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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 that public R&D conducted by NASA contractors increased manufacturing value added, employment, and capital accumulation in space related sectors. While migration responses were important, they were not sufficient to generate a wedge between local and national effects. The iconic Moonshot R&D program had meaningful economic effects for both the local and national space related sectors. Yet the magnitudes of the estimated effects seem to align with those of other non-R&D types of government expenditures.

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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 US 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. To the extent that we hope to uncover the nuances of how public R&D seeds economic growth, the Cold War era Space Race provides a unique episode in modern US economic history to examine in depth.

We analyze the effects of this large 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.

To estimate our models we develop a novel empirical approach to isolate the exogenous variation in NASA contractor R&D. The imperative to win the Space Race meant that NASA was compelled to rapidly allocate funding to space sector firms 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 American firms could supply 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 US patents before 1958 to determine which US industries in which counties specialized in space-relevant technologies before the Space Race began. We term county-industries as having "High Space Capability" 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 industries to other industries, before and after the Space Race, in county-industries with varying pre-1958 space technology capabilities.

To carry out our empirical analysis we construct a new panel dataset containing highly granular data on US manufacturing and NASA activity for large urban counties from 1947 to 1992. For each county-industry we have digitized the amount that NASA contractors received. 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 government ownership and funding of patents from Fleming, et al. (2019).

NASA spending was highly concentrated in a few sectors (Figure 2A) that grew faster than others in terms of output, employment, capital, and TFP over the 1958 to 1992 period (Figure 2B). These trends may not reflect a causal relationship, however. Our analysis that addresses potential endogenenity of NASA's spending decisions reveals five main results. First, we establish that the Space Race caused NASA contracting activity to expand more in the industry-county pairs that had already specialized in the building blocks of space technology before Sputnik. The amount of NASA spending and NASA patents expanded significantly relative to other industry-counties that were not already specialized in the rudiments of space technology.

Second, we show that the Space Race caused manufacturing value added, employment, and capital to expand more in those industry-county pairs that had already specialized in early space technology before Sputnik. One possible concern is that NASA activity followed trends in manufacturing. We show that there were negligible differential trends before the Space Race began between "high space capability" industry-county pairs relative to their counterparts around the country, thus ruling out that NASA spending decisions simply followed local private sector trends. Our results are also robust to controlling for industry specific trends, military contracting, and skill.

Space Race spending was economically large so we might expect local effects through a fiscal multiplier channel even without technological spillovers. We compare the fiscal multiplier for NASA contractor spending implied by our estimates to the literature to get a sense of this. Our results imply a localized NASA contractor fiscal multiplier of about 1.6 during the Space Race period, as measured by changes in manufacturing value added, and a fiscal multiplier of 1.6 in the post-Space Race period. Our estimates are close to the cross-sectional estimate of 1.8 in Chodorow-Reich (2019) and at the upper end of the range (2.0) of Ramey's (2011) time-series estimates. Thus, we find that R&D contractor spending on the Space Race had a similar impact as typical government expenditures.

Third, we estimate localized productivity spillovers from NASA contractor spending. If technologies discovered by NASA contractors spilled over to neighboring firms, then we would expect local productivity enhancements. In addition, new technologies may take time to diffuse so NASA contractor spending may have increased local productivity into the short- or long-term. Our analysis does not detect such local technological spillovers, however. One important caveat is that our estimates are likely to be lower bounds for technological spillovers from NASA as they do not account for other types of NASA spending (e.g., at universities or at NASA's own research centers), international technology diffusion, or any effects that may have accrued outside of the manufacturing sector.

Our estimated multiplier effects based on manufacturing value added reflect local rather than national effects. Local estimates would overstate national effects if workers migrated from other locations toward places that experienced windfall NASA activity. Thus, our fourth set of results explores migration responses and implications. 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 inventors migrated toward industry-county pairs that had the ex ante capabilities to accomplish the R&D work of the Space Race. The results reveal that inventors working in space industries did in fact migrate toward these space locations, and the results are robust to typical county-to-county migration patterns and state tax policies.

While these migration responses would imply that the national effects of the space program would be smaller than the localized effects, other positive spatial spillovers – i.e., 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 and long-term, overall market effects were small enough not to amplify or attenuate the positive local effects from Space Race activity. The implication of these findings is that the local and national fiscal multipliers associated with NASA contractor spending were largely the same.

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; Myers and Lanahan 2022; Gross and Sampat 2022) and productivity (Moretti, Steinwender, and Van Reenen forthcoming).[1] Perhaps most closely related to our work here is Schweiger, Stepanov, and Zacchia (2022) 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 2022), trade protection (Juhasz 2018), or university funding (Kantor and Whalley 2014 and 2019; Hausman 2022; Andrews 2023) 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 in advanced economies. We complement work showing that large-scale industrial policy in South Korea during the 1970s had persistent effects on economic development and welfare (Lane 2021; Choi and Levchenko 2022). Our analysis provides new empirical insights into the spatial and temporal lags associated with public R&D that directly engaged private firms.

Third, we connect to the literature on government spending multipliers.[2] Our findings complement Ramey's (2021) work on short- versus long-term effects of public infrastructure and the work of Antolin-Diaz and Surico (2022) on the short- versus long-term effects of public spending. 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 responses

[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 (2022) for a literature review.

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

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 US 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] While our estimates imply iconic Moonshot R&D had first-order effects on economic growth in space sectors, given that the magnitude of the effect lines up with typical government spending fiscal multipliers indicates that the Moonshot's role in broad based productivity growth was more limited.

2 Historical Background

The Origins of NASA. The Space Race effectively began with the Soviet launch of Sputnik on October 4, 1957. The US government had intelligence that a launch was im-

[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.

minent (Logsdon 1995, 329), but the high-profile failure of the US'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 security concerns, as President 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] The immediate need was to forcefully respond to Sputnik and to the national realization that the US was slipping behind the Soviet Union technologically.

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 US 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.[7]

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,

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

[7]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.

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).[8] This emphasis 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).

NASA 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).[9] 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).

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 the Marshall Space Flight Center, put the logic simply: "you cannot put a man on

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

[9]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).

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).

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 online 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 online 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.

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 US patents, thus enabling us to identify space sector industry-county pairs based on technological similarity; (ii) county-industry level NASA contractor spending data that are used to measure space sector activity, and patents to measure innovation outcomes; and (iii) county-industry-level manufacturing census data used to measure outcomes in the real economy. In this section, we briefly 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-Capable Places. Our research design compares changes in outcomes between county-industry combinations 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 US leadership in specific technologies that could help win the race to the Moon. Locations that specialized in technologies where the US had technological superiority – and selected by NASA for that reason – may have been poised for growth regardless of the space program. 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 US had technological superiority, as a lack of US-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.[10]

We classify the county-industry pairs with regard to pre-Space Race spaceflight technology by searching for post-Sputnik Soviet spaceflight technologies in the US patent record prior to the launch of Sputnik in 1957. 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 Myers and Lanahan 2022). To estimate a numerical similarity score between each NIE document and each US patent we use term frequency cosine similarity for a set of scientific terms. 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.[11] We aggregate these textual similarity measures across all pre-1958 US patents in a county industry cell to create our "space capability" measure. We discuss our approach in detail in

[10]The titles and dates of the NIE documents are provided in online appendix table A1. Our primary space capability measure is based on the post-1958 documents as these are more likely to have an exclusive focus on space.

[11]Examples of Science Direct (SD) technology terms most frequent in patents owned or funded by NASA, shown in online appendix table A2, include "Aircraft," "Antennae," and "Propellant." Examples of SD technology terms most frequent in NIE space technology intelligence reports, shown in online appendix table A3, include "Missiles," "Satellites," and "Orbitals." Online 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.

online appendix section 2.2.

NASA Contractor Spending and Patents. 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.[12] 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. Moreover, NASA contractor spending was highly concentrated in two space sectors – transportation equipment and electronics equipment – accounting for nearly 90% of NASA manufacturing contractor spending.[13]

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 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 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. For patents with multiple inventor locations we assign a proportional fraction to each location.[14]

An important limitation with using patent data to measure government-sponsored innovation is that before the 1980 Bayh-Dole Act began the process of creating a uniform patent policy, different agencies had different assignment and reporting policies, in a way that matters for measurement.[15] When NASA was created in 1958, the founding legislation gave the government all rights to the inventions made within NASA programs, but the administrator had the discretionary ability to waive such rights and grant contractors ownership of their

[12]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).

[13]Figure 2A shows the distribution of average NASA contractor spending across industries.

[14]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.

[15]We thank an anonymous referee for alerting us to this issue.

intellectual work product.[16] Thus, NASA patents may measure NASA activity with significant error if in fact contractors were able to successfully lobby for waivers.[17] For this reason we measure NASA activity using both NASA contractor spending and NASA patents.[18]

The challenge of measuring military-sponsored innovation – an important control in our analysis – using patents is likely to be significant. The Army and Navy were historically "license agencies" whereby patents were assigned to contractors, so we will likely undercount military-supported innovation. To address this concern we control for a variety of measures of potential military research activity locally and develop a new measure of military patents at the county-industry-year level by searching patent texts for technologies contained in the military technology glossary, as described in the online data appendix.

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 never returned to the Space Race peak. In panel B we see that NASA patents were very low before NASA was founded in 1958.[19] 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. NASA contractor spending fell after the peak of the Space Race in the mid-1960s, while patenting remained elevated.

[16]See McDougall (1985, 175-76) and Kraemer (2001). Eisenberg (1996) discusses the legal tradeoffs between so-called "title policy" versus "license policy" that was inconsistently utilized across federal government agencies.

[17]Jaffe, Fogarty, and Banks (1998, 188-9) note that the NASA waiver policy became increasingly lenient through the 1970s and by the early 1980s waivers were "essentially automatically granted." The Bayh-Dole Act of 1980 eliminated the need for universities, non-profit institutions, or small businesses to apply for formal waivers from NASA. President Ronald Reagan issued an executive order in 1983 that directed government agencies to extend the Bayh-Dole titling privileges over federally-funded research to all government contractors, including large businesses. See Eisenberg (1996, 1665).

[18]Map A1 in the online appendix shows which sample counties had a NASA patent or any NASA spending from 1947 to 1992. In online 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 (see online appendix section 2.2 for further discussion). Online appendix table A6 shows that NASA spending and NASA patenting variables are spatially correlated, though perhaps less correlated than would be expected given the patent-based measurement challenges noted above.

[19]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).

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.[20] We obtain data on total value added, total employment, total annual wages, and total plant and equipment additions for each county-industry cell. We use 2-digit SIC industries (1972 definition) in the county as the unit of analysis.[21]

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 online 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 or those that are not in an MSA.[22] 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 the 1958 census and in at least eight censuses to address issues that might arise with a highly unbalanced sample. Additional sample restrictions include a requirement that both value added and employment were reported and that one of the county-industry cells within a county is space related and that the county belongs to an MSA. We also drop the observations that appear in ND, SD, or WY because only a single county in each state reported manufacturing data. Our analysis sample contains 6,759 county-industry observations from 86 counties and 19 two-digit SIC industries from 1947 to 1992.

Map 1 shows the spatial distribution of space capability scores for the sample counties.

[20]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.

[21]The census manufacturing data are also available at the 3- and 4-digit SIC $\times$ 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.

[22]We exclude these counties without pre-1958 patents because we are unable to compute a space capability score for them. We exclude those without an MSA as we cluster our standard errors at the MSA level.

The map displays county level averages for the urban counties within defined MSAs that had manufacturing activity in the space sector in 1958 and that consistently reported manufacturing throughout our sample period (i.e., 1947 to 1992). The map shows that many space places – i.e., those with a relatively high space capability score – were distributed throughout the country, with a small amount of clustering in the Northeast. In Section 4 below we show econometrically that our measure of pre-Sputnik space-related research performs well in explaining how and where NASA subsequently allocated its spending.

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 first stratify county-industry pairs based on their level of pre-1958 space relevant technology capability. In columns (2) and (3) we stratify based on whether a county-industry had an above or below median space capability score, as defined above. Column (4) reports the p-value for differences in the baseline variables for the full sample. In columns (5)-(7) we conduct the same analysis where we stratify by whether the industry was a space industry or not. In column (8) we report p-values for the difference between the differences in the baseline values.

Columns (1) to (4) show that county-industries that would later be more exposed to the Space Race were quite similar in 1958. In columns (2) and (3) we see that those locations that were eventually more heavily exposed to the Space Race generally had higher average labor income in manufacturing, more Navy patents, and higher skill, but were otherwise quite similar in other manufacturing outcomes, patents, population, and skill measures. The results in columns (5) to (7) show similarly that only baseline differences in manufacturing average labor income and total patents existed across space and non-space industries. Turning to column (8) we only see statistically significant baseline differences between the two differences for Navy patents. Table 1 provides evidence that triple difference treatment and control county-industry pairs were quite balanced in 1958 before the US embarked on the Space Race.

4 Local Effects of Public R&D

Conceptual Framework. Space spending in a location could affect manufacturing output through either a local fiscal multiplier or through technological spillovers that enhanced productivity within the target industry or co-located industries. To the extent that NASA spending contributed to local economic growth, one of the goals of our empirical analysis is to parse the productivity contributions from the more standard fiscal multiplier effects.

Furthermore, the manifestation of the economic effects of space activity in a county-industry could accrue over time or across locations, which our empirical analysis also seeks to quantify. With respect to spatial lags in the effects of the space economy in a specific location, the impact on other regions could be two-fold. On the one hand, the effect on neighbors could be positive if the space-stimulated regions demanded goods and services of their neighbors or if they acquired manufacturing productivity gains associated with their neighbors' space activity. On the other hand, if labor migrated from neighboring areas to space-active areas, then that could have had a deleterious effect on neighbors' economies. The magnitude of these potentials gains or losses accruing to neighbors will help to determine how well the local multiplier we calculate represents the overall impact of NASA space spending on the broader economy.

Empirical Approach. This section presents our main approach and results. We analyze how the launch of the Space Race in 1958 affected a variety of activities in relatively high space-capable industry-county pairs – that is, industries within 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.

We test whether NASA resource allocation and manufacturing disproportionately grew in county-industry cells that specialized in the early building blocks of space research before the Space Race even began. We estimate our triple difference model using the following equation:

$$
\begin{aligned}
Y_{ijt} = &\beta_1 + \beta_2 \text{High Space Capability}_{ij<1958} \times \text{Space Race}_t + \\
&\beta_3 \text{High Space Capability}_{ij<1958} \times \text{Post-Space Race}_t + \\
&\beta_4 \text{High Space Capability}_{ij<1958} \times \text{Space Race}_t \times \text{Space Industry}_j + \\
&\beta_5 \text{High Space Capability}_{ij<1958} \times \text{Post-Space Race}_t \times \text{Space Industry}_j + \\
&\text{Total Pre-1958 Patents}_{ij} \times \gamma_t + \delta_i + \theta_j + \gamma_t + \nu_{ijt}.
\end{aligned} \tag{1}
$$

The outcome variables are NASA activity and manufacturing activity measures, in county i, industry j, and year t. High Space Capability$_{ij<1958}$ is a binary variable that takes a value of one when the text similarity between technologies mentioned in pre-1958 patents in county i-industry j 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. Space Industry$_j$ is a dummy variable that takes a value of one if industry j is a space industry (i.e., transportation or electronics) and zero otherwise. δ_i is a full set of county fixed effects, θ_j is the full set of industry fixed effects, and γ_t is a full set of year effects.

As county-industries 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 both industry and county fixed effects in our analysis. We include Pre-1958 Patents$_{ij} \times \gamma_t$ controls to account for differential trends based on the pre-existing level of patenting in a county-industry. In other versions of the model we include MSA $\times$ year fixed effects to flexibly control for MSA-level trends. To account for potential correlation of shocks within MSAs across time and within industries across time, we two-way cluster standard errors at the MSA $\times$ industry level.

Our coefficients of interest are β_4 and β_5. We expect them to be positive in the NASA expenditure estimation as county-industries that were specialized in space-relevant technologies before 1958 were likely to experience more NASA activity after 1958, once the Space Race began. We expect the coefficients to reflect larger effects during the Space Race than after as NASA scaled down after the successful Moon landing. For the manufacturing estimation, we expect the coefficients to be positive if NASA expenditure generated growth. Whether β_4 or β_5 would be larger for manufacturing depends on what benefits the Space Race activity provided. If NASA spending primarily acted as a government expenditure shock, any fiscal multiplier effects would decline as NASA scaled down after the Space Race. Alternatively, for a technological shock where spillovers took time to manifest, then the measured effects would be expected to grow over time.

Our research design is based on the idea that county-industries that specialized in the 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 after the launch of Sputnik in 1957. In addition, as space funding was highly targeted toward just a few sectors – Figure 2A shows that two sectors (transportation and electronics) accounted for 89% of contractor funding – our research design harnesses the industry-specific nature of the shock. As NASA did not even exist until 1958, we cannot examine pre-Space Race trends for NASA expenditure. We do, however, examine the possibility that NASA may have allocated space funding in response to pre-existing trends in the county-industry manufacturing sector in later analyses.

NASA Contractor Spending and Patents. The results of estimating equation (1) using NASA contractor spending and NASA patents as outcome variables are reported in Table 2. We use the inverse hyperbolic sine transformation for NASA outcomes $\text{arsinh}(x) = ln(1 + \sqrt{x^2 + 1})$. This approximation to the log transformation retains zero values of the NASA activity in our estimation sample. In columns (1) and (2) we see that NASA contractor spending both during (1958-1972) and after (1973-1992) the Space Race was larger in county-industry pairs that had previously attained the expertise to conduct NASA work. Our preferred estimates in column (1) imply that NASA spent \$80 million (\$1958) more during and \$88 million (\$1958) more after the Space Race in county-industries with a relatively strong prior history in space-related research. We use these magnitudes to estimate local fiscal multiplier effects below.

In columns (3) and (4) we report results that use patents owned or funded by NASA as the outcome variable. The positive and precise point estimates are consistent with the NASA spending results. They differ in that the post-Space Race effects are nearly double those during the Space Race.[23]

Differences in effect dynamics between NASA contractor spending and NASA patenting could indicate that it takes time for contractor activity to translate to new innovations. This finding is consistent with a contemporary assessment of the technological developments that occurred during the Space Race (see Robbins, Kelly, and Elliot 1972). An important caveat for this interpretation is that patent attribution to NASA is measured with error, particularly during the Space Race era when government interest statements were not yet required for patents.[24]

Manufacturing. In Table 3 we report the main manufacturing results. The results in columns (1) and (2) show that manufacturing value added grew faster in the space sectors and counties that were predisposed to conduct space research needed to complete the Moon mission, as evidenced by their pre-Sputnik patent similarity to later Soviet space research. The point estimates during the Space Race are similar to those for the era after the race

[23]Online appendix figure A1 shows the dynamics effects for an annual series of NASA patents. There are no pre-trends evident in the series.

[24]We thank a referee for making us aware of this issue. Using an internal list of NASA patents identified in the NASA Technical Reports Server (NTRS) after 1972, we find large agreement with the Fleming et al. (2019) measure of patents with NASA involvement and NASA's own assessment. Thus, it appears that NASA largely followed a "title policy" in that the agency seems to have retained ownership of the patents developed with its funding. Or, if the agency did license the patent to the private contractor, it appears that an explicit government interest was routinely declared.

to the Moon had ended after 1972. This finding may be expected if contemporaneous NASA expenditures during the Space Race stimulated manufacturing activity that continued similarly with post-Space Race NASA contractor spending. The evidence is not strong that knowledge gained during the Space Race era manifest into larger long-term gains for contractors. In columns (3) to (4) we see a similar pattern of results for employment. Again, the effects are larger and more precise during the Space Race than after it had ended. Our results differ for capital, reported in columns (5) and (6), where post-Space Race effects are larger than those during the race to the Moon. This outcome might be expected if capital accumulation occurs with a lag.

That the magnitudes of the value added, employment, and capital effects are quite similar may suggest little productivity effect. We measure total factor revenue-based productivity by estimating the production function $Y_{ijt} = A_{ijt}K_{ijt}^{\alpha}L_{ijt}^{\beta}$ to recover manufacturing revenue total factor productivity at the county-industry-year level (i.e., A_{ijt}). We see no statistically significant effects of the Space Race on measurable productivity in columns (7) and (8). The point estimates are quite close to zero and even trend negative. Despite the caveats that this productivity measure is revenue-based and does not account for endogenous choices of inputs, there is little evidence that a positive productivity effect or resulting technological spillovers from the Space Race played a role in boosting manufacturing value added.[25]

Prior Trends. A potential lingering concern 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 a county-industry 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 quickly, exploring prior trends is an important specification check.

In Figure 5 we graphically present dynamic versions of our main econometric model

[25] Changes in revenue, holding constant measured inputs, have several components: changes in the quantity of output produced; changes in the quality of output produced; and changes in the quality-adjusted price. We cannot separately identify these components so our results capture effects across all of these margins. We thank a referee for clarifying what our measure captures.

with 1958 as the reference year.[26] 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 US featured dramatic expansions in military-sponsored research and skill accumulation. Both factors 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), (3), (5), and (7) of Table 4-Panel A does little to alter our estimates of NASA's effect on manufacturing.[27] Since measuring military involvement in private-sector patenting has many challenges, we add non-patent controls for military involvement in local economies in columns (2), (4), (6), and (8) in panel A of Table 4. Controlling for county-level military spending or 1962 defense-funded research scientists×year fixed effects does little to alter our manufacturing point estimates or precision.

In panel B of Table 4 we add controls for worker skill. We first add controls for two measures reflecting levels of general human capital within the manufacturing sector. The fraction of non-production workers has the advantage that it is measured at the same unit

[26]The model we estimate is:

$$\begin{aligned}\log(Y_{ijt}) =&\alpha_1 + \sum_{k=1947,k\neq 1958}^{1992} \gamma_{k1}\text{High Space Capability}_{ij<1958} \times \text{Year=k}_t + \\ &\sum_{k=1947,k\neq 1958}^{1992} \gamma_{k2}\text{High Space Capability}_{ij<1958} \times \text{Year=k}_t \times \text{Space Industry}_j + \\ &\delta_i + \gamma_t + \theta_j + \text{Total Pre-1958 Patents}_{ij} \times \gamma_t + \nu_{ijt}.\end{aligned} \tag{2}$$

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 (1). Online appendix table A7 reports the coefficients γ_{k2}.

[27]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. Patent assignment to government agencies before the 1980 Bayh-Dole Act was largely agency specific as Fleming et al. (2019) note. Defense funders were so-called "license agencies," which thereby enabled contractors to hold the patent title. Further, in the era we study, government interest statements were not required (see Eisenberg (1996)). Thus, our military patent measures likely significantly undercount the number of military patents during the Space Race era. We thank a referee for making us aware of this limitation in the data.

of observation as our outcome variables – county × industry × year. It has the disadvantage, however, that it likely captures occupational, as well as educational attainment, variation. To capture trends that may differ by educational levels we include the county-level high school graduate percentage in 1960 × year as controls. The results in panel B columns (1), (3), (5), and (7) show that adding these skill controls has little effect on our main Space Race results. These variables, however, likely capture little variation in upper-tail skill that may matter for growth (Squicciarini and Voigtländer 2015). In our next set of models we add a control for the number of research scientists in a county in 1962 × year to capture differential trends in the upper-tail of human capital accumulation. We also include the number of IBM mainframes within a county in 1961 × year to capture differential trends from the installation of advanced information technology in a location. Our results remain largely unchanged across these experiments. In sum, our results on the effect of the Space Race on manufacturing outcomes appear highly robust to controls for local military activity and local human capital characteristics.

Multipliers. To compare the effects of public R&D spending relative to government expenditures in general, we compute the contemporaneous fiscal multiplier.[28] We use the estimates in Table 3 column (1) to compute: *Space Race Output Effect* $= \hat{\beta}_4^{VA} \times \overline{\text{Value Added}_{ijt}} \times \overline{\text{Output-Value Added Ratio}_{ijt}}$ and analogously a *Post-Space Race Output Effect* $= \hat{\beta}_5^{VA} \times \overline{\text{Value Added}_{ijt}} \times \overline{\text{Output-Value Added Ratio}_{ijt}}$. In other words, this measure computes the local value added effect associated with the highly space-capable industry-county pairs from Table 3 times the sample mean of value added, but scaled up by the output/value added ratio.[29] We also compute *Space Race Spending Effect* $= \hat{\beta}_4^{SPENDING} \times \overline{\text{NASA Spending}_{ijt}}$ and *Post-Space Race Spending Effect* $= \hat{\beta}_5^{SPENDING} \times \overline{\text{NASA Spending}_{ijt}}$ using estimates in Table 2 column (1). 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 1.6 during the Space Race (i.e., 1958 to 1972, inclusive) and 1.6 after the Space Race (i.e., after 1972). Our multiplier estimates accord quite closely to the literature estimating the cross-sectional effects of other government spending. A recent survey (Chodorow-Reich 2019) indicates that the literature

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

[29]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 do not include the effects from non-space-capable industry-counties (i.e., β_2 or β_3) since these spillover effects are estimated to be zero.

supports a local fiscal multiplier of 1.8. Our estimates are also below the upper bound of time-series based national multiplier estimates. Ramey (2011) finds that time-series evidence supports estimates ranging from 0.5 or 2.0. That our multiplier estimates are similar to the effects of other types of government spending and do not increase over time indicate that the Space Race generated little in terms of local technological spillovers in space related manufacturing.

Our contemporaneous local multiplier estimates are subject to many caveats. First, our calculation does not account for the effect of NASA research and development on output in other industries or locations, or how the expenditure was financed. Second, 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. Third, and more broadly, our focus on NASA contractor spending does not include NASA spending at universities or at NASA research centers that may have been more basic research intensive than NASA contractor spending. If technology spillovers primarily came from non-contractor NASA spending, then our approach will understate the aggregate multiplier effects of overall NASA spending. We regard our multiplier estimates, therefore, as a lower bound. While keeping these caveats in mind, our local fiscal multiplier estimates are quite similar to the fiscal multiplier estimates in the literature.

Rates of Return. A strength of our approach is that we can recover estimates of the marginal social rate of return to NASA contractor spending from output estimates directly. We follow Jones and Summers (2022) in computing the internal rate of return of NASA contractor spending. As space spending and resulting effects on output had a specific time path of initially high costs with benefits spread over time, we use the calculation in online appendix section 3 rather than Summers and Jones's (2022) balanced growth path approach to compute these estimates.

Using our preferred estimates in Table 3-column (1) we find an internal rate of return of 77% over the Space Race era. Our estimates are comparable to the range of estimates of the social returns to R&D reported in other studies. Bloom, Schankerman, and Van Reenen (2013) estimate a social return to private R&D of 55%, while Myers and Lanahan (2022) find marginal social returns to R&D of about 100–300%. An older literature summarized by Griliches (1992) finds estimates of the rates of return to public R&D in the agricultural sector of 20-67%.

To the extent that we do not account for international or even inter-regional spillovers, our estimate may be a lower bound. Myers and Lanahan (2022) find that local spillovers only account for just under half of total spillovers from public R&D.[30] 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 represent another impact that is unaccounted. 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.[31]

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 many times larger than this estimate.

Robustness. In our main analysis we employ two-way clustering of the standard errors at the MSA $\times$ industry level. As NASA involvement in local economies represented a localized persistent shock, we regard this clustering strategy as appropriate to address concerns of correlation in the errors term within an MSA. Within-industry clustering accounts for any unobservable correlated shocks to specific industries. Our manufacturing results are robust to inference procedures that cluster standard errors at different levels or that allow for spatial correlation in the error term (see online appendix table A8). The results are robust to estimation approaches that allow for heterogeneous effects (Chaisemartin and D'Haultfoeuille 2020), that adjust standard errors to allow for correlations depending on sector-specific NASA shares (see online appendix table A9), or that drop a single state or industry one at a time (see online appendix figures A2 to A5). Further, measuring the effect on productivity in terms of growth rates rather than levels does not alter our interpretation of the results (see online appendix table A10).

Another way to estimate the effects of NASA contracting is to use an instrumental variables procedure with NASA contractor spending as the endogenous variable. Doing so we obtain a precise estimates of 0.27 to 0.34 on NASA contractor spending for all outcomes except productivity (see online appendix table A11). We also estimate models using na-

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

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

tional industry totals by comparing NASA to non-NASA industries before and after 1958. Estimating the model at higher levels of aggregation has the strength that it includes non-localized effects, but the research designed is weakened – any unobserved shocks that are NASA-sector-specific could bias estimates of the impact of NASA spending. In online appendix table A12, we see that NASA industries were larger after the launch of Sputnik, but not more productive.

Our triple difference research design utilizes changes in non-space industries as a control group, where limited spillovers to non-space industries are part of the research design. We test for cross-industry spillover effects using a sample of only non-space industries in two ways in online appendix table A13. Our results show little effect of pre-1958 space technology capability after the Space Race began for these non-space industries, thus lending further credence to our triple difference design. We find little evidence of spillovers from space industries to their co-located non-space industry neighbors across the models.

In our main analysis we utilize similarity of US patent documents to Soviet technology to measure the presence of space-relevant technology in a county-industry cell before 1958. Similarity to US space technology could, arguably, be a more relevant measure. In online appendix table A14 we define space capability by comparing post-Sputnik NASA patents to US space technology that existed locally prior to Sputnik. In this experiment we obtain similar estimates to those in Table 3. The dynamic effects using this US space technology-defined capability, shown in online appendix figure A6, again fail to reveal prior trends in manufacturing outcomes.

A final set of robustness analyses we consider are alternative text processing procedures and controls. We first examine the robustness of our computing the similarity of a county-industry's pre-1958 patenting to later Soviet space technology. We show in online appendix table A15 that our estimates are robust to how we treat terms, the rule we use to allocate a cell to treatment or control groups, and which CIA documents are included in our similarity calculation. One concern with our measure of military patents during the Space Race era is that government disclosure statements were not mandatory, so our measure may undercount military patents. In online appendix table A16 we develop a measure of patent similarity to military technology using the textual similarity of a patent to a glossary of military technology terms. Our main results are robust to these alternative ways to measure technological similarity or local military activity.

5 Spatial Spillovers of Public R&D

Our estimated value added effects from NASA contractor spending represent the impact on the local economy rather than the national economy. To the extent we want to think about the localized space-spending infusion as a place-based policy of sorts, a question remains whether the benefits to the local economy come at the cost to other regions. Local estimates would overstate national effects if, for example, labor was supplied elastically and workers migrated toward space-related opportunities from other locations. Such an increase in employment in space locations would come at the cost of reduced employment elsewhere.[32] Such worker mobility would be consistent with historical accounts and the fact that adjustment through migration can take substantial time (Blanchard and Katz 1992).[33] Alternatively, local estimates can understate national effects if there are positive demand or technology spillovers across areas.[34] 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.[35] 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 US 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 three differences.[36] First, we study county-to-county migration flows within an industry and construct the data at the county × industry

[32]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.

[33]For example, while almost all of the technical and clerical workers for the new 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).

[34]Myers and Lanahan (2022) 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).

[35]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.

[36]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.

$\times$ patent application year level.[37] Second, our migration model includes time-invariant measures of space technology scores interacted with space era and space industry dummies. Third, we use a larger sample of inventors who are in the top 50% of patent producers which enables us to employ a research design that utilizes industry variation.

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:

$$\begin{aligned}
\log\left(\frac{P_{odjt}}{P_{oojt}}\right) = {} & \eta_1 \left([\log(\text{Space Score}_{dj}) - \log(\text{Space Score}_{oj})] \times \text{Space Race}_t\right) \\
& + \eta_2 \left([\log(\text{Space Score}_{dj}) - \log(\text{Space Score}_{oj})] \times \text{Post-Space Race Era}_t\right) \\
& + \eta_3 \left([\log(\text{Space Score}_{dj}) - \log(\text{Space Score}_{oj})] \times \text{Space Race Era}_t \times \text{Space Industry}_j\right) \\
& + \eta_4 \left([\log(\text{Space Score}_{dj}) - \log(\text{Space Score}_{oj})] \times \text{Post-Space Race Era}_t \times \text{Space Industry}_j\right) \\
& + \eta_5[\log(1 - I_{dt}) - \log(1 - I_{ot})] + \eta_6[\log(1 - C_{dt}) - \log(1 - C_{ot})] \\
& + \eta_7[\log(1 + R_{dt}) - \log(1 + R_{ot})] + \gamma_t + \gamma_o + \gamma_d + \gamma_j + \\
& + \gamma_{od} + \text{Pre-1958 Patents}_{oj} \times \gamma_t + \text{Pre-1958 Patents}_{dj} \times \gamma_t + u_{odjt}.
\end{aligned} \tag{3}$$

We denote origin locations o and destination locations d. The number of inventors who move from o to d in industry j is P_{odjt} and the number of inventors in industry j who begin in o and do not move is P_{oojt}, so that $\log\left(\frac{P_{odjt}}{P_{oojt}}\right)$ is the log odds ratio for inventor out-migration. We examine how the odds of moving depend on the differences in space scores, $(\log(\text{Space Score}_{dj}) - \log(\text{Space Score}_{oj}))$, interacted with indicator variables for the Space Race and post-Space Race periods. 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, industry fixed effects (γ_j), as well as pair fixed effects (γ_{od}) to capture time-invariant pair-specific features such as distance or travel costs.[38] To account for trends by initial innovation intensity, as in our analysis above, we also control for both origin and destination pre-1958 patent count in the county-industry times year fixed effects $(\text{Pre-1958 Patents}_{oj} \times \gamma_t$

[37]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 by using application year instead of grant year. We use the modal industry across all patents filed by an inventor to classify them by sector.

[38]For this analysis, we follow Moretti and Wilson (2017) in showing standard errors that allow for three-way clustering by origin county $\times$ year, destination county $\times$ 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.

and Pre-1958 Patents$_{dj} \times \gamma_t$, respectively). We consider a few variants of this specification – with and without tax rates and including state $\times$ year fixed effects – in our analysis.

The coefficient estimates η_3 and η_4 capture how the relationship between space capability score differentials between origin and destination county-industry pairs affected migration during and after the Space Race relative to the pre-NASA era. If NASA spending caused inventors to migrate toward space capable places, then we would expect η_3 and η_4 to be positive. Time invariant factors that affected wages or amenities in the origin and destination locations, as well as typical migration patterns, are controlled using origin, γ_o, and destination, γ_d, and pairwise γ_{od} fixed effects. A potential threat to our approach would occur if changes in wages or amenities during and after the Space Race were correlated with differentials in ex ante space capabilities. Based on our results above and historical accounts, we do not expect this issue to be likely.

Table 5 reports the results of estimating alternative versions of our migration model. In column (1) we see that inventors moved toward areas with relatively higher space capability scores in the Space Race and post-race periods. That the post-Space Race effects are larger may indicate it takes some time for researchers to adjust to a demand shock through migration. 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 $\times$ application year and destination state $\times$ application year fixed effects. Across all of these specifications our results change little and the robust conclusion is that Space Race spending in space industries led to inventors' migration toward opportunity, which is consistent with the employment effects found in Table 3 and with historical accounts.

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 might generate 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.[39] The theoretical framework leads to the following

[39] 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.

estimating equation:

$$
\begin{aligned}
\log(Y_{ijt}) =& \beta_1 + \beta_2 \text{High Space Capability}_{ij<1958} \times \text{ Space Race}_t + \\
& \beta_3 \text{High Space Capability}_{ij<1958} \times \text{post-Space Race}_t + \\
& \beta_4 \text{High Space Capability}_{ij<1958} \times \text{ Space Race}_t \times \text{Space Industry}_j + \\
& \beta_5 \text{High Space Capability}_{ij<1958} \times \text{post-Space Race}_t \times \text{ Space Industry}_j + \\
& \beta_6 \text{High Space Market}_{ij<1958} \times \text{Space Race}_t + \\
& \beta_7 \text{High Space Market}_{ij<1958} \times \text{Post-Space Race}_t \\
& \beta_8 \text{High Space Market}_{ij<1958} \times \text{Space Race}_t \times \text{ Space Industry}_j + \\
& \beta_9 \text{High Space Market}_{ij<1958} \times \text{Post-Space Race}_t \times \text{ Space Industry}_j \\
& + \delta_i + \theta_j + \gamma_t + \text{Total Pre-1958 Patents}_i \times \gamma_t + \nu_{ijt}.
\end{aligned} \tag{4}
$$

We define High Space $\text{Market}_{ij<1958}$ as a binary variable where county-industries 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_8 and β_9 which will capture the market-level effects of Space Race activity elsewhere during and after the race to the Moon that may have affected space industries locally. With these estimates in hand we can get a sense of how spatial spillovers may affect our estimates of the fiscal multiplier and implied rate of return reported above.

In Table 6 we report the results of estimating equation (4). The results show that including controls for market-level effects does little to alter the local space-capability effects estimated above. Their magnitude is little changed and remain precisely estimated. The point estimates for the market effects are quite close to zero, with signs that are outcome or specification dependant, and imprecisely estimated. A lack of market effects would be consistent with the worker mobility toward space county-industries described above, which seem to have counterbalanced any positive market-level demand or technology spillover effects. These results indicate that the lack of spatial spillovers, on net, imply that the local impact of NASA R&D spending that we estimated above is a reasonable proxy for NASA's impact on the broader economy.

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 seeks to address fundamental questions about the role of public R&D in facilitating economic growth, both locally and more broadly. 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 economically meaningful, stable, and precisely estimated effects of public R&D on long-term manufacturing growth in the space sector. Yet the magnitudes of the estimated effects seem to align with those of other non-R&D types of government expenditures.

While we show significant positive effects from NASA contractor spending during and after the Moonshot era, some caution is warranted in applying our estimates to R&D more broadly. As Mowery et al. (2010) note, mission-oriented R&D is unusually focused on a specific goal and highly centralized. Whether non-mission-oriented public R&D would generate similar returns to those of NASA's Space Race remains subject to debate. Similarly, our focus on NASA contractor spending enables a tight research design and captures the majority of NASA spending, but at the same time may be limited in capturing all of NASA's technological spillovers. Public R&D spending at NASA centers or in universities may have been more basic and a more important source of technological spillovers that our approach does not capture.

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 a role for public policy and public R&D in generating economic growth. Today the US 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 investments provides some credence to some policymakers' and advisors' calls for a new Sputnik Moment to seed a new era of US economic growth in targeted sectors.

7 References

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth through Creative Destruction." *Econometrica* 60 (2): 323-51.

Akcigit, Ufuk, John Grigsby, Tom Nicholas, and Stefanie Stantcheva. 2022. "Taxation and Innovation in the 20th Century." *Quarterly Journal of Economics* 137 (1): 329-85.

Andrews, Michael J. 2023. "How Do Institutions of Higher Education Affect Local Invention? Evidence from the Establishment of U.S. Colleges." *American Economic Journal: Economic Policy* 15 (2): 1-41.

Antolin-Diaz, Juan, and Paolo Surico. 2022. "The Long-Run Effects of Government

Spending." CEPR Discussion Paper 17433.

Arora, Ashish, Sharon Belenzon, and Lia Sheer. 2021. "Knowledge Spillovers and Corporate Investment in Scientific Research." *American Economic Review* 111 (3): 871-98.

Arrow, Kenneth J. 1962. "Economic Welfare and the Allocation of Resources to Invention." In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, edited by Universities-National Bureau Committee for Economic Research and the Committee on Economic Growth of the Social Science Research Council, 609-26. Princeton, NJ: Princeton University Press.

Azoulay, Pierre, Joshua S. Graff Zivin, Danielle Li, and Bhaven N. Sampat. 2019. "Public R&D Investment and Private-sector Patenting: Evidence from NIH Funding Rules." *Review of Economic Studies* 86 (1): 117-52.

Bianchi, Nicola, and Michela Giorcelli. 2022. "The Dynamics and Spillovers of Management Interventions: Evidence from the Training Within Industry Program." *Journal of Political Economy* 130 (6): 1630-75.

Bilstein, Roger E. 1996. *Stages to Saturn*. Washington, DC: National Aeronautics and Space Administration.

Blanchard, Olivier Jean, and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1992 (1): 1-75.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013."Identifying Technology Spillovers and Product Market Rivalry." *Econometrica* 81 (4): 1347-93.

Bloom, Nicholas, John Van Reenen, and Heidi Williams. 2019. "A Toolkit of Policies to Promote Innovation." *Journal of Economic Perspectives* 33 (3): 163-84.

Brady, Kevin M. 2007. "NASA Launches Houston into Orbit: The Political, Economic, and Social Impact of the Space Agency on the Southeast Texas, 1961–1969." In *Societal Impact of Spaceflight*, edited by Steven J. Dick and Roger D. Launius, 451-65. Washington, DC: National Aeronautics and Space Administration.

Chodorow-Reich, Gabriel. 2019. "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?" *America Economic Journal: Economic Policy* 11 (2): 1-34.

Choi, Jaedo, and Andrei A. Levchenko. 2022. "The Long-Term Effects of Industrial Policy." NBER Working Paper 29263.

Criscuolo, Chiara, Ralf Martin, Henry G. Overman, and John Van Reenen. 2019. "Some Causal Effects of an Industrial Policy." *American Economic Review* 109 (1): 48-85.

Divine, Robert A. 1993. *The Sputnik Challenge*. New York: Oxford University Press.

Donaldson, Dave, and Richard Hornbeck. 2016. "Railroads and American Economic Growth: A 'Market Access' Approach." *Quarterly Journal of Economics* 131 (2): 799–858.

Dunar, Andrew J., and Stephen P. Waring. 1999. *Power to Explore: A History of Marshall Space Flight Center, 1960-1990*. Washington, DC: National Aeronautics and Space Administration.

Eisenberg, Rebecca S. 1996. "Public Research and Private Development: Patents and Technology Transfer in Government-Sponsored Research." *Virginia Law Review* 82 (8): 1663-727.

Ferguson, Robert G. 2013. *NASA's First A: Aeronautics from 1958 to 2008*. Washington, DC: National Aeronautics and Space Administration.

Fleming, L., H. Greene, G. Li, M. Marx, and D. Yao. 2019. "Government-funded Research Increasingly Fuels Innovation." *Science* 364 (6446): 1139-41.

Fogel, Robert William. 1966. “Railroads as an Analogy to the Space Effort: Some Economic Aspects.” *Economic Journal* 76 (301): 16–43.

Giorcelli, Michela. 2019. “The Long-Term Effects of Management and Technology Transfers.” *American Economic Review* 109 (1): 121-52.

Gordon, Robert J. 2000. “The Boskin Commission Report and its Aftermath.” NBER Working Paper 7759.

Griliches, Zvi. 1992. “The Search for R&D Spillovers.” *Scandinavian Journal of Economics* 94 (Supplement): S29-47.

Gross, Daniel P., and Bhaven N. Sampat. 2022. “America, Jump-started: World War II R&D and the Takeoff of the U.S. Innovation System.” Unpublished.

Gruber, Jonathan, and Simon Johnson. 2019. *Jump-Starting America: How Breakthrough Science Can Revive Economic Growth and the American Dream.* New York: Public Affairs.

Hansen, James R. 1995. *Spaceflight Revolution: NASA Langley Research Center from Sputnik to Apollo.* Washington DC: National Aeronautics and Space Administration.

Hausman, Naomi. 2022. “University Innovation and Local Economic Growth.” *Review of Economics and Statistics* 104 (4): 718-35.

Holman, Mary A., and Ronald M. Konkel. 1968. “Manned Space Flight and Employment.” *Monthly Labor Review* 91 (3): 30-36.

Hunley, J.D., editor. 1993. *The Birth of NASA: The Diary of T. Keith Glennan.* Washington DC: National Aeronautics and Space Administration.

Jaffe, Adam F., Michael S. Fogarty, and Bruce A. Banks. 1998. “Evidence from Patents and Patent Citations on the Impact of NASA and Other Federal Labs on Commercial Innovation.” *Journal of Industrial Economics* 46 (2): 183-205.

Jones, Benjamin F., and Lawrence H. Summers. 2022. “A Calculation of the Social Returns to Innovation.” In *Innovation and Public Policy*, edited by Austan Goolsbee and Benjamin F. Jones, 13-59. Chicago, IL: University of Chicago Press.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M. Taylor. 2019. “The Rate of Return on Everything, 1870–2015.” *Quarterly Journal of Economics* 134 (3): 1225–98.

Juhász, Réka. 2018. “Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade.” *American Economic Review* 108 (11): 3339-76.

Kantor, Shawn, and Alexander Whalley. 2014. “Knowledge Spillovers from Research Universities: Evidence from Endowment Value Shocks.” *Review of Economics and Statistics* 96 (1): 171-88.

Kantor, Shawn, and Alexander Whalley. 2019. “Research Proximity and Productivity: Long-Term Evidence from Agriculture.” *Journal of Political Economy* 127 (2): 819-54.

Kraemer, Sylvia Katharine. 2001. “Federal Intellectual Property Policy and the History of Technology: The Case of NASA Patents.” *History and Technology* 17 (3): 183-216.

Lane, Nathan. 2021. “Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea.” Unpublished.

Logsdon, John M., editor. 1995. *Exploring the Unknown: Selected Documents in the History of the U.S. Civil Space Program, Volume I: Organizing for Exploration.* Washington DC: National Aeronautics and Space Administration.

McDougall, Walter A. 1985. *. . . the Heavens and the Earth: A Political History of the*

Space Age. New York: Basic Books.

Mazzucato, Mariana. 2021. *Mission Economy: A Moonshot Guide to Changing Capitalism.* New York: Harper Business.

Moretti, Enrico, Claudia Steinwender, and John Van Reenen. Forthcoming. "The Intellectual Spoils of War? Defense R&D, Productivity and International Spillovers." *Review of Economics and Statistics*.

Moretti, Enrico, and Daniel J. Wilson. 2017. "The Effect of State Taxes on the Geographical Location of Top Earners: Evidence from Star Scientists." *American Economic Review* 107 (7): 1858–903.

Mowery, David C., Richard R. Nelson, and Ben R. Martin. 2010. "Technology Policy and Global Warming: Why New Policy Models Are Needed (or Why Putting New Wine in Old Bottles Won't Work)." *Research Policy* 39 (8): 1011-23.

Myers, Kyle R. 2020. "The Elasticity of Science." *American Economic Journal: Applied Economics* 12 (4): 103-34.

Myers, Kyle R., and Lauren Lanahan. 2022. "Estimating Spillovers from Publicly Funded R&D: Evidence from the U.S. Department of Energy." *American Economic Review* 112 (7): 2393-423.

Nakamura, Emi, and Jón Steinsson. 2014. "Fiscal Stimulus in a Monetary Union: Evidence from US Regions." *American Economic Review* 104 (3): 753–92.

Nelson, Richard R. 1959. "The Simple Economics of Basic Scientific Research." *Journal of Political Economy* 67 (3): 297–306.

OECD. 2022. "Table 50: Government intramural expenditure on R&D (GOVERD) at current prices and PPP." In *Main Science and Technology Indicators*. https://doi.org/10.1787/f55d212c-en (accessed on 13 April 2022).

Petralia, Sergio, Pierre-Alexandre Balland, and David L. Rigby. 2016. "Unveiling the Geography of Historical Patents in the United States from 1836 to 1975." *Nature-Scientific Data* 3 (160074).

Ramey, Valerie A. 2011. "Can Government Purchases Stimulate the Economy?" *Journal of Economic Literature* 49 (3): 673–85.

Ramey, Valerie A. 2019. "Ten Years after the Financial Crisis: What Have We Learned from the Renaissance in Fiscal Research?" *Journal of Economic Perspectives* 33 (2): 89-113.

Ramey, Valerie A. 2021. "The Macroeconomic Consequences of Infrastructure Investment." In *Economic Analysis and Infrastructure Investment*, edited by Edward L. Glaeser and James M. Poterba, 219-68. Chicago: University of Chicago Press.

Robbins, Martin D., John A. Kelly, and Linda Elliot. 1972. *Mission-oriented R&D and the Advancement of Technology: The Impact of NASA Contributions*. Washington DC: National Aeronautics and Space Administration.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy* 98 (5): S71–102.

Rosholt, Robert L. 1966. *An Administrative History of NASA, 1958-1963*. Washington, DC: National Aeronautics and Space Administration.

Rumerman, Judy A. 2000. *NASA Historical Data Book, 1979-1988. volume VI*. Washington DC: National Aeronautics and Space Administration.

Schnee, Jerome E. 1977. "Space Program Impacts Revisited." *California Management Review* 20 (1): 62-73.

Schweiger, Helena, Alexander Stepanov, and Paolo Zacchia. 2022. "The Long-run Effects of R&D Place-Based Policies: Evidence from Russian Science Cities." *American Economic Journal: Economic Policy* 14 (3): 322-51.

Solow, Robert M. 1957. "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics* 39 (3): 312–20.

Squicciarini, Mara P., and Nico Voigtländer. 2015. "Human Capital and Industrialization: Evidence from the Age of Enlightenment." *Quarterly Journal of Economics* 130 (4): 1825–83.

Van Nimmen, Jane, and Leonard C. Bruno. 1976. *NASA Historical Data Book, 1958-1968. Volume I.* Washington, DC: National Aeronautics and Space Administration.

Weinzierl, Matthew. 2018. "Space, the Final Economic Frontier." *Journal of Economic Perspectives* 32 (2): 173-92.

TABLE 1: Descriptive Statistics of Pre-Space Race Era

	All	Space Capability $Score_{ij<1958}$ >=Median	Space Capability $Score_{ij<1958}$ <Median	Difference (2)-(3)	Space $Industry_j$ Yes	Space $Industry_j$ No	Difference (5)-(6)	Difference (4)-(7)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Manufacturing Census Data								
Value $Added_{ij}$ ($1958 Million)	72	81	64	0.205	113	68	0.116	0.352
	(153)	(177)	(123)		(275)	(131)		
$Employment_{ij}$ (1958)	7,760	8,571	6,947	0.232	12,044	7,266	0.110	0.177
	(15,789)	(17,374)	(13,997)		(27,739)	(13,712)		
Labor $Income_{ij}$ ($1958)	4,832	4,914	4,749	0.017	4,981	4,814	0.016	0.496
	(840)	(771)	(898)		(746)	(850)		
Capital $Investment_{ij}$ ($1958 ‘000’s)	3,572	4,125	3,016	0.163	4,126	3,508	0.443	0.389
	(8,941)	(11,400)	(5,345)		(9,436)	(8,887)		
Panel B: Patent Data								
Total $Patents_{ij}$ (1953-1958)	60	71	49	0.050	127	52	0.000	0.812
	(137)	(161)	(109)		(217)	(123)		
Navy $Patents_{ij}$ (1953-1958)	0.03	0.05	0.00	0.007	0.14	0.01	0.032	0.034
	(0.21)	(0.29)	(0.06)		(0.53)	(0.13)		
Army $Patents_{ij}$ (1953-1958)	0.01	0.02	0.01	0.325	0.03	0.01	0.461	0.340
	(0.12)	(0.13)	(0.11)		(0.16)	(0.11)		
Panel C: Population Census and Other County Data								
$Population_i$ (1960)	1,003,562	1,063,508	943,451	0.320				
	(1,193,431)	(1,287,886)	(1,089,000)					
High School Graduate $Percent_i$ (1960)	44	45	43	0.002				
	(8)	(8)	(8)					
Research $Scientists_i$ (1962)	4,634	5,233	4,013	0.044				
	(6,144)	(6,564)	(5,642)					
IBM Mainframe $Computers_i$ (1961)	2.94	3.29	2.58	0.054				
	(3.95)	(4.17)	(3.70)					
No. of County-Industry Observations	735	368	367		76	659		

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 Capability Score is the $\widetilde{\rho_c}$ as discussed in section 2.2 of the appendix. The unit of observation is county × 2-digit SIC industry in panels A and B, and county in panel C, where i and j index county and industry, respectively. In columns (1), (2), (3), (5), and (6) 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 (7) reports the p-value for the hypothesis test that the values in (5) and (6) are different. Column (8) reports the p-value for the hypothesis test that the values in (4) and (7) are different. All columns are for the full sample for 1958.

TABLE 2: Space Capability, NASA Spending, and NASA Patents

Dependent Variable =	Arsinh(NASA Spending_{ijt})		Arsinh(NASA Patents_{ijt})	
	(1)	(2)	(3)	(4)
High Space $\text{Capability}_{ij<1958}$ × Space Race_t × Space Ind_j	1.24	1.30	0.06	0.07
	(0.23)	(0.35)	(0.02)	(0.02)
High Space $\text{Capability}_{ij<1958}$ × Post-Space Race_t× Space Ind_j	1.39	1.48	0.11	0.12
	(0.45)	(0.55)	(0.04)	(0.04)
County Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Pre-1958 Patents_{ij}× Year Fixed Effects	Y	Y	Y	Y
MSA × Year Fixed Effects		Y		Y
R^2	0.16	0.20	0.37	0.51
Observations	6,759	6,759	6,759	6,759

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. The unit of observation is 2-digit SIC industry × county × year, indexed by j, i, and t, respectively. Each column in the table reports the results from estimating one version of equation (1) in the text. High Space $\text{Capability}_{ij<1958}$ is an indicator variable reflecting a county-industry'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 Capability Score), as described in the text and the data appendix. Space Race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. Space Ind_j is an indicator variable for the industry j being a space industry. The models in all columns includes county, industry, and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in column (2) and (4) also include MSA × year fixed effects. Main entries report coefficient estimates. Standard errors are two-way clustered at the MSA × industry level and are reported in parentheses. Dependent variables are transformed using the inverse hyperbolic sine: $arsinh(x) = \ln\left(x + \sqrt{x^2 + 1}\right)$.

TABLE 3: Space Capability and Manufacturing

Dependent Variable =	Log(Value Add$_{ijt}$)		Log(Employ$_{ijt}$)		Log(Capital$_{ijt}$)		Log(TFP$_{ijt}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.35	0.38	0.42	0.45	0.31	0.25	-0.04	-0.03
	(0.06)	(0.07)	(0.08)	(0.08)	(0.13)	(0.15)	(0.03)	(0.04)
High Space Capability$_{ij<1958}$ × Post- Space Race$_t$ × Space Ind$_j$	0.38	0.36	0.36	0.34	0.56	0.50	-0.02	-0.02
	(0.09)	(0.11)	(0.10)	(0.13)	(0.17)	(0.16)	(0.03)	(0.03)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents$_{ij}$ × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
MSA × Year Fixed Effects		Y		Y		Y		Y
R^2	0.66	0.68	0.53	0.55	0.40	0.46	0.85	0.86
Observations	6,759	6,759	6,759	6,759	6,759	6,759	6,759	6,759

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. The unit of observation is 2-digit SIC industry × county × year, indexed by *j*, *i*, and *t*, respectively. Each column in the table reports the results from estimating one version of equation (1) in the text. Log(TFP) is defined as log(A_{ijt}) from estimating the production function $Y_{ijt} = A_{ijt}K_{ijt}^{\alpha}L_{ijt}^{\beta}$ by OLS. High Space Capability$_{ij<1958}$ is an indicator variable reflecting a county-industry'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. Space Ind$_j$ is an indicator variable for the industry *j* being a space industry. The models in all columns includes county, industry, and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in column (2), (4), (6) and (8) also include MSA × year fixed effects. Main entries report coefficient estimates. Standard errors are two-way clustered at the MSA × industry level and are reported in parentheses.

TABLE 4: Space Capability and Manufacturing: Military and Skill Controls

Dependent Variable =	Log(Value Add$_{ijt}$)		Log(Employ$_{ijt}$)		Log(Capital$_{ijt}$)		Log(TFP$_{ijt}$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Military Controls								
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.34	0.34	0.41	0.41	0.31	0.30	-0.04	-0.04
	(0.06)	(0.07)	(0.08)	(0.09)	(0.13)	(0.13)	(0.03)	(0.04)
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.36	0.36	0.35	0.34	0.55	0.55	-0.02	-0.03
	(0.08)	(0.08)	(0.10)	(0.10)	(0.16)	(0.17)	(0.04)	(0.04)
<u>Additional Military Controls:</u>								
Army Patents$_{ijt}$	Y	Y	Y	Y	Y	Y	Y	Y
Navy Patents$_{ijt}$	Y	Y	Y	Y	Y	Y	Y	Y
Military Spending$_{it}$		Y		Y		Y		Y
1962 Defense Scientist$_i$ × Year Fixed Effects		Y		Y		Y		Y
R^2	0.66	0.66	0.53	0.53	0.40	0.40	0.85	0.85
Observations	6,759	6,759	6,759	6,759	6,759	6,759	6,759	6,759
Panel B: Skill Controls								
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.34	0.34	0.41	0.41	0.29	0.29	-0.03	-0.03
	(0.07)	(0.09)	(0.08)	(0.10)	(0.14)	(0.13)	(0.03)	(0.04)
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.37	0.37	0.36	0.36	0.53	0.54	-0.02	-0.02
	(0.09)	(0.11)	(0.10)	(0.11)	(0.16)	(0.17)	(0.04)	(0.05)
<u>Additional Skill Controls:</u>								
Non-Production Worker Share$_{ijt}$	Y	Y	Y	Y	Y	Y	Y	Y
1960 High School Graduate$_i$ × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
1961 IBM Mainframes$_i$ × Year Fixed Effects		Y		Y		Y		Y
1962 Research Scientist$_i$ × Year Fixed Effects		Y		Y		Y		Y
R^2	0.66	0.66	0.53	0.53	0.40	0.41	0.85	0.85
Observations	6,759	6,759	6,759	6,759	6,759	6,759	6,759	6,759

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. The unit of observation is 2-digit SIC industry × county × year, indexed by j, i, and t, respectively. Each column in a panel reports the results from estimating one version of equation (1) in the text. Log(TFP) is defined as log(A_{ijt}) from estimating the production function $Y_{ijt} = A_{ijt}K_{ijt}^{\alpha}L_{ijt}^{\beta}$ by OLS. High Space Capability$_{ij<1958}$ is an indicator variable reflecting a county-industry'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. Space Ind$_j$ is an indicator variable for the industry j being a space industry. In panel A the models in columns (1), (3), (5) and (7) include county, industry and year fixed effects, the count of pre-1958 patents in a county × year fixed effects, Army patents, and Navy patents; the models in columns (2), (4), (6) and (8) further include military spending and the 1962 count of defense funded scientists × year fixed effects. In panel B the models in columns (1), (3), (5) and (7) include county, industry and year fixed effects, the count of pre-1958 patents in a county × year fixed effects, non-production worker share, and the 1960 percentage of high school graduates × year fixed effects; the models in columns (2), (4), (6) and (8) further include the 1961 count of IBM mainframes × year fixed effects and the 1962 count of research scientists × year fixed effects. Main entries report coefficient estimates. Standard errors are two-way clustered at the MSA × industry level and are reported in parentheses.

TABLE 5: Space Capability Differences and Patent Inventor Migration

Dependent Variable =	Log(Out Migration Ratio$_{odjt}$)		
	(1)	(2)	(3)
Space Capability Score Difference$_{odj,<1958}$× Space Race$_t$ × Space Ind$_j$	0.27	0.27	0.28
	(0.10)	(0.10)	(0.10)
Space Capability Score Difference$_{odj,<1958}$× Post-Space Race$_t$× Space Ind$_j$	0.68	0.62	0.52
	(0.23)	(0.23)	(0.24)
Corporate Income Tax Rate (1-CIT)$_{odt}$		-2.15	
		(0.84)	
Personal Average Income Tax Rate, 90th percentile (1-ATR)$_{odt}$		1.72	
		(0.53)	
R&D Credit (1+credit)$_{odt}$		0.04	
		(0.06)	
Origin County Fixed Effects	Y	Y	Y
Destination County Fixed Effects	Y	Y	Y
Industry 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	0.75	0.75	0.80
Observations	11,950	11,950	11,950

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. The unit of observation is origin county × destination county × industry × application year. Each column in the table reports the results from estimating one version of equation (3) in the text. Space Capability Score Difference$_{odj<1958}$=Log(Space Capability Score$_{dj<1958}$)-Log(Space Capability Score$_{oj<1958}$) is the difference in space capability scores between the origin and destination counties in industry *j*, 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 models in all columns include county (both origin and destination) fixed effects, year fixed effects, industry fixed effects, the count of pre-1958 patents in a county (both origin and destination) × year fixed effects, and origin-destination pair 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.

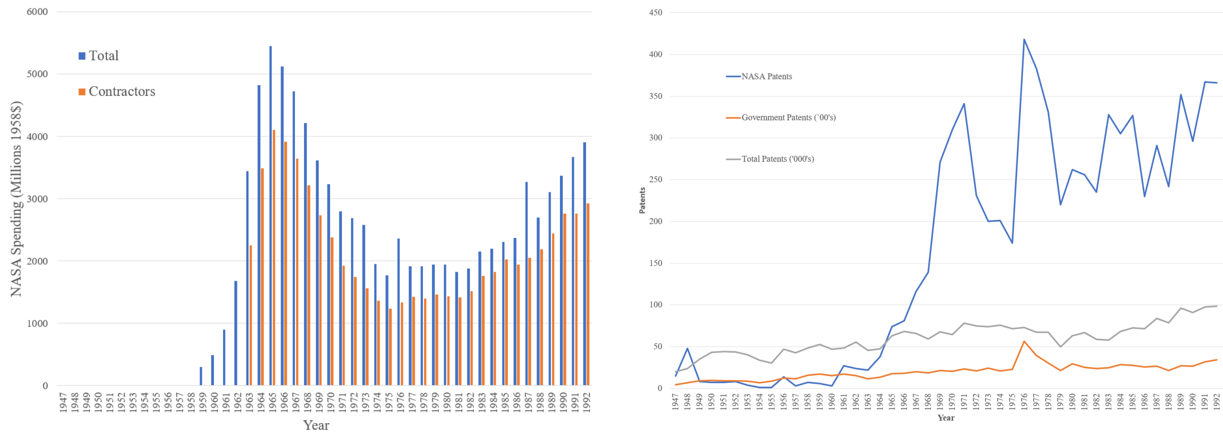
TABLE 6: Space Capability and Manufacturing: Local and Market Effects

Dependent Variable =	Log(Value Add$_{ijt}$)		Log(Employ$_{ijt}$)		Log(Capital$_{ijt}$)		Log(TFP)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Space Capability$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.32	0.38	0.39	0.47	0.28	0.26	-0.04	-0.03
	(0.07)	(0.09)	(0.10)	(0.11)	(0.12)	(0.15)	(0.04)	(0.05)
High Space Capability$_{ij<1958}$ × Post-Space Race$_t$ × Space Ind$_j$	0.49	0.42	0.50	0.44	0.63	0.59	-0.04	-0.05
	(0.12)	(0.12)	(0.12)	(0.14)	(0.16)	(0.17)	(0.04)	(0.04)
High Space Market$_{ij<1958}$ × Space Race$_t$ × Space Ind$_j$	0.05	0.00	0.08	0.01	0.00	-0.12	0.00	0.02
	(0.06)	(0.07)	(0.06)	(0.07)	(0.08)	(0.06)	(0.04)	(0.04)
High Space Market$_{ij<1958}$ × Post-Space Race$_t$ × Space Ind$_j$	-0.11	0.00	-0.10	0.03	0.04	-0.06	-0.05	-0.01
	(0.09)	(0.10)	(0.09)	(0.09)	(0.08)	(0.11)	(0.04)	(0.05)
County Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Pre-1958 Patents$_i$ × Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
MSA × Year Fixed Effects		Y		Y		Y		Y
R^2	0.66	0.68	0.53	0.56	0.40	0.46	0.85	0.86
Observations	6,759	6,759	6,759	6,759	6,759	6,759	6,759	6,759

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. The unit of observation is 2-digit SIC industry × county × year, indexed by *j*, *i*, and *t*, respectively. Each column in the table reports the results from estimating one version of equation (4) in the text. Log(TFP) is defined as log(A_{ijt}) from estimating the production function $Y_{ijt} = A_{ijt}K_{ijt}^{\alpha}L_{ijt}^{\beta}$ by OLS. High Space Capability$_{ij<1958}$ is an indicator variable reflecting an industry-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 Capability Score), as described in the text and appendix. High Space Market$_{ij<1958}$ takes a value of one in industry-counties with above median space capability score in their market, 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. Space Ind$_j$ is an indicator variable for the industry *j* being a space industry. The models in all columns include county, industry, and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. The models in column (2), (4), (6) and (8) also include industry × year fixed effects. Main entries report coefficient estimates. Standard errors are two-way clustered at the MSA × industry level and are reported in parentheses.

Figure 1: NASA Spending and Patenting, 1947-1992

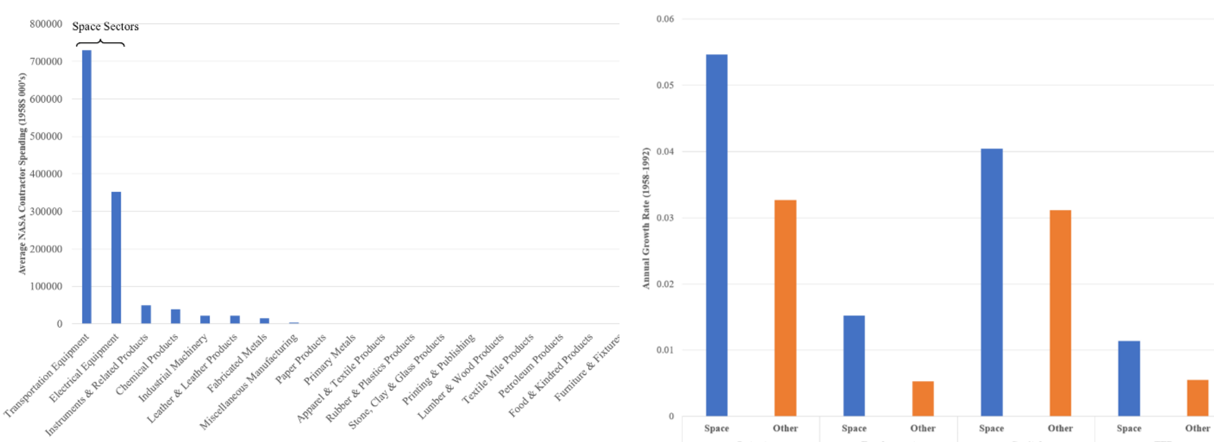
Panel A: NASA Spending Panel B: Patenting



Notes: Data are drawn from United States Patent and Trademark Office, and Fleming et al. (2019) and NASA Historical Data Books. Reported NASA contractor 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.

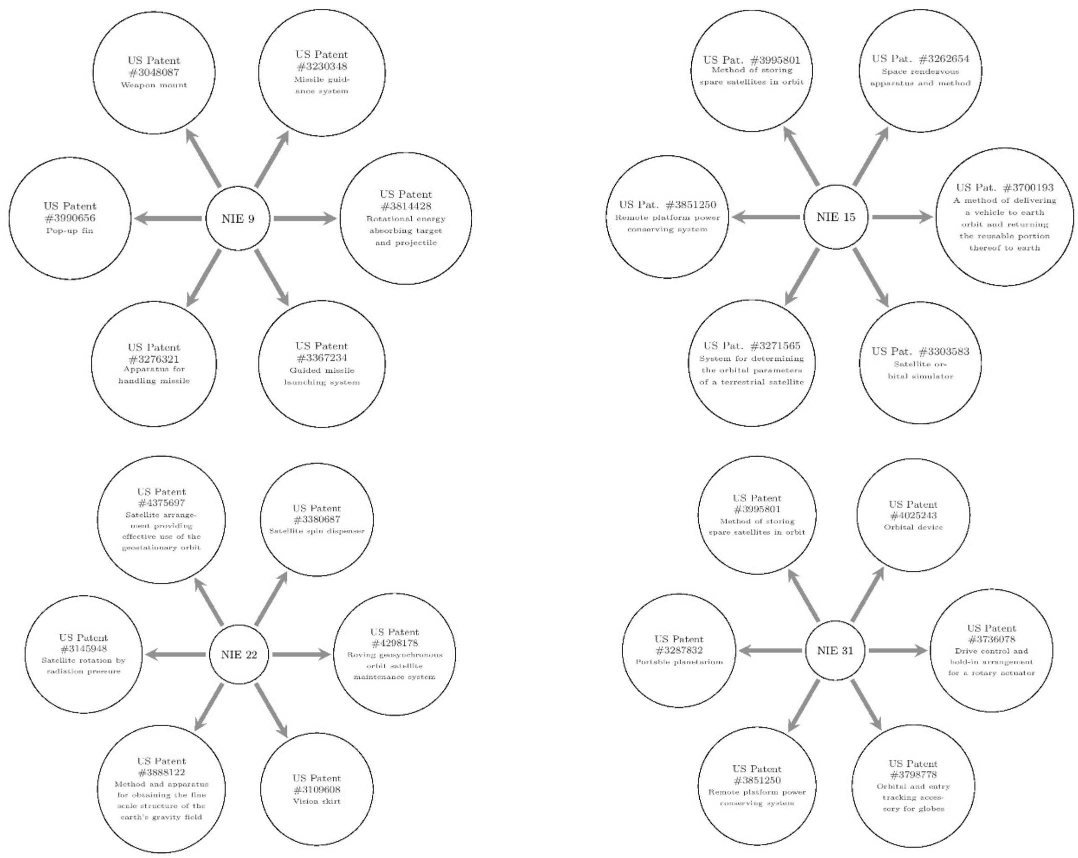
Figure 2: NASA Contractor Spending and Growth by Industry, 1958-1992

Panel A: NASA Contractor Spending, by Industry Panel B: Growth, by Industry



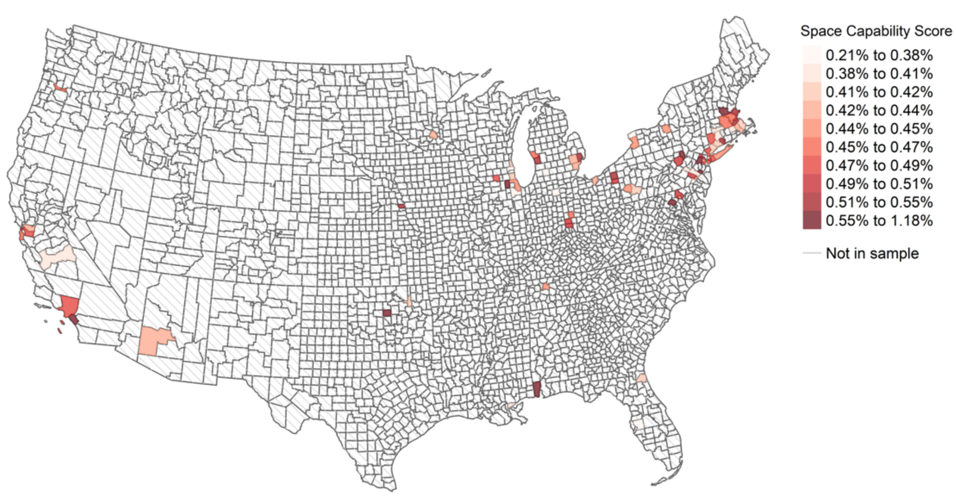
Notes: Data are drawn from NASA Historical Data Books and the NBER Manufacturing database.

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



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

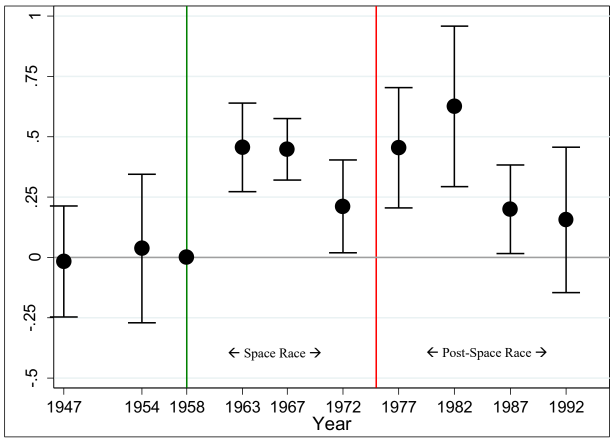
Figure 4: Space Capability Scores of Space-Active Counties in 1958



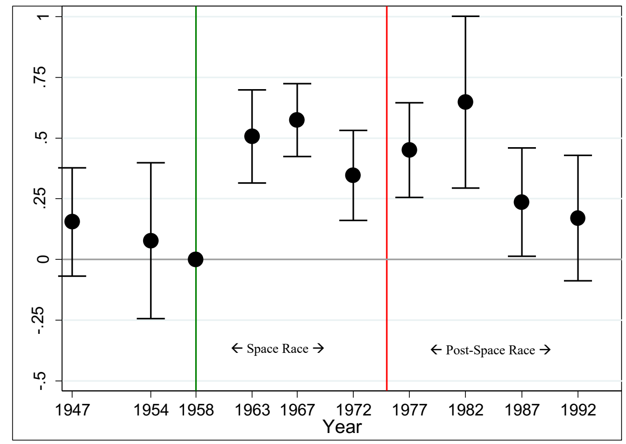
Source: Authors' calculations using National Intelligence Estimate data from 1958 to 1992 and United States Patent and Trademark data from 1945 to 1958. The space capability score is the $\widehat{\rho_i^c}$ as discussed in section 2.2 of the appendix. The map displays county level averages for the urban counties within defined MSAs that had manufacturing activity in the space sector in 1958 and that consistently reported manufacturing throughout our sample period (i.e., 1947 to 1992).

Figure 5: Space Capability and Manufacturing - Effect Dynamics

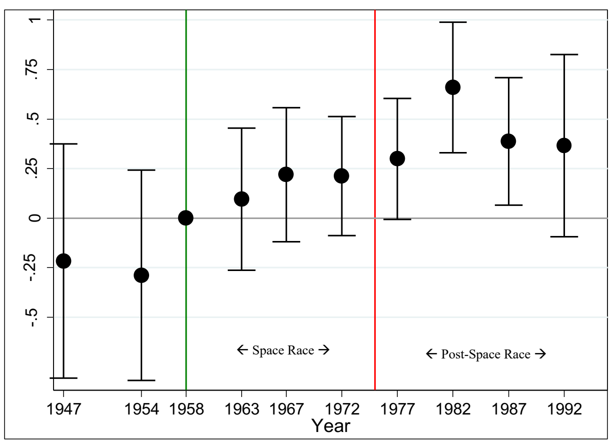
Panel A: Log(Value Added)



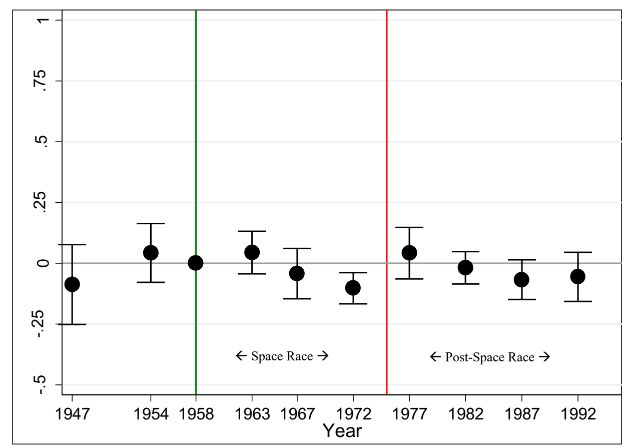
Panel B: Log(Employment)



Panel C: Log(Capital)



Panel D: Log (TFP)



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 (2) in the text for the outcome indicated, with 1958 serving as the omitted base year. The unit of observation is 2 digit SIC industry × county × year. Log(TFP) is defined as log(A_{ijt}) from estimating the production function $Y_{ijt} = A_{ijt}K_{ijt}^{\alpha}L_{ijt}^{\beta}$ by OLS. The points plot year by year coefficients on High Space Capability$_{ij<1958}$ × Space Ind$_j$ interactions with the 95% confidence intervals indicated by the range. Space race years are 1963, 1967 and 1972. Post-Space Race years are 1977, 1982, 1987, and 1992. The models in all columns includes county, industry, and year fixed effects, and the count of pre-1958 patents in a county × year fixed effects. Standard errors are two-way clustered at the MSA × industry level.