(0.02)	(0.02)	(0.02)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.75	0.81	1.29	0.08	0.08	0.09
	(0.56)	(0.56)	(0.54)	(0.03)	(0.03)	(0.03)
County Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects		Y	Y		Y	Y
State × Year Fixed Effects			Y			Y
R^2	0.48	0.49	0.61	0.34	0.37	0.50

Notes: This table is analogous to Table 2 in the main paper, but instead uses a limited sample of counties that excludes those locations with more than the 75th percentile level of pre-1958 patents and less than the 25th percentile of pre-1958 patents. Data are drawn from National Intelligence Estimates, NASA Historical Data Book, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (1) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992 (the Space Score), as described in the text and the appendix. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is county × year. The models in columns (1) and (4) includes county and year fixed effects, the models in columns (2) and (5) also include the count of pre-1958 patents in a county × year fixed effects, and the models in columns (3) and (5) also include state × year fixed effects. Dependent variables are transformed using the inverse hyperbolic sine: $arsinh(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$. All models have 2,450 county-year observations and 245 county observations.

TABLE A8: Space Places, Value Added, and Employment – Alternative Inference Procedures

Dependent Variable =	Log(Value Added)				Log(Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.14	0.14	0.14	0.14	0.13	0.13	0.13	0.13
	(0.06)	(0.07)	(0.04)	(0.04)	(0.06)	(0.07)	(0.04)	(0.03)
Inference Procedure:								
Clusters	County	County× Industry	State-Industry		County	County× Industry	State-Industry	
Spatial				HAC-100				HAC-100
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50

Notes: This table is analogous to Table 3, columns (4) and (8) in the main paper. The exception here is that the models in column (1) and (5) cluster the standard errors by county, the models in columns (2) and (6) double cluster the stand errors by county and industry, the models in column (3) and (7) cluster the standard errors by state-industry, and the models in columns (4) and (8) compute standard errors using a spatial HAC procedure with a 100km cutoff. Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in its pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. The models in all columns include county fixed effects, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and industry fixed effects. All models have 26,862 2-digit SIC industry × county × year observations, 20 2-digit SIC industries, and 791 county observations.

TABLE A9: Space Places, Value Added, and Employment – Limited Sample

Dependent Variable =	Log(Value Added)				Log(Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	0.13	0.14	0.13	0.11	0.14	0.14	0.14	0.11
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.21	0.21	0.22	0.22	0.23	0.23	0.23	0.22
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects		Y	Y	Y		Y	Y	Y
Industry Fixed Effects			Y	Y			Y	Y
Industry × Year Fixed Effects				Y				Y
R^2	0.22	0.24	0.40	0.44	0.17	0.17	0.29	0.37

Notes: This table is analogous to Table 3, except that the sample of counties excludes those locations with more than the 75th percentile level of pre-1958 patents and less than the 25th percentile of pre-1958 patents. Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in its pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. The models in columns (1) and (5) includes county and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in columns (2) and (6) also include state × year fixed effects; columns (3) and (7) also include industry fixed effects; and the models in columns (4) and (8) further include industry × year fixed effects. Standard errors are clustered at the 2-digit SIC industry-county level. Models in columns (1) and (5) have 13,468 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 245 county observations. Models in columns (2)-(4) and (6)-(8) have 13,453 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 244 county observations.

TABLE A10: Space Places, Value Added and Employment: Own Versus Other Industry Effects

Dependent Variable =	Log(Value Added)			Log(Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
High Own-Industry Space Score$_{ij,<1958}$ × Space Race$_t$	0.04		0.04	0.04		0.05
	(0.03)		(0.03)	(0.03)		(0.03)
High Own-Industry Space Score$_{ij,<1958}$ × Post-Space Race$_t$	0.06		0.06	0.07		0.08
	(0.03)		(0.03)	(0.03)		(0.03)
High Other-Industry Space Score$_{i\ -j,<1958}$ × Space Race$_t$		0.00	0.01		0.00	0.02
		(0.04)	(0.04)		(0.04)	(0.04)
High Other-Industry Space Score$_{i\ -j,<1958}$ × Post-Space Race$_t$		0.09	0.11		0.08	0.10
		(0.05)	(0.05)		(0.04)	(0.04)
County Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
R^2	0.50	0.50	0.50	0.47	0.47	0.47

Notes: Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. High Own-Industry Space Score$_{ij,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992 in industry *j*, as described in the text. High Other-Industry Space Score$_{ij,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992 in industries other than *j*, as described in the text. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. The models in all columns include county and year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and industry fixed effects. Standard errors are clustered at the 2-digit SIC industry - state level. All models have 22,878 2-digit SIC industry × county × year observations, 19 2-digit SIC industry, and 605 county observations.

TABLE A11: Space Places, Value Added, and Employment – Levels & Limited Sample

Dependent Variable =	Value Added (Millions 1958$)				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	3.47	2.04	1.65	1.39	322	305	285	178
	(2.45)	(2.53)	(2.54)	(2.40)	(169)	(174)	(173)	(160)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	11.03	9.97	10.25	11.07	751	751	752	696
	(3.29)	(3.47)	(3.47)	(3.20)	(206)	(214)	(216)	(197)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects		Y	Y	Y		Y	Y	Y
Industry Fixed Effects			Y	Y			Y	Y
Industry × Year Fixed Effects				Y				Y
R^2	0.16	0.19	0.26	0.29	0.15	0.17	0.24	0.27

Notes: This table is analogous to Table 3, except that the sample of counties excludes those locations with more than the 75th percentile level of pre-1958 patents and less than the 25th percentile of pre-1958 patents and that the dependent variables are not in logs. Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (2) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county's being above median in terms of the similarity between the technologies present in its pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix. Space Race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2-digit SIC industry × county × year. The models in columns (1) and (5) includes county and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in columns (2) and (6) also include state × year fixed effects; columns (3) and (7) also include industry fixed effects; and the models in columns (4) and (8) further include industry × year fixed effects. Standard errors are clustered at the 2-digit SIC industry-county level. Models in columns (1) and (5) have 13,468 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 245 county observations. Models in column (2)-(4) and (6)-(8) have 13,453 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 244 county observations.

TABLE A12: Space Places, Value Added, and Employment – Alternative Text Processing Procedures

Dependent Variable =	Log(Value Added)				Log(Employment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Space Place$_{i,<1958}$ × Space Race$_t$	0.05	0.05	0.04	0.02	0.04	0.07	0.05	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Post-Space Race$_t$	0.10	0.12	0.10	0.08	0.09	0.12	0.09	0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Space Place Text Measure:	Unstemmed	All	Mean	Exclusive	Unstemmed	All	Mean	Exclusive
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.50	0.50	0.50	0.50	0.34	0.35	0.46	0.50

Notes: Source: Authors' Calculation from National Intelligence Estimate, Manufacturing Census Data, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (3) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text and appendix table A1. Space race years are 1963, 1967 and 1972. Post space race years are 1977, 1982, 1987, and 1992. The unit of observation is 2 digit SIC industry × county × year. All models includes county, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and include industry fixed effects. Standard errors are clustered at the 2 digit SIC industry-county level. All models have 26,862 2 digit SIC industry × county × year observations, 20 2 digit SIC industry, and 791 county observations.

TABLE A13: Space Places, Value Added, and Employment – Dynamic Models

Dependent Variable =	Log(Value Added)	Log(Employment)
	(1)	(2)
Space Place$_{i,<1958}$ × Year=1947$_t$	0.00	-0.01
	(0.07)	(0.06)
Space Place$_{i,<1958}$ × Year=1954$_t$	-0.01	0.00
	(0.05)	(0.05)
Space Place$_{i,<1958}$ × Year=1958$_t$	0	0
Space Place$_{i,<1958}$ × Year=1963$_t$	0.04	0.04
	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Year=1967$_t$	0.06	0.07
	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Year=1972$_t$	0.07	0.08
	(0.03)	(0.03)
Space Place$_{i,<1958}$ × Year=1977$_t$	0.12	0.13
	(0.04)	(0.03)
Space Place$_{i,<1958}$ × Year=1982$_t$	0.14	0.13
	(0.04)	(0.03)
Space Place$_{i,<1958}$ × Year=1987$_t$	0.14	0.13
	(0.04)	(0.04)
Space Place$_{i,<1958}$ × Year=1992$_t$	0.16	0.14
	(0.04)	(0.04)
County Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
Pre-1958 Patents × Year Fixed Effects	Y	Y
State × Year Fixed Effects	Y	Y
Industry Fixed Effects	Y	Y
R^2	0.50	0.46

Notes: Data are drawn from National Intelligence Estimates, Census of Manufactures, and United States Patent and Trademark data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (4) in the text. Space Place$_{i,<1958}$ is an indicator variable reflecting a county being above median in terms of the similarity between the technologies in pre-1958 patents and the National Intelligence Estimates of Soviet Space Capabilities between 1958 and 1992, as described in the text. The omitted year interaction is 1958. The unit of observation is 2-digit SIC industry × county × year. Standard errors are clustered at the 2-digit SIC industry-county level. The models in all columns include county fixed effects, year fixed effects, the count of pre-1958 patents in a county × year fixed effects, state × year fixed effects, and industry fixed effects. Models in all columns have 26,862 2-digit SIC industry × county × year observations, 20 2-digit SIC industry, and 791 county observations.

TABLE A14: Space Places and Patent Inventor Migration – Top 25% Inventors

Dependent Variable =	Log(Out Migration Ratio)		
	(1)	(2)	(3)
Space Score Difference$_{od,<1958}$× Space Race$_t$	0.07	0.07	0.16
	(0.05)	(0.05)	(0.06)
Space Score Difference$_{od,<1958}$× Post-Space Race$_t$	0.32	0.33	0.34
	(0.07)	(0.07)	(0.08)
Corporate Income Tax Rate (1-CIT)$_{ijt}$		0.59	
		(0.23)	
Personal Average Income Tax Rate, 90th percentile (1-ATR)$_{ijt}$		0.47	
		(0.15)	
R&D Credit (1+credit)$_{ijt}$		0.03	
		(0.01)	
Origin County Fixed Effects	Y	Y	Y
Destination County Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Origin Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Destination Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Origin County × Destination County Fixed Effects	Y	Y	Y
Origin State × Year Fixed Effects			Y
Destination State × Year Fixed Effects			Y
R^2	0.74	0.90	0.92

Notes: This table is analogous to Table 7 in the main paper, except that the sample is those in the top 5% of the lifetime patent distribution. Data are drawn from National Intelligence Estimates, United States Patent and Trademark and Akcigit, Grigsby, Nicholas, and Stantcheva (2022) data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (6) in the text. Space Place Difference$_{ij,<1958}$ is an indicator variable reflecting a county pair being above median in terms of the similarity between the counties' pre-Sputnik space related patents, as described in the text. τ_{ij} is a measure of travel costs between county i and j as computed by Jaworski and Kitchens (2019). Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is origin county × destination county × application year. The models in columns (1) and (2) include county fixed effects and year fixed effects; column (3) further adds the count of pre-1958 patents in a county × year fixed effects and county-pair fixed effects; and column (4) adds state x year fixed effects. Standard errors with three-way clustering by origin county × year, destination county × year, and county-pair are in parentheses. All models have 83,140 origin-county × destination-county × application year observations and 790 county observations.

TABLE A15: Space Places and Patent Inventor Migration – Top 50% Inventors

Dependent Variable =	Log(Out Migration Ratio)		
	(1)	(2)	(3)
Space Score Difference$_{od,<1958}$× Space Race$_t$	0.09	0.10	0.15
	(0.06)	(0.06)	(0.06)
Space Score Difference$_{od,<1958}$× Post-Space Race$_t$	0.34	0.36	0.40
	(0.09)	(0.09)	(0.09)
Corporate Income Tax Rate (1-CIT)$_{ijt}$		0.07	
		(0.28)	
Personal Average Income Tax Rate, 90th percentile (1-ATR)$_{ijt}$		1.04	
		(0.21)	
R&D Credit (1+credit)$_{ijt}$		0.00	
		(0.02)	
Origin County Fixed Effects	Y	Y	Y
Destination County Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Origin Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Destination Pre-1958 Patents × Year Fixed Effects	Y	Y	Y
Origin County × Destination County Fixed Effects	Y	Y	Y
Origin State × Year Fixed Effects			Y
Destination State × Year Fixed Effects			Y
R^2	0.90	0.90	0.91

Notes: This table is analogous to Table 7 in the main paper, except that except that the sample is those in the top 50% of the lifetime patent distribution. Data are drawn from National Intelligence Estimates, United States Patent and Trademark and Akcigit, Grigsby, Nicholas, and Stantcheva (2022) data from 1947 to 1992, as described in the data appendix. Each column in the table reports the results from estimating one version of equation (6) in the text. Space Place Difference$_{ij,<1958}$ is an indicator variable reflecting a county pair being above median in terms of the similarity between the counties' pre-Sputnik space related patents, as described in the text. τ_{ij} is a measure of travel costs between county i and j as computed by Jaworski and Kitchens (2019). Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The unit of observation is origin county × destination county × application year. The models in columns (1) and (2) include county fixed effects and year fixed effects; column (3) further adds the count of pre-1958 patents in a county × year fixed effects and county-pair fixed effects; and column (4) adds state x year fixed effects. Standard errors with three-way clustering by origin county × year, destination county × year, and county-pair are in parentheses. All models have 83,140 origin-county × destination-county × application year observations and 790 county observations.