

# Moonshot: Public R&D and Economic Development\*

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## Abstract

We estimate the aggregate effects of a large-scale public research endeavor – the Cold War Era Space Race – using a spatial general equilibrium model with both technological spillover and market rivalry effects. The natural experiment of the Space Race, coupled with newly-digitized Census of Manufactures data at the county-industry level from 1947 to 1992, is used to estimate our models. We find that NASA provided technological spillovers to local manufacturing firms that increased their value added. NASA spillovers to regional market competitors also result in business stealing that reduced those local manufacturing firms’ value added. Our estimates indicate that aggregate value added in manufacturing was 11% to 17% higher in 1977 due to Space Race research. Allowing for the presence of inter-regional spillovers implies much smaller aggregate economic gains from public R&D than considering local spillovers alone.

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*“Will the increase in national income made possible by the space programme exceed the increase in income that would be obtained if the same resources were invested in other activities?”* Fogel (1966, 16).

# 1 Introduction

Economists have long sought to understand the macroeconomic effects of large public investments in R&D. Federal expenditure accounts for over 80% of public R&D in the US (NSF, 2020), making the aggregate effect of such public investment highly relevant for innovation policy and spending. Yet, modern studies very often employ reduced-form analyses to understand how policy shocks might impact different researchers, firms, or regions. While these analyses can identify the local effects of an innovation or industrial policy, they say little about the overall effects on output, employment, or other aggregate outcomes. In this paper we estimate the aggregate effects of one of the largest public R&D projects ever undertaken - the Cold War era Space Race to send Americans to the Moon.

Our contribution is threefold. First, we develop a spatial equilibrium approach to quantify the aggregate effects of public R&D. In our model, production takes place in spatially distinct locations where in each location there is a continuum of heterogeneous firms producing intermediate goods following Eaton and Kortum (2002) and Donaldson and Hornbeck (2016). We capture local spillovers from public R&D by embedding public knowledge stock as one component of firms’ productivity in each location (Griliches 1979).<sup>1</sup> Exogenous shocks to the local public knowledge stock increase the productivity of firms in that location. These are the localized spillovers captured by a standard reduced-form analysis.

Second is the incorporation of market-level effects into the evaluation of innovation policy. Inter-regional effects from public R&D arise because firms participate in regional markets, which raise two possibilities. Firms may suffer business stealing from a market competitor located elsewhere who becomes more productive because of increases in the public knowledge stock in the competitor’s location. Business stealing means that productive research conducted elsewhere will produce negative effects locally.<sup>2</sup> Firms may also learn to imitate

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<sup>1</sup>There is a significant literature on local knowledge spillovers. Recent contributions finding evidence of localized knowledge spillovers include Buzard, Carlino, Hunt, Carr, and Smith (2017), Andrews (2019a), Moretti (2019), Kantor and Whalley (2014, 2019), Ganguli, Lin and Reynolds (2020), and Zacchia (2020). An exception is Waldinger (2012) who finds little evidence of local knowledge spillovers among scientists.

<sup>2</sup>Bloom, Schankerman and Van Reenen (2013) separately identify business stealing and technological spillovers effects. Rotemberg (2019) documents the importance of the business-stealing effect in evaluating

new technology that is developed elsewhere by trading in a regional market.<sup>3</sup> Inter-regional imitation leads to positive local effects from research conducted elsewhere.<sup>4</sup> Ultimately, how market-level innovation affects firms is an empirical question.

Our third contribution is to quantify the aggregate effects of one of the largest mission-orientated public R&D projects ever undertaken - the Space Race. The ambitious mission of sending a person to the Moon led to a massive expansion of federal investment in technology – NASA received over 0.7 percent of GDP in the mid-1960s (Weinzierl 2018), employing over 400,000 workers at the peak of the Space Race. The Moon mission led to a number of discoveries in telemetry, integrated circuits, cryogenics, and computer simulation that had real economic value.<sup>5</sup> Those advocating for significant government spending to tackle concrete social problems often call for a new “Sputnik Moment” (Mazzucato, 2013; Gruber and Johnson, 2019).<sup>6</sup> Yet some economists since Fogel (1966), who was commenting in real time during the Space Race, have expressed skepticism that commercially relevant technology can be developed from mission-orientated R&D and public investment may crowd out the private sector. Despite the prominence of the proverbial “moonshot” in discussions of modern innovation policy, conclusive evidence of their economic impact is significantly lacking (Bloom, Van Reenen, and Williams 2019). This paper seeks to fill that gap.

The Space Race has a number of attractive features from a research design perspective. First, the timing of the Space Race technological investment was virtually independent of local economic conditions the United States. The shock of the Soviet launch of Sputnik in 1957 led to a geopolitical crisis that initiated the creation of NASA in 1958 and the launch of the race to the Moon in 1961. Furthermore, NASA’s areas of focus were driven by the evolving

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the equilibrium effects of firm subsidies.

<sup>3</sup>There is an active literature that links international trade to the diffusion of ideas. See Lucas (2009), Perla, Tonetti, and Waugh (2015), and Burea and Oberfield (2020). Peri (2005) is a seminal contribution linking transportation costs to the diffusion of ideas within countries. More recent work has demonstrated that road infrastructure causes idea diffusion. Agrawal, Galasso and Oettl (2017) find an effect of road infrastructure on patenting similar to what Duranton and Turner (2012) find for employment.

<sup>4</sup>Quantifying this positive inter-regional spillover effect is not widespread in the economics of innovation literature. Important precursors to our work are Lychagin, Pinkse, Slade and Van Reenen (2019) and Kantor and Whalley (2019) who estimate positive inter-regional spillovers from private sector R&D.

<sup>5</sup>Scranton (2007, 123) concludes, “NASA projects added critical momentum and capability to nascent innovations, providing essential test-beds for them (and the funding for revision and redesign), and to explore projects where the complexity of NASA-posed problems galvanized cross-disciplinary amalgams of technique and materials, with implications for the industrial world outside.”

<sup>6</sup>President Barack Obama, in his 2011 State of the Union, argued, “Half a century ago, when the Soviets beat us into space with the launch of a satellite called Sputnik, we had no idea how we’d beat them to the moon, the science wasn’t there yet. NASA didn’t even exist. But after investing in better research and education, we didn’t just surpass the Soviets – we unleashed a wave of innovation that created new industries and millions of new jobs.”

technological needs of a never-before-attempted public space program, not private industry.<sup>7</sup> NASA’s shifting technological demands for scientific and engineering breakthroughs in physics and jet propulsion in the early 1960s, to software and biology in the late 1960s, and finally robotics in the early 1970s were driven by the haphazard and novel challenges posed during the Moon mission and those that came subsequently. Second, because the Space Race was very much a race, NASA quickly allocated research to locations where NASA’s precursor, the National Advisory Committee for Aeronautics (NACA) established in 1915, already had facilities before 1958. Therefore, the Space Race provides a setting in which the geography of new public R&D demands was largely exogenous to the local private sector’s preexisting locations.

To estimate our models we use newly digitized data on the manufacturing sector and government-sponsored patents. For each industry-county unit in the Census of Manufactures from 1947 to 1992, we measure the number of local NASA patents using data from Fleming, Greene, Li, Marx and Yao (2019). We measure market-level NASA patents by weighting NASA patents in other counties by travel costs, as computed by Jaworski and Kitchens (2019). We thus obtain measures of both local- and market-level NASA patenting for each industry-county unit in our manufacturing census data.

Our analysis begins by examining how NASA patents affected manufacturing value added. Our results reveal a positive local effect of NASA patents, reflecting local knowledge spillovers from NASA research. Market-level effects of NASA patents are quite different, however, as increases in the level of NASA patents in local firms’ regional market reduced value added. The negative market effect reflects negative inter-regional business stealing that dominated any positive inter-regional technological spillovers. Our results are highly robust to a variety of controls for local military contracting or research activity and worker skills.

We explore our approach’s credibility in three ways. We first examine whether any effects appeared before NASA patents occurred to rule out the idea that NASA activity simply followed local private sector trends. Then we harness the granularity of our data to include industry  $\times$  year fixed effects to control for unobserved industry specific shocks as NASA-intensive industries may have been subject to other contemporaneous events. Similarly, because our identification is at the industry-county level, we can control for county  $\times$  year fixed effects. Controlling location specific trends could be important if NASA selected re-

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<sup>7</sup>As NASA historian Bromberg (1999) wrote of those early years: “[NASA Administrator James L.] Webb believed that national space policy should not be turned over to private firms. It was government acting in the public interest that had to determine what should be done, when it should be done, and for how much money.”

search locations that happened to be poised for growth or decline. Finally, we employ a shift share instrumental variable approach, exploiting variation in the technological needs of the space program over time interacted with initial technological specializations in an industry-county cell. We find little evidence from any of these analyses that our identification strategy is undermined.

What do our estimates of the local and market effects of NASA patents mean for the aggregate measure of the impact of space research? We consider a simple counterfactual. Our thought experiment takes the level of NASA patenting in 1958, the year NASA was founded, as the baseline and asks how much lower value added would have been in 1977 had NASA patenting from 1958 to 1972 not occurred. Our estimates imply that absent NASA patenting from 1958 to 1972, aggregate value added in U.S. manufacturing would have been between 11 and 17 percent less. These estimates imply a macro social rate of return to public R&D of over 50%. It is important to highlight that these aggregate effects of the Space Race are substantially smaller than those implied by local effects alone. That is, if we were to ignore business stealing effects and aggregate up local effects, our estimates imply we would overstate the calculated aggregate effect of Space Race research by a factor of three.

Turning to NASA R&D's impact on labor market and technology outcomes, we find very similar results for employment but not for labor income. We find that mission-orientated NASA patenting increased complementary local private sector patenting.<sup>8</sup> We find little effect on measured productivity, reflecting that workers are highly mobile in response to labor demand shocks.

Our work relates to three literatures. Interest has grown in the differing effects of policies at the micro and macro levels (Chodorow-Reich 2020). Yet, differing methodologies, data sources, and approaches make micro versus macro comparisons of the social rate or return to public research challenging.<sup>9</sup> Model-driven approaches in Jones and Williams (1998) and Jones and Summers (2020) estimate macroeconomic social returns of over 40%. However, econometric estimates of the macro effects from country-level analysis are more mixed with, for example, Coe and Helpman (1995) finding very large returns, while Moretti, Steinwender,

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<sup>8</sup>Returns to different types of public R&D may be heterogeneous. Mission-orientated projects may be central to private sector growth if complementarities between basic research – funded by government – and applied research – funded by private firms – lead to large measurable returns from public R&D (Akcigit, Hanley, and Serrano-Velarde, 2019 and Azoulay, Zivin, Li, and Sampat, 2019). When returns to different types of R&D are similar, large economic effects of mission-orientated R&D may simply be the result of geopolitical crises stimulating a significant increase in the overall level of research activity, as Bloom, Van Reenen, and Williams (2019) suggest.

<sup>9</sup>see Carlino and Kerr (2015) for a recent survey on the local effects of innovation and Jones and Summers (2020) for a survey of micro and macro returns to innovation expenditures.

and Van Reenen (2019) find smaller returns. Microeconomic case studies, such as the seminal Griliches (1958) study of hybrid corn, imply an internal rate of return of at least 35%. Firm-level analyses of the return to research and development, such as Bloom, Schankerman and Van Reenen (2013), imply an estimated social return of 55%. We provide a tractable framework that allows the recovery of both local and aggregate effects of public R&D.

Second, much work has examined how local technology shocks affect regional development (Greenstone, Hornbeck and Moretti, 2010; Juhasz, 2018; Kantor and Whalley, 2014, 2019; Giorcelli, 2019; Helm, 2020; and Gross and Sampat, 2020). The contributions that seek to obtain aggregate effects do not focus on inter-regional effects of technology (Moretti, 2019; Fan and Zou, 2019; Baum-Snow, Gendron-Carrier and Pavan, 2020).<sup>10</sup> We are the first paper to demonstrate the existence and importance of inter-regional business stealing effects from large scale public R&D programs and its importance for estimating aggregate effects. In this way our findings echo Akcigit, et al. (2018) who show that inter-regional business stealing creates a wedge between local and macro effects of tax policy on innovation and Hornbeck and Moretti (2020) who find that distant TFP shocks influence wages, rents, and inequality.

Third, our research on the Space Race contributes to the literature utilizing spatial models to estimate policy effects. The value of spatial modelling to estimate the effect of transportation infrastructure is now well established.<sup>11</sup> The use of similar models to evaluate productivity policy is less well developed. While some recent contributions have considered the effects of exogenous changes in productivity in an inter-regional setting, the focus to date has been on understanding the implications of spatial frictions rather than measuring the effects of productivity policy.<sup>12</sup> Our results demonstrating how inter-regional business stealing effects generate a significant wedge between the local and aggregate effects of the space program highlight the potential importance of a spatial model in estimating the aggregate effects of large-scale productivity or industrial policy.

<sup>10</sup>Recent work by Moretti, Steinwender and Van Reenen (2019) does quantify positive international technology spillovers from defense R&D. However, business stealing effects may be stronger within than between countries. Myers and Lanahan (2020) do allow for inter-regional spillover effects, however their focus is on idea production and so do not study business stealing in the product market.

<sup>11</sup>See, for example, Redding and Sturm (2008), Duranton and Turner (2012), Faber (2014), Duranton, Morrow, and Turner (2014), Allen and Arkolakis (2014), Hornbeck and Donaldson (2016), Tsivanidis (2018), Baum-Snow (2019), Jaworski and Kitchens (2019), Hornbeck and Rothemberg (2019), and Jaworski, Kitchens, and Nigai (2020)

<sup>12</sup>For recent work see Desmet, Nagy, and Rossi-Hansberg (2016), Caliendo, Parro, Rossi-Hansberg, and Sarte (2018), and Tombe and Zhu (2019). Redding and Rossi-Hansberg (2017) provide a recent review of this literature. Also closely related is Desmet and Rossi-Hansberg (2014) which features an exogenous spatial technology diffusion process, in contrast to our setting where technology diffuses endogenously through inter-regional trade.

## 2 Historical Background

The Space Race began with the launch of Sputnik on October 4, 1957. President Eisenhower was not surprised by Sputnik; he had been forewarned by information derived from U2 spy plane overflight photos, as well as signals and telemetry intercepts.<sup>13</sup> Eisenhower initially played down the importance of Sputnik, but after the high-profile failure of the U.S.'s initial satellite effort – Project Vanguard – on live TV on December 6, 1957, public fear grew (Divine 1993). It was clear to many how important missile, space, and satellite technology was to surviving a potential nuclear war with the Soviet Union.<sup>14</sup> While perceived American technological inferiority brought to bear immediate national security concerns, as Eisenhower emphasized in his 1958 State of the Union Address, “what makes the Soviet threat unique in history is its all-inclusiveness. Every human activity is pressed into service as a weapon of expansion. Trade, economic development, military power, arts, science, education, the whole world of ideas – all are harnessed to this same chariot of expansion. The Soviets are, in short, waging total cold war.”

Eisenhower’s new Cold War footing led the administration to propose defense reorganization and increased funding and the National Defense Education Act that provided federal funding to expand scientific and foreign language education in secondary and higher education institutions. In addition, in 1958, the administration proposed the National Aeronautics and Space Administration (NASA) that would bring space activities under civilian control, except as they related to weapons systems, military operations, and national defense. Exploring space transcended the simple military imperative, for as McDougall (1985, 172) notes, “The purposes of space activities were the expansion of human knowledge, improvement of aircraft and space vehicles, development of craft to carry instruments and living organisms in space, preservation of the United States as a leader in space science and applications, cooperation with other nations, and optimal utilization of American scientific and engineering resource.” Sorting the inevitable conflicts and ambiguities associated with civilian versus military space efforts, handling cooperation versus competition with other countries, and choosing appropriate spending levels would be left for later political wrangling. The im-

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<sup>13</sup>Logson (1995, 329) summarizes a July 5, 1957, memo from Allen W. Dulles, Director of Central Intelligence, to Donald Quarles, Deputy Secretary of Defense, “By 1957, the Central Intelligence Agency was aware that the Soviet Union had an active ballistic missile program and was preparing to launch a satellite. But the exact date of the launch was still uncertain. This memorandum from Director of Central Intelligence Allen Dulles to Deputy Secretary of Defense Donald Quarles indicates that American intelligence knew a Soviet space launch was imminent, but, as of early July 1957, was still unsure of the exact date of the launch.”

<sup>14</sup>Satellites allowed Cold War adversaries to see over the Iron Curtain and accurately assess the strength of their opponent’s intercontinental ballistic missile (ICBM) arsenal. They also allowed the targeting of the precise locations where the ICBMs were located – crucial information in the event of nuclear war. In an era of very limited information, satellites provided a major advantage.

mediate need was to respond to Sputnik and to the national realization that the U.S. was slipping behind her Soviet geopolitical counterweight.

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

While much of the nation’s infant space research program was adopted whole-cloth from NACA or parts of the military, NASA itself soon established a few of its own physical research centers and operational facilities to fulfill its mission. First, in 1959 NASA began construction of a new research center (to be named the Goddard Space Flight Center (GSFC)) in Beltsville, MD on a 550-acre tract formerly part of the U.S. Department of Agriculture’s Agricultural Research Center. NASA’s choice to establish its own first research center so close to its headquarters in Washington, DC is perhaps best described as expedient given that NASA had suddenly absorbed the Navy’s Project Vanguard program that was housed at the Naval Research Lab in Washington, DC. As Rosenthal (1968, 28) notes, “NASA Deputy Administrator Dr. Hugh L. Dryden appears to have been a key figure in selection of the Beltsville site. When the need for the new Space Center became apparent, he remembered the availability of surplus Government land near the Beltsville Agricultural Research Center. Believing that most of the Project Vanguard staff lived in Maryland, he had encouraged consideration of the Beltsville site. ‘Later, I learned that I may have been mistaken, since many of the Vanguard people actually lived in Virginia,’ Dr. Dryden recalled.”

GSFC at its inception had broad responsibilities for manned and unmanned Earth-orbiting missions, while JPL was given the task of managing planetary missions. GSFC’s



early responsibilities ranged from theoretical physics research to support space science, to satellite development and operation, to project planning and development of instruments to fabricate and test, launch and track satellites (Wallace 1999, 4). Manned space flight was a clear objective of the space program from NASA's beginning, but in a further blow to American technological prestige, Soviet Yuri Gagarin's 108-minute April 1961 orbital flight was significantly more dramatic than American Alan Shepard's suborbital 15-minute counterpart about three weeks later. The Soviet's successful manned flight was enough to convince NASA that an "independent NASA field center responsible for the conduct of programs for manned spacecraft" was necessary (Dethloff 1993, 37). With Congressional support for a new manned spaceflight center anticipated in the 1962 fiscal year, NASA planning began in earnest during spring and summer 1961.

The site selection criteria were widely circulated, to both Congress and the public, which included: access to water transportation sufficient for barges, moderate climate, all-weather commercial jet service, mature industrial complex and sufficient labor resources, close proximity to a culturally attractive community in the vicinity of an institution of higher education, strong electric utility and water supply, and at least 1000 acres of land.<sup>15</sup> While NASA's geographic preferences were very similar to those that NACA used to site a new research center on the west coast in 1939, which led to the Ames Lab in Santa Clara County, water access and favorable climate seemed to be the primary objective when it came to building, testing, and moving very large space equipment.<sup>16</sup> NASA's first list of nine target cities for a manned flight center included Jacksonville, FL (Green Cove Springs Naval Station), Tampa, FL (MacDill Air Force Base), Baton Rouge, LA, Shreveport, LA (Barksdale Air Force Base), Houston, TX (San Jacinto Ordnance Depot), Victoria, TX (FAA Airport), Corpus Christi, TX (Naval Air Station), San Diego, CA (Camp Elliott), and San Francisco, CA (Benicia Ordnance Depot). Additional sites were identified in St. Louis, MO, Houston, Liberty, Beaumont, and Harlingen, TX, Bogalusa, LA, and Berkeley, Richmond, and Santa Clara, CA. Boosters for Boston, Rhode Island, and Norfolk pitched their locations, and they were added to the list, but NASA had clearly showed its hand with a strong preference for the Gulf area and CA.

By early September 1961, MacDill Air Force Base in Tampa was deemed the preferred site, primarily because the Air Force planned to close down its Strategic Air Command

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<sup>15</sup>The history of the choice to place NASA's new manned spaceflight center in Houston documented here is drawn from Dethloff 1993, chapter 3.

<sup>16</sup>For a short history of NACA's site selection for its new research center in 1939, see Hartman (1970, 20-21). Interestingly, NACA was relying heavily on criteria established by the Navy in 1930 as it was considering a location for a new airship base.

operations at that base. A Houston site offered by Rice University was second, and the Benicia Ordnance Depot northeast of San Francisco was third. Just before a final decision was made, the Air Force decided not to close MacDill, which elevated Houston as the top choice, which was announced publicly on September 19. The bias for a Gulf location was clearly salient because the Houston location provided ready interconnection by deep water transportation with Cape Canaveral and the Michoud Plant on the Mississippi River near New Orleans, where space vehicles were to be fabricated. NASA had secured those facilities during summer 1961. While Houston certainly made sense from a strategic perspective, it is worth highlighting another important force working in Texas's favor: Texan Vice President Lyndon Johnson was the head of the National Aeronautics and Space Council; Representative Albert Thomas from Houston chaired the House Appropriations Committee; Representatives Bob Casey (Houston) and Olin E. Teague (Dallas) were members of the House Committee on Science and Astronautics, and Teague headed the Subcommittee on Manned Space Flight; and finally, Sam Rayburn (northeast TX) was Speaker of the House.

Two additional NASA main centers deserve brief discussion. The location at Cape Canaveral in 1962 became the Launch Operations Center (renamed Kennedy Space Center (KSC) in December 1963), having acquired that responsibility from the GSFC. In addition to hosting all manned space flight in the U.S., KSC's massive Vehicle Assembly Building is one of the largest buildings in the world where most of the personnel are NASA contractors. Finally, in 1961 NASA located its largest rocket test facility (now Stennis Space Center) in southern Mississippi (Hancock County) on the Pearl River.<sup>17</sup> From manufacturing, testing, launch, and control, the Gulf location, or what became known as the "Space Crescent," was critical to NASA's early growth (Swenson 1968, Ling 1984).

**Growth and Organization.** While Eisenhower's early efforts may have "ensure[d] that the United States remain *a* leader, not *the* leader in space, [they] 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 Shepard's successful flight: "I believe that this nation should commit itself to achieving the goal, before this decade is out, of landing a man on the Moon and returning him safely to Earth." Of course, the U.S. was nowhere close to having the technological capability to immediately fulfill that mission, so Kennedy's commitment to send a manned crew to the Moon and returning them to Earth by the end of the decade required a massive investment in space technology. NASA's budget grew accordingly, from \$744 million (or about 0.9% of all federal spending) in 1961 to a peak of \$5.933 billion (4.4% of the federal budget) in 1966. With the rapid escalation in

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<sup>17</sup>See Herring 1997, especially chapter 1, for a history of the Stennis location.

public funds devoted to space exploration, the Space Race was very much a race. 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 20<sup>th</sup> century.

The Space Race is the canonical example of mission-oriented research and development spending where the mission was to land astronauts on the Moon and safely return them to Earth. The Space Act of 1958 gave NASA broad powers to develop, test, and operate space vehicles and to make contracts for its work with individuals, corporations, government agencies, and others (Rosholt 1966, 61). NASA, from its inception, made the decision to contract out much of the R&D work to private contractors.<sup>18</sup> 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 only 56 percent of them employed by contractors (Rumerman 1999, 468).

Space Race spending was highly concentrated in relatively few sectors and firms. According to an input-output table constructed for NASA expenditures for fiscal year 1967 (Orr and Jones 1969), the top five manufacturing sectors accounted for about half of NASA expenditures.<sup>19</sup> Similarly, relatively few firms served as primary NASA contractors. In 1965, for example, the top 10 contractors alone received nearly 70% of the 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).

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<sup>18</sup>T. Keith Glennan, the first administrator of NASA, was an advocate for contracting out. He wrote of his early decisions in 1958: "First, having the conviction that our government operations were growing too large, I determined to avoid excessive additions to the Federal payroll. ... I was convinced that a major portion of our funds must be spent with industry, education and other institutions." (Hunley 1993, 5)

<sup>19</sup>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).

**Technology Impacts.** What did NASA scientists discover? How did NASA spending affect productivity? From the beginning NASA officials recognized that the transfer of technology to commercial applications was vital in securing public support. They sought partnerships with universities and established information distribution centers where private sector firms could access information on their latest discoveries.

Despite the prominence of the Space Race as one of the largest ever public investments in innovation, pinpointing a blockbuster consumer product solely attributable to NASA spending is hard. Indeed, many space-associated consumer products were already developed and the Space Race simply diffused them more broadly (e.g., Tang (Scranton 2006, 122)). Yet, the Space Race did have broader impacts on technological change.

Robbins, Kelly and Elliot (1972) interviewed 161 recognized technological leaders to identify 109 major developments in a field's technology during the decade prior to the Moon landing. For each breakthrough they classify NASA's role in the technology's development: (1) an entirely new technology - 6.3% of developments, (2) an incremental advance in a technology - 64.8 % of developments, or (3) a consolidation of existing knowledge about a technology - 23.3 % of developments. Their findings echo an earlier analysis that concluded that early Space Race research largely sped up progress with existing technologies rather than developed entirely new technologies (Denver Research Institute 1971).

The areas where Robbins, Kelly and Elliot (1972) identify entirely new technologies from NASA spending are: Cryogenics, Energy Conservation, Ceramics, Metals, Integrated Circuits, Gas Dynamics, Non-Destructive Testing, and Telemetry. Telemetry, Integrated Circuits, Cryogenics, and Simulation are the areas with the greatest fraction of development that would not have occurred without NASA contributions. A few examples include the development of powdered metallurgy techniques in the field of high temperature metals, the computer enhancement of radiographs, high frequency power transistors, and the simulation of lunar landings (Robbins, Kelly and Elliot 1972, 18-21).

While the direct economic effects of space research were of modest magnitude, many argued that the harder to estimate indirect effects that occurred over a much longer time horizon were substantially larger. These later studies focus on some technologies where NASA's contribution became clearer over time. For example, NASA played an important role in the development of integrated circuits, first launching them into space in 1962 (Mathematica 1976, p. 101), structural simulation software - Nastran - between 1965 and 1970 (Mathematica 1976, p. 119), and digital communications, including the use of error-correcting codes and data compression in processing digital signals for modern-day digital communication

and data storage (Midwest Research Institute 1988). Mazlish (1965) draws the comparison between the indirect effects of space science and the development of the railroad.

Summing up the contributions of NASA spending, Scranton (2007) concludes, “Contrary to consumer expectations, virtually all these contributions have been indirect, as a Denver Research Institute (DRI) study explained in the early 1960s, and hence imperceptible to most observers.” Scranton (2007, 129) notes, however, that many innovations were directly applicable to manufacturing: “on the manufacturing process front, we can note innovations such as chemical milling and high-energy forming . . . as well as electron-beam, thermal, numerical control, ultra-cold, and electrical discharge machining; electrolytic grinding; plasma and induced magnetic field welding; plus stretch, magnetic, and shear forming.” On instrumentation: “The rise of reliable, precise, and speedy instrumentation as a key dimension of technical practice preceded NASA’s inauguration, but its momentum accelerated at a rapid pace once piloted spaceflight became a national priority” (Scranton 2007, 136). On management practices: “NASA projects provided test platforms or incubators for a number of managerial techniques as well: project management and team-tasking, high-level quality control, reliability analyses, and handling concurrency/redesign challenges” (Scranton 2007, 137). Others also noticed the staggering developments in computerization and automation. Describing NASA’s Performance, Evaluation and Reporting Technique (PERT), Bilstein (1996, 286) notes that “PERT was a sophisticated and complex computerized system, with inputs beginning, literally, at the tool bench. Technicians on the floors of the contractor plants around the country monitored the progress of nearly all the the hardware items and translated the work into computer cards and tapes. The PERT network was broken down into 800 major entities and summarized 90,000 key events taking place around the country.” A major improvement in quality control was the automated checkout procedure. As Bilstein (1996, 240) describes: “manual checkout techniques for the the earliest S-IV stages; pre-checkout, acceptance firing, and post-checkout required a total of 1200 man hours per stage. Veteran “switch flippers” who had for so long been vital links in the loop ... were now replaced by ranks of grey-enameled computers . . . Although the magnitude of testing rose 40 percent per stage the new automated systems reduced checkout time to just 500 man hours total.” Indeed, if the Space Race had a significant effect on the development of the leading general purpose technology – the digital computer – the effects may have taken some time to fully manifest and may have occurred outside of the space sector. Our analysis investigates this possibility directly.

### 3 Aggregate Effects of Public R&D: A Spatial Approach

In this section we describe our empirical approach to estimate the effect of public R&D on aggregate economic outcomes. We embed a Griliches (1979) public R&D knowledge stock into a simple county to county trade model based on Hornbeck and Donaldson (2016) that allows us to capture the aggregate effects of interest. For ease of exposition we follow the notation and presentation in Hornbeck and Donaldson (2016) closely.

**Set Up.** We index counties by  $o$  if they are origin of trade and  $d$  if they are destinations. Consumers have CES preferences over a continuum of differentiated product varieties, where the elasticity of substitution across varieties is given by  $\sigma$ . Producers in each county combine a fixed factor land ( $L_o$ ), and mobile factors labor ( $N_o$ ) and capital ( $K_o$ ) using a Cobb-Douglas technology to produce varieties. The marginal cost of each variety is given by:

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

where  $q_o$  is the land rental rate,  $w_o$  is the wage,  $r$  is the interest rate, and  $z_o(j)$  is the local productivity shifter drawn from a Frechet distribution with a CDF  $F_o(z) = e^{-T_o z^{-\theta}}$ . Here  $T_o$  is the local knowledge stock. Higher levels of the knowledge stock shift the distribution making high productivity draws more likely.

Trade costs between  $o$  and  $d$  are iceberg: for each unit shipped from  $o$  to  $d$ ,  $\tau_{od} \geq 1$  is the cost to ship. That is, if a variety is produced and sold in the same county the price is  $p_{oo}(j)$ , while the same variety sold in a different county has price  $p_{od}(j) = \tau_{od} p_{oo}(j)$ . Workers are perfectly mobile across counties so that  $w_o = \bar{U} \times P_o$  where  $\bar{U}$  is the level of utility obtained by workers in each county and  $P_o$  is the price index in county  $o$ .

Assuming perfect competition, unit costs (including marginal and trade costs) are equal, letting consumers buy from the cheapest origin county, using the assumption that  $r_c = r$ , Donaldson and Hornbeck (2016) note that the price index in destination  $d$  is defined by

$$(P_d)^{-\theta} = \kappa_1 \sum_o T_o (q_o^\alpha w_o^\gamma)^{-\theta} \tau_{od}^{-\theta} = CMA_d \quad (2)$$

where  $CMA_d$  is customer market access and  $\kappa_1 = [\Gamma(\frac{\theta+1-\sigma}{\theta})]^{1-\sigma} r^{(1-\alpha-\gamma)\theta}$ .

**Defining the Knowledge Stock.** We depart from the prior literature in how we model the local knowledge stock  $T_o$  in two ways. First, the local knowledge stock depends on the exogenous level of public R&D – in our setting NASA patents – in the origin county. This assumption captures local technological spillovers from public R&D that directly increases productivity in that location. We term this the *Local Effect* of public R&D.

Second, the local knowledge stock evolves endogenously through trade. Firms learn about new technologies used by other firms from visiting export destinations and observing the technology in the destination market. The amount of knowledge an origin location receives through trade depends on the knowledge stock in destination markets.<sup>20</sup> Public R&D in destination counties will then increase productivity in the origin county through an increase in the origin county’s knowledge stock. Public R&D in destination markets, however, also increases the productivity of the origin firms’ competitors. Competitors become more productive and, thus, have the opportunity to steal business from the origin location firms, reducing the latter’s output.

We term the effect that public R&D in destination locations has on the origin location firms as *Market Effects*. The market effect can go in either direction. Market effects will be positive when firms learn a great deal from trade. Positive inter-regional knowledge spillovers can dominate negative inter-regional business stealing effects so that the effects of public R&D in destination markets increases output. In contrast, market effects will be negative where inter-regional knowledge spillovers are small. In this case negative inter-regional business stealing effects dominate the effects of public R&D in destination markets and lead to reduced output among origin location firms.

**Knowledge Stocks and Trade.** To obtain equilibrium knowledge stock in location  $o$ , we first write down the local knowledge stock in location  $o$  as a function of private local knowledge stock, local public R&D, and technology observed in the destination market. Because comparative advantage determines trade flows into a firm’s destination market, the technology an origin firm has access to in the destination market is captured by consumer market access. We express this as:

$$T_o = \underbrace{A_o}_{\text{Private Local Knowledge Stock}} \times \underbrace{S_o^\delta}_{\text{Public Local Knowledge Stock}} \times \underbrace{CMA_d^\beta}_{\text{Destination Market Technology}} \quad (3)$$

where  $A_o$  is the private knowledge stock held by firms unrelated to public R&D in location  $o$ ,  $S_o$  is the knowledge stock from public R&D in location  $o$ , and  $CMA_d^\beta$  is the county market

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<sup>20</sup>Buera and Oberfield (2020) term this learning from producers.

access in location  $d$ . We assume that the knowledge stock from public R&D is complementary to the private knowledge stock, following Akcigit, Hanley and Serrano-Velarde (2019), and that  $\delta < 1$ .

We then substitute equation (3) into (2) to obtain the local knowledge stock at market clearing prices. Doing so gives:

$$(P_d)^{-\theta} = \left( \kappa_1 \sum_o A_o S_o^\delta (q_o^\alpha w_o^\gamma)^{-\theta} \tau_{od}^{-\theta} \right)^{\frac{1}{1-\beta}} = CMA_d \quad (4)$$

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

$$X_{od} = T_o (q_o^\alpha w_o^\gamma)^{-\theta} \tau_{od}^{-\theta} \kappa_1 CMA_d^{-1} Y_d \quad (5)$$

We introduce local knowledge stocks and inter-regional knowledge spillovers into the gravity equation of inter-regional trade using equation (3) to substitute for  $T_o$  in (5). Doing so we obtain:

$$X_{od} = A_o S_o^\delta (q_o^\alpha w_o^\gamma)^{-\theta} \tau_{od}^{-\theta} \kappa_1 CMA_d^{\beta-1} Y_d \quad (6)$$

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

$$Y_o = \sum_d X_{od} = \kappa_1 A_o S_o^\delta (q_o^\alpha w_o^\gamma)^{-\theta} \sum_d \tau_{od}^{-\theta} CMA_d^{\beta-1} Y_d \quad (7)$$

**Solving the Model.** We now solve the model for output in county  $o$  and obtain our estimation equation. First, we substitute  $w_o = \bar{U} CMA_o^{\frac{-1}{\theta}}$ , firm market access  $FMA_o \equiv \sum_d \tau_{od}^{-\theta} CMA_d^{\beta-1} Y_d$  into equation (7) to obtain,

$$Y_o = \kappa_2 A_o S_o^\delta q_o^{-\theta\alpha} CMA_o^\gamma FMA_o \quad (8)$$

where  $\kappa_2 = \kappa_1 \bar{U}^{\gamma\theta}$ .

Next we express  $CMA_o$  in terms of  $FMA_o$ . We can use equation (7) to solve for  $A_o S_o^\delta (q_o^\alpha w_o^\gamma)^{-\theta}$  and substitute into (4) to get:

$$CMA_d = \left( \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \right)^{\frac{1}{1-\beta}} \quad (9)$$

Under symmetric trade costs (i.e.  $\tau_{od} = \tau_{do}$ ) equation (9) and the definition of  $FMA_o$ ,



implies there exists a constant  $\rho$  such that  $FMA_o = \rho CMA_o^{1-\beta}$ .<sup>21</sup> We further define  $MA_o \equiv FMA_o = \rho CMA_o^{1-\beta}$ . Substituting for  $FMA_o = MA_o$  and  $CMA_o = \left(\frac{MA_o}{\rho}\right)^{\frac{1}{1-\beta}}$  into equation (8) and rearranging we obtain,

$$Y_o = \kappa_3 A_o S_o^\delta q_o^{-\theta\alpha} MA_o^{(1+\frac{\gamma}{1-\beta})} \quad (10)$$

where  $\kappa_3 = \kappa_2 \rho^{\frac{\gamma}{\beta-1}}$ .

**Market Effects of Public R&D.** Finally we express  $MA_o$  as a function of  $S_d$  to incorporate the market effects of public R&D. We solve for the expression for the market access term  $MA_o$ . With  $MA_o \equiv FMA_o = \sum_d \tau_{od}^{-\theta} CMA_d^{\beta-1} Y_d$ ,  $CMA_d = \left(\frac{MA_d}{\rho}\right)^{\frac{1}{1-\beta}}$  and  $Y_d = \kappa_1 A_d S_d^\delta (q_d^\alpha w_d^\gamma)^{-\theta} MA_d$  from equation (7) we obtain

$$MA_o = \kappa_1 \rho \sum_d \tau_{od}^{-\theta} A_d S_d^\delta (q_d^\alpha w_d^\gamma)^{-\theta} \quad (11)$$

Due to data constraints on wages and land values in our data, we follow Donaldson and Hornbeck (2016) and approximate  $MA_o$  with:

$$MA_o \approx \sum_d \tau_{od}^{-\theta} S_d^\delta \quad (12)$$

This approximation is useful because it only depends on NASA patenting and distance, both of which we observe for every location.

To obtain our estimation equation we take logs of equation (11) and obtain,

$$\log(Y_o) = \psi + \delta \log(S_o) + \left(1 + \frac{\gamma}{1-\beta}\right) \log\left(\sum_d \tau_{od}^{-\theta} S_d^\delta\right) - \theta\gamma \log(q_o) + \log(A_o), \quad (13)$$

where  $\psi = \log\left(\frac{\kappa_1}{\rho^{\frac{1}{1-\beta}} \bar{U}^{\theta\gamma}}\right)$  is a constant. Equation (13) is the basis of our estimation approach. The effect of changes in the local knowledge stock are captured by  $\delta$ . These local effects are expected to be positive. The effects of changes in the market knowledge stock is captured by  $\left(1 + \frac{\gamma}{1-\beta}\right)$ . These market effects can be in either direction. When inter-regional technological spillover effects are large so that  $\beta > 1 - \gamma$  the market effects are positive. Conversely, when inter-regional technological spillover effects are small so that  $\beta < 1 - \gamma$  the market effects are negative. Thus, whether the market effects from public R&D increase or

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<sup>21</sup>See online appendix section 1 for the proof of this proposition. Donaldson and Hornbeck (2016) and Allen and Arkolakis (2014) make use of a similar relationship.

decrease output is an empirical question.

**Empirical Implementation and Discussion.** Estimating (13) with our available data, which define knowledge stocks based on NASA patents, raises a number of issues. First, while our theoretical model refers to a single sector model, we utilize data on multiple manufacturing sectors for our econometric model. We take this empirical approach because the error term includes the unobserved local private knowledge stock in an industry and land values that could be correlated with local or market level NASA research activity. Our baseline models allow for unobserved heterogeneity since we include county, industry, and year fixed effects. The use of multiple industries in a single location allow us to control for national industry-level trends by including industry $\times$ year controls. These industry trend variables are likely to be important since unobserved determinants of industry growth in, say, Electronic Other Electric Equipment are likely to be correlated with NASA innovation. Having multiple industry observations for a county-year cell allows us to also control for county $\times$ year fixed effects. We view these controls as important because unobserved determinants of city growth, say in the form of improved amenities or human capital stock, may also be correlated with NASA patents. The importance of controlling for these trends remains an empirical question. While many NASA patents emanate from cities with warm climates or high human capital stocks – i.e. Los Angeles or Boston – that were poised for growth, other locations that experienced substantial NASA patenting – such as Cleveland or Huntsville – did not have such favorable endowments.

Second, our baseline model considers only the local effects of NASA innovation in the same industry as the manufacturing industry. This approach is valid if cross-industry knowledge spillovers are not relevant. We include cross-industry specifications as an additional analysis and a multi-industry version of the model in online appendix table A6. These additional analyses demonstrate that cross-industry effects are not present in our data, echoing the findings in Moretti (2019). We prefer the parsimonious model that only includes own-industry spillovers since separately identifying cross-industry spillovers from common local shocks would be an additional challenge.

Third, our baseline models are identified from NASA’s seemingly haphazard technological needs that might have varied over time, according to the specific mission at hand, and based on the specific engineering demands that evolved as novel projects were being developed in real time. To validate this approach we explore the dynamics of both the local and market NASA innovation effects by including leads and lags of these variables. If NASA patenting were endogenously responding to industry-location levels of manufacturing, we should see

evidence of prior trends in these outcomes. Even in absence of prior trends, common shocks may invalidate our approach. We address this concern by implementing a shift share instrumental variables approach that exploits time series variation in the technologies that NASA needed to complete its mission, coupled with research locations determined before Sputnik.

Fourth, to separately identify the effects of local- and market-level public R&D, we do not include own-county public R&D in the market public R&D measure. We, thus, define  $MarketS_{it-x}$  as:

$$MarketS_{ijt-x} = \sum_d \tau_{od}^{-\theta} S_{jd}^{\delta} \quad (14)$$

This measure only considers market effects for the own industry where we expect both inter-regional technology spillovers and product competition to be most pronounced. All variation in market innovation comes from shocks to NASA patenting elsewhere so that it is likely exogenous to county-level outcomes. For this reason we do not seek instruments for market innovation.

Fifth, construction of our market-level innovation term  $MA_o$  requires  $\delta$  and  $\theta$  values. We estimate  $\delta$  - the impact of local public R&D - using our data by estimating equation (15) without the  $\text{arcsinh}(MarketS_{ijt-x})$  covariate as reported in Table 2 column (1).<sup>22</sup> We use  $\theta = 8.28$ , the preferred estimate in Eaton and Kortum (2002), and assess the robustness of our results to alternative values.<sup>23</sup>

Sixth, we measure local-level NASA knowledge stock with the count of NASA patents in that county-industry cell and the market-level NASA knowledge stock with the count of NASA patents in that county-industry cell's market. Since a number of county-industry cells have no NASA patents, we cannot take the logarithm of  $S_{ijt-x}$  or  $MA_{ijt-x}$  without losing observations. Thus, we use the inverse hyperbolic sine of  $S_{ijt-x}$  or  $MA_{ijt-x}$ ,  $\text{arsinh}(X) = \ln(X + \sqrt{(X)^2 + 1})$ , which converges to  $\ln(Ni) + \ln(2)$  and has the advantage that  $\text{arsinh}(0) = 0$ .

We take these concerns into account by estimating the model:

$$\log(Y_{ijt}) = \gamma_1 + \gamma_2 \text{arcsinh}(LocalS_{ijt-5}) + \gamma_3 \text{arcsinh}(MarketS_{ijt-5}) + \psi_i + \psi_j + \psi_t + \epsilon_{ijt} \quad (15)$$

<sup>22</sup>Empirically there is little correlation between the local and market measures so that including or excluding the market level effects from the regression does little to alter the estimate of  $\delta$  in practice. See Table 2 columns (1) and (3).

<sup>23</sup>The preferred estimate in Eaton and Kortum (2002) is also very close to the trade elasticity in Donaldson and Hornbeck (2016) of  $\theta = 8.22$ .

where  $i = \text{county}$ ,  $j = \text{industry}$ , and  $t = \text{year}$ , and  $\psi_i$ ,  $\psi_j$ ,  $\psi_t$  are county, industry and year fixed effects. The effect of local public R&D is captured by  $\gamma_2$ , which is equivalent to  $\delta$  in equation (13). The effects of market R&D are captured by  $\gamma_3$ , this is equivalent to  $\left(1 + \frac{\gamma}{1-\beta}\right)$  in equation (13). We use the flow of NASA patents over the prior five years to measure the knowledge stock lagged by one manufacturing census (five years) to help address concerns associated with correlated unobserved common shocks. We cluster the standard errors by industry  $\times$  county to account for autocorrelation within location-industry cells. We weight the industry-location cells by their employment in 1958 to enhance the efficiency of our estimates and so that they represent the effect for the average worker, not the average location-industry cell.

## 4 Data and Descriptive Statistics

**Patent Data.** Using data from the USPTO Historical Master file to determine the list of all patents issued, we define NASA patents as those where ownership was assigned to NASA or those that acknowledged government funding from NASA. To allocate the patents to NASA and to specific locations we require two further databases. For patents granted after 1976 we use the USPTO PatentsView data to determine ownership and government funding, as well as the location of the first inventor. For patents granted before 1976 we use the Fleming et al. (2019) data that has scraped assignee and government funding information from the full text of USPTO patents.

Figure 1 plots the number of patents by application year from 1947 until 1992. We see that patents were very low before NASA was founded in 1958.<sup>24</sup> During the Space Race the number patents granted per year increases from 21 in 1961 to 256 in 1969. From 1967 until today the number of patents per year fluctuates in the 200 to 300 range. In the postwar period the total number of patents and total number of government patents increase much more slowly and gradually than NASA’s.

We next allocate granted patents to locations. We utilize a few sources to obtain a county for each patent. For the data before 1975 we use the HISTPAT database that scrapes the full text of the patent to assign each patent to the most appropriate county (Petralia, Balland and Rigby, 2016).<sup>25</sup> For the post-1975 data we use the USPTO Patentsview data that has

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<sup>24</sup>The few patents from before 1958 are likely from patents under NASA’s precursor National Advisory Committee for Aeronautics. The patents were later reassigned to NASA (Ferguson, 2013).

<sup>25</sup>Andrews (2019b) shows that the frequentist approach underlying Histpat overweights populous locations. However, any over-reporting effects are modest – the population-patent elasticity implies a 10% increase in population would increase patenting by 4% in Histpat, but would increase patenting by 3% in the Andrews

the exact address for each inventor. We use the address for the first inventor to assign a patent to a county.<sup>26</sup>

Map 1 shows the spatial distribution of NASA local patents and NASA market patents in 1958 and 1992, the years of manufacturing census data we have just before and after the Space Race. The map shows both the total number of NASA local patents over the previous five year period in the county in green circles as well as the total number of NASA market patents over the same previous five years in the county’s market in blue shading. We use the count over the previous five years throughout our analysis. Panel A shows that there are few locations that had patents in 1958 and the ones that did only produced a small number.<sup>27</sup> Few of the cities within counties that had the largest number of patents in 1958, such as Chicago, IL, Los Alamos, NM, Hampton, VA, or Cincinnati, OH, were associated with strong growth during the 1960s. In 1958 the region with the largest level of NASA market patents was in the Northeast centered on Washington DC. We see this degree of market-level influence because a larger number of counties in 1958 had patents in this region and those locations with the most patents, such as Los Alamos, were more isolated, thus leading to smaller market level effects on nearby counties.

Panel B of the map shows the spatial distribution of local NASA and market NASA patents in 1992 after the pinnacle of the Space Race when the level of NASA patenting was much higher. Cities within counties with the heaviest patenting include Los Angeles, CA, Huntsville, AL, Cleveland, OH, Palo Alto, CA, Hampton, VA, and Boston, MA. These locations are much more typically associated with space activity and some certainly may have grown without NASA’s research presence during the Cold War era. Again, the Northeast features the largest levels of NASA market patents.<sup>28</sup> Compared to 1958, however, areas with a large number of market-level patents are much more dispersed across the country, with high levels of market patents in the Midwest, West Coast, and parts of Texas.

Map 1 shows that much NASA patenting occurred in areas that did not have higher NASA activity in 1958. This highlights the possibility that NASA patents may have flowed to areas that were poised to grow anyway and highlights the value of being able to control

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(2019b) data.

<sup>26</sup>We build a cross-walk between fips counties and state-city name text field from the USPTO patent technology team database (<https://bulkdata.uspto.gov/data/patent/ptmtdvd/>). This database has assigned each address on a patent from 1969 to 2014 to a fips county. While most city-state text fields are assigned to a unique location, a few are not. For those that are not we assign the city-state text to the largest county listed.

<sup>27</sup>We report the list of top 10 counties for NASA local and market patents in appendix figure A1.

<sup>28</sup>We present region specific maps in appendix figure A2. Here the importance of Boston in the Northeast, Cleveland in the Midwest, and Los Angeles in the West becomes easier to see.

for location specific trends in our empirical analysis.<sup>29</sup>

We next assign patents based on their patent technology code to the relevant two-digit SIC industry code. We use the crosswalk in Lybbert and Zolas (2014) to match each patent’s technology class to the most likely two-digit industry code.<sup>30</sup> Figure 2 shows that NASA patents are over-represented in electrical technology areas and under-represented in mechanical or miscellaneous technology areas. We present a more detailed analysis in appendix figure A4 which shows that NASA patents are over-represented in chemicals, fabricated metals, machinery, and electronics industries, while under-represented in wood products, furniture, paper, printing, and leather industries.

**Manufacturing Data.** The primary data we use to estimate the impact of NASA research 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. 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, we do not examine later years of data. 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 two-digit SIC industries (1972 definition) in the county as the unit of analysis.<sup>31</sup>

**Transportation Costs Data.** We measure  $\tau$  using county-to-county transportation costs in 1960 (Jaworski and Kitchens 2019). This measure is based on Rand McNally’s atlas of the 1959 highway network to compute the travel costs between all county pairs in the contiguous United States. Transportation costs are computed by measuring the road surface, taking into consideration historical travel speeds on specific road surface types, and legislated speeds. Monetary travel costs are obtained by using the per mile wage of a truck driver multiplied by the travel time plus the per mile fuel cost times the distance. Our

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<sup>29</sup>We present maps for each year in Appendix Figure A3. In these maps we see that the level of NASA patents were higher after the second world war than the dawn of the Space Race. We also see that the changes between 1958 and 1972 are gradual with NASA patenting growing in locations such as Cleveland and Virginia where NASA pre-cursor research centers were already located. From there NASA research expands in California, the North East and South. After 1972 the locational distribution of NASA patenting is largely stable.

<sup>30</sup>Not all patents are assigned to a manufacturing industry. In our data about 70% of NASA patents are assigned to a manufacturing industry.

<sup>31</sup>The census of 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. A smaller fraction of missing values results when using the 2-digit level data.

measure of  $\tau$  captures county-to-county monetary transportation costs.<sup>32</sup>

**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 in various locations, and defense spending. Details of the construction and source of each variable are in the data appendix.

**Sample Selection and Descriptive Statistics.** We select our sample of counties and industries to capture major urban labor markets that we observe in 1958 and other years. Few county-industry cells report in every year of the manufacturing census. Data may not be reported because the number of establishments was below the threshold for confidentiality or because there was no activity in the county-industry cell in a given year. To address this issue we require that a county-industry cell must report in at least five years – half of our sample years. A separate issue in the data is a few extreme values where a county has a much larger wage bill than value added. We address this issue by trimming the sample of observations where the wage bill to value added ratio is above 3. Our analysis sample contains 16,555 county-industry observations from 621 counties and 20 two-digit SIC industries from 1947 to 1992.

Table 1 provides a first look at summary statistics of relevant measures in 1958, the first year immediately after Sputnik was launched. Column (1) presents the means and standard deviation of key variables for the full sample. Because the Space Race had not yet occurred in 1958, we stratify locations based on whether local- or market-level NASA patenting occurred after 1958. In columns (2) and (3) we stratify based on whether post-1958 local NASA patents existed in an county-industry cell or not. In columns (5) and (6) we stratify based on whether a location had a below- or above-median maximum market-level NASA patenting in a county-industry cell.

Table 1 shows that firms that would later be exposed to either local or market NASA patents were quite different before the Space Race compared to those firms that would not. Columns (2) and (3) show that those that will be exposed to local NASA patents were generally larger, more patent intensive, and in counties that were more populous with a higher skilled population. Similarly, we see in columns (5) and (6) that those that will be exposed to more market NASA patents were larger, more patent intensive, located in larger population and more skilled counties. These significant differences in levels highlight the importance of controlling for location and location-specific fixed effects in our analysis. An important

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<sup>32</sup>See Jaworski and Kitchens (2019) for further details.

concern remains that prior trends in manufacturing could predict NASA patenting. We present results allaying concerns about this possibility when we discuss our main results below.

## 5 Results

**Main Results.** Our main results estimating the impacts of local and market NASA patents are reported in Table 2. In columns (1) we see that local NASA patents in the same industry lagged five years (one manufacturing census) increased value added, demonstrating a local technological spillover effect from public R&D. This finding is to be expected given the large literature on local spillover effects from R&D. The negative market-level spillovers of NASA patents reported in column (2) indicate that the cross-county business stealing effects dominated any cross-county knowledge spillover effects.

Including both variables measuring the market-level innovation effect and the local spillover effect does not seem to influence each of their independent effects on value added. The results reported in column (3) show little change in the respective coefficients when both variables are jointly included in the estimation. The effects also change little when we add controls for industry $\times$ year fixed effects in column (4) and county $\times$ year as well as industry $\times$ year fixed effects in column (5).<sup>33</sup> That our results are robust to flexibly controlling for industry or location time-fixed effects indicates that unobserved industry or location trends are not central to our results.<sup>34</sup> This outcome is important as NASA research was concentrated in relatively few locations or industries.

Our method utilizes a geographically defined market coupled with an estimate of the trade elasticity to obtain market-level NASA patents. In Appendix Table A2 we consider our estimates in alternative samples and market measures.<sup>35</sup> Our local and market NASA

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<sup>33</sup>We check the sensitivity of our results to outliers by dropping one industry or one state region at a time. We report the industry results in appendix figure A5. Here we see that the results are highly robust to dropping a single industry, as the local and market effects change little. In Appendix figure A6 we drop one state a time from the analysis. We see that the results are highly stable with regards to dropping a single state, only substantively changing when a very large state such as California or New York is dropped from the sample.

<sup>34</sup>A possible concern is the use of the Arcsign instead of logarithmic transformation of patents. We show in appendix table A1 that the results are very similar if we instead use a logarithmic transformation of the patent value plus one. We prefer the arcsign transformation because it explicitly accommodates values of zero rather than requiring an ad hoc adjustment (i.e., +1) to include these observations in the sample.

<sup>35</sup>In column (2) we restrict the sample to just the county-industry cells that report in every year of our data. Our local and market NASA patent point estimates are very similar to our main sample in column (1).



patent variables are constructed using only own-industry variation. In Appendix Table A3 we show there is little evidence of cross-industry effects similar to the results in Moretti (2019). In sum, the central conclusions of our analysis do not depend on specific samples, market definitions, or values of the trade elasticity.

**Prior Trends.** A potential concern with our estimates thus far is that NASA patents may be endogenous to firm outcomes. It could be the case, for example, that unobserved shocks to an industry-county cell drive NASA patents. While our reading of the historical evidence indicates that NASA research did not follow trends in the productivity of manufacturing firms, exploring pre-trends is an important specification check.

We test for evidence of pre-trends in value added by including leads and lags of both patent variables in our main specification by estimating a dynamic version of our baseline model:

$$\log(Y_{ijt}) = \gamma_1 + \sum_{t-20}^{t+20} \gamma_{2,x} \text{arcsignh}(LocalS_{ijt-x}) + \sum_{t-20}^{t+20} \gamma_{3,x} \text{arcsignh}(MarketS_{ijt-x}) + \psi_i + \psi_j + \psi_t + \epsilon_{ijt} \quad (16)$$

where again  $i = \textit{county}$ ,  $j = \textit{industry}$ , and  $t = \textit{year}$ , and  $\psi_i, \psi_j, \psi_t$  are county, industry, and year fixed effects. The lagged effect of local public R&D that we estimate above is captured by  $\gamma_{2,t-5}$ . The lagged effects of market R&D that we estimate above are captured by  $\gamma_{3,t-5}$ . Our coefficients of interest in this analysis are the leads of the local effects,  $\gamma_{2,t+5}, \gamma_{2,t+10}$ , and the leads of the market effects,  $\gamma_{3,t+5}, \gamma_{3,t+10}$ . We would expect these coefficients to be zero if pre-trends in value added within an industry-county fail to predict later trends in NASA patenting.

We present the results graphically in Figure 4. In each panel we plot the coefficient

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We then examine how our results change if we construct NASA market measures at the county instead of county  $\times$  industry level. In column (3) we see that our local effects are strengthened and the market effects are diminished, though both remain statistically significant at the 5% level. This outcome may result because cross-industry technological spillovers effects are positive while business stealing effects are concentrated in the same industry. An important parameter in constructing our market-level NASA patent measure is the trade elasticity  $\theta$ . For our baseline measure we use  $\theta = 8.28$ , the preferred estimate in Eaton and Kortum (2002). This value is also very close to the trade elasticity in Donaldson and Hornbeck (2016) of  $\theta = 8.22$ . To assess the importance of this specific value of the trade elasticity for our findings we consider a low value of  $\theta = 3.60$  and a high value of  $\theta = 12.86$ , covering the upper and lower values in Eaton and Kortum (2002). In column (4) we see that for a smaller value of the trade elasticity the point estimates for both the local and market NASA effects are closer to zero, though the market point estimate changes much more. This outcome would be expected as a lower trade elasticity implies that trade is less responsive to shocks leading to a weaker cross-area business stealing effect. When we consider a higher value for the trade elasticity in column (5) we see that the market NASA patents effect and the local NASA patent effects are slightly larger than those in the baseline.

estimates with their 95% confidence intervals for two leads and lags of each of NASA patent variables. The estimates in the first row of figures are from the same model, though we present them separately for ease of visualization. The estimates show little evidence of statistically significant pre-trends for local NASA patents (Panel 1A) or market NASA patents (Panel 1B) in our baseline model. When we add industry $\times$ year fixed effects in panels 2A and 2B the pre-trend coefficients move closer to zero and the first and zero lag coefficients become more statistically significant. When we control for industry $\times$ year and county $\times$ year fixed effects the results become tighter with the point estimates of the statistically insignificant pre-trends moving closer to zero and the first lag (in Panel 3A) and zero lag (in Panel 3B) estimates becoming more pronounced. We present the results in table form in appendix table A4. These results provide substantial reassurance that our central estimates are not picking up unobserved trends driving both NASA patenting and local manufacturing value added.

**Military and Skill Controls.** The Cold War period in the United States featured dramatic expansions in military sponsored innovation and skill accumulation. Both factors may have been important for the growth of manufacturing output and potentially correlated with the rise of NASA patenting.<sup>36</sup> A simple approach to address this concern is to control for these factors at the county or preferably county $\times$  industry level.

In Table 3 we add controls for military innovation and spending. 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 $\times$ industry level. Controlling for these patents in columns (2) and (3) of Table 4 does little to alter our estimates.<sup>37</sup> Another important control to consider is county-level military spending. A county-level measure is unavailable before 1966, so we create a county-level series back to 1940 using annual state-level defense spending allocated to counties based on their actual shares of contracting within their respective states in 1967 (see details in the data appendix). Controlling for county-level military spending also has little effect on our results. Our last model takes advantage of data on a cross section of research scientists in 1962 that include information on their location and whether they received military funding for their research. When we add controls for

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<sup>36</sup>Nelson and Wright (1992) note that NASA was just one element of Cold War research spending in the military-industrial complex. Similarly, Griliches (1979) discusses the challenge of separately identifying the effects of NASA research from those sponsored by other government agencies. Gross and Sampat (2020) find persistent effects of WWII OSRD research. A number of authors have found skill to be important in predicting where post-WWII economic growth occurred in the United States. See Glaeser and Gottlieb (2009) and Moretti (2012) for a discussion.

<sup>37</sup>This may be expected as the spatial correlation between military patents and NASA patents turns out to be quite small. See appendix table A5.

defense scientist×year fixed effects in column (5) our results change little.

In Table 4 we add controls for worker skill. In the first column we add controls for the fraction of manufacturing workers that were non-production workers since the fraction of managers or engineers in a firm is a useful measure of skill. This measure is the only available indicator of skill that we have at the county×industry×year cell. Our results change little when we add these variables as controls in column (2). This measure of skill has the advantage that it is measured at the same unit of observation as our outcome variable. It has the disadvantage that it likely captures occupational as well as years of schooling variation. In column (3) we add controls for years of schooling at the county level from the decennial census. In column (4) we add a control for the number of research scientists×year to capture differential trends in upper-initial-tail human capital. Lastly, in column (5) we add a control for the number of IBM mainframes in 1961×year to capture differential trends by installed advanced information technology in a location that may reflect a highly skilled population. The results change little across these variety of experiments. Our results appear highly robust to controls for military activity and local human capital.

**Instrumental Variables and Heterogeneity.** Our estimates display little evidence of pre-trends and are robust to important controls for military R&D and skill, yet we may still be concerned about unobserved common shocks. To address this concern we develop a shift share instrumental variables approach based on two ideas. First, we assume that locations of NASA-relevant technologies prior to the Space Race were driven by local technological advantages independent of future NASA research growth to come after Sputnik. Second, the timing of the technologies that NASA required to complete its various missions was driven by demands from the Space Race, not the availability of technologies. Conceptually, we follow Jaravel et al. (2020) in thinking of the share as predetermined and the time series of the NASA patents by technology as exogenous. The idea is that the areas of technology in which NASA patented were determined by national scientific and engineering needs and these were exogenous to local trends in manufacturing.

Our first stage model is thus:

$$\begin{aligned} \text{arcsigh}(LocalS_{ijt-5}) = & \lambda_1 + \lambda_2 \text{arcsigh}\left(\sum_{ij} LocalUSPC_{ijut-5} \times NationalNASAUSPC_{ut-5}\right) \\ & + \lambda_3 \text{arcsignh}(MarketS_{ijt-5}) + \eta_i + \eta_j + \eta_t + \epsilon_{ijt} \end{aligned} \tag{17}$$

where  $i = county$ ,  $j = industry$ , and  $t = year$ , and  $\eta_i$ ,  $\eta_j$ ,  $\eta_t$  are county, industry and year

fixed effects.  $LocalUSPC_{ijut}$  is the share of USPC technology area  $u$  in county  $i$  and industry  $j$  in period  $t-5$  (the previous manufacturing census year) and  $NationalNASAUSPC_{ut}$  is the national level of NASA patenting in USPC technology area  $u$  in year  $t-5$ . We summarize this product to create our shift share IV at the county-industry-year level. We do not instrument for  $MarketS_{ijt-5}$  as it is a weighted average of NASA patenting in other locations.<sup>38</sup> We require that  $\lambda_2$  is positive and highly statistically significant to be a strong instrument.

In Table 5 we estimate our model using this shift share instrumental variables procedure. In column (1) we see that our shift share IV estimates are similar to those in our baseline model above. The point estimate on local NASA patents is positive and statistically significant with a slightly larger magnitude than the baseline model. The point estimate and statistical significance for the market NASA coefficient is remarkably similar to those above.<sup>39</sup>

Our next results stratify the sample to examine heterogeneous responses. We consider two stratifications where we expect stronger and weaker effects. In columns (2) and (3) we stratify by whether the industry-county cell had any patents before 1958. Firms that are patent intensive should have larger effects since public and private knowledge stocks are complements. We find only statistically significant effects for patent intensive industries. In columns (4) and (5) we stratify by output weight to value ratio. Firms with a low weight to value ratio likely faced a market that was geographically larger and more likely to be affected by market level NASA patents. This result is indeed what we find. All of the statistically significant results are for the low output weight to value industries. Our IV and heterogeneity results further strengthen the causal interpretation of our main results.

**Labor Markets, Productivity, and Private Sector Patents.** Our next analysis looks at the effects of NASA patents of employment, labor income, productivity, and private sector patents. In Table 6 we find that the effects of both local and market NASA patents on employment are quite similar to those we found for value added. Columns (1)-(3) show a positive local spillover effect from local NASA patents and a negative effect of market NASA patents. In columns (4)-(6) we find little evidence of a local NASA spillover effect on labor income, though there is some evidence of a response to market NASA patents. When inputs are highly mobile in response to local technological shocks, we may expect to see

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<sup>38</sup>Recall in constructing the market measure that we exclude patents in the reference industry and location from the calculation.

<sup>39</sup>Because our NASA market measure is constructed using NASA patent information from a weighted average of other locations, endogeneity is much less of a concern than for the local NASA patent measure. We, therefore, do not instrument for market level NASA patents.

little in terms of the effects on measured total factor productivity using the methods from Akerberg, Caves, and Frazer (2015).<sup>40</sup> As reported in Table 7 we find little effect of local- or market-level NASA patents on measured TFP.<sup>41</sup> That the value added results are driven primarily by labor flows across regions and industries further highlights the importance of considering general equilibrium effects in determining the aggregate impacts of innovation policy (Chodorow-Reich, 2020).

In Table 8 we ask whether NASA innovations crowded in or out other private sector innovation. On the one hand, basic NASA research may have stimulated private investment in complementary applied technologies. On the other, NASA research may have raised the costs of research inputs and reduced private sector innovation. In Table 8 we find that NASA research generated local crowd in whether we use all non-NASA or only private sector patents as the outcome variable.<sup>42</sup>

## 6 Aggregate Impacts

What was the long-term effect of Space Race research on aggregate manufacturing value added? To answer this question we consider the cumulative impact of NASA patents during the Space Race on manufacturing value added in 1977. We conduct a simple back of the envelope calculation to estimate how much lower manufacturing value added would have been in 1977 if the NASA research embedded patents between 1958 and 1972 had not happened.

**Cumulative Models.** We estimate a model similar to our baseline model as:

$$\log(VA_{ijt}) = \beta_1 + \beta_2 \text{arcsignh}(\text{Cumulative}S_{ijt-x}) + \beta_3 \text{arcsignh}(\text{Cumulative}MA_{it-x}) + \psi_i + \psi_j + \psi_t + \epsilon_{ijt} \quad (18)$$

where  $i = \text{county}$ ,  $j = \text{industry}$ , and  $t = \text{year}$ , and  $\psi_i$ ,  $\psi_j$ ,  $\psi_t$  are county, industry and year fixed effects.  $\text{LocalCumulativeNASAPatents}_{ijt-x}$  measures the total number of local

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<sup>40</sup>The methods and data we use to estimate productivity are in online appendix section 3. Our data and methods recover revenue based productivity. As such they can reflect effects of both price and technological changes. Our revenue based approach may underestimate NASA driven technological changes as Baum-Snow, Gendron-Carrier, and Pavan (2020) show revenue-based productivity estimates understate local technological spillovers between Canadian firms.

<sup>41</sup>In a similar vein Kantor and Whalley (2019) find that agricultural research in the late 19th and early 20th centuries had larger effects on land productivity than measured total factor productivity. As much of their analysis relates to a time period before migration costs dropped with the diffusion of the automobile and telephone and the development of the interstate highway system, we would expect factors to be much more mobile in the Space Race era.

<sup>42</sup>These results are consistent with Akcigit, Hanley, and Serrano-Velarde (2019)

NASA patents since 1930 in the industry-county cell.  $MarketCumulativeNASAPatents_{it-x}$  measures the total number of market NASA patents since 1930 in the industry-county cell. The effect of cumulative local NASA patents is captured by  $\beta_2$ . The effects of market NASA patents are captured by  $\beta_3$ .

**Space Race Counterfactuals.** We present estimates for three versions of the cumulative model in Table 9. We find positive effects of local NASA patents and negative effects of NASA market patents in all three columns of Panel A as expected. We then turn to Panel B that shows what the estimates in panel A imply for the counterfactual level of manufacturing value added in 1977 had the NASA patents from 1958 to 1972 not occurred.<sup>43</sup>

Our estimates in Panel B are economically meaningful, ranging from a loss of 11% to 17% of 1977 value added had NASA patenting from 1958 to 1972 not happened. As there is little research that has provided estimates for similar programs, we consider the implied social rate of return to public R&D to compare our results to prior work. A simple back of the envelope calculation suggests that our estimates imply a rate of return on NASA spending between 50-74 percent.<sup>44</sup> Our social rate of return estimates are comparable to what the literature finds for the social returns to private innovation.<sup>45</sup> Our simple calculation is subject to many

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<sup>43</sup>To do so we calculate the implied difference in 1977 Value Added Without 1958-1972 NASA Patents using both the local and market effects,  $\Delta_{L+M}^{1977}$ , as:

$$\Delta_{L+M}^{1977} = \beta_2 \overline{(1972-1958 \text{ Percent Change in Cumulative } S_{ij})} + \beta_3 \overline{(1972-1958 \text{ Percent Change in Cumulative } MA_{ij})} \quad (19)$$

Where  $\overline{(1972-1958 \text{ Percent Change in Cumulative } S_{ij})}$  is the sample average of the 1958 to 1972 percentage change in cumulative local NASA patents and  $\overline{(1972-1958 \text{ Percent Change in Cumulative } MA_{ij})}$  is the sample average 1958 to 1972 percentage change in cumulative market NASA patents. To understand the implications of including market level effects in our analysis we also calculate the implied difference in 1977 Value Added Without 1958-1972 NASA Patents using only the local effects,  $\Delta_L^{1977}$ , so that,  $\Delta_L^{1977} = \beta_2 \overline{(1972-1958 \text{ Percent Change in Cumulative } S_{ij})}$ .

<sup>44</sup>We use our estimates for the aggregate effects in 1997 to estimate the implied rate of return on NASA spending from 1958 to 1972. Our aggregate effects coupled with an aggregate value added in manufacturing in 1977 in nominal terms (585 \$1977 Billion) imply that value added,  $VA_{1958-1972}^{1977\$}$ , was between 64 \$1977 Billion and 94 \$1977 Billion. To calculate the rate of return we need an estimate of the cost. We first use the GDP deflator to put NASA spending in each year from 1958 to 1972 in 1977 \$ and term this  $NASA_t^{1977\$}$ . We then use a 4% discount rate to calculate the discounted cost for the 1977 value added impact of the Space Race. We construct the discounted costs of 1958 to 1972 spending in 1977\$ with the formula  $C_{1958-1972}^{1977\$} = \sum_{x=1}^{20} NASA_{1977-x}^{1977\$} \times (1.04)^x = 127\$1977 \text{ Billion}$ . The rate of return,  $R$  is given by the ratio of value added increase over the discounted cost so that  $R = \frac{VA_{1958-1972}^{1977\$}}{C_{1958-1972}^{1977\$}}$ . We obtain estimates of  $R = 0.50$  and  $R = 0.78$ .

<sup>45</sup>Model driven approaches in Jones and Williams (1998) and Jones and Summers (2020) provide estimated macroeconomic social returns of over 40%. Microeconomic case studies such as the seminal Griliches (1958) results imply a internal rate of return of at least 35%. Firm-level analyses of research and development, such as Bloom, Schankerman and Van Reenen (2013), imply an estimated social return of 55%.

caveats as it implicitly assumes that all of the benefits associated with NASA research were embodied in patents and implicitly excludes other important benefits such as geopolitical gains or even enhanced national pride having landed on the Moon first.<sup>46</sup>

## 7 Conclusion

We develop a spatial equilibrium approach to quantifying the aggregate effects of public research and development expenditures from spatial data. In our model public research directly increases the local knowledge stock, thus making local firms more productive and larger. Indirect effects operate through trade between firms. When trading partners' knowledge stock is increased by public research in their locations, they can steal business from firms located in the location of interest, thus making them smaller. Public R&D may also provide technology spillovers to firms in other regions through trade which makes those firms more productive and larger. We investigate the importance of direct and indirect effects, and their implications for the aggregate returns to public research, empirically.

The natural experiment of Space Race innovation, coupled with new Census of Manufactures data at the county-industry level from 1947 to 1997, is used to estimate our models. Our analysis reveals that NASA patents had significant aggregate effects on manufacturing value added. The results imply that aggregate value added in manufacturing would have been 11% to 17% lower in 1977 had Space Race innovation not occurred. Because cross-area product market rivalry effects were significant, allowing for the presence of inter-regional spillovers implies much smaller aggregate economic gains from public RD than would be derived from considering local spillovers alone.

A major challenge in evaluating large scale productivity and innovation policy is constructing credible counterfactuals using aggregate data alone. We see our approach to leverage spatial data as applicable across a broad range of contexts. Limitations of our analysis also suggest directions for future research. A dynamic approach that endogenizes private innovation in response to public investments would be useful extension. Extending the model to understand the role of spatial frictions in determining the returns to public research would also be an exciting avenue for future inquiry.

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<sup>46</sup>Returning to Fogel's (1966) comparison between the aggregate effects of the railroads and the space program is interesting. Recent work in Hornbeck and Rotemberg (2019) estimates the aggregate annual social rate of return to railroad spending as 43%, largely due to reallocation based productivity improvements. Their estimate lines up quite closely with an annual social rate of return estimate for space race spending.

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Table 1: Descriptive Statistics, 1958

Sample:	Full	Max Local NASA Patent>0			Max Market NASA Patent		
		Yes	No	(2)-(3) Difference	Above Median	Below Median	(5)-(6) Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Panel A: 1958 Manufacturing Census</i>							
Value Added (\$Millions)	39 (101)	89 (181)	28 (68)	3.53 [0.000]	54 (125)	25 (68)	4.24 [0.000]
Employment	2,625 (7,525)	5,734 (15,572)	1,935 (3,592)	2.95 [0.003]	3,464 (10,065)	1,827 (3,594)	3.38 [0.001]
<i>Panel B: 1958 Cumulative Patent Counts Over Prior Five Years</i>							
Total	34 (110)	118 (221)	16 (46)	4.41 [0.000]	59 (150)	11 (33)	4.35 [0.000]
Government Assigned	19 (40)	50 (65)	12 (27)	3.99 [0.000]	26 (47)	11 (30)	4.78 [0.000]
Army Assigned	0.44 (1.21)	1.00 (2.01)	0.31 (0.90)	2.80 [0.005]	0.64 (1.49)	0.24 (0.82)	4.66 [0.000]
Navy Assigned	0.55 (1.49)	1.49 (2.64)	0.35 (0.98)	3.42 [0.001]	0.77 (1.78)	0.35 (1.13)	3.39 [0.001]
<i>Panel C: 1960 Population Census</i>							
Population	529,419 (860,565)	1,107,436 (1,420,953)	401,053 (605,812)	2.73 [0.007]	659,467 (988,677)	405,603 (695,927)	3.65 [0.000]
Years of Schooling	10.66 (1.17)	11.31 (0.93)	10.52 (1.16)	7.66 [0.000]	10.78 (1.01)	10.55 (1.28)	2.93 [0.004]
Median Family Income	5,887 (1,137)	6,634 (876)	5,721 (1,122)	10.47 [0.000]	6,236 (972)	5,555 (1,183)	9.93 [0.000]
Rent	70 (14)	79 (11)	68 (14)	9.37 [0.000]	74 (13)	66 (14)	8.94 [0.000]
n	1,915	348	1,567		934	981	

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column reports the results from one estimate of equation (14) with only the leads and lags for the indicated NASA innovation present, not both at the same time. All models include year, 2 digit industry and county fixed effects.



Table 2: NASA Patents and Value Added

Dependent Variable= Model:	Log (Value Added)				
	Baseline	Baseline	Baseline	Industry Trends	Industry & County Trends
	(1)	(3)	(3)	(4)	(5)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.11*** (0.03)		0.12*** (0.04)	0.12*** (0.04)	0.10** (0.05)
ArcSign(Market NASA Patents) <sub>t-5</sub>		-0.11*** (0.04)	-0.15*** (0.05)	-0.23*** (0.07)	-0.18** (0.08)
Observations	17,501	16,555	16,555	16,550	14,430
R <sup>2</sup>	0.69	0.69	0.69	0.71	0.73
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	No	No	Yes	Yes
County × Year Fixed Effects	No	No	No	No	Yes

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 3: NASA Patents and Value Added – Military Controls

Dependent Variable= Additional Controls:	Log (Value Added)				
	None	Army Patents	Navy Patents	Military Spending	Defense Scientist Trends
	(1)	(2)	(3)	(4)	(5)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.12*** (0.04)	0.10** (0.04)	0.09** (0.04)	0.10*** (0.04)	0.16*** (0.05)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.15*** (0.05)	-0.15*** (0.05)	-0.14*** (0.05)	-0.15*** (0.05)	-0.15*** (0.05)
Observations	16,555	16,555	16,555	15,149	16,555
R <sup>2</sup>	0.69	0.69	0.69	0.69	0.69
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 4: NASA Patents and Value Added – Skill Controls

Dependent Variable= Additional Controls:	Log (Value Added)				
	None	Skilled Worker Share	Years of Schooling	Scientist Trends	IBM Mainframe Trends
	(1)	(2)	(3)	(4)	(5)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.12*** (0.04)	0.12*** (0.04)	0.12*** (0.04)	0.14*** (0.04)	0.11*** (0.04)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.15*** (0.05)	-0.15*** (0.05)	-0.15*** (0.05)	-0.13*** (0.04)	-0.13*** (0.05)
Observations	16,555	13,901	15,149	16,555	16,555
R <sup>2</sup>	0.69	0.69	0.69	0.69	0.69
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 5: NASA Patents and Value Added – Instrumental Variables and Heterogeneity

Dependent Variable= Stratify by:	Log (Value Added)				
	None	Patents Per Employee 1958		Output Weight-Value Ratio	
		No	Yes	Above Median	Below Median
Estimation	IV	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.20** (0.10)	-0.06 (0.22)	0.13*** (0.04)	0.03 (0.04)	0.20*** (0.08)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.17*** (0.05)	-0.06 (0.09)	-0.15*** (0.05)	-0.04 (0.05)	-0.26*** (0.08)
Observations	16,555	5,234	11,221	7,547	9,008
R <sup>2</sup>	0.69	0.62	0.70	0.73	0.69
First Stage F-Statistic	22.23 [0.0000]				
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 6: NASA Patents, Employment, and Labor Income

Dependent Variable= Model:	Log (Employment)			Log(Annual Labor Income)		
	Baseline	Industry Trends	Industry & County Trends	Baseline	Industry Trends	Industry & County Trends
	(1)	(3)	(3)	(4)	(5)	(6)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.12*** (0.04)	0.12*** (0.05)	0.12*** (0.05)	-0.05 (0.02)	-0.04 (0.03)	-0.01 (0.01)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.17*** (0.05)	-0.25*** (0.07)	-0.21*** (0.08)	0.11*** (0.04)	0.08* (0.04)	0.03 (0.04)
Observations	16,555	16,550	14,430	16,555	16,550	14,430
R <sup>2</sup>	0.56	0.57	0.61	0.35	0.38	0.44
Additional Controls:						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
County × Year Fixed Effects	No	No	Yes	No	No	Yes

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 7: NASA Patents and Revenue Productivity

Dependent Variable= Model:	Revenue Productivity: Cobb-Douglas			Revenue Productivity: Trans-Log		
	Baseline	Industry Trends	Industry & County Trends	Baseline	Industry Trends	Industry & County Trends
	(1)	(3)	(3)	(4)	(5)	(6)
ArcSign(Local NASA Patents) <sub>t-5</sub>	-0.02 (0.04)	-0.02 (0.03)	0.01 (0.06)	0.01 (0.09)	-0.01 (0.08)	0.04 (0.13)
ArcSign(Market NASA Patents) <sub>t-5</sub>	0.00 (0.05)	0.02 (0.05)	0.05 (0.06)	-0.03 (0.07)	-0.08 (0.08)	-0.03 (0.08)
Observations	9,742	9,738	8,461	9,742	9,738	8,461
R <sup>2</sup>	0.96	0.97	0.83	0.79	0.81	0.83
Additional Controls:						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
County × Year Fixed Effects	No	No	Yes	No	No	Yes

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 8: NASA Patents and Other Patents

Dependent Variable= Model:	ArcSign(Non-NASA Patents)			ArcSign(Private Sector Patents)		
	Baseline	Industry Trends	Industry & County Trends	Baseline	Industry Trends	Industry & County Trends
	(1)	(3)	(3)	(4)	(5)	(6)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.11*** (0.03)	0.12*** (0.03)	0.09*** (0.03)	0.11*** (0.03)	0.12*** (0.03)	0.09*** (0.03)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.06 (0.04)	-0.11*** (0.04)	0.00 (0.03)	-0.06 (0.04)	-0.11*** (0.04)	-0.01 (0.03)
Observations	16,555	16,550	14,430	16,555	16,550	14,430
R <sup>2</sup>	0.84	0.85	0.92	0.84	0.85	0.92
Additional Controls:						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
County × Year Fixed Effects	No	No	Yes	No	No	Yes

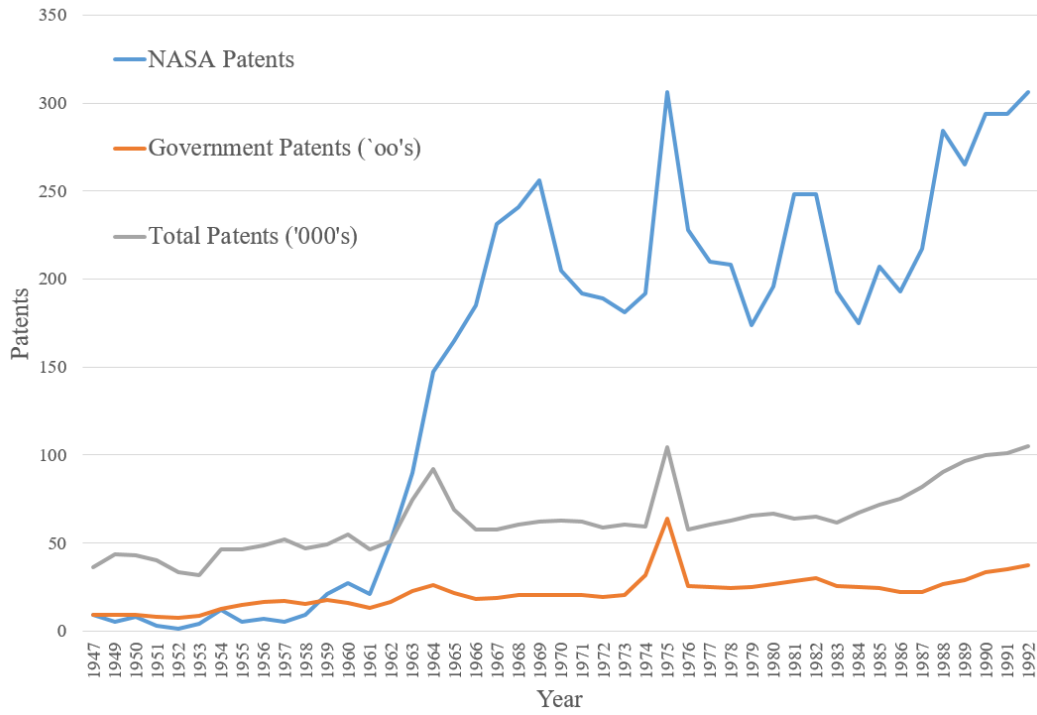
Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table 9: Cumulative NASA Patents and Value Added

Dependent Variable= Model:	Log (Value Added)		
	Baseline	Industry Trends	Industry + County Trends
	(1)	(2)	(3)
<i>Panel A: Regression Results</i>			
ArcSign(Local Cumulative NASA Patents) <sub>t-5</sub>	0.10*** (0.03)	0.09* (0.05)	0.11** (0.05)
ArcSign(Market Cumulative NASA Patents) <sub>t-5</sub>	-0.17*** (0.06)	-0.12* (0.06)	-0.19* (0.10)
Observations	16,555	14,432	14,430
R <sup>2</sup>	0.69	0.72	0.73
<i>Panel B: Counterfactuals</i>			
Implied Difference in 1977 Value Added Without 1958-1972 NASA Patents:			
Total Local + Market Effect	-13%	-17%	-11%
Only Local Effect	-46%	-41%	-48%
Additional Controls:			
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Industry × Year Fixed Effects	No	Yes	Yes
County × Year Fixed Effects	No	No	Yes

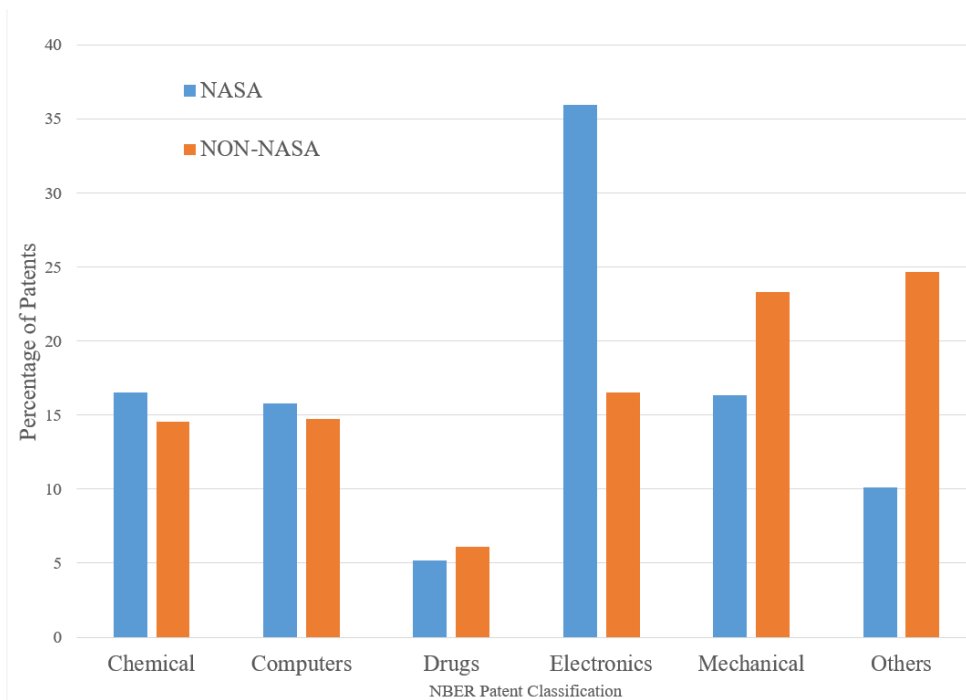
Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (17) with measures based on the total number of patents since 1930 in an industry-county cell. All models include year, 2 digit industry and county fixed effects.

Figure 1: Patents Time Series



Notes: Source authors calculation with USPTO, Histpat and Fleming (2019) data.

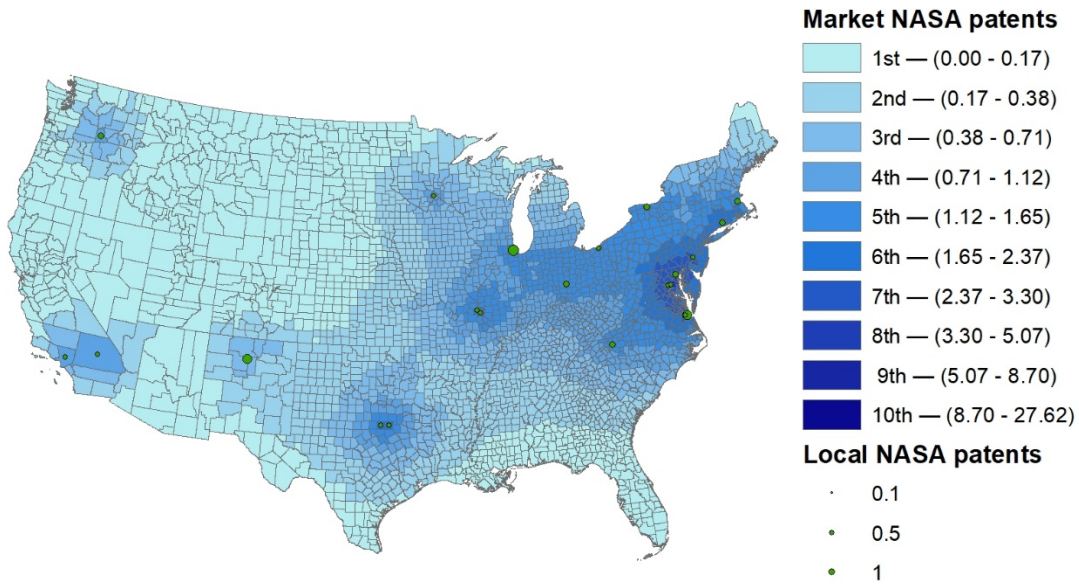
Figure 2: Patent Shares by NBER Technology Categorization



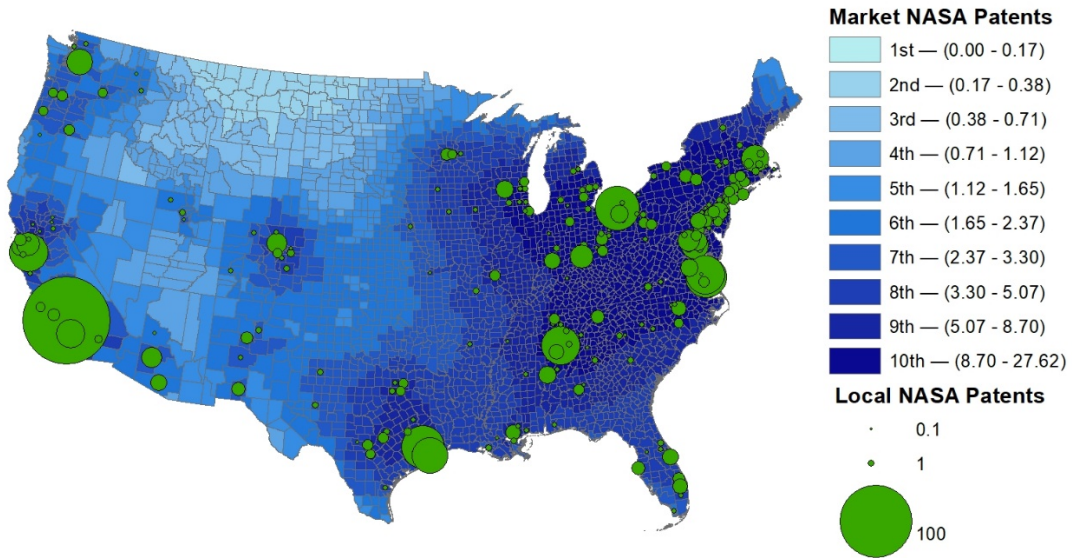
Notes: Source authors calculation with USPTO, Histpat and Fleming (2019) data.

# Map 1: NASA Local and Market Patents

A. 1958



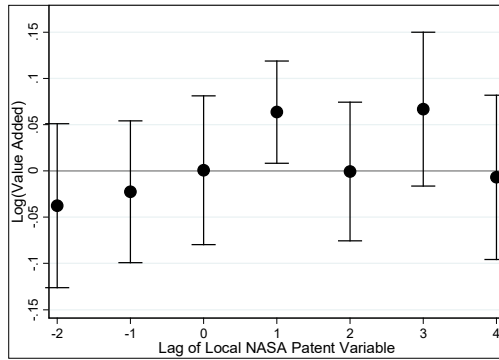
B. 1992



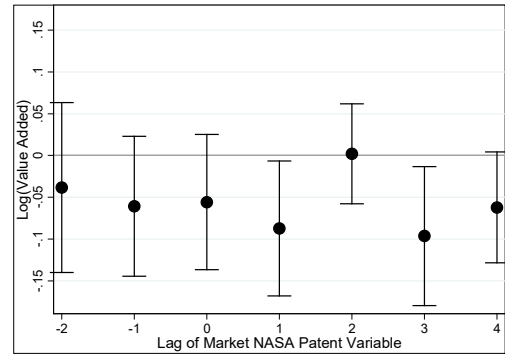
Notes: Source authors calculation with USPTO, Histpat and Fleming (2019) data. Local NASA patents are the total number of NASA patents over the previous 5 years in the county. Market NASA patents are the total number of NASA patents in for the counties market as defined in equation (12) in the text with  $\delta=0.11$ .

Figure 3: Dynamic Response

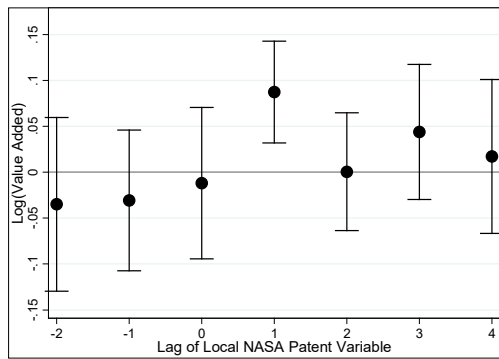
1A. Local NASA Patents Baseline



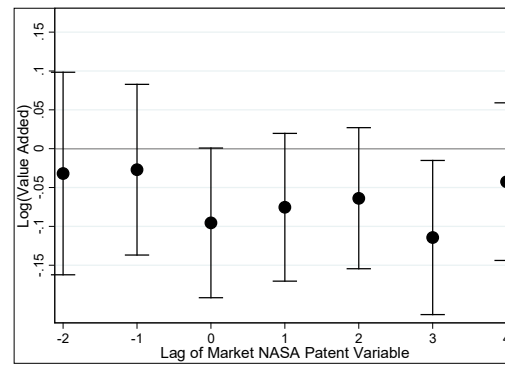
1B. Market NASA Patents Baseline



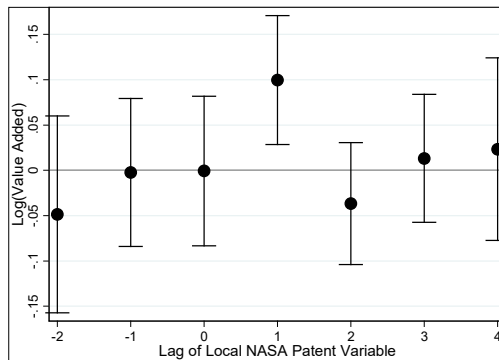
2A. Local NASA Patents with Industry Trends



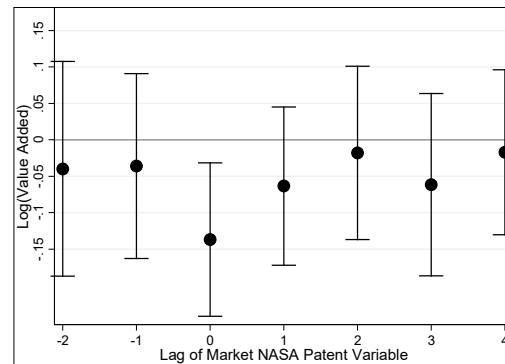
2B. Market NASA Patents with Industry Trends



3A. Local NASA Patents with Industry and County Trends



3B. Market NASA Patents with Industry and County Trends



Notes: Source: Authors' calculations with USPTO patent data and Manufacturing Census data from 1947 to 1992. The unit of observation is county-industry. The figures present estimates from dynamic versions of equation (XX) weighted by employment in 1958. Each figure plots coefficients and 95% confidence intervals for the model indicated. Panels 1A and 1B are for the baseline model with year, county and industry fixed effects. Panels 2A and 2B are for the industry trends model with year, county, and industry, and industry  $\times$  year fixed effects. Panels 3A and 3B are for the industry trends model with year, county, and industry, industry  $\times$  year, and county  $\times$  year fixed effects. The coefficients in panels 1A and 1B are for models that include dynamic effects of both local and market NASA patents, and are reported in Appendix Table A.?



Online Appendix for  
“Moonshot: Public R&D and Economic Development”

Shawn Kantor & Alexander Whalley

October 2020

## Contents

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# 1 Proof $\rho$ is Constant

Define key equations

$$FMA_o = \sum_d \tau_{od}^{-\theta} CMA_d^{\beta-1} Y_d \quad (\text{A1})$$

$$CMA_d = \left( \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \right)^{\frac{1}{1-\beta}} \quad (\text{A2})$$

and

$$FMA_o = \sum_d \tau_{od}^{-\theta} (FMA_d)^{-1} Y_d \quad (\text{A3})$$

and

$$FMA_o = \rho_o CMA_o^{1-\beta} \quad (\text{A4})$$

**Step 1:** Rearrange (A4) for  $CMA_o$ , change index from  $o$  to be  $d$  to sub in for  $CMA_d$  into (A1) so that:

$$FMA_o = \sum_d \tau_{od}^{-\theta} \left( \frac{FMA_d}{\rho_d} \right)^{\frac{\beta-1}{1-\beta}} Y_d \quad (\text{A5})$$

and

$$FMA_o = \sum_d \tau_{od}^{-\theta} (FMA_d)^{-1} Y_d \rho_d \quad (\text{A6})$$

**Step 2:** Substitute in for  $CMA_d$  into (A2) so that:

$$\left( \frac{FMA_d}{\rho_d} \right)^{\frac{1}{1-\beta}} = \left( \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \right)^{\frac{1}{1-\beta}} \quad (\text{A7})$$

then

$$FMA_d = \rho_d \sum_o \tau_{od}^{-\theta} FMA_o^{-1} Y_o \quad (\text{A8})$$

Changing indexes we get

$$FMA_o = \rho_o \sum_d \tau_{od}^{-\theta} FMA_d^{-1} Y_d \quad (\text{A9})$$

Noting that (A6) and (A9) are both expressions for  $FMA_o$ , we can see that only  $\rho_o = \rho_d = \rho$  can be a solution to this system of equations.

## 2 Variable Definitions and Sources

### 2.1 Manufacturing

**Value Added:** Total value added in the sector and location. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census.*

**Employment:** Total employment in the sector and location. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census.*

**Labor Income:** Average annual labor income in the sector and location. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census.*

**Skill Share:** Ratio of non-production to production workers in the sector and location. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census.*

**Revenue Productivity, Cobb-Douglas:** Estimated revenue productivity using a Cobb-Douglas value added production function with capital and labor as inputs. Estimated using the De Loecker and Warzynski (2012) implementation of the Akerberg, Caves, and Frazer (2015) method. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census; authors calculations.*

**Revenue Productivity, Trans-Log:** Estimated revenue productivity using a second degree Trans-Log value added production function with capital and labor as inputs. Estimated using the De Loecker and Warzynski (2012) implementation of the Akerberg, Caves, and Frazer (2015) method. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: U.S. Census Bureau (Various), Manufacturing Census; authors calculations.*

### 2.2 Patents

**Local Total Patents:** Total Patents over the previous 5 years. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); authors calculations.*

**Local NASA Patents:** Total NASA patents over the previous 5 years. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016)); Fleming, Greene, Li, Marx, and Yao (2019); USPTO (2020); authors calculations.*

**Local Army Patents:** Total Army patents over the previous 5 years. NASA patents are patents where either NASA is the assignee on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Navy Patents:** Total Navy patents over the previous 5 years. NASA patents are patents where either NASA is the assignee on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Patents per Employee, 1958:** Total patents over the previous 5 years divided by number of manufacturer employees in 1958. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Predicted NASA Patents, IV:** Total predicted NASA patents over previous 5 years based on local detailed technology share and NASA trends by detailed technology area= $\sum_c Share_{c,i,j,t} \times NASA_{c,t}$ . Where  $Share_{c,i,j,t}$  is the national share of a USPC technology class  $c$  in the industry-county cell in a given year and  $NASA_{c,t}$  is the total number of NASA patents in a USPC technology class in year  $t$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.*

*Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Non-NASA Patents:** Total Non-NASA patents over the previous 5 years. Patents where NASA is neither an assignee nor listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Government Patents:** Total government patents over the previous 5 years. Patents where the federal government is either an assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Private Sector Patents:** Total government patents over the previous 5 years. Patents where the federal government is neither an assignee nor listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Cumulative NASA Patents:** Total NASA patents since 1932. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year.* *Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Own NASA Patents:** Total NASA patents over the previous 5 years in own manufacturing sector. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Local Other NASA Patents:** Total NASA patents over the previous 5 years in all other manufacturing sectors. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); authors calculations.*

**Market NASA Patents:** Total NASA patents over the previous 5 years in own manufacturing sector and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{ijt-x} = \sum_d \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 8.28$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market Cumulative NASA Patents:** Total NASA patents since 1932 in own manufacturing sector and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketC_{ijt-x} = \sum_d \tau_{od}^{-\theta} C_{jd}^{\delta}$ . Where  $C_{ijd}$  is the total NASA patents since 1932 in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 8.28$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015);*

*Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market NASA Patent, County Level:** Total NASA patents over the previous 5 years in all manufacturing sector within in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{it-x} = \sum_{d,j} \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 8.28$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market NASA Patents, Low Theta:** Total NASA patents over the previous 5 years in own manufacturing sector and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{ijt-x} = \sum_d \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 3.60$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market NASA Patents, High Theta:** Total NASA patents over the previous 5 years in own manufacturing sector and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{ijt-x} = \sum_d \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 12.86$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley,*

*Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market Own NASA Patents:** Total NASA patents over the previous 5 years in own manufacturing sector and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{ijt-x} = \sum_d \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 8.28$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

**Market Other NASA Patents:** Total NASA patents over the previous 5 years in all other manufacturing sectors and in transportation cost defined market. NASA patents are patents where either NASA is the assignee or listed as a funder on the patent according to Fleming, Greene, Li, Marx, and Yao (2019) patent data before 1976 and using USPTO patents view government reliance after 1976.  $MarketS_{i-jt-x} = \sum_{d,-j} \tau_{od}^{-\theta} S_{jd}^{\delta}$ . Where  $S_{ijd}$  is the total NASA patents over the previous 5 years in industry  $j$  and location  $d$ ,  $\theta$  is the travel costs between locations  $i$  and  $d$  in 1960 according to Jaworski and Kitchens (2019),  $\delta = 0.097$  and  $\theta = 8.28$ . *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: Marco, Carley, Jackson and Myers (2015); Lybbert and Zolas (2014); USPTO (2013); Petralia, Balland, and Rigby (2016); Fleming, Greene, Li, Marx, and Yao (2019); USPTO(2020); Jaworski and Kitchens (2019); authors calculations.*

## 2.3 Population Census

**Population:** Total population of the county. *Unit of measurement: County  $\times$  year. Sources: Haines (2010).*

**Years of Schooling:** Average years of schooling of adults age 25+. *Unit of measurement: County  $\times$  year. Sources: Haines (2010).*



**Median Family Income:** Median household income. *Unit of measurement: County  $\times$  year. Sources: Haines (2010).*

**Rent:** Average gross rent. *Unit of measurement: County  $\times$  year. Sources: Haines (2010).*

## 2.4 Transportation Costs and Other

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

**Military Spending:** Total military contract spending by year. The 1947-1966 data is based on state level data allocated using 1967 sic2-county weights to each location and industry. The 1967 to 1992 data is based on totals on individual contracts over 10,000 at the sic2-county level. The earliest year for the state data is 1951. The data we use for 1947 is based on reported values in 1951. The post 1967 contract data only has industry in a few years. We use the federal supply codes for equipment cross walked to SIC2 industries to get the industry level data. *Unit of measurement: County  $\times$  SIC 2 digit  $\times$  year. Sources: USDOD(1975); USDOD(1981); USDOD(2007); authors calculations.*

**Defense Scientist:** Number of research scientists who have received funding from a defense agency before 1962. *Unit of measurement: County. Sources: National Register of Scientific and Technical Personnel (NRSTP) (1962).*

**Research Scientist:** Number of research scientists in 1962. *Unit of measurement: County. Sources: National Register of Scientific and Technical Personnel (NRSTP) (1962).*

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

**Weight-Value Ratio:** Weight divided by total value shipped from the Commodity Flow

Survey (cfs). *Unit of measurement: SIC 2 Digit Industry*. Sources: Duranton, Morrow, and Turner (2014).

### 3 Productivity Estimation

#### 3.1 Approach

We follow De Loecker and Warzynski (2012)'s implementation of the Akerberg, Caves, and Frazer (2015) method. We assume a production function that transforms inputs - labor and capital - into output - value added, so that

$$Y_{ijt} = f(K_{ijt}, L_{ijt}) \tag{A10}$$

We consider two functional forms for (A10). For ease of exposition here we focus on the Cobb-Douglas approach where value added is defined by,

$$Y_{ijt} = A_{ijt} K_{ijt}^{\beta_k} L_{ijt}^{\beta_l} \tag{A11}$$

where  $Y_{ijt}$  is value added at in county  $i$  industry  $j$  and year  $t$ ,  $K_{ijt}$  and  $L_{ijt}$  are inputs of capital and labor, and  $A_{ijt}$  is the Hicks-neutral efficiency level.

Taking logs of (A11) we obtain,

$$y_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + \underbrace{\omega_{ijt} + \eta_{ijt}}_{\epsilon_{ijt}} \tag{A12}$$

where lower cases refer to the natural logarithms of the levels,  $\beta_0$  is the mean efficiency across all industries, locations, and over time,  $\epsilon_{ijt}$  is the time-, industry-, and location-specific deviation from that mean. The shock can be further decomposed into two components. The component that is observed by the producer  $\omega_{ijt}$  - perhaps due to a product innovation or demand shock - and the component that is i.i.d representing deviations from the mean  $\eta_{ijt}$  due to unexpected tax changes or manager exit for example. The central econometric issue arises because of firms observed  $\omega_{ijt}$  and then make optimal input choices, leading to a correlation with between  $\omega_{ijt}$  and  $k_{ijt}$  and  $l_{ijt}$ . Econometricians however do not observe  $\omega_{ijt}$ , so an OLS estimates of (A.12) are likely to be biased. To obtain an unbiased estimate of productivity requires unbiased estimates of the  $\beta$ 's.

To address this issue we follow Akerberg, Caves and Frazer (2014) who utilize the timing structure of when firms know about productivity and an assumption on the input adjustment process to recover  $\omega_{ijt}$ . Specifically we assume that labor is the static input and capital is the dynamic input and that,

$$i_{ijt} = f_t(k_{ijt}, \omega_{ijt}) \quad (\text{A13})$$

where  $i_{ijt}$  is investment and is a function of capital  $k_{ijt}$  and productivity  $\omega_{ijt}$ . Assuming that (A.13) is invertible, then

$$\omega_{ijt} = f_t^{-1}(k_{ijt}, i_{ijt}, l_{ijt}) \quad (\text{A14})$$

substituting into (A.12) we have

$$y_{ijt} = \beta_0 + \beta_k k_{ijt} + \beta_l l_{ijt} + f_t^{-1}(k_{ijt}, i_{ijt}, l_{ijt}) + \eta_{ijt} \quad (\text{A13})$$

The estimation proceeds in two steps. We first estimate (A.13) using a semi-parametric technique. This does not recover  $\beta_l$  or  $\beta_k$  since labor and capital are collinear with the  $f_t^{-1}(k_{ijt}, i_{ijt})$  function. However, we can estimate  $\Gamma(i_{ijt}, k_{ijt}, l_{ijt}) = \beta_k k_{ijt} + \beta_l l_{ijt} + f_t^{-1}(k_{ijt}, i_{ijt}, l_{ijt})$  in the first stage we can estimate  $\eta_{ijt}$ . To estimate the second stage we assume that  $\omega_{ijt}$  follows the first order markov process:  $\omega_{ijt} = E[\omega_{ijt}|i_{ijt-1}] + \xi = E[\omega_{ijt}|\omega_{ijt-1}] + \xi$ . We also impose two timing assumptions - that capital is chosen based on last periods  $\eta$  and that labor adjusts with a delay. Together these assumptions allow us to identify  $\beta_l$  and  $\beta_k$  to recover an estimate of  $\omega_{ijt}$ .

## 3.2 Variables

To estimate the production function we use the following variables.

**Value Added:** The difference between county-industry value of shipments and expenditure on materials. Directly reported in manufacturing census data. Measured in nominal dollars as local price deflators do not exist.

**Labor:** Measured as the number of employees in the industry-county cell. Directly reported in the manufacturing census data.

**Capital:** Measured by the capital stock in the industry-county cell. We construct our capital stock measure from the reported investment series using the perpetual inventory method. We follow Bloom, Shankerman, and Van Reenen (2013) and choose the baseline

value of the capital stock in 1958:  $k_{ij1958} = i_{ij1958}0.08 + g_{kij1958}$ , where  $g_{kij1958}$  is the growth rate of investment between 1954 and 1958 in the county-industry cell. We follow Bloom, Bond and Reenen (2007) in assuming a 8% deflation rate. Our capital stock measure in years other than 1958 is given by  $k_{ijt} = i_{ijt} + (1 - 0.08)^{2.5}k_{ijt-1}$ . We assume that investment occurs at the mid-point between the 5 year differences in manufacturing census years. If investment is missing we assume it is zero, and depreciate the prior capital. If the lagged capital stock is missing, use the sic 2 digits capital-employment ratio and observed employment in the industry-county cell to impute lagged capital stock. Measured in nominal dollars as local price deflators do not exist.

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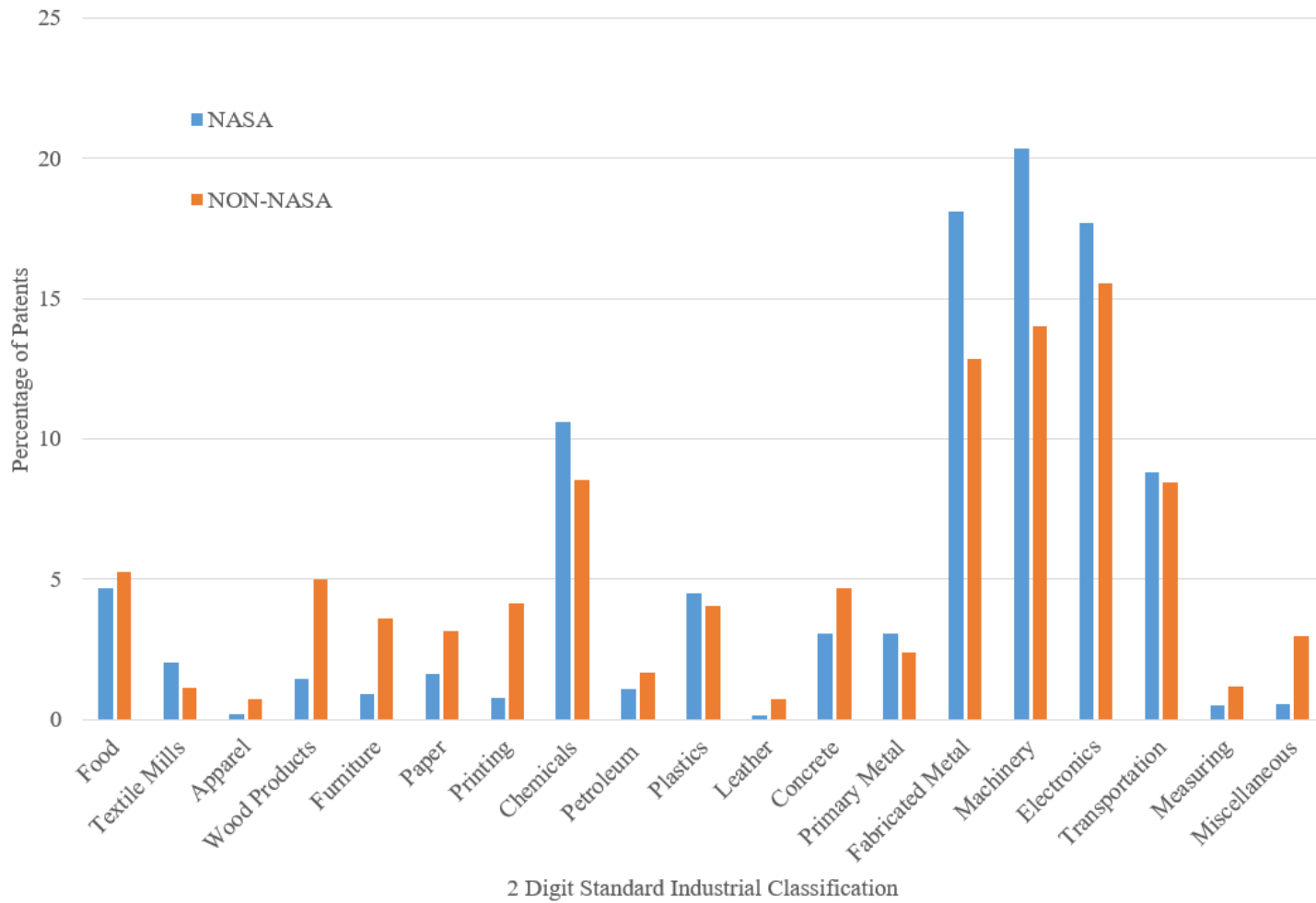
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Figure A1: Top 10 Counties by Local and Market NASA Patents

Local NASA Patents				Market NASA Patents			
	1958	1972	1992		1958	1972	1992
1	Cook, IL	Los Angeles, CA	Los Angeles, CA	1	Alexandria City, VA	Baltimore City, MD	Philadelphia, PA
2	Los Alamos, NM	Madison, AL	Cuyahoga, OH	2	Washington, DC	Union , NJ	Baltimore City, MD
3	Hampton City, VA	Cuyahoga, OH	Harris, TX	3	Arlington, VA	Mercer, NJ	Merced NJ
4	Monroe, NY	Santa Clara, CA	Newport News, VA	4	Baltimore City, MD	Delaware, PA	Middlesex, NJ
5	Watauga, NC	Hampton City, VA	Santa Clara, CA	5	Cumberland, VA	Middlesex, NJ	Delaware, PA
6	Benton, WA	Middlesex, MA	Madison, AL	6	Prince Georges, MD	Philadelphia, PA	Union, NJ
7	Montgomery, OH	Harris, TX	York, VA	7	Anne Arundel, MD	Hudson, NJ	Somerset, NJ
8	Middlesex, CT	Newport News, VA	Galveston, TX	8	Howard, MD	Saratoga, NY	Washington, DC
9	Baltimore City, MD	Prince Georges, MD	Hampton City, VA	9	Montgomery, MD	Somerset, NJ	Erie, PA
10	Benton, WA	Brevard, FL	Orange, CA	10	Prince William, VA	Essex, NJ	Montgomery, PA

Notes: Source authors calculations using patent data for 1947-1997 from the USPTO historical masterfile, Petralia, Balland and Rigby (2016), Fleming, Greene, Li, Marx, and Yao (2019), and transportation cost data from Jaworski and Kitchens (2019).

Figure A2: Patent Shares by SIC 2 Digit Industry

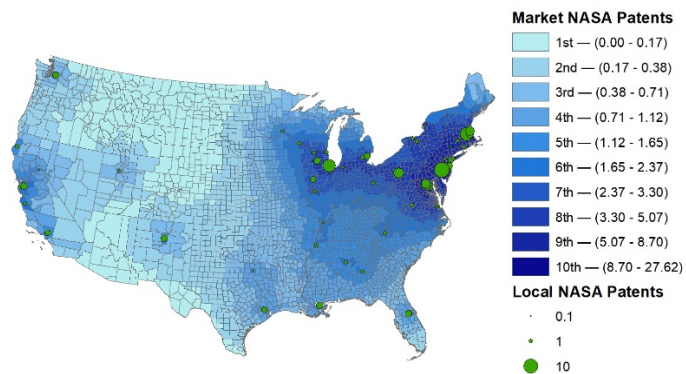


Notes: Source authors calculations using patent data for 1947-1997 from the USPTO historical masterfile, Fleming, Greene, Li, Marx, and Yao (2019), and industry crosswalk data from Lybbert and Zolas (2014).

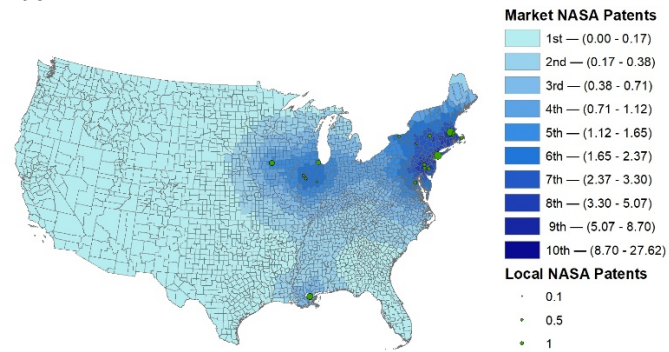


Figure A3: Maps of Local and Market NASA, by Manufacturing Census Year

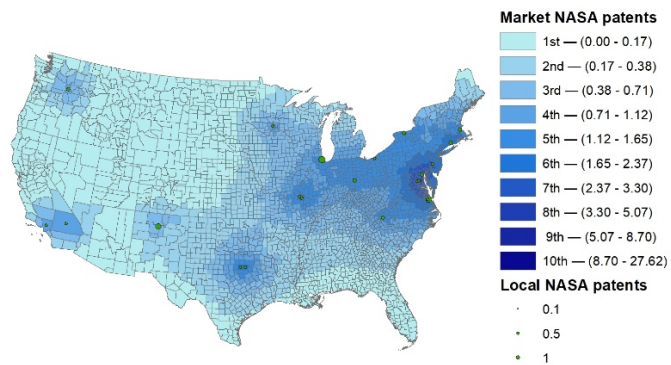
A. 1947



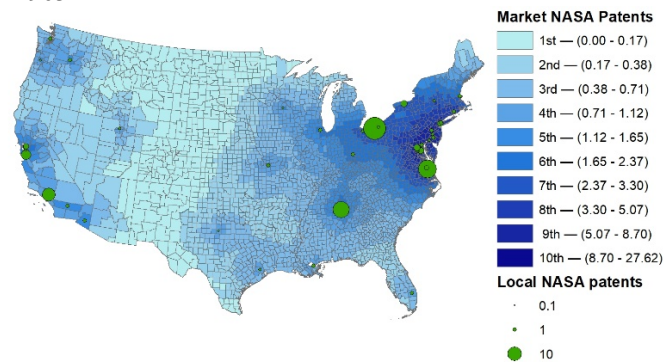
B. 1954



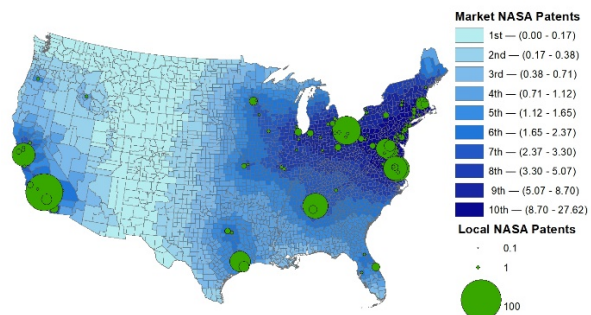
C. 1958



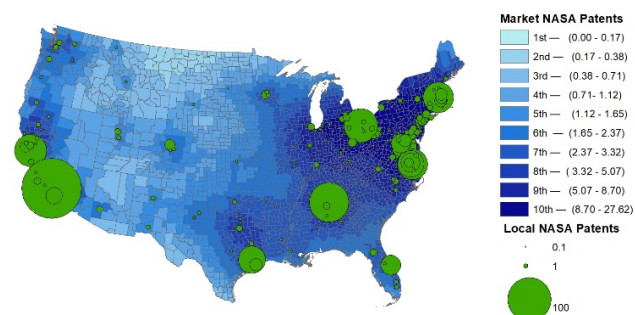
D. 1963



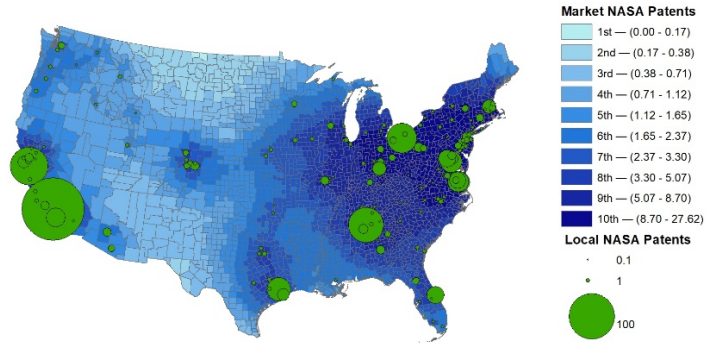
E. 1967



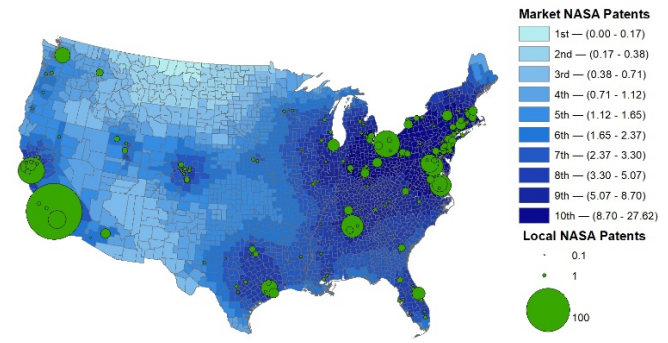
F. 1972



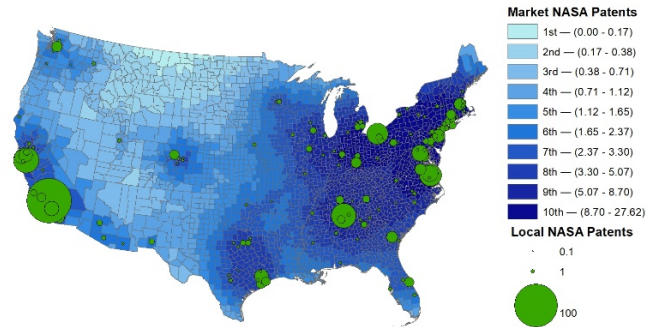
G. 1977



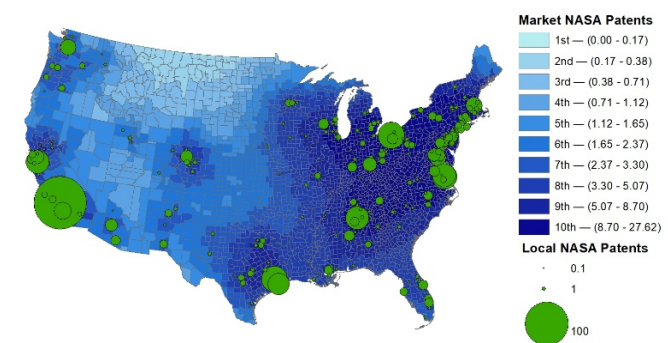
H. 1982



I. 1987



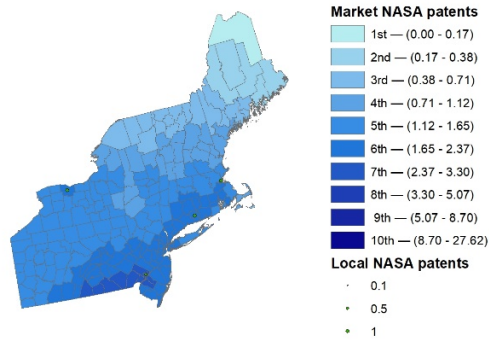
J. 1992



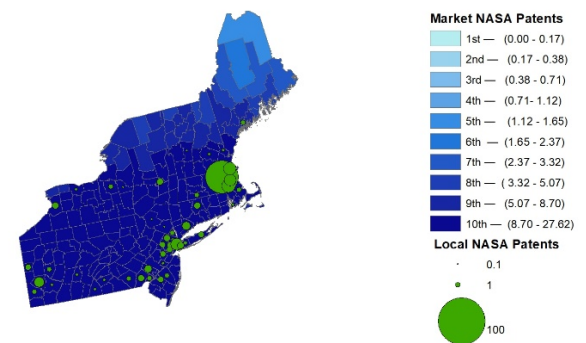
Notes: Source authors calculations using patent data for 1947-1997 from the USPTO historical masterfile, Petralia, Balland and Rigby (2016), Fleming, Greene, Li, Marx, and Yao (2019), and transportation cost data from Jaworski and Kitchens (2019).

Figure A4: Maps of 1958-1972 Change in Local and Market NASA, by Selected Region

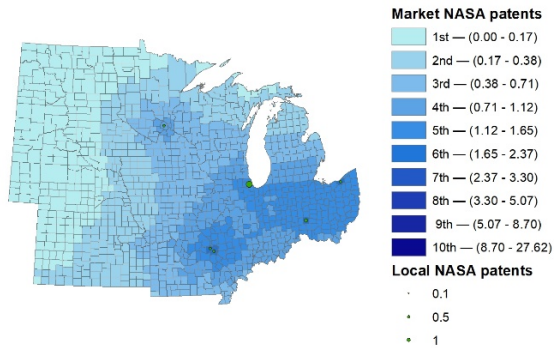
A. 1958 – North East



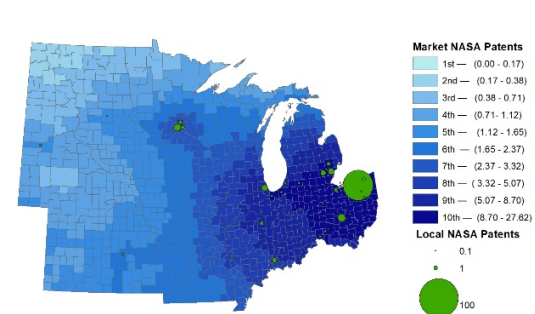
B. 1972 - North East



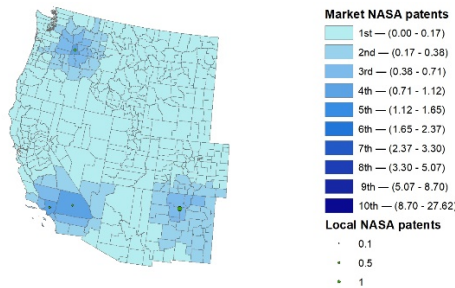
C. 1958 – Mid West



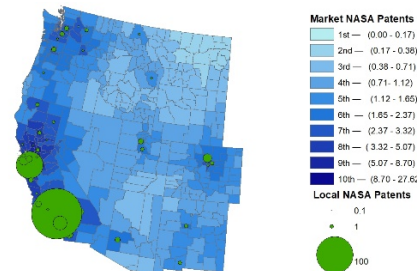
D. 1972 – Mid West



E. 1958 - West

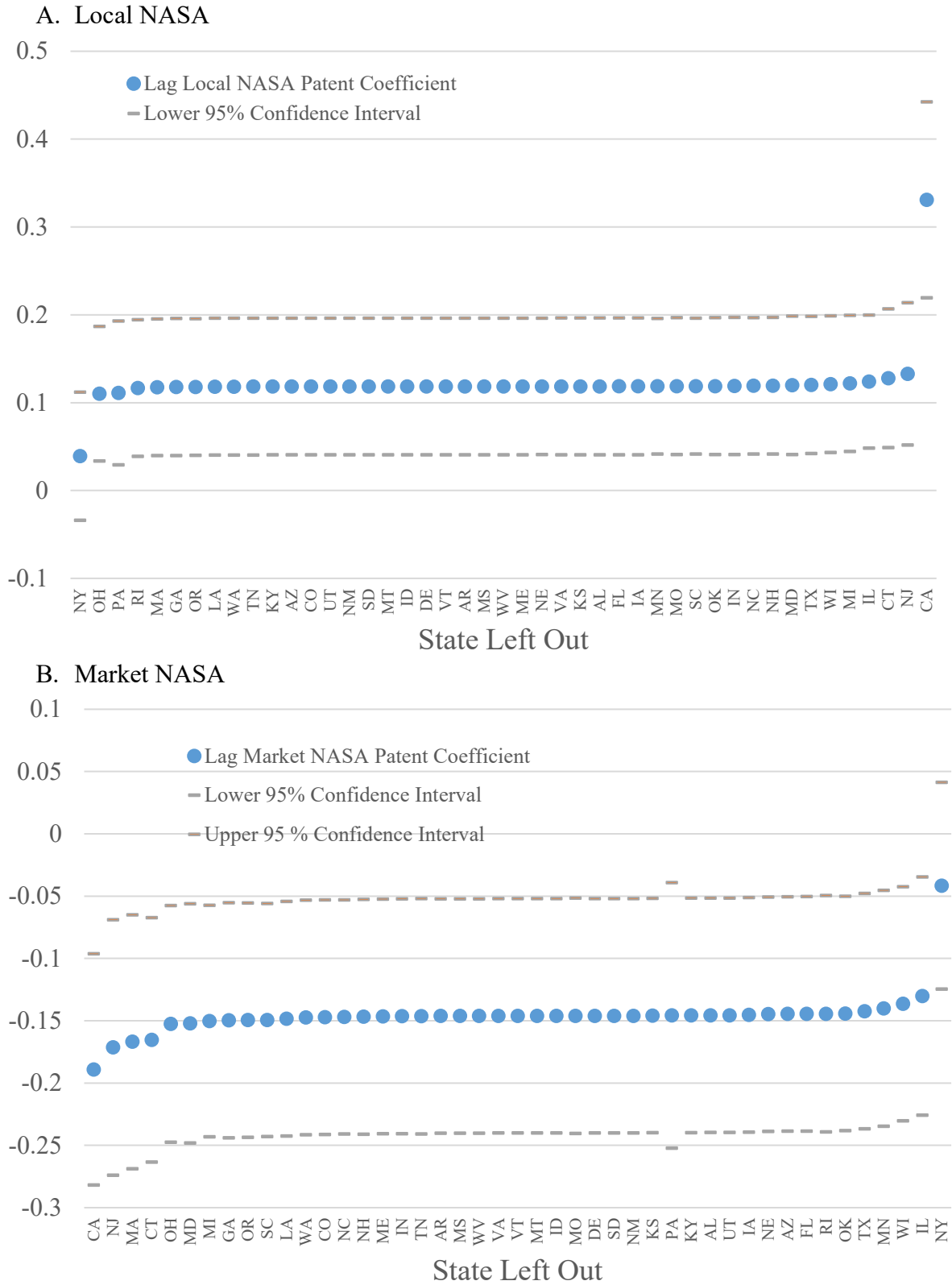


F. 1972 – West



Notes: Source authors calculations using patent data for 1947-1997 from the USPTO historical masterfile, Petralia, Balland and Rigby (2016), Fleming, Greene, Li, Marx, and Yao (2019), and transportation cost data from Jaworski and Kitchens (2019).

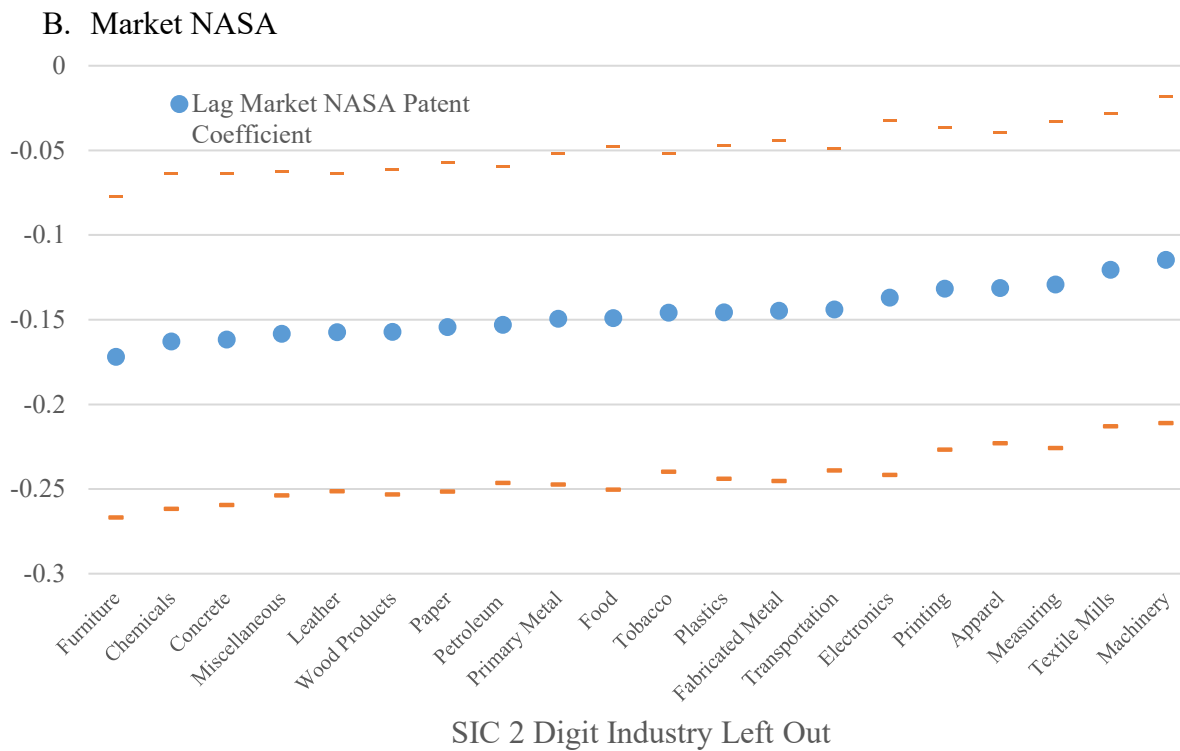
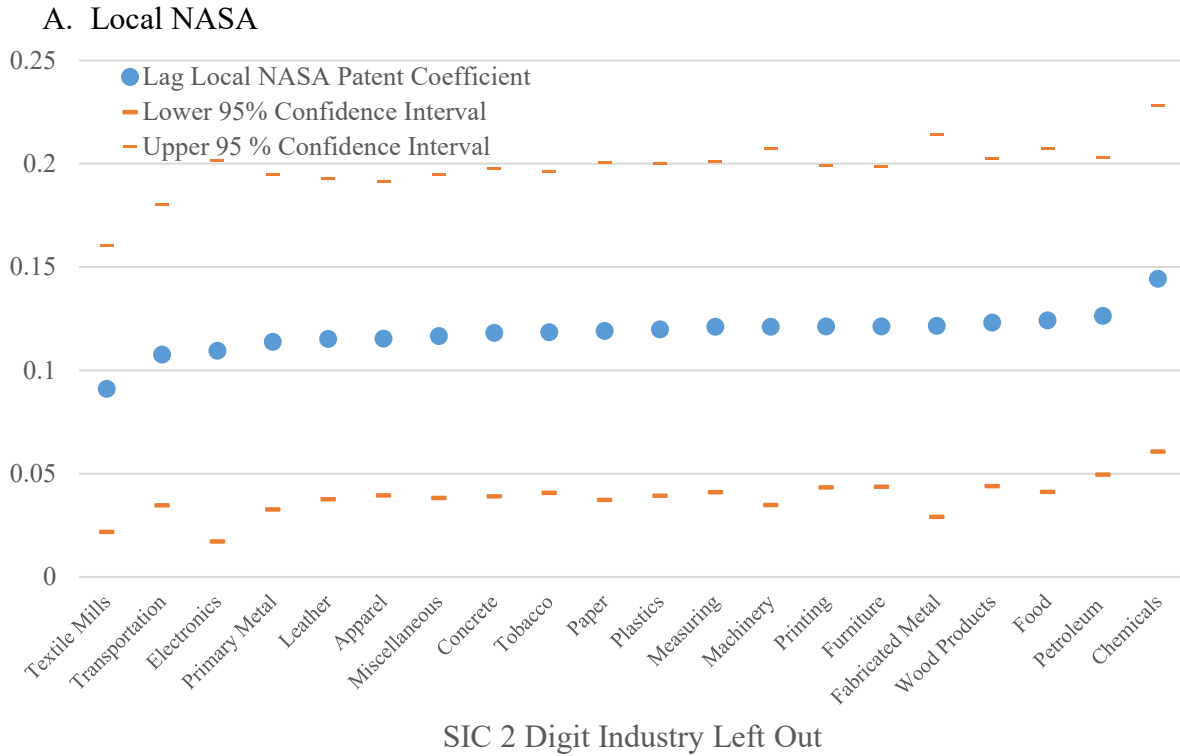
Figure A5: Baseline effects Excluding one State at a Time



Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each blue dot represents a coefficient estimate for the local (panel A) or market (panel B) effect from one estimate of equation

(14) with the 95% confidence interval reflected in the solid dash leaving the indicated state out of the sample. All models include year, 2 digit industry and county fixed effects.

Figure A6: Baseline Effects Excluding one Industry at a Time



Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each blue dot represents a coefficient estimate for the local (panel A) or market (panel B) effect from one estimate of equation (14) with the 95% confidence interval reflected in the solid dash leaving the indicated industry out of the sample. All models include year, 2 digit industry and county fixed effects.

Table A1: NASA Patents and Value Added - Log(Patents +1) Specification

Dependent Variable= Model:	Log (Value Added)				
	Baseline	Baseline	Baseline	Industry Trends	Industry & County Trends
	(1)	(3)	(3)	(4)	(5)
Log(1+Local NASA Patents) <sub>t-5</sub>	0.14*** (0.04)		0.14*** (0.05)	0.15*** (0.05)	0.11* (0.06)
Log(1+Market NASA Patents) <sub>t-5</sub>		-0.13*** (0.06)	-0.19*** (0.06)	-0.30*** (0.09)	-0.23** (0.10)
Observations	17,501	16,555	16,555	16,550	14,430
R <sup>2</sup>	0.69	0.69	0.69	0.71	0.73
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	No	No	Yes	Yes
County × Year Fixed Effects	No	No	No	No	Yes

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table A2: NASA Patents and Value Added – Alternative Market Definitions

Dependent Variable= Market NASA Patents	Log (Value Added)				
	Baseline	Baseline	County Level	Low Theta	High Theta
Sample=	Full	Balanced	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.12*** (0.04)	0.16*** (0.05)	0.10*** (0.03)	0.09*** (0.04)	0.13*** (0.04)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.15*** (0.05)	-0.16*** (0.07)	-0.28*** (0.05)	-0.06* (0.03)	-0.17*** (0.06)
Observations	16,555	3,347	17,501	16,555	16,555
R <sup>2</sup>	0.69	0.72	0.62	0.69	0.69
Additional Controls:					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.

Table A3: NASA Patents and Value Added – Including Other Industry Effects

Dependent Variable= Model:	Log (Value Added)					
	Baseline	Baseline	Baseline	Industry Trends	Industry Trends	Industry Trends
	(1)	(2)	(3)	(4)	(5)	(6)
ArcSign(Local Own NASA Patents) <sub>t-5</sub>	0.10*** (0.04)	0.12*** (0.04)	0.10*** (0.04)	0.11*** (0.05)	0.18*** (0.04)	0.11*** (0.04)
ArcSign(Local Other NASA Patents) <sub>t-5</sub>	0.03 (0.02)		0.03 (0.02)	0.02 (0.02)		0.02 (0.02)
ArcSign(Market Own NASA Patents) <sub>t-5</sub>	-0.15*** (0.05)	-0.14*** (0.05)	-0.15*** (0.05)	-0.23*** (0.07)	-0.23*** (0.07)	-0.23*** (0.07)
ArcSign(Market Other NASA Patents) <sub>t-5</sub>		0.02 (0.06)	0.00 (0.06)		0.04 (0.05)	0.03 (0.05)
Observations	16,555	15,149	16,555	15,144	16,550	15,144
R <sup>2</sup>	0.69	0.69	0.69	0.71	0.71	0.71
Additional Controls:						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	No	No	No	Yes	Yes	Yes
County × Year Fixed Effects	No	No	No	No	No	No

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. All monetary values are nominal dollars. Each column and panel reports the results from one estimate of equation (14) with only the leads and lags for the indicated innovation measure present. All models include year, 2 digit industry and county fixed effects.



Table A4: NASA Patents and Value Added: Pre-Trends and Dynamics

Dependent Variable=	Log (Value Added)		
	(1)	(2)	(3)
Model:	Baseline	Industry Trends	Industry & County Trends
ArcSign(Local NASA Patents) <sub>t+10</sub>	-0.04 (0.05)	-0.03 (0.05)	-0.05 (0.06)
ArcSign(Local NASA Patents) <sub>t+5</sub>	-0.02 (0.03)	-0.03 (0.04)	0.00 (0.04)
ArcSign(Local NASA Patents) <sub>t</sub>	0.00 (0.04)	-0.01 (0.04)	0.00 (0.04)
ArcSign(Local NASA Patents) <sub>t-5</sub>	0.06** (0.03)	0.09** (0.03)	0.10** (0.04)
ArcSign(Local NASA Patents) <sub>t-10</sub>	0.00 (0.04)	0.00 (0.03)	-0.04 (0.03)
ArcSign(Local NASA Patents) <sub>t-15</sub>	0.07 (0.04)	0.04 (0.04)	0.01 (0.04)
ArcSign(Local NASA Patents) <sub>t-20</sub>	-0.01 (0.05)	0.02 (0.04)	0.02 (0.05)
ArcSign(Market NASA Patents) <sub>t+10</sub>	-0.03 (0.05)	-0.03 (0.07)	-0.04 (0.08)
ArcSign(Market NASA Patents) <sub>t+5</sub>	-0.06 (0.04)	-0.03 (0.06)	-0.04 (0.06)
ArcSign(Market NASA Patents) <sub>t</sub>	-0.06 (0.04)	-0.10* (0.05)	-0.14*** (0.05)
ArcSign(Market NASA Patents) <sub>t-5</sub>	-0.09** (0.04)	-0.08 (0.05)	-0.06 (0.06)
ArcSign(Market NASA Patents) <sub>t-10</sub>	0.00 (0.03)	-0.06 (0.05)	-0.03 (0.06)
ArcSign(Market NASA Patents) <sub>t-15</sub>	-0.10** (0.03)	-0.11** (0.05)	-0.06 (0.06)
ArcSign(Market NASA Patents) <sub>t-20</sub>	-0.06* (0.03)	-0.04 (0.05)	-0.02 (0.06)
Observations	11,841	11,839	10,290
R <sup>2</sup>	0.70	0.71	0.73
Additional Controls:			
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Industry × Year Fixed Effects	No	Yes	Yes
County × Year Fixed Effects	No	No	Yes

Notes: Source authors calculations using patent, manufacturing census and population census data for 1947-1997. All monetary values are nominal dollars. Each column reports the results from one estimate of equation (14) with only the leads and lags for the indicated NASA innovation present, not both at the same time. All models include year, 2 digit industry and county fixed effects.

Table A5: Patents Correlation Matrix

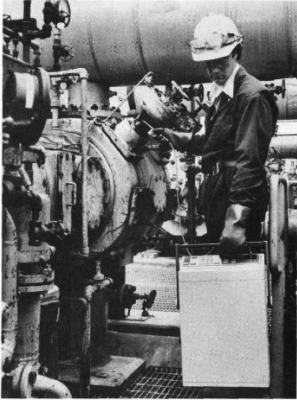
	NASA Patents	Army Patents	Navy Patents	Government Patents	Non-Government Patents
NASA Patents	1				
Army Patents	0.1547	1			
Navy Patents	0.3190	0.2411	1		
Government Patents	0.6086	0.3614	0.5838	1	
Non-Government Patents	0.3212	0.1440	0.1909	0.4992	1

Notes: Source authors calculations using patent and manufacturing census data for 1947-1997. Each entry in the table is the correlation coefficient between the variables in the row and column.

## Exhibit 1: NASA Spinoff Examples

### A. Gas Analyzer:

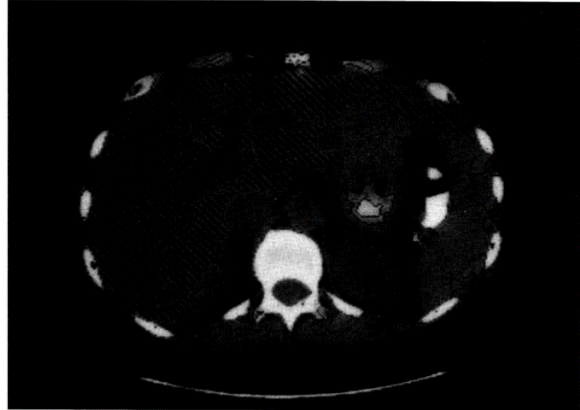
1983: Mircosensor Technology, California



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

### B. Magnetic Resonance Imaging (MRI):

1990: University of Michigan, Michigan



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

### A. Remote Sensing

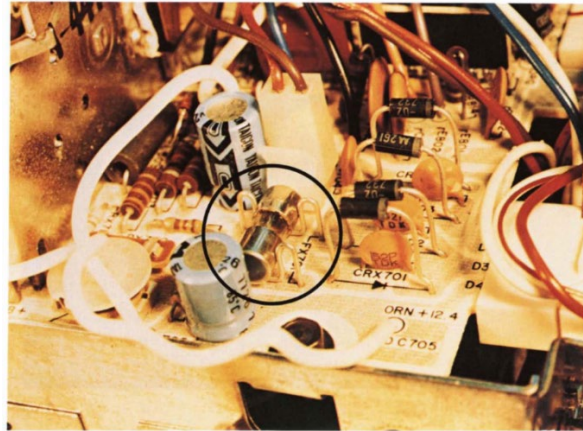
1989: NASA, District of Columbia



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

### B. Circuit Connectors

1979: Components Corporation, New Jersey



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