America, Jump-started: World War II R&D and the Takeoff of the U.S. Innovation System*

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Abstract:

During World War II, the U.S. government's Office of Scientific Research and Development (OSRD) supported one of the largest public investments in applied R&D in U.S. history. Using data on all OSRD-funded invention, we show that this shock had a formative impact on the U.S. innovation system, catalyzing technology clusters across the country, with accompanying increases in high-tech entrepreneurship and employment. These effects persist until at least the 1970s, and appear to be driven by agglomerative forces and endogenous growth. In addition to creating technology clusters, wartime R&D permanently changed the trajectory of overall U.S. innovation in the direction of OSRD-funded technologies.

JEL Classification: H56, N42, N72, O31, O32, O33, O38, R11, R12

Keywords: World War II; OSRD; Government R&D; Applied R&D policy; National innovation systems; Technology clusters

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A large literature in economics has studied the determinants of innovation (Cohen 2010, Bryan and Williams 2021), including government funding (Bloom et al. 2019). The U.S. innovation system is especially rich in specialized, regional technology clusters which are thought to be important to overall technological progress (Chatterji et al. 2014, Carlino and Kerr 2015), while also contributing to growing gaps in regional economic performance (Gruber and Johnson 2019). Yet this literature has few examples of systemic R&D shocks, and underexplores issues such as (i) the long-run effects of public R&D investments, (ii) the impacts of large, actively-managed applied research programs (Azoulay et al. 2019a, Gross and Roche 2023), and (iii) to what degree, and how, these investments affect regional economic development—issues which are central to policy today.[1]

In this paper, we study the long-run effects of the largest R&D shock in U.S. history. In World War II, the newly-created Office of Scientific Research and Development (OSRD) led an expansive effort to develop technologies and medical treatments for the Allied war effort. From 1940 to 1945, OSRD engaged industrial and academic contractors in more than 2,200 R&D contracts at over $9 billion (2022 dollars), despite no pre-war tradition of funding extramural (externally-performed) R&D. At the height of the war, the U.S. government was funding the research behind nearly 1 of every 8 U.S. patents—more than five times pre-war and modern levels, and nearly twice the level at the peak of the Cold War in the 1950s and 1960s (Figure 1).

[Figure 1 about here]

The immediate effect of these investments was a range of technological advances which were not only instrumental to the success of the Allied campaign, but also of wide civilian value after the war ended.[2] Its longer-run impact was to reshape the U.S. innovation system. We document four main findings. First, World War II R&D kicked off the postwar growth of technology clusters (counties x technologies) around the country: despite parallel trends prior to the war, the most heavily-treated clusters were by 1970 producing another 40% to 50% more patents per year than untreated clusters. Second, this sustained growth benefited from, but did not depend on, postwar federal

[1] These gaps have recently become relevant: in August 2022, the U.S. initiated its largest public investment in applied, use-oriented R&D since the Cold War (via the CHIPS and Science Act). Among its provisions, it adds a $20 billion technology directorate to the National Science Foundation (NSF) and a $10 billion investment in regional technology hubs, aiming to develop new domestic capabilities in frontier technologies and to create new capacity in regions which have not previously been major R&D centers (Gruber and Johnson 2019).

[2] OSRD itself existed only for the duration of the war, but in that time it was responsible for foundational technological developments in radar, electronic communication and early computing, underwater detection (sonar), rockets and jet propulsion, and atomic fission, as well as medical and pharmaceutical advances such as mass-produced penicillin, influenza and other vaccines, new malaria treatments, new approaches to managing myriad human hardships from sleep and oxygen deprivation to nutrient deficiencies, and dozens more.

R&D investment. Instead, our evidence suggests OSRD catalyzed self-sustained agglomeration, including firm in-migration, entry, and growing spillovers across inventors and technologies. Third, we find evidence that these changes were accompanied by growth in local industrial employment and firm creation in related high-tech industries. Finally, we show that wartime R&D had permanent effects on the direction of U.S. innovation, which pivoted towards electronics and communications. By (rapidly) extending the frontier of key emerging technologies while stimulating agglomeration, the impacts of this shock were thus to enhance competitiveness but widen differences in inventive productivity, and in turn economic performance, across the country.

Making this analysis possible is a new dataset of the universe of OSRD contracts, which we have collected from archival records, including detailed information on the contractors, contracts, and patents they produced. We merge these records with the complete U.S. patent record, new administrative data on postwar government-funded patenting, and SIC-level measures of local firm creation and industrial employment. We use these data to study the effects of the OSRD shock on postwar invention, local innovation ecosystems, and real economic outcomes from 1930 to 1970. Our empirical design compares pre- and post-war patenting in clusters shocked by the war effort, which we measure as the OSRD share of cluster patents in the 1940s. We take a similar logic in evaluating other outcomes at the cluster, county, and national levels.

We observe a consistent pattern across our different analyses: parallel pre-war trends, a wartime spike in invention in OSRD-funded technologies, and a postwar takeoff that continues through the end of our analysis window. The magnitudes of these effects are large: for example, a doubling of the OSRD share of 1940s patents in a given cluster is associated with 20% higher patenting by 1960 and 30% by 1970, relative to pre-war levels. In a subset of clusters, these magnitudes were off the charts: Middlesex, MA (the locus of World War II radar R&D; see Gross and Roche 2023) experienced a nearly *30-fold* increase in electronics patenting during the war, a short-lived reversion, and then a sustained takeoff—with patenting in 1960 ten times pre-war levels.

In addition to estimating the effects of this shock, we also examine why they were so long-lived. We first establish that the post-war takeoff in patenting is not driven by direct follow-on to OSRD invention, nor by patents of firms and inventors involved in the war effort. Having ruled out these explanations, we consider two other possibilities: (i) continued government R&D investment in the same locations, or (ii) self-sustaining agglomeration dynamics. Our evidence is consistent with the latter: it appears entire local research ecosystems sprung up in many locations and technology areas where OSRD activity was concentrated. In more heavily-shocked clusters, we see increases in both public and private patenting, and increases from a wide variety of entities, including by in-migrating firms and entrants. Beyond patents, we show that postwar firm creation and employment were higher in counties and industries which were targets of OSRD-funded research. We then document a sharp postwar divergence between U.S. and foreign patenting in OSRD-funded technologies, suggesting its local effects rolled up to a large aggregate impact.

There is widespread recognition that World War II was a sea-change event in government-science relations and in science and technology policy. Although policymakers and scholars appeal to the war effort as a paradigmatic example of the benefits of federal research funding (Bush 1945, Gruber and Johnson 2019), there has been limited empirical grounding to these claims. A sizable literature has studied the impacts of other public R&D investments on innovation (e.g., Azoulay et al. 2019b, Myers and Lanahan 2022) and other outcomes (Howell 2017).[3] Most existing evidence, however, is drawn from studies of marginal changes in funding, and often for basic science. As a result, there is limited evidence as to what effects a systemic shock to R&D funding of this scope and scale may have, over what horizons, and through what mechanisms these effects are realized. This is the main gap we address. Crucially, the passage of time allows us to evaluate long-run effects. Our results suggest that investments made in World War II may be important to understanding the postwar golden age of innovation and to rapid postwar economic growth.

Our results also contribute to research in the geography of innovation (Feldman 1994, Audretsch and Feldman 2004), especially around agglomeration (Carlino and Kerr 2015, Kerr and Robert-Nicoud 2020). This literature frequently documents the localization of inventive activity (e.g., Jaffe et al. 1993, Audretsch and Feldman 1996) and relates this to R&D productivity (e.g., Kantor and Whalley 2019, Andrews 2023, Moretti 2021, Gruber et al. 2022), identifying reasons why innovation has locally increasing returns. The literature has made less progress on the inverse question—whether discrete R&D shocks trigger agglomeration (Duranton 2007, Kerr 2010), and more generally what catalyzes change (e.g., Chattergoon and Kerr 2022, Kim et al. 2022). Because innovation is often tied to population and industrial activity, our results link to the broader literature on industrial agglomeration (see Duranton and Puga (2004) for a review), including place-based industrial policy (Chatterji et al. 2014, Kline and Moretti 2014a,b).[4] We use this literature to frame our analysis as we explore why this transitory shock had such long-lived effects.[5]

[3] Also see Santoleri et al. (2022) and Bergeaud et al. (2022), among others.

[4] A contextually related paper in this vein is Garin and Rothbaum (2022), who find that counties where government-financed manufacturing facilities were sited in World War II had higher manufacturing employment and income for decades. Empirically, these counties were quite different from those where OSRD research took place, as the latter tended to be in urban centers (located near researchers), and the former in more distant regions (to mitigate congestion and security risks, per Garin and Rothbaum 2022).

[5] In closely-related research, Buenstorf and Klepper (2009) and Klepper (2010) study the emergence of high-tech U.S. clusters, attributing their growth to spinoffs from industry pioneers. Arthur (1990) explores the effects of historical

Beyond these themes, this paper relates to a wider literature on endogenous growth (Romer 1986, 1990), where innovation features increasing returns to scale but which has few examples of discrete shocks and takeoffs. Most recently, Kantor and Whalley (2022) have examined the impacts of the Cold War expansion of aerospace R&D on local manufacturing and used this context to estimate a large fiscal multiplier on public R&D. Our paper complements this literature, highlighting the growth initiated by the World War II shock, and the long-lasting changes this event brought about. As such, we bring a renewed perspective to the origins of the modern U.S. innovation system, while adding to research that studies defense R&D (Mowery 2010, Howell et al. 2021, Moretti et al. 2023, Belenzon and Cioaca 2021) and the impacts of war on innovation (e.g., Ruttan 2006)—including much of our own recent work (e.g., Gross and Sampat 2021, 2022a,b,c).

We proceed as follows. In Section 1 we review the World War II research effort, describing OSRD's work and legacy. Section 2 introduces our data and characterizes the World War II shock. Section 3 documents the effects of World War II R&D on local, postwar invention, and Section 4 explores the myriad changes we see taking places in treated clusters. In Section 5, we examine downstream impacts on employment and firm creation. Section 6 then evaluates impacts of World War II R&D on the direction of innovation at the national level. Section 7 offers concluding remarks, including insights for open and long-running policy debates today.

1 Historical and Policy Background

1.1 The World War II research effort

World War II was one of the largest shocks in the history of the U.S. innovation system. Prior to the war, there was very little federal funding of research outside of agriculture. Most academic research was funded by philanthropic foundations (Rockefeller and Carnegie, in particular) and industry. There was, if anything, an aversion among academics to public funding, reflecting concerns that it may restrict scientific freedom.

World War II changed this. Even before the attack on Pearl Harbor and the United States' official entry into the conflict, scientists, the military, and politicians anticipated that the development and application of technology would be critical for an Allied victory, that existing U.S. military R&D was inadequate, and that coordination would be required to mobilize the scientific and technological capabilities that had developed in the interwar era.

The World War II research effort began in June 1940, when Vannevar Bush (a former vice president

accidents on clustering via path dependence in an evolutionary framework.

and dean of engineering at MIT, president of the Carnegie Institution of Washington, and chairman of the National Advisory Committee for Aeronautics) together with other members of the U.S. scientific and technological establishment convinced President Roosevelt to establish and fund a National Research Defense Committee (NRDC) to "correlate and support scientific research on the mechanisms and devices of warfare" (Roosevelt 1940). NRDC was to supplement existing military research "by extending the research base and enlisting the co-operation of institutions and scientists" (James Conant, quoted in Stewart 1948, p. 21).

Perhaps as important as any of the technologies it helped to develop, the wartime research effort was a major innovation in the way science was supported and conducted.[6] While the first World War disrupted universities and firms by drawing scientists out of laboratories, and U.S. government agencies themselves had previously some done research internally, the NDRC effort primarily funded research "extramurally" through contracts, engaging both firms and universities, from individual investigators to larger laboratories. Impressed by its early successes, NDRC was expanded by a 1941 Executive Order to emphasize more development work (beyond just research), to solidify links with military agencies conducting research, and to take over wartime medical research and development. The new organization, the Office of Scientific Research and Development (OSRD), was also eligible for regular Congressional budget appropriations. As *The New York Times* wrote, this effectively made Vannevar Bush "the czar of research" (Kaempffert 1941).

This effort helped develop a range of technologies that were crucial to the Allied victory. Radar, mass-produced penicillin, and the atomic bomb are its most memorable achievements, but OSRD also produced significant advances in rocketry, jet propulsion, radio communications, and electronic computing, plus treatments for malaria, pesticides like DDT, and more—all of which had commercial applications. Much of this R&D was concentrated in a network of new, university-based central laboratories, which conducted R&D on specific problems and connected researchers, firms and military users.[7] These early "national labs" attracted scientists and engineers from around the country, some of whom dispersed after the war—and some of whom stayed. In parallel research, we and others have documented how these coordinated R&D programs laid foundations of new industries

[6]Scholars have since described the wartime arrangement as having "portended the beginning of a new relationship between the federal government and the nation's universities" (Geiger 1993, p. 3).

[7]For example, radar development was centered at the MIT Radiation Laboratory (the "Rad Lab"), and radar countermeasures at the nearby Harvard Radio Research Lab (RRL). Rocket and jet propulsion research was based at the CalTech Jet Propulsion Lab (JPL), and proximity fuze development at the Johns Hopkins Applied Research Lab (APL). Early, NDRC-supported research on uranium fission took place at academic labs at the University of Chicago, UC Berkeley, and Columbia University before spinning out into the Manhattan Project, which was based in Los Alamos, New Mexico, supported by project sites around the country. These labs were the predecessors of postwar national labs in these locations, most of which are still operating today.

which emerged after the war (e.g., Klepper 2016, Agarwal et al. 2021, Gross and Roche 2023), potentially to the benefit of regions where these industries were based.

1.2 Transitions to the postwar era

Even before the war was over, there was broad agreement that the government should be involved in funding research at universities after the war. Perhaps ironically, the initial attempts to create a structure for postwar funding came from a critic of OSRD, Senator Harley Kilgore (D-W.Va.). Kilgore, a New Deal Democrat, was concerned about the concentration of OSRD funding in big business and a handful of universities (Kevles 1977a). Kilgore had other concerns about OSRD model, including that many of the contracts allowed the recipients to retain patent rights—making the intellectual output of government-supported research private property—and that there was a lack of representation from small business, independent inventors, and non-elite universities in the wartime effort. He believed each of these feautures of OSRD hurt the rate of technological development during the war and also led to concentration of the benefits of federal funding in a few research fields, institutions and regions (Kevles 1977a, Kleinman 1995). In a series of bills introduced during the war, culminating in a 1944 proposal of a new "National Science Foundation", Kilgore attempted to forge a peacetime research policy that would fund basic and applied research in response to specific socio-economic problems, with a mandate for broad geographical and institutional distribution of funds, wide dissemination of research results (with public ownership of resulting patents), and political accountability of researchers.

Vannevar Bush's seminal report *Science, The Endless Frontier* (Bush 1945), written at the request of President Roosevelt and published near the end of the war, was, in many ways, a rejoinder to Kilgore's arguments and proposal. Like Kilgore, Bush recommended a single agency (a "National Research Foundation"), but with a focus on basic research, run by scientists, with broad scientific autonomy, and aimed at stimulating high-quality research by the best institutions and scientists. In making the case for federal funding of fundamental research at universities, the Bush Report also anticipated the market failure rationale for federal R&D funding(Arrow 1962) and the linear model of science and innovation (Mowery 1997, Nelson 1997).

Though the Bush Report had a strong ideological impact on U.S. policy, many of its specific proposals met a cool reception, including from Kilgore and other liberals, who preferred a more egalitarian peacetime approach, and from President Truman, who insisted on a politically-appointed director. By the time NSF legislation was enacted in 1950—following five years of debate around Bush and Kilgore's competing visions—many of OSRD's remaining research contracts had been transferred to mission agencies (e.g., the Office of Naval Research, the Atomic Energy Commission, and the National Institutes of Health), precluding the single-agency approach Bush (and Kilgore) had envisioned. Though the NSF was in large part "a triumph for Bush" (Kevles 1977a, p. 25)—primarily focused on basic research, administered by scientists—its budget was small, and it was a "puny partner" in the overall enterprise (Kevles 1977b, p. 358).

While each of the other major postwar R&D funding agencies had their own rules and procedures, a striking feature of federal research funding in the decades that followed was its continued geographic and institutional concentration. Though a variety of legislative initiatives and programs, historical and recent, have attempt to widen the distribution of funding—channeling Kilgore's criticism of OSRD and concerns about extending the OSRD model in peacetime—opponents of these programs typically argue that funding should be directed to the best researchers and institutions, as determined by the scientific community, echoing Bush. One reason for this tension is disagreement over what the goals of R&D policy are, or should be. But a key and complementary gap in this debate is evidence on the impacts of these choices: whether the geographic distribution of R&D funding matters for local economic development, and the degree to which returns accrue locally versus more broadly. One goal of this paper is to speak to these questions.

2 Data

To assess the effects of the World War II shock, we have collected, transcribed, and harmonized a complete record of all 2254 OSRD contracts (to 461 distinct contractors), all 7910 inventions reported under them, and all 2637 patents on these inventions.[8] Through additional sources not included in OSRD's public records (e.g., the Manhattan Project), we identified a total of 3,137 OSRD-funded, patented inventions, which we use to measure the OSRD shock, preferring these to OSRD's prime contract spending because they represent outputs, merge to other sources, and bring us closest to the level where the work was performed.[9]

We link these data to the U.S. patent record. To do so, we compile data on U.S. patents granted between 1920 and 1979, merging a USPTO master file of patents with patent number, patent class (USPC), and issue date (Marco et al. 2015) with data on (i) serial numbers and filing dates;

[8]We observe detailed data on each contract, including the contractor, subject matter (OSRD division which wrote the contract), total value, security classification, patent policy, and termination date.

[9]Beyond the 3382 patent applications (2637 issued patents) identified in OSRD records, we measure an additional 461 OSRD-funded serials (388 patents) associated with the Manhattan Project through a public records request (Streifer 2017) and 36 serials (8 patents) from records of the Army's Judge Advocate General's office (see Gross 2023). We also supplement these records with an automated, text-based search for continuations and divisions of these patent applications, which identifies another 104 OSRD-supported patents.

(ii) front-page citations; (iii) harmonized assignee names and types; and (iv) inventor locations, which we measure using data from Petralia et al. (2016), Berkes (2018), and Bergeaud and Verluise (2022) (see Appendix B.1).[10] We supplement these data with new administrative, archival data on government-funded patents since the early 1900s, which we introduce in Appendix B.2 (also see Gross and Sampat 2023), and which comprises a significantly larger set than can be measured from patent publications (Fleming et al. 2019). For our cross-country comparisons, we add data from the European Patent Office (EPO) PATSTAT database on granted patents in the U.S., Great Britain, and France over the same period, which includes similar information to that of our USPTO base layer: patent number, patent class (IPC), and issue date.

In Section 5, we measure county-level employment and firm creation by industry using the U.S. Census Bureau's County Business Patterns (CBP) and Dun & Bradstreet's (D&B) historical data files. We use CBP and D&B data from 1980 (the latter lists over 4.5 million U.S. establishments, including their 4-digit SIC and founding year) to study long-run outcomes, and we apply a USPTO crosswalk to map SIC codes and patent subclasses to a common, SIC-derived (but USPTO-generated) classification, enabling us to perform analysis that links our treatment to industry outcomes.[11,12,13] We restrict the D&B sample to single-location firms and headquarters establishments, and to firms which we can accurately geocode using address information (89% of the sample). We then aggregate up firm counts to the county x industry x founding decade level, to smooth over bunched rounding in founding years. From the CBP, we thus obtain a 1980 cross section of county-industries, and from D&B, we build a 1920-1980 panel of county-industries.

Distribution of OSRD activity across space and subject matter

OSRD contracted for research in a wide range of subject areas, and with an array of contractors. Table 1 lists the top 10 OSRD patent classes and their share of OSRD patents, contrasting this with the share of patents these classes comprised in the recent pre-war era. Together with Figure 1, the table brings into relief how large a shock World War II was for U.S. innovation, both in scale

[10] We are grateful to all three sets of authors for sharing the data.

[11] Our choice to use 1980 data files has several motivations. Earlier CBP editions which we have experimented with (e.g., 1956, 1959, 1970) report 3- and 4-digit SICs with much lower frequency, undermining the patent-industry crosswalk and limiting power, whereas the CBP from the late 1970s onwards provides finer disaggregation. Earlier D&B files are significantly smaller, and we believe only a partial accounting. Additionally, we prefer data produced under the same SIC edition as the USPTO crosswalk (1972). We lose relatively little by limiting the CBP-based analysis to 1980, as the CBP only exists post-1947, precluding pre-/postwar comparisons.

[12] The D&B data cover a large sample of U.S. establishments, approximating the universe (4.531 million establishments in 1980, versus 4.543 million in the CBP and 4.533 million in the Census Bureau's Longitudinal Business Database). Note that the D&B firm counts are by construction conditioned on survival to 1980. We will use industry x founding year fixed effects to account for differential survival rates across firm birth cohorts.

[13] Data available at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/sic_conc/.

and in the subject matter of the technologies OSRD was pushing.

[Table 1 about here]

In the appendix we provide additional context. Of particular note are Appendix Tables C.1 and C.2, which report the top (i) broad technology areas and (ii) and specific patent classes with OSRD patents in the 1940s, ranked by the OSRD-funded share of 1940s patents—measuring the size of the shock. Atop Table C.1 is nuclear energy, but most other high ranking subjects are in the domain of electronics and communications, including radar and microwave engineering, semiconductors, electrical computing, and cryptography, highlighting the role that World War II research made in advancing these fields, with potential applications beyond warfighting.

Figure 2 maps locations in the continental U.S. with OSRD-funded patents, demonstrating OSRD's geographic scope: although a handful of states received a large majority of its funding (Appendix Table A.2), and particular programs were concentrated in specific locations, OSRD-funded R&D spanned the country. Table 2 weaves these threads together, listing the top five counties with the most OSRD patents in select technology areas, and the OSRD-funded share of local patenting in the 1940s—i.e., the shock whose effects we will examine next.

[Figure 2 and Table 2 about here]

3 Postwar Take-off of World War II Technology Clusters

To understand the impacts of World War II on the U.S. innovation system, our starting point is to examine its constituent parts: the growth of regional innovation hubs.

A closer look at an example can motivate our approach. Middlesex County, Massachusetts—home to the Route-128 postwar technology hub—is in many ways the canonical example. Prior to the war, the Boston area was not an electronics hub, but during the war, OSRD stood up two large, central laboratories (the MIT Radiation Laboratory and its offshoot Harvard Radio Research Laboratory) to perform and manage wartime radar research. These programs drew in researchers from around the country—and not only did many of them stay, but the advances in electronics and microwave engineering that this effort produced were then parlayed into a wide range of postwar technological developments (Buderi 1996, Mindell 2002). The Rad Lab has been widely credited as jump-starting the Route-128 technology hub (Saxenian 1996) by helping to establish an ecosystem of universities, government laboratories, large firms, and postwar startups and spinoffs.[14]

To put numbers to this example, Figure 3, Panel (A) shows the time series of filed patents in the 12 largest Massachusetts counties from 1935 to 1965. Prior to the war, Middlesex produced more annual patents in levels but was not on a noticeably different time trend than other counties. During the war, invention spiked, driven by OSRD-funded R&D (see Table 2), and after the war returned to pre-war levels, before taking off in the 1950s. By the mid-1960s, Middlesex was producing twice its number of pre-war patents, as this modern cluster was taking shape.

[Figure 3 about here]

What technologies were behind this postwar takeoff? In Panel (B) we look within-county, comparing Middlesex County patenting in high-level technology areas (1-digit NBER categories) around the war. We plot time series for six technology categories (chemical, communications, pharmaceutical, electrical and electronic, mechanical, other), indexed to 1935 levels, and find similar patterns of even larger magnitude. Communications patenting—which microwave technologies group into—grew nearly 30-fold in the war, returned to pre-war levels, and was by 1965 over 10 times higher. Electronics patenting followed a similar, if attenuated, pattern. The evidence is consistent with the area's well-documented postwar technological and economic development, which others have qualitatively traced to OSRD-led R&D activity (e.g. Saxenian 1996).

This evidence motivates the empirical comparisons we make in the rest of this section, where we systematically compare patenting over time in clusters (counties x technology areas) with higher vs. lower levels of OSRD investment. We will henceforth measure technology areas at the slightly more disaggregated level of 2-digit NBER patent categories (which group up USPTO patent classes; see Hall et al. 2001). Our baseline specification to compare treated and untreated clusters is motivated by certain classes of endogenous growth models (e.g., Romer 1990). This specification—which we derive in Appendix D from first principles—will effectively provide a test of whether Romerian endogenous growth took hold in treated clusters as a result of OSRD-driven increases in the stock

[14] Other examples of clusters we observe as having OSRD-funded R&D and postwar growth (through 1970) include communications and electronics in central New Jersey and greater New York City (e.g., Mercer, NJ or Long Island), and to some degree Santa Clara, CA—although the growth of Silicon Valley is, in our view, more attributable to postwar developments. An important corollary question is why some of these clusters later diverged—including the classic question of why Silicon Valley took off, but central New Jersey did not.

of innovation or inventive capabilities. The specification is as follows:

$$Ln(Patents)_{ict} = \sum_{t=1931}^{1970} \beta_t \cdot Ln(\text{OSRD rate})_{ic} \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict} \quad (1)$$

where i indexes counties, c indexes patent categories, and t indexes years, and the sample runs from 1930 to 1970, with standard errors clustered at the county level. Our principal treatment measure is what we henceforth call the "OSRD rate": the fraction of patents filed in a given cluster between 1941 and 1948 which were OSRD-funded. Our primary specification uses a continuous measure of the logged OSRD rate, which mechanically restricts the sample to clusters with at least one OSRD patent.[15] We at times present results from specifications with treatment quartiles, which allows us to compare segments of the treatment distribution in a more flexible way, against each both other and clusters with no OSRD patents (the reference group):

$$Ln(Patents)_{ict} = \sum_{q=1}^{4} \sum_{t=1931}^{1970} \beta_{qt} \cdot \mathbb{1}(\text{Treatment quartile } q)_{ict} \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict} \quad (2)$$

It is important to note that these specifications will not necessarily identify the effects of the OSRD shock on local invention in isolation, because in equilibrium our units may be interdependent: each cluster's outcomes are co-determined with others' (e.g., a migration response would implicate both treated and untreated clusters). What we do identify is the effects of the shock on agglomeration, and on widening gaps between clusters that by implication follow.

3.1 Identification

A potential concern is the endogeneity of the locations and subjects of OSRD research, and the possibility that funding choices may correlate with other determinants of innovation. This concern can take multiple forms. For example, OSRD investment may have been directed to technologies that were ripe for exploiting—and places that were ripe for exploiting them. Or concurrent war-driven shocks, like the (massive) surge in military production, may correlate with OSRD investment in technology and geographic space, and concurrently affect the outcomes we study. Each of these possibilities would result in upwardly-biased empirical estimates.

[15] The analytical approach we take is designed to evaluate how intensely local innovation systems were engaged in the OSRD effort, and relate this intensity to their future growth. An alternative is to measure the treatment as OSRD patents (rather than the OSRD rate), and estimate the elasticity of postwar patents and OSRD patents—though even then, we would want to control for total war-era patenting, to not confound OSRD clusters with generally-inventive clusters. This alternative is mechanically nearly equivalent, since Ln(OSRD rate) = Ln(OSRD patents) – Ln(1941-1948 patents), but relaxes the implicit parameter restriction. We evaluate this alternative in Appendix D, where we find similar results to those we estimate under Equation (1).

Formally, the identifying assumption is that the OSRD shock is not correlated with unobserved determinants of pre- or post-war cluster patenting. This requires that these clusters were not otherwise likely to change around World War II (due to latent, location-specific technological potential or contemporaneous shocks). Sufficient conditions, in turn, are that either the places or technologies OSRD supported were independent of unobserved factors.

Our understanding of how OSRD worked provides support for this assumption. Though OSRD's R&D priorities were not randomly chosen, they were mainly product of short-run military need, rather than than long-run commercial promise. These priorities were set in collaboration with the military, through which it identified needs that could potentially be met by new technology. In some cases, it engaged in new problems (e.g., engineering controlled nuclear reactions). In other cases, it took existing problems that were stuck and pushed them forward (e.g., microwave radar). Its portfolio included projects with high uncertainty, some unsuccessful despite early enthusiasm (e.g., synthetic penicillin), and others with long odds that succeeded. Technical feasibility was a criterion in deciding how to allocate scarce inputs (especially research talent, more than funding), but postwar civilian demand was not a major consideration, given the existential crisis facing the nation. OSRD's first condition for any project was thus that it would help win the war—which, for example, led to the atomic bomb being prioritized over advanced rocketry, which was viewed as a weapon of future wars (Zachary 1997). Table 1 illustrates how different OSRD's priorities were from the status quo ante. In a postwar retrospective, OSRD Secretary Irvin Stewart reinforces this point, commenting on the independent nature of the shock:

> The shift in emphasis and even in direction was enormous ... subjects of minor importance in peacetime become of controlling importance in war. Some subjects are born of war. (Stewart 1948, p. 102)

The argument that short-run military need and the potential for immediate payoff drove OSRD funding choices—and hence, that resource allocations were not structurally endogenous to the outcomes we study—does not preclude a possible confounding effect if these were correlated with long-run demand or technological promise. Our reading of history, however, is that OSRD discontinuously pushed out the frontier for most technologies it funded.[16] Many of the technologies that existed at the end of the war were barely conceived or considered impossible before it, and others were conceived or known but not commercially pursued until OSRD developed them—overcoming market failures that caused commercial development to stall.

[16] The radar project, for example, was described as "five years of furious technology [development]... [that] advanced knowledge in its field by 25 years" (Massachusetts Institute of Technology 1946, p. 7).

With respect to OSRD's geography, research performers were explicitly chosen on their ability to deliver high-quality results, as fast as possible (Stewart 1948). Often, however, these were new and non-obvious: many World War II R&D problems were novel, and the U.S. lacked a deep bench of researchers with direct experience (it is telling that academic physicists led most of the major OSRD programs, rather than firms or engineers; see Kevles 1977b). Features of each R&D problem also shaped OSRD's choices over who would do the work, and whether and how it was divided: for example, complex systems engineering problems like radar were not easily divisible, and their R&D was thus geographically concentrated—often in university-hosted, government-funded central laboratories. These not only presented a new, "big science" approach to applied R&D, but also a new set of performers and a new geographic distribution.

Insofar as OSRD contract placement was non-random, empirical evidence (e.g., Figure 3) suggests this was more so the case on levels than trends. We show later in this paper that this pattern is quite general: pre-war invention in more- and less-intensively treated clusters followed precisely-estimated parallel trends until 1940 and only diverged after the OSRD shock took place. Despite these parallel trends, a remaining threat to identification could be other war-driven shocks coinciding with OSRD investment. A specific example is the possibility that large, wartime military equipment demand may have spilled in private R&D by war equipment suppliers, in the same locations and technologies OSRD funded. We systematically examine this alternative in Appendix E, but find that a range of evidence suggests against demand-based interpretations.

3.2 Baseline effects

Figure 4, Panel (A) presents our main result, displaying β_t estimates from Equation (1) with 95% confidence intervals. Clusters with a larger OSRD shock: (i) did not grow statistically differently than in clusters with a smaller shock prior to 1940, (ii) experienced a relative surge during the war, (iii) briefly contracted from their mid-war peak when the war ended, and then (iv) experienced a sustained takeoff. The magnitudes indicate that a doubling of a cluster's OSRD rate was associated with 20% greater cluster patenting by 1960—and 30% by 1970.

[Figure 4 about here]

In Panels (B) and (C), we re-estimate Equation (1) for non-OSRD and non-government interest patents, where we see similar long-run patterns, but a smoothing out of the 1940s, indicating that the mid-1940s "bump" in Panel (A) was the OSRD shock itself.

Appendix C provides several supporting results. Appendix Figure C.2 shows similar effects for citation-weighted patents and per-capita patenting, which rules out that the results are driven by population changes—and thus indicates real impacts on local inventive productivity. Appendix Figure C.4 re-estimates Equation (1), omitting individual states—and establishing that the result is not driven by any one state, county, or cluster. Appendix Figure C.5 reproduces Figure 4, but with estimates from Equation (2), plotting the β_t parameters for clusters in the top quartile of the OSRD shock. Patenting in these clusters is 60% higher by 1970.

In Appendix F, we show that our results are similar—if anything, more precise—when estimated for inverse hyperbolic sine (IHS) patents, which approximates the log transformation but is defined at zero, and thus includes cluster-years with no patents. In Appendix G we show that our results are the same for more aggregated geographic units such as CBSAs (core-based statistical areas). Given that our analysis window spans the pre-war to postwar era, which saw a dispersion of population and economic activity from urban centers, it is ambiguous whether a more appropriate geographic unit of analysis would be counties (for the earlier era) versus CBSAs (for the later era), but it is reassuring that results are not sensitive to this choice.

3.3 Heterogeneity

The most striking implication of the results thus far is that World War II was a formative event setting in motion increasing agglomeration of inventive activity around the country, and ostensibly the takeoff of technology clusters persisting to this day. A corollary question is whether it was an equalizing force, or merely deepened existing geographic differences.

To further explore this question, we partition counties into the top 5% versus bottom 95% of 1930s patenting (by patent count). When Equation 1 is estimated for each group, it becomes apparent that the effects are entirely driven by counties which were already among the most inventive before World War II (Figure 5). Yet even in these clusters, the OSRD treatment does not coincide with any differential growth leading up to the war: the entirety of the OSRD effect takes place with the wartime surge in patenting and the postwar takeoff. The evidence thus supports an interpretation of both continuity and change, like that seen in our Massachusetts example (in Figure 3): pre-war differences persisted, but the war caused a trend shift. In simpler terms, the OSRD's effect was to catalyze long-run growth in existing geographic centers of invention.

[Figure 5 about here]

A second question is whether the OSRD effect was general across all technologies whose development it funded, or stronger for some fields over others. We evaluate this question by partitioning the sample by 1-digit NBER categories (Chemicals, Computers & Communications, Drugs & Medical, Electrical & Electronics, Mechanical, and Other). Appendix Figure C.3 re-estimates Equation (1) for each of these categories. Consistent with the history, we find that our main result is primarily (although not exclusively) driven by the electrical and electronics field, where the long-run impact of OSRD was a 40% increase in cluster patenting by 1970.

3.4 Spillovers

Thus far, our analysis presumes and estimates localized impacts of the OSRD shock in the counties and technology areas where R&D investments were made. Yet investments in specific technologies may filter down to others, including via direct linkages or shared inputs and customers. Given that spillovers may be a means through which the effects of the OSRD shock compounded for specific cities and regions, we seek to more closely examine their magnitude.

Our focus will be on within-county spillovers across technology areas. We estimate an augmented version of Equation (2), where we include measures not only of a given cluster's treatment quartile, but also measures of whether (i) whether a "nearby" technology area was in each treatment quartile, and (ii) whether a more distant technology area was in each treatment quartile, where proximity is measured vis-à-vis 1-digit NBER categories: two technologies under the same parent category are considered proximate. We will effectively estimate a horserace regression, pitting localized shocks against nearby and more distant shocks (in technology space).

Figure 6 plots estimates (and 95% confidence intervals) for all treatment quartiles (columns) across all three types of shocks: local, nearby, and distant (rows). Standard errors increase somewhat, as we are estimating more than ten times as many parameters as in Equation (1) (because the specification includes annual parameters for four treatment quartiles, crossed by three levels of technological distance). Several patterns are nevertheless apparent.

[Figure 6 about here]

First, our baseline effects are largest for the top treatment quartile and attenuate at lower quartiles (matching Appendix Figure C.6, which shows the full set of parameters from Equation 2). Second, these effects are largest for localized shocks (in the same technology area). Third, we find evidence of spillovers that attenuate with technological distance. Fourth, low-treatment clusters experience *declining* invention post-World War II, suggesting that the widening regional differences we observe may have been accelerated by (or even driven by) invention migrating to heavily-treated clusters. Although the evidence thus far suggests this migration was not a result of population movements per se (Appendix Figure C.2), a postwar relocation of R&D activity may have one means through which agglomeration took place. More fully understanding how these agglomerative clusters took shape after World War II is the task we take on next.[17]

4 Emergent Local Innovation Systems

Despite the fact that World War II was, on its own, an inherently temporary shock to the innovation system, the evidence thus far indicates that its effects not only persisted but compounded for several decades. Our question for this section is why. To understand the mechanisms of persistence, we first, we consider OSRD's direct impacts in the form of growing postwar invention building directly on OSRD-funded research, which our evidence rules out as a driving force behind the divergence we found in Section 3. We are left with two possibilities. One is postwar government R&D investment in the same regions and technology areas which OSRD funded—i.e., a sustained push—driven by continuity in defense R&D funding structures and military need. The other is an organic growth takeoff, powered by Marshallian increasing returns to scale.

4.1 Direct follow-on to OSRD invention

We begin by exploring the more direct channels through which OSRD-funded R&D might affect local invention, such as direct follow-on invention, or invention by firms or inventors who participated in the OSRD effort and developed capabilities and expertise that it could harness after the war ended. We measure follow-on invention in the form of patents which cite OSRD patents, and OSRD firms as firm assignees which produced an OSRD patent.[18]

In Figure 7, we estimate Equation (1) over these categories. Panels (A1) and (A2) estimate the effects of the OSRD shock on patents that do and do not cite OSRD patents (respectively), where it is apparent that the effect is entirely driven by the latter. In Panels (B1) and (B2) we estimate the effect on patents of OSRD firms and other assignees, again finding that the effect is primarily

[17] This evidence is consistent with recent perspectives on technology spillovers attenuating with technological distance (e.g., Myers and Lanahan 2022). While in principle, the evidence of spillovers could challenge identification of our core results if technologically-proximate clusters tended to be jointly treated, we are (paradoxically) reassured on this matter by the same evidence which raises it, because Figure 6 controls for nearby technology area shocks and still finds effects in the focal cluster. Moreover, as we are aiming to evaluate the effect of the OSRD program, we consider the bundled direct and spillover effects to be the object of interest.

[18] Given the challenges of longitudinal inventor linking and disambiguation, and our own hesitations in the resulting links, we do not attempt to link all OSRD inventors to their pre- and postwar patents, but rather focus on researchers at two of the largest OSRD-funded research labs (the MIT Radiation Laboratory and Harvard Radio Research Lab), which we have hand-matched to patents in concurrent research (Gross and Roche 2023).

driven by the latter. For brevity, we do not show the inventor results, though the patterns are the same—which is consistent with our priors, given the magnitudes of our effects and that many of these individuals' careers had waned by the end of our sample. Collectively, the evidence suggests against an interpretation of long-lasting direct impacts.

[Figure 7 about here]

4.2 Postwar government R&D investment

Our second hypothesis is that the postwar takeoffs we find were powered by continued government R&D investment in the same subjects and regions. In the context of the Cold War expansion of federal R&D, and the continuity in many military R&D priorities (e.g., aerospace, missiles, radar, nuclear arms), this is a natural conjecture.[19] To evaluate this question, we take two approaches. First, we re-estimate Equation (1), controlling for clusters' government-funded share of postwar patents (henceforth, the "USG rate"), crossed by year—in effect, accounting for the fact that many of these clusters remained "defense R&D places" (in the language of Kantor and Whalley 2022), which may have grown differentially in the postwar era. The results are unchanged (and thus, for brevity, not reported here). Second, we partition the sample into clusters with zero, below median (conditional on non-zero), and above median postwar USG rates, and re-estimate Equation (1) for each group. Figure 8, Panels (A) and (B) show that the OSRD shock had similar effects in clusters with higher and lower postwar government-funded invention.

[Figure 8 about here]

A related question is whether the results in Section 3 could be attributable to local universities, many of which expanded their research mission in the Cold War era (Geiger 1993, Lowen 1997). In additional analysis (Appendix Figure C.7), we examine whether our main results vary in counties with or without a top university. We identify top universities in two ways. First, we use a National Academy of Sciences report on PhD production at U.S. universities from 1920 to 1962 (NAS 1963), and the NSF Survey of Earned Doctorates (its successor), to measure PhD graduates in the physical and biological sciences between 1950 and 1969 and identify the top 20 and 50 universities in terms of PhDs granted in these fields. Second, we borrow a measure of "top 40" universities from the NAS (1963) report. When we control for these measures, our results are unchanged. However, across

[19] Indeed, our data indicate substantial path dependence in Cold War government R&D (Appendix Table C.3).

all three measures, we find that the effects of OSRD are roughly twice as large in clusters with a leading university—and still substantial in those without one. The results suggest that although educational institutions were not the direct drivers of the OSRD effect, they reinforced its effect by supporting the growth of local ecosystems in the postwar era.

4.3 Increasing returns to scale

The remaining possibility we see is a Marshallian takeoff, springing from wartime R&D investments that established a collection of firms, inventors, and institutions with experience in new, frontier technologies developed in the war around which clusters could grow.

In this case, we would expect a wide range of changes to take place. With our data, we are able to examine if—and show evidence that—the OSRD shock led to an expanding set of local, R&D-performing firms and institutions; increasing private and public invention; growth of incumbent firms, in-migration, and de novo entry; deepening linkages between local invention; and, ultimately, deconcentration of invention, as these local innovation systems grew.

We begin by examining the growth in patenting across a range of actors. To do so, we transition from a specification with annual parameters to estimating quinquennial parameters, to simplify the presentation. Table 3 estimates the effect of the OSRD shock on firm patenting, which Column (1) shows grew significantly over the postwar period. To understand the source of these patterns, we divide our sample into patents by incumbent firms (i.e., those with prior patents) and new firms (without prior patents), and further subdivide incumbent firms into those with prior patents in the given cluster versus those whose prior patents were in other counties or technology areas. This will allow us to look for evidence of firms crowding into treated clusters.

[Table 3 about here]

We find growing firm patenting from multiple directions, including by cluster incumbents (Column 2), but also by local firms migrating into the cluster from other technology areas (Column 3) and more geographically-distant firms in the same technology area reallocating R&D activity to treated clusters (Column 4), as well as by new patenting firms (Column 6). We do not find a comparable effect for patenting by geographically and technologically distant firms (Column 5), suggesting that the agglomerative impacts of OSRD shock had some limits in scope.

We find similar results when outcomes are measured as the number of unique firms filing patents in the given cluster and year, rather than the number of firm patents—reflecting the broadening inventive base. Complementing, and in some cases even feeding, this firm growth was government-funded invention. The well-known history of the Silicon Valley and Boston-area clusters, for example, are rich in stories of both industry and military-led research in this era. Though government invention does not explain the effects of the OSRD shock, in Table 4 we examine to what degree it followed. Column (1) shows that government-funded invention grew rapidly after the war in clusters which OSRD itself funded—but as Column (2) conveys, non-government funded R&D grew at a similar rate. The growth in government-funded invention was entirely driven by defense R&D (Columns 3 to 6), which dominated the federal R&D budget in the postwar era.

[Table 4 about here]

In Table 5 we examine patent citation flows, which has traditionally been applied as a proxy for knowledge spillovers—a tradition we continue, despite known limitations. We estimate, in parallel, the share of backward (forward) citations made by (accruing to) patents in a given cluster and year that are to prior (from future) patents in the same county and/or technology area, as a function of the OSRD shock. Because citations were only included in patent publications beginning in 1947, our analysis of backward citations applies to post-1947 patents. Since these citations point to earlier patents, forward citations can be measured for the full sample.

[Table 5 about here]

Broadly, Table 5 provides evidence of growing local citation flows following the OSRD shock. As a benchmark, the share of backward and forward citations that occur in the immediate neighborhood of a given patent (same county and technology area) is low, at roughly 2% and 4%, respectively—reflecting the literal definition of citations as references to prior art against which the novelty of a patent's claims are evaluated by examiners, which exists widely. However, we note a few patterns. By the late 1960s, patents in more heavily shocked clusters have a higher fraction of backward citations to others in the same cluster (an increase of roughly 15% of the mean), as well as a higher fraction to patents in the same county but a different area (up 10% of the mean), or the same area but a different county (up 2% of the mean). These patents are likewise accruing a higher fraction of their forward citations within-cluster (up 25% of the mean).

The final result we present is a summary statistic for the collective evidence. Table 6 estimates the concentration of cluster patenting across filers as a function of the OSRD shock. In Column (1) we measure a Herfindahl index, and in Columns (2) to (5) we measure concentration ratios for the top 1, 5, 10, and 20 filers (respectively). The results suggest that the shocked clusters experienced a significant broadening of their inventive base over the postwar era, with much of this effect driven by deconcentration away from the single dominant filer. In effect, what used to be company towns became significantly more diverse in their R&D performers.

[Table 6 about here]

The evidence is broadly consistent with prior research on industrial agglomeration. The economic geography literature has consolidated around three sources of agglomeration economies, which Duranton and Puga (2004) have characterized as "sharing" (of indivisible local assets, like universities or infrastructure), "matching" (of buyers and sellers of goods and labor), and "learning" (knowledge spillovers). Though these mechanisms are typically observationally equivalent, they provide useful structure for interpreting our results. The growth of local R&D-performing firms and institutions (insofar as we can measure them), including (i) firms migrating into the treated clusters from other locations and technology areas, and (ii) government agencies locating labs and contracting with firms in these clusters, is consistent with the local advantages borne out of assets like large talent pools, financial capital, and research facilities. This density also supports more efficient matching, particularly through labor mobility.[20] Insofar as patent citations may reflect intellectual linkages, we explicitly find evidence of growing knowledge spillovers.

5 Downstream: Entrepreneurship and Employment

Did the growth of these postwar innovation clusters have broader impacts on local economies? The downstream effects of local and regional R&D investments is an important question not only for research on agglomeration but also for policy to improve local economic performance through place-based public R&D investments (Glaeser and Hausman 2020). What are the downstream effects of big, applied push R&D investments on local economic outcomes?

Research has increasingly begun to speak to these questions, especially in the context of Cold War-era R&D shocks. Schweiger et al. (2022), for example, show that Soviet "Science Cities"—R&D centers created by the Soviet government in the mid-twentieth century to support R&D in key technologies—today have higher education, skilled employment, patenting activity, and incomes.

[20] We do not document labor mobility directly, due to data limitations: linked employee panels are difficult to construct for this period. We forgo building a linked inventor panel across the universe of inventors due to hesitations with the quality of the links we can make, including selection into linking, disambiguation challenges, and the sensitivity of mobility measurement to the standardization of assignee names, firm reorganization, and name changes—as well as limited power, given that patenting is a rare event for most individuals, and the median inventor has one patent. We instead note that improved matching is a corollary of thick labor markets.

Kantor and Whalley (2022) show that in U.S. counties which were target locations for Space Race R&D, manufacturing employment, output, and productivity grew more quickly in and after the Space Race era. We complement this literature by examining the impacts of public investments in specific technologies on the industries that produce them, and with a shock that provides variation both within and across counties, technologies, and industries.

We use CBP data to measure local employment in select industries in 1980, and D&B data to measure local business creation in these industries from 1920 to 1980. We link industries to the patent data (where we observe the OSRD shock) using a USPTO-produced crosswalk, which concords both SIC industries and patent subclasses to a common set of 41 unique industry codes. Several of these codes group up into an "Electrical and Electronic Equipment and Supplies" category—including the industry code with the most associated OSRD patents ("Electronic components and accessories and communications equipment"). This, together with prior evidence that the electrical and electronics area is where the OSRD shock had bite (Appendix Figure C.3) and the broader growth of the electronics industry in the postwar period, motivates our focus on this category, and the analysis below will be performed across counties and industries in the electrical field. Appendix B lists the complete set of industries included in this sample.

We first explore OSRD's long-run, downstream employment effects. For this analysis, we estimate the effects of both extensive and intensive treatment measures on industry employment. Where employment counts are suppressed by the CBP (e.g., for small county-industry cells which pose a risk of disclosure), we impute employment from the establishment size distribution (in the spirit of Duranton et al. 2014). To accommodate sparse samples, we replace log transformations with inverse hyperbolic sine transformations, which retains zeros in the explanatory and outcome variables but otherwise resembles the shape of our standard approach, and in successive specifications we control for counties' manufacturing employment (across all manufacturing SICs) and total employment (across all SICs). Formally, we estimate the regression below:

$$IHS(Employment)_{id} = \beta \cdot OSRD\ Treatment_{id} + \alpha_i + \gamma_d + X_{id}\phi + \varepsilon_{id} \tag{3}$$

where i and d index counties and industries, α_i and γ_d are fixed effects, X_{id} are controls, and standard errors are clustered at the county level. Because employment in a given county and industry is determined in equilibrium with others, the results we obtain under this approach should not be interpreted as a multiplier on R&D (as in Kantor and Whalley 2022), but rather as divergence: without more structure, we are unable to distinguish net job growth from share-stealing, either of which could increase differences between counties. As with the rest of this paper, however, our goal is to evaluate the degree to which the OSRD shock led economic activity to agglomerate in the treated clusters and widened gaps in economic performance.

Table 7 presents the results. Columns (1) to (3) show that county-industries which engaged in OSRD R&D have roughly 90% greater employment in associated manufacturing industries in 1980 than those which did not, while Columns (4) to (6) suggest that a doubling of the OSRD rate is associated with a more than doubling of manufacturing employment. These results should be interpreted with caution, since we do not observe the pre-war period and the relationship could potentially be endogenous. However, it is reassuring that many of these industries (e.g., electronic components) did not take much shape until after World War II.

[Table 7 about here]

In Table 8 we repeat this analysis for firm creation. Here we replace county and industry fixed effects with county-industry fixed effects, exploiting the longer panel, and estimate differences relative to 1920 (the omitted category). Year fixed effects also serve an important role in this context, given that the sample of firms is conditioned on survival to 1980, and earlier decades have fewer firms in 1980 due to intervening exits. Columns (1) to (3) indicate that counties that produced OSRD patents were increasingly likely to produce firms in associated industries, particularly during and after the 1940s, though we see a (quantitatively modest) pre-trend in the 1930s. Columns (4) to (6) indicate that a doubling of the OSRD rate is associated with a steady increase in new manufacturing businesses over the postwar era, from 15% to 25% in the 1940s and 1950s to a more than doubling by the 1970s, with no visible pre-trend on the intensive margin.

[Table 8 about here]

6 Aggregate U.S. Invention

A corollary question to the results in Section 3 is whether the OSRD shock affected aggregate U.S. invention. To answer this question, we estimate a cross-country triple-difference specification, comparing patenting at the USPTO and patent offices in two other Allied countries: the UK and France. In effect, the triple-difference design will estimate country-specific changes in patenting over time in patent classes (2-digit International Patent Classes, or IPCs) which were more vs. less intensively OSRD-treated (the difference-in-difference), and compare these changes across countries (the third difference). This approach will thus identify differential growth in patenting in OSRD-funded technologies in the U.S. relative to other countries.

Similar to our prior analyses, our treatment measure is the fraction of U.S. patents in a given patent class between 1941 and 1948 that were OSRD-funded. We bin this treatment into quartiles (conditional on ≥1 OSRD patent), with the reference category being classes with no OSRD patents. Our principal specification compares U.S. and foreign log patenting, in patent classes at different treatment quartiles, before and after war. We estimate this specification over a sample of country-class-years from 1930 to 1970, omitting 1940 to 1945, as follows:

$$\begin{aligned} Ln(Patents)_{ict} = &\sum_{q=1}^{4} \beta_q \cdot (\text{Country } i = \text{US}) \cdot (\text{Class } c \in \text{quartile } q) \cdot (t > 1945) \\ &+ Country_i \times Class_c + Country_i \times Post_t + Class_c \times Post_t + \varepsilon_{ict} \end{aligned} \tag{4}$$

where i, c, and t index countries (grouped up to U.S. vs. foreign), technology classes, and years, and standard errors are clustered at the country-class level.[21] Figure 9, Panel (A) plots the results (with 95% confidence intervals). We find that U.S. patenting in the most heavily-treated classes increases over 50 percent more after the war than in other countries, and this effect attenuates in both magnitude and significance as treatment intensity declines.

We also make an analogous comparison within USPTO patent records only, where we compare patenting by U.S. vs. all foreign inventors. Here we use U.S. patent classes (USPCs), and index time by filing dates. Panel (B) illustrates that the differences here are even larger than across patent offices. In the most heavily-treated patent classes, postwar patenting by U.S. inventors increases nearly 80% more than patenting by foreign inventors.

[Figure 9 about here]

In Appendix C we estimate a variant of Equation 4 with annual parameters. Paralleling Figure 9, Appendix Figure C.8 presents the estimates for patenting at USPTO vs. foreign patent offices, and Appendix Figure C.9 for USPTO patents with U.S. vs. foreign inventors. We find similar patterns to those throughout the paper: patenting in the most heavily treated classes is on a parallel pre-war trend at USPTO (vs. foreign patent offices) or among U.S. inventors at USPTO (vs. foreign inventors), but then differentially grows in the postwar era.

[21] Because historical PATSTAT data only provide grant (not filing) dates, t indexes grant years for the U.S. vs. foreign patent office comparisons, where we also restrict to patents with a family size of one (to ensure we are measuring the primary location), although the results are generally not sensitive to this restriction. For domestic vs. foreign USPTO patents, we measure filing dates, and t indexes filing years.

7 Concluding Remarks

"Although its part in the winning of the war was its greatest contribution... the full impact of its work must await the judgment of the future..."

— Irvin Stewart, Secretary of the OSRD (Stewart 1948, p. 298)

Despite a large historical and science policy literature on the run effects of OSRD on the institutions of postwar science policy, we believe this paper to be the first quantitative empirical assessment of the long-run effects of what President Roosevelt called a "unique experiment" in research policy (Roosevelt 1944) on innovation and other economic outcomes.

With newly digitized archival data on OSRD contracts, linked to data on postwar patenting, firm creation, and employment, we found persistent effects of the World War II R&D shock on technology clusters. Treated clusters were producing another 40% to 50% more patents annually than untreated clusters by 1970, despite parallel trends in patenting before the war. In exploring mechanisms, we rule out that this was due to patenting by OSRD contractors themselves, or to patents citing OSRD patents. We also used newly digitized data on the history of government patenting to show that the effects are not driven by follow-on government research investment in the same technology clusters. Instead, our evidence suggests that the effects are due to Marshallian agglomeration: with growing patenting by new and older firms, public and private, in-migrant firms and established firms, and with innovation becoming increasingly dispersed over time. Beyond patents, we also find evidence that postwar firm creation and employment were higher in OSRD treated counties, decades out. Finally, there was also an aggregate shift in the trajectory of U.S. innovation towards the most heavily treated technology areas, namely electronics and communications.

The results provide new evidence on the persistent impacts of a large, broad, applied R&D shock on innovation, complementing a growing body of evidence on the returns to publicly funded research. The nature of the shock and its impacts evokes parallels to modern place-based industrial policies, including those introduced in the CHIPS and Science Act (recently-enacted, at the time of writing). Whether these results generalize to other R&D investments, in a very different innovation system, is difficult to say. On the one hand, our results offer support for place-based R&D policy and large, public applied R&D investments. On the other, OSRD's effects may be specific to its time: today's innovation system is bigger, better developed, and global, and knowledge may be more mobile. We are also acutely aware that past public policies directed at cultivating new regional technology hubs have often fallen short of their aims (e.g., see Lerner 2009). These factors make it difficult to make direct claims on the generalizability of this example to modern problems.

The results nevertheless point to several insights. In this paper we show that a large R&D shock drove long-lasting changes in economic performance, and evidence on the mechanisms—something which, to our knowledge, has not previously been shown. The evidence establishes that place-based R&D investments can have long-lasting local effects, while at the same time pointing to how, in this case, they did so. Our interpretation of the evidence is that it was not any single activity or institution, but rather an integrated set of institutions and actors, that provided a foundation for OSRD-funded clusters to continue to grow. OSRD's approach to crisis R&D policy may have played a key role in creating this foundation: its programs integrated researchers, manufacturers, and end users, not only funding the research but also coordinating efforts and ensuring R&D was connected to production and the battlefield (Gross and Sampat 2022c). Key institutional partners included universities, firms, and government-funded laboratories. Here again, Middlesex (MA) is our canonical example: the Rad Lab hosted a close-knit collaboration between academic researchers, industrial scientists, manufacturing firms, and the military—relationships which carried over into the postwar era, while also spilling over to commercial innovation. If this interpretation is correct, it suggests that the cultivation of innovation ecosystems requires complementary policies and investments, rather than any one intervention alone.

There are also wider implications for research, policy, and practice. At a high level, these results support Vannevar Bush's argument that federally-funded research can fuel innovation and improve economic performance. But whereas Bush argued for funding "basic" research in *Science, The Endless Frontier*, OSRD's funding was primarily for applied R&D. Our results suggest that large-scale federal investments in applied research can also have large returns, or at least did in this case, potentially important given resurgent interest in "mission-oriented" R&D.

Our results also suggest that on concentration and inequality, Bush's nemesis Harley Kilgore was right to be concerned. Much of the OSRD support was directed to researchers at elite institutions and research labs (Appendix Table A.3). Lacking a counterfactual, it is difficult to know whether the elite funding model of OSRD was the most efficient one for wartime—were there, literally, any lost Einsteins?—but it is also hard to argue with the results. Nevertheless, Kilgore's concerns about persistent concentration of innovative activity and economic power generated by such an approach seems prescient, given the results of this paper suggesting they fueled agglomeration. Gruber and Johnson (2019) have argued that broader funding, even if it reduces efficiency, could promote not only equity but also geographically-diffuse public and political buy-in for increasing federal research spending, a question we hope to explore in future research.

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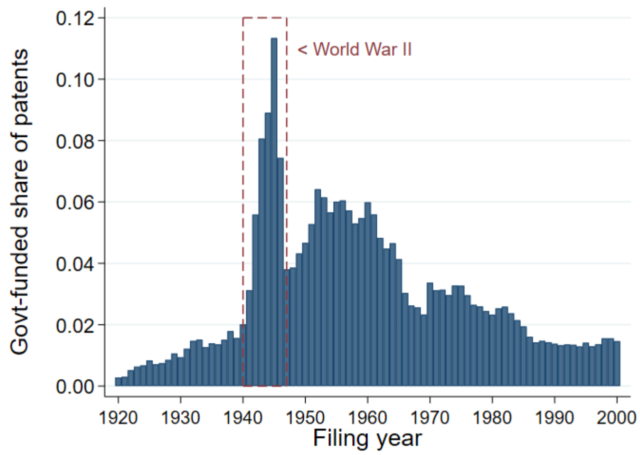
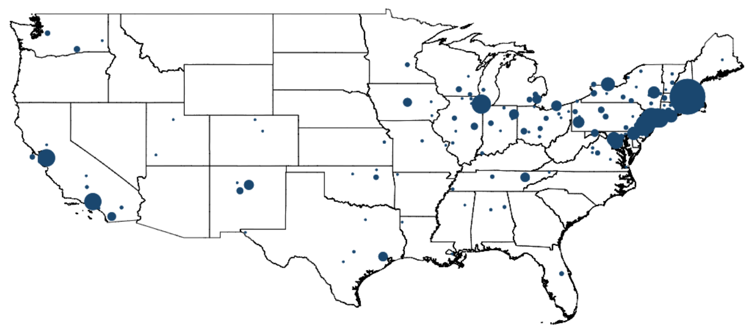
Figure 1: Government-funded share of U.S. patents, 1920 to 2000



Notes: Figure plots the government-funded share of annual U.S. patenting (by filing year), using administrative data. World War II was the peak intensity of government-funded invention in U.S. history. See appendix for data details.

Figure 2: Geography of OSRD-funded invention in World War II

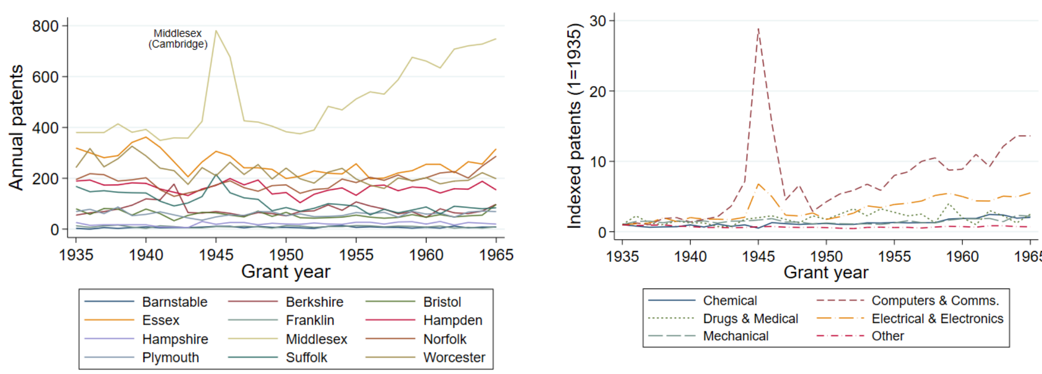


Notes: Figure maps counties with OSRD-funded patents. Bubble sizes proportional to each county's total number of OSRD patents.

Figure 3: Patenting trends in Massachusetts counties, 1935 to 1965

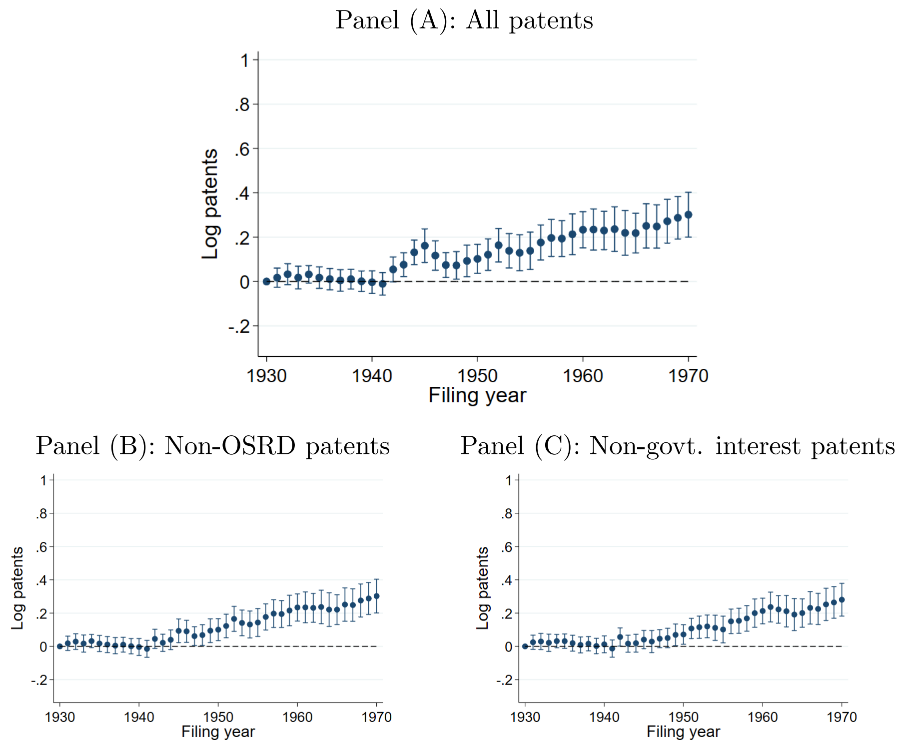
Panel (A): Twelve largest MA counties (all technology areas)

Panel (B): Middlesex, MA (by technology area, indexed)



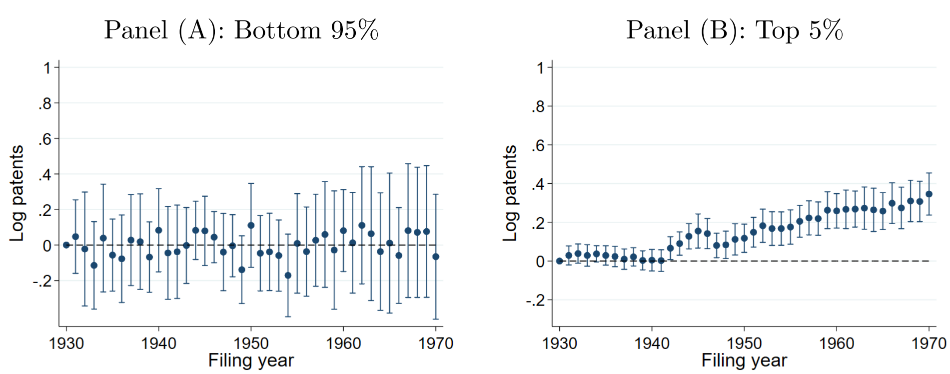
Notes: Figure shows total annual patents filed in the top 12 Massachusetts counties. The figure illustrates, for Middlesex County (location of Cambridge, home to Harvard and MIT): (i) relatively constant, pre-1940 level differences in patenting; (ii) a mid-1940s spike (doubling) of patenting, driven by war-related research; (iii) a return to approximately pre-war levels; and (iv) a take-off in the early 1950s. The raw data illustrate the general pattern that we find throughout the paper.

Figure 4: Effects of OSRD on cluster patenting, 1930-1970



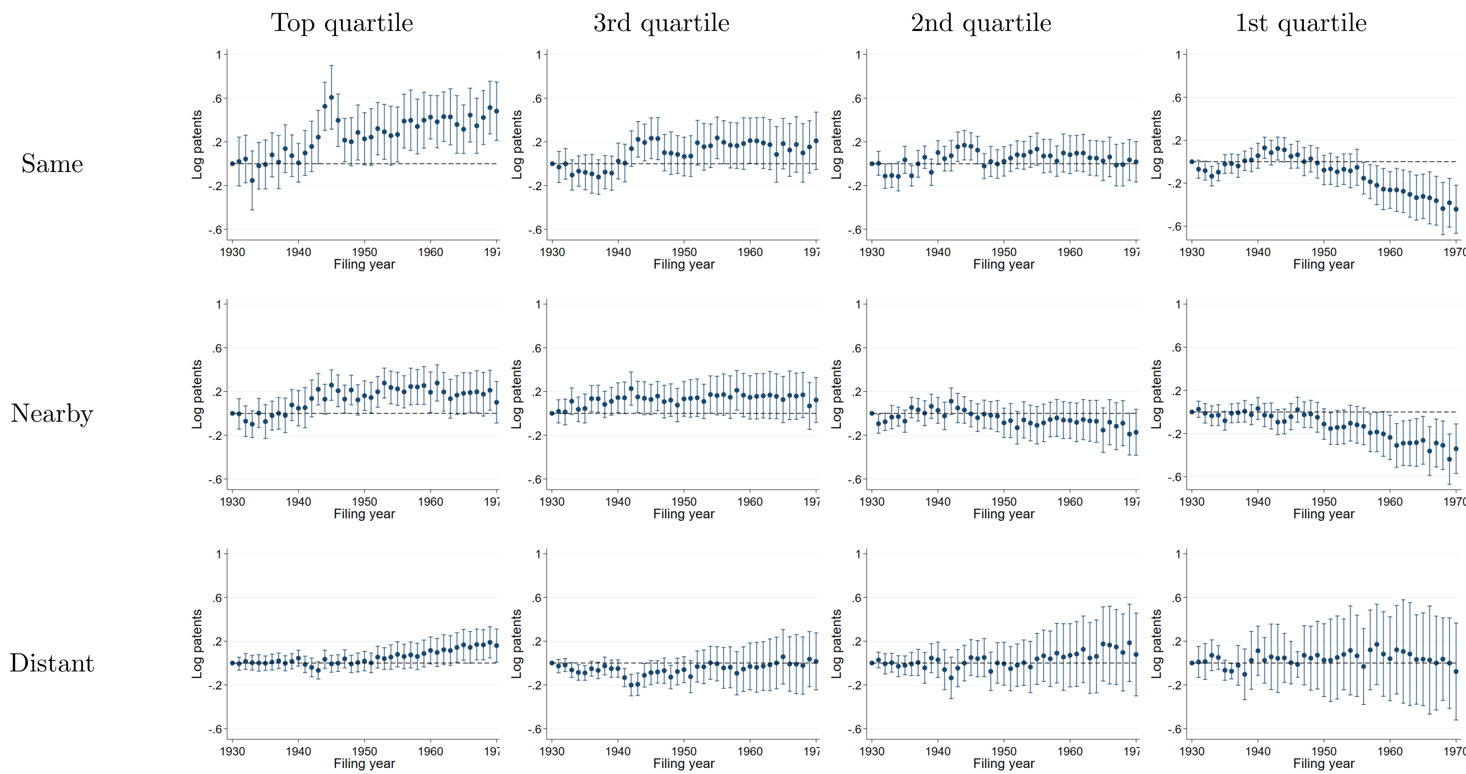
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure 5: Effects of OSRD on cluster patenting, for clusters in counties in the bottom 95% versus top 5% of 1930s patenting



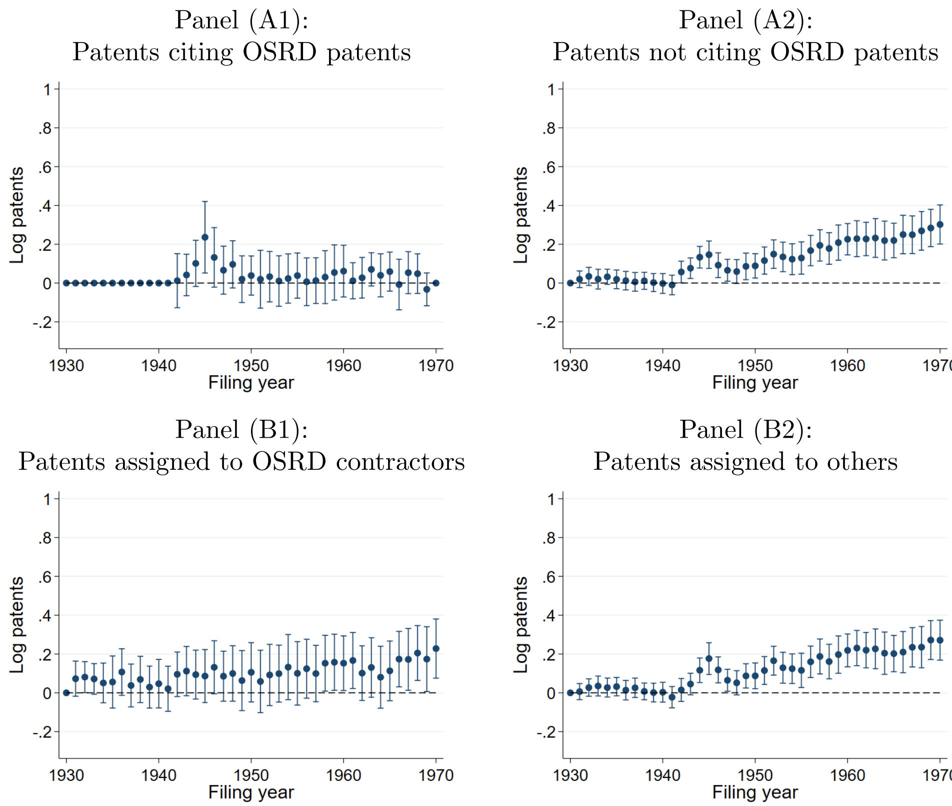
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting, for counties in the bottom 95% and top 5% of 1930s patenting. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure 6: Effects of OSRD on cluster patenting, 1930-1970, cross-technology area spillovers
horserace regression of treatment in (i) same technology area, (ii) nearby technology areas, (iii) more distant technology areas



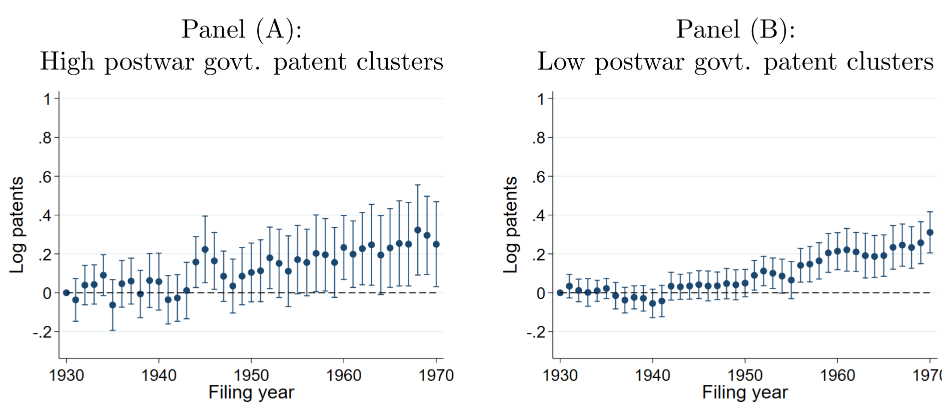
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the quartile of treatment intensity, conditional on treatment (the fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded, conditional on any), of three types: (i) in the given county-category (top row); (ii) in the same county and proximate technology categories (same 1-digit NBER category, per Hall et al. (2001); middle row); and (iii) in the same county and more distant technology categories (other 1-digit NBER categories; bottom row). Parameters across all panels are estimated jointly (in one regression) relative to a reference group of county-categories without any OSRD patents. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure 7: Effects not explained by OSRD's direct impacts on local invention



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category (i) patents citing versus not citing OSRD patents, and (ii) patents assigned to OSRD contractors versus others, as an exploration of the direct impacts of OSRD on postwar invention in the treated clusters. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure 8: Effects not explained by sustained government investment in local invention

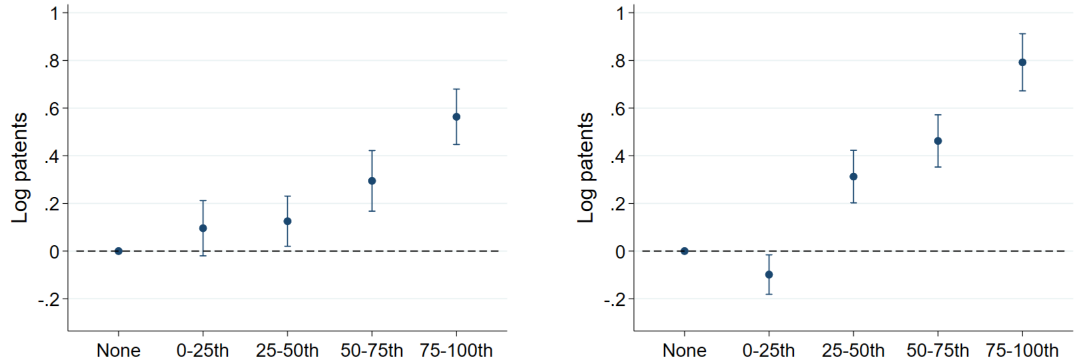


Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patents in county-categories with above and below median postwar (1950-1969) government-funded patent rates, as an exploration of the role of sustained public R&D investment as an explanation for persistence. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure 9: U.S. versus foreign patenting in each quartile of treated patent classes (difference-in-differences, pre-1940 vs. post-1945)

Panel (A): Patenting at U.S. vs. foreign patent authorities, by treatment quartile

Panel (B): Patenting by U.S. vs. foreign inventors at USPTO, by treatment quartile



Notes: Figure shows difference-in-difference estimates of the effects of the OSRD shock on U.S. versus foreign patenting, in patent classes (2-digit IPC in Panel A, USPC in Panel B) at different quartiles of OSRD treatment, as measured by the fraction of U.S. patents in those classes between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the country-class level.

Table 1: Top 10 patent classes of OSRD patents (denominator: OSRD patents)

		OSRD patents		1933-40 patents	
USPC	Description	Percent	Rank	Percent	Rank
342	Directive radio wave systems/devices (radar)	6.6%	1	0.2%	167
102	Ammunition and explosives	5.8%	2	0.2%	170
315	Electric lamp and discharge devices: systems	4.8%	3	0.6%	302
250	Nuclear energy	4.0%	4	0.1%	117
333	Wave transmission lines and networks	3.6%	5	0.2%	164
343	Radio wave antennas	3.4%	6	0.2%	141
423	Inorganic chemistry	3.2%	7	0.7%	309
367	Acoustic wave systems/devices	3.1%	8	0.1%	79
324	Electricity: measuring and testing	3.0%	9	0.5%	284
327	Misc. electrical devices, circuits, and systems	2.9%	10	0.1%	85

Notes: Table lists the top patent classes of OSRD patents, alongside their share of OSRD patents and of post-Depression 1930s patents for comparison.

Table 2: Top clusters with OSRD patents, 1941-1948 (select technology areas)

Technology area: All				Technology area: Communications (21)			
		OSRD patents, 1941-1948				OSRD patents, 1941-1948	
Rank	County	Number	Share of cluster	Rank	County	Number	Share of cluster
1	Middlesex, MA	446	12.3%	1	Middlesex, MA	216	45.5%
2	Essex, NJ	139	2.5%	2	Mercer, NJ	37	14.3%
3	Mercer, NJ	129	10.2%	3	Suffolk, MA	35	35.7%
4	Cook, IL	121	0.7%	4	Essex, NJ	31	6.8%
5	Alameda, CA	98	3.7%	5	Suffolk, NY	27	9.2%

Technology area: Electrical lighting (41)				Technology area: Electrical devices (42)			
		OSRD patents, 1941-1948				OSRD patents, 1941-1948	
Rank	County	Number	Share of cluster	Rank	County	Number	Share of cluster
1	Essex, NJ	39	10.1%	1	Middlesex, MA	61	21.7%
2	Middlesex, MA	38	14.4%	2	Nassau, NY	25	10.4%
3	Mercer, NJ	25	17.5%	3	Washington, DC	13	7.4%
4	Schenectady, NY	17	8.5%	4	Suffolk, NY	12	5.7%
5	Allen, IN	9	22.5%	5	Suffolk, MA	11	15.1%

Technology area: Measuring, testing (43)				Technology area: Nuclear, X-rays (44)			
		OSRD patents, 1941-1948				OSRD patents, 1941-1948	
Rank	County	Number	Share of cluster	Rank	County	Number	Share of cluster
1	Monroe, NY	22	20.0%	1	Alameda, CA	56	68.3%
2	Middlesex, MA	20	16.9%	2	Cook, IL	41	28.9%
3	Nassau, NY	18	13.0%	3	Santa Fe, NM	14	66.7%
4	Harris, TX	9	7.1%	4	Anderson, TN	8	17.0%
5	Los Angeles, CA	9	3.5%	5	Mercer, NJ	7	24.1%

Notes: Table lists the top clusters in select technology areas by number of OSRD patents and the share of local patents which were OSRD funded. Displayed technology areas are shown alongside their NBER technology subcategory (Hall et al. 2001) and selected due to their prominence or importance to OSRD's agenda.

Table 3: Firm patents: All, incumbents, and entrants
(incumbents by geographic and technological proximity)

		Same county		Diff. county		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Same field	Diff. field	Same field	Diff. field	Entrants
Ln(OSRD rate) * 1(1935-1939)	-0.008	-0.006	0.016	0.013	-0.013	0.023
	(0.015)	(0.021)	(0.015)	(0.021)	(0.026)	(0.020)
Ln(OSRD rate) * 1(1940-1944)	0.032	0.019	0.062***	0.058***	0.024	0.066***
	(0.024)	(0.030)	(0.016)	(0.019)	(0.027)	(0.022)
Ln(OSRD rate) * 1(1945-1949)	0.049	0.041	0.077***	0.076***	0.017	0.060***
	(0.034)	(0.044)	(0.016)	(0.017)	(0.021)	(0.019)
Ln(OSRD rate) * 1(1950-1954)	0.080**	0.063	0.078***	0.069***	0.023	0.092***
	(0.040)	(0.049)	(0.024)	(0.023)	(0.016)	(0.027)
Ln(OSRD rate) * 1(1955-1959)	0.125***	0.127**	0.053*	0.046*	0.037**	0.100***
	(0.045)	(0.055)	(0.030)	(0.026)	(0.017)	(0.028)
Ln(OSRD rate) * 1(1960-1964)	0.158***	0.135**	0.107***	0.095***	0.015	0.088**
	(0.049)	(0.059)	(0.033)	(0.029)	(0.025)	(0.039)
Ln(OSRD rate) * 1(1965-1970)	0.188***	0.182***	0.101***	0.041	0.002	0.088**
	(0.054)	(0.062)	(0.033)	(0.034)	(0.016)	(0.040)
N	20376	17691	10823	10474	3197	9123
R^2	0.75	0.71	0.47	0.37	0.19	0.59
Y mean	1.89	1.79	0.67	0.61	0.21	0.66
County-cat FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X

Notes: Table estimates the effect of the OSRD shock on firm patenting. Observations are at the county-category-year level. Outcome variables measured in logs. Column (1) measures all firm patents; Column (2), those by firms with prior patents in the same county and technology area; Columns (3) to (5), those by firms with prior patents only in a different county and/or technology area; and Column (6), those by firms with no prior patents. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county-category and year fixed effects, and the omitted (reference) category for each county-category is the 1930-1934 period. Each row thus indicates the percentage increase in cluster patenting in a given period associated with a doubling of the cluster's OSRD rate. Log transformations restrict the sample in each column to observations with patents of the given type and clusters with $\geq$1 OSRD patent. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Table 4: Non-government vs. government-funded patents (total and by agency)

	(1)	(2)	(3)	(4)	(5)	(6)
	Non govt.	Govt.	DOD	DOE	NASA	USDA
Ln(OSRD rate) * 1(1935-1939)	-0.006	0.007	0.003			0.127
	(0.012)	(0.031)	(0.036)			(0.098)
Ln(OSRD rate) * 1(1940-1944)	-0.003	0.089	0.060	-0.052		0.288
	(0.018)	(0.058)	(0.056)	(0.062)		(0.234)
Ln(OSRD rate) * 1(1945-1949)	0.026	0.145**	0.144**	0.009		0.208
	(0.026)	(0.072)	(0.073)	(0.056)		(0.227)
Ln(OSRD rate) * 1(1950-1954)	0.084***	0.131*	0.145**	-0.064		0.270
	(0.030)	(0.073)	(0.071)	(0.043)		(0.232)
Ln(OSRD rate) * 1(1955-1959)	0.133***	0.153*	0.173**	-0.029		0.220
	(0.036)	(0.081)	(0.079)	(0.057)		(0.221)
Ln(OSRD rate) * 1(1960-1964)	0.193***	0.181**	0.197***	0.017	0.022	0.353
	(0.042)	(0.075)	(0.072)	(0.046)	(0.074)	(0.222)
Ln(OSRD rate) * 1(1965-1970)	0.221***	0.212***	0.219***	-0.004	0.087	0.334
	(0.046)	(0.072)	(0.066)	(0.036)	(0.080)	(0.222)
N	22251	9571	8057	1344	254	279
R^2	0.79	0.44	0.44	0.44	0.44	0.48
Y mean	2.01	0.73	0.68	0.44	0.42	0.51
County-cat FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X

Notes: Table estimates the effect of the OSRD shock on government-funded patenting. Observations are at the county-category-year level. Outcome variables measured in logs. Column (1) measures non-government funded patents; Column (2), government funded patents; and Columns (3) to (6), patents by agency: Department of Defense (DOD), Department of Energy (DOE), National Aeronautics and Space Administration (NASA), and Department of Agriculture (USDA). Columns are labeled with modern agencies, but the DOD and DOE categories include predecessor agencies before they were established in 1947 and 1977, respectively. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county-category and year fixed effects, and the omitted (reference) category for each county-category is the 1930-1934 period. Each row thus indicates the percentage increase in cluster patenting in a given period associated with a doubling of the cluster's OSRD rate. Log transformations restrict the sample in each column to observations with patents of the given type and clusters with $\geq$1 OSRD patent. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Table 5: Share of forward and backward citations to local patents

	Backward citations			Forward citations		
	(1)	(2)	(3)	(4)	(5)	(6)
	Same county and field	Same county, diff. field	Diff. county, same field	Same county and field	Same county, diff. field	Diff. county, same field
Ln(OSRD rate) * 1(1935-1939)				-0.001	-0.000	0.005
				(0.001)	(0.000)	(0.004)
Ln(OSRD rate) * 1(1940-1944)				-0.001	-0.001	0.011**
				(0.001)	(0.000)	(0.004)
Ln(OSRD rate) * 1(1945-1949)				-0.000	0.001	0.015***
				(0.001)	(0.001)	(0.004)
Ln(OSRD rate) * 1(1950-1954)	0.002	-0.000	0.003	0.001	0.001*	0.017***
	(0.002)	(0.001)	(0.005)	(0.001)	(0.001)	(0.004)
Ln(OSRD rate) * 1(1955-1959)	0.002	0.001	0.001	0.002**	0.001***	0.013***
	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)	(0.004)
Ln(OSRD rate) * 1(1960-1964)	0.005***	-0.000	0.012**	0.003***	0.002***	0.011***
	(0.002)	(0.001)	(0.005)	(0.001)	(0.000)	(0.004)
Ln(OSRD rate) * 1(1965-1970)	0.006***	0.002*	0.009*	0.005***	0.002***	0.007*
	(0.002)	(0.001)	(0.005)	(0.001)	(0.000)	(0.004)
N	13803	13803	13803	22613	22613	22613
R^2	0.29	0.17	0.17	0.23	0.13	0.29
Y mean	0.04	0.02	0.46	0.02	0.01	0.28
County-cat FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X

Notes: Table estimates the effect of the OSRD shock on local vs. distant citation flows. Observations are at the county-category-year level. Outcome variable in Columns (1) to (3) is the share of backward citations made by patents filed in a given cell that are to prior patents in the same county and technology category (Column 1), the same county but different technology category (Column 2), and a different county but same technology category (Column 3). Outcome variable in Columns (4) to (6) is the analogue for forward citations accruing to patents in the given cell from future patents of each column type. The front-page patent citation record begins in February 1947. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county-category and year fixed effects, and the omitted (reference) category for each county-category is the 1930-1934 period. Each row thus indicates the percentage increase in cluster citation shares in a given period associated with a doubling of the cluster's OSRD rate. Log transformations restrict the sample in each column to observations with citations of the given type and clusters with ≥1 OSRD patent. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Table 6: Concentration of cluster patenting (assignee HHI and patent shares)

	(1)	(2)	(3)	(4)	(5)
		Share held by top X assignees			
	HHI	Top 1	Top 5	Top 10	Top 20
Ln(OSRD rate) * 1(1935-1939)	-0.003	-0.005	-0.006	-0.001	-0.005
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)
Ln(OSRD rate) * 1(1940-1944)	-0.009	-0.011	-0.008	-0.003	-0.002
	(0.006)	(0.008)	(0.006)	(0.005)	(0.005)
Ln(OSRD rate) * 1(1945-1949)	-0.028***	-0.010	-0.004	0.002	0.003
	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
Ln(OSRD rate) * 1(1950-1954)	-0.029***	-0.017**	-0.011	-0.007	-0.001
	(0.008)	(0.009)	(0.011)	(0.008)	(0.007)
Ln(OSRD rate) * 1(1955-1959)	-0.039***	-0.028**	-0.008	-0.004	-0.001
	(0.008)	(0.012)	(0.012)	(0.008)	(0.007)
Ln(OSRD rate) * 1(1960-1964)	-0.058***	-0.040***	-0.006	-0.002	0.006
	(0.009)	(0.013)	(0.013)	(0.009)	(0.007)
Ln(OSRD rate) * 1(1965-1970)	-0.055***	-0.064***	-0.030*	-0.024***	-0.017***
	(0.008)	(0.013)	(0.015)	(0.008)	(0.006)
N	22938	22938	22938	22938	22938
R^2	0.63	0.51	0.46	0.33	0.20
Y mean	0.38	0.65	0.98	1.03	1.05
County-cat FEs	X	X	X	X	X
Year FEs	X	X	X	X	X

Notes: Table estimates the effect of the OSRD shock on the concentration of local patenting. Observations are at the county-category-year level. Column (1) measures an assignee Herfindahl index, and Columns (2) to (5) measure concentration ratios. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county-category and year fixed effects, and the omitted (reference) category for each county-category is the 1930-1934 period. Each row thus indicates the percentage increase in cluster concentration in a given period associated with a doubling of the cluster's OSRD rate. Log transformations restrict the sample in each column to observations with patents and clusters with ≥1 OSRD patent. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Table 7: Effects on 1980 county employment in high-tech manufacturing industries

	Extensive			Intensive		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Any OSRD patents)	0.898***	0.914***	0.922***			
	(0.226)	(0.166)	(0.166)			
IHS(OSRD rate)				1.712**	1.137*	1.175*
				(0.868)	(0.614)	(0.614)
N	3770	3770	3770	2022	2022	2022
R^2	0.54	0.77	0.77	0.62	0.86	0.86
Y mean	4.37	4.37	4.37	4.08	4.08	4.08
County FEs	X	X	X	X	X	X
Industry FEs	X	X	X	X	X	X
IHS mfg. empl.		X	X		X	X
IHS all empl.			X			X

Notes: Table estimates the relationship between counties' postwar employment in select industries and OSRD patenting in classes which crosswalk to these industries. Observations are at the county-industry level, with the sample restricted to industries in the broader domain of "Electrical and Electronic Equipment and Supplies" (see text). Industrial employment measured from the 1980 U.S. County Business Patterns (CBP). The outcome in all columns is the inverse hyperbolic sine (IHS) of industry employment. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county and industry fixed effects. Successive columns add controls for IHS manufacturing employment and IHS total employment. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Table 8: Effects on firm creation in high-tech manufacturing industries

	Extensive			Intensive		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Any OSRD patents) * 1930s	0.067**	0.066**	0.066**			
	(0.033)	(0.033)	(0.033)			
1(Any OSRD patents) * 1940s	0.413***	0.412***	0.415***			
	(0.077)	(0.077)	(0.077)			
1(Any OSRD patents) * 1950s	0.642***	0.640***	0.642***			
	(0.094)	(0.093)	(0.093)			
1(Any OSRD patents) * 1960s	1.125***	1.127***	1.128***			
	(0.111)	(0.110)	(0.110)			
1(Any OSRD patents) * 1970s	1.425***	1.419***	1.421***			
	(0.137)	(0.135)	(0.135)			
IHS(OSRD rate) * 1930s				-0.021	-0.050	-0.072
				(0.039)	(0.039)	(0.048)
IHS(OSRD rate) * 1940s				0.180*	0.165	0.178
				(0.098)	(0.102)	(0.108)
IHS(OSRD rate) * 1950s				0.251*	0.228	0.240
				(0.147)	(0.143)	(0.148)
IHS(OSRD rate) * 1960s				0.763***	0.749***	0.741***
				(0.273)	(0.276)	(0.279)
IHS(OSRD rate) * 1970s				1.057***	1.025***	1.018***
				(0.378)	(0.363)	(0.360)
N	128214	128214	128214	14616	14616	14616
R^2	0.56	0.57	0.57	0.57	0.58	0.58
Y mean	0.05	0.05	0.05	0.29	0.29	0.29
County-Ind FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
IHS mfg. firms		X	X		X	X
IHS all firms			X			X

Notes: Table estimates the relationship between counties' firm creation in select industries and OSRD patenting in classes which crosswalk to these industries. Observations are at the county-industry-decade level, with the sample restricted to industries in the broader domain of "Electrical and Electronic Equipment and Supplies" (see text). Firm creation measured from the 1980 issue of the Dun & Bradstreet establishment listings, which reports founding year for all firms in its data. Sample is restricted to headquarters and single-branch establishments, and by construction conditioned on survival to 1980. The outcome in all columns is the inverse hyperbolic sine (IHS) of industry firm creation. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948. All columns include county-industry fixed effects, and the omitted (reference) category for each county-industry is the 1920s decade. Successive columns add controls for IHS manufacturing firms and IHS total firms in the given year. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

Web Appendix

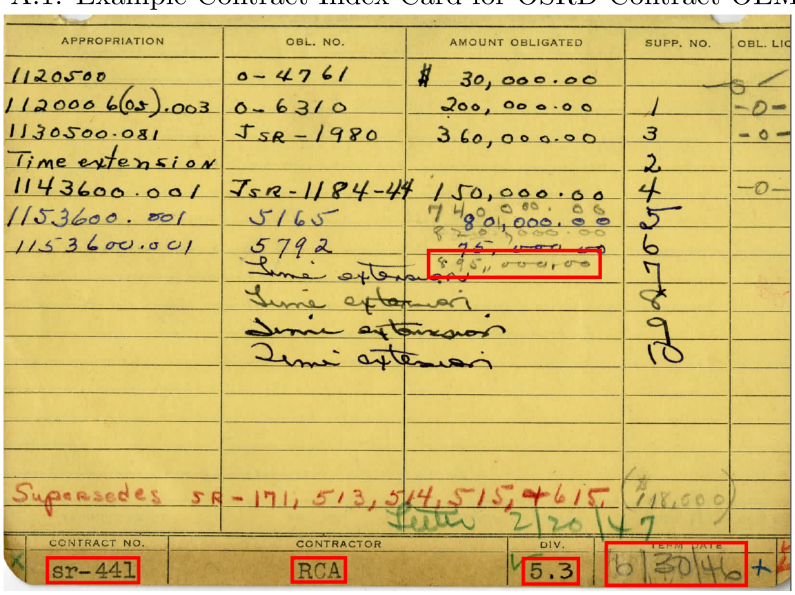
A OSRD History and Data

A.1 Data collected from OSRD archival records

Data on OSRD contractors, contracts, inventions, and patents were obtained from archival records at the U.S. National Archives and Records Administration (NARA).[1] NARA's OSRD record collection includes narrative records (such as correspondence between Vannevar Bush and other OSRD administrators, contractors, and government agencies) that provide rich background on OSRD's day-to-day operation and precedent-setting policy choices throughout the war.

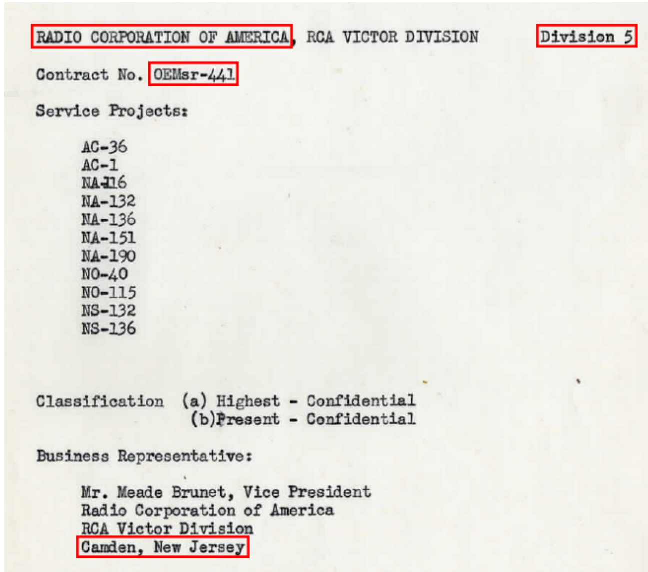
For this paper, we make use of several sets of records from OSRD collection. The three key data sources on contracts, contractors, and inventions are (i) a collection of contract index cards, which identify each contract with the contract ID, contractor, OSRD division managing the contract, termination date, and obligated value through the end of life; (ii) a directory of contractors, by contract, with the contractor's principal headquarters location; and (iii) a set of invention disclosure cards, which document inventions generated in the course of OSRD-supported research, with the associated contract, applicable patent clause (short form vs. long form), contractor, inventor(s), invention title, date reported, and if a patent application was filed, the application date and serial number. Examples of each are provided in Figures A.1 to A.3.

Figure A.1: Example Contract Index Card for OSRD Contract OEMsr-441



[1] See NARA Record Group 227, "Records of the Office of Scientific Research and Development". The key record sets for this paper are the *Index to Contracts* (NC-138, Entry 27, Stack area 130, Row 20, Compartment 11, Shelf 1, Boxes 1-5), *Contractor Lists* (NC-138, Entry 16, Stack area 130, Row 20, Compartment 11, Shelf 4, Boxes 1-2), and *Register of Invention Disclosures* (NC-138, Entry 35, Stack area 130, Row 20, Compartment 38-39, Shelf 7/1, Boxes 1-8), though other records were used to complete and cross-validate these data.

Figure A.2: Example Contractor Directory Page for OEMsr-441



RADIO CORPORATION OF AMERICA, RCA VICTOR DIVISION Division 5

Contract No. OEMsr-441

Service Projects:

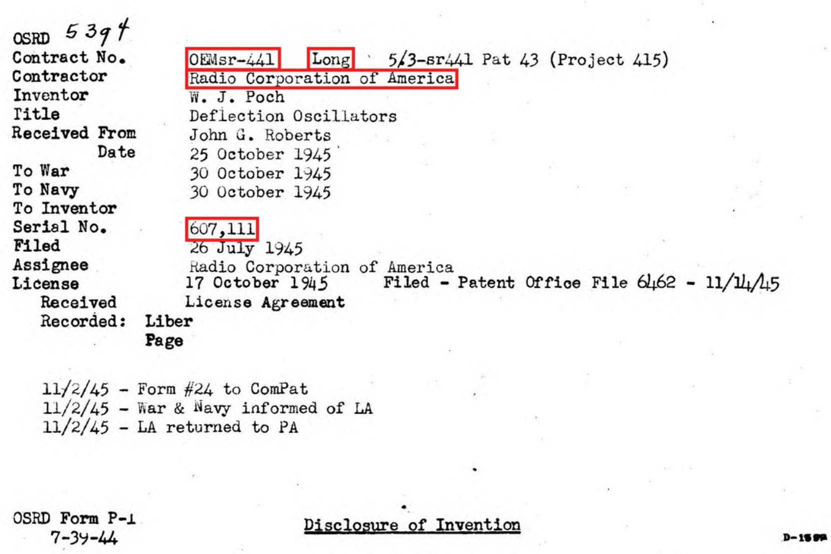
AC-36
AC-1
NA-116
NA-132
NA-136
NA-151
NA-190
NO-40
NO-115
NS-132
NS-136

Classification (a) Highest - Confidential
(b) Present - Confidential

Business Representative:

Mr. Meade Brunet, Vice President
Radio Corporation of America
RCA Victor Division
Camden, New Jersey

Figure A.3: Example Invention Disclosure Card for OEMsr-441



OSRD 5394
Contract No. OEMsr-441 Long 5/3-sr441 Pat 43 (Project 415)
Contractor Radio Corporation of America
Inventor W. J. Poch
Title Deflection Oscillators
Received From John G. Roberts
Date 25 October 1945
To War 30 October 1945
To Navy 30 October 1945
To Inventor
Serial No. 607,111
Filed 26 July 1945
Assignee Radio Corporation of America
License 17 October 1945 Filed - Patent Office File 6462 - 11/14/45
Received License Agreement
Recorded: Liber
Page

11/2/45 - Form #24 to ComPat
11/2/45 - War & Navy informed of LA
11/2/45 - LA returned to PA

OSRD Form P-1
7-39-44
Disclosure of Invention
D-1597

In addition to these records, we also collected three supplementary, independent lists of contractors and contracts which can be used to validate these data and fill in gaps. The first is a list of contractors, which lists contracts for each contractor provides the total obligations and counts the number of contracts with the short form vs. long form patent clause. The second is a list of contracts by contractor, and provides the associated OSRD division and patent clause. The third is a list of contracts by OSRD division. Using the collective set of records, we compile a master list of 2,288 OSRD contracts, 573 of which were CMR contracts.[2] For comparison, internal correspondence

[2]This list of contracts comprises the union of all record sets. Although the vast majority of contracts appear across all sources, there are gaps (missing contracts) in each data source: the contract index cards contain 2,275 of the

from OSRD's patent division dated October 30, 1945 counts 2,266 research contracts, with the remaining 22 contracts appearing in our data as administrative contracts for the purchase/lease of office space, equipment rentals, and publication services. As another point of comparison, the administrative history of the CMR published in 1948 (Andrus 1948) lists 571 of the 573 CMR contracts in our data (of the remaining two, one was last contract OSRD entered into and likely simply did not make it into this published list).[3]

Given that for a few contract-level variables we have multiple sources (namely, OSRD division and patent clause), we make an additional effort to cross-validate these variables and reconcile differences as we describe below. We also harmonize contractor names and match them to assignees in the patent record (see discussion of patent datasets in the next subsection).

- The OSRD division of each contract indicates the subject matter and can be reported in up to four sources: the contract index cards, the contractor directory, and two supplemental contract lists. For 2,117 out of 2,288 contracts in the master list, at least one source reports an OSRD division and all reporting sources agree. In 152 cases, they disagree, and for these cases we take the most commonly-reported division as the true division (in the nine cases where there is no single most commonly-reported division, we prioritize the division reported in the contract index cards and contractor directory). In the 19 remaining cases, the contract's OSRD division is not reported in any of our sources and is unknown.

- The patent clause of each contract is typically either "short form" or "long form", which gives the government or the contractor (respectively) the first rights to patent inventions developed under the contract. The short form clause was used predominantly with academic contractors, and the long form clause with industrial contractors (as a means to incentivize their participation in the war effort). The patent clause of each contract is reported in one of the supplemental contract lists as well as on invention disclosure cards – but only known for 2,020 contracts in the supplemental contract list, and for an additional five contracts via the invention disclosures. Determining the applicable patent clause is further complicated by the fact that some contracts (i) had their patent clauses changed mid-contract, and/or (ii) had custom patent clauses (which were usually variants on the standard short form and long form clauses).[4] Custom patent clauses and patent clause amendments, as well as the

2,288 total known contracts; the contractor directory contains 2,259 contracts (the 573 CMR contracts were not included in this directory per se, but the contractor information was available in separately-maintained CMR contract ledgers); the supplementary contractor list contains 2,192 contracts; and the supplementary contract list contains 2,112 contracts. These latter two lists were compiled before the end of the war, and most of contracts missing from these lists are missing because they post-date the sample. For the 13 contracts missing from the contract index cards, the contractor and OSRD division are available from other sources, but the contract value and termination date are unknown. For the 29 contracts missing from the contractor directory, we infer contractor locations from other contracts with the same contractor where available, and otherwise through manual research.

[3] As a final piece of validation: OSRD contract IDs were written with three different prefixes (NDCrc, OEMsr, OEMcmr) followed by an identification number. The maximum number of each series in the data is NDCrc-208, OEMsr-1507, and OEMcmr-573, and these numbers add to a total of 2,288.

[4] For example, all long form atomic energy research contracts (let under OSRD's S-1 division) were converted to

date of amendment, are noted in this list and thus measured in our data. In addition, several contracts are tagged as having a patent clause of "Purchase Contract" or "Overhead" (these are typically administrative contracts, previously described), or even "None". The information on patent clauses from this contract list and in the invention disclosure cards overwhelmingly agrees, but where it conflicts, we use the information from the contract list, which appears to have been created specifically for this purpose.

After dropping administrative and cancelled contracts, there are 2,254 contracts in our data, made to 461 unique contractors, with a total value of $462 million in 1940-45 dollars (equivalent to roughly $7.4 billion today). For comparison, in the official administrative history of OSRD, Stewart (1948) claims that OSRD contractors had spent "appoximately 457 million dollars through November 30, 1945" – a difference of less than one percent. We observe the contractor and OSRD division for every contract, the patent clause for 2,006 of the contracts (89%), and the obligated value and termination date for 2,208 of the contracts (98%).

We also observe the inventions produced under these contracts, which contractors were contractually required to disclose and OSRD subsequently catalogued. As mentioned above, these index cards list the contract that the invention was developed under and also include information on patent applications, which we use to link OSRD contracts to granted patents – these patents are what we denote in the paper as "OSRD patents". We discuss how we do so below.

Using these index cards alone, we identify 7,879 reported inventions. Each card has an identifying number in the top left corner, numbering from 1 to 8040 (e.g., see Figure A.3), with some also suffixed with letters. In all, the numbering suggests there may have been as many as 8,056 inventions, and the 177 (=8056-7879) missing index cards could either be unobserved inventions or numbers which were skipped or discarded. To fill in these potential gaps, we do a wider search for data on OSRD-funded inventions across other archival collections at NARA, and find additional lists of OSRD-supported inventions in the records of the U.S. Army Judge Advocate General's Office (Record Group 153). Using these records, we recover data for five of the 177 missing index cards, and identify an additional 26 unnumbered inventions which were reported after the index card file was no longer maintained. For the inventions on which patent applications were filed, we use the serial number to link these to granted patents, as we explain in more detail in the next subsection. In all, we have 7,910 inventions, on which 3,382 patent applications were filed, and 2,659 patents granted (which we identify by linking serials to granted patents). 2,657 of these patents were granted by 1980, when our sample for this paper ends.

For completeness, we also search for continuations, divisions, and continuations-in-part of OSRD patent applications. To do so, we parse the first 800 characters of the text of patents filed between 1935 and 1969 (application series 2, 3, and 4) to identify patents which mention an OSRD serial, and manually check these cases to determine whether they were continued or divided from earlier

short form in 1942, when the research program was spun off into a weapons development program (the Manhattan Project), to ensure that the government controlled the intellectual property.

OSRD-supported filings. Through this process we find an additional 104 OSRD-supported patents, bringing our total to 2,763 patents (2,761 granted by 1980).

Our final source of data on OSRD-supported invention is a distinct list of patent applications and granted patents related to the Manhattan Project, obtained by FOIA (from the U.S. Department of Energy) by researchers at the Woodrow Wilson Center and available at its digital archives.[5] This document lists over 1,000 U.S. government-supported, nuclear energy-related patent applications (and >850 grants) from the World War II period, along with the contracts under which they were produced, including many OSRD contracts. Most of these inventions were placed into secrecy at the time of filing (see Gross 2019) and were not in the NARA records, likely due to their sensitive nature, and through this list we identify another 374 OSRD-supported patents (373 granted by 1980), bringing our total to 3,137 patents (3,134 granted by 1980).

A.2 Descriptive characterization of OSRD R&D investment

Administrative records from OSRD offer additional insight into the nature of the work it funded, and the firms and institutions it mobilized into the war effort. In prior work we have used these data to study how OSRD organized research for war and managed the World War II research effort (Gross and Sampat 2022c). Here we reproduce some of this evidence, while also adding more, to bring color to the specific features of the OSRD-led research effort.

Borrowing from Stewart (1948), Table A.1 shows OSRD's organizational structure in the form it eventually evolved into as the scope of its work grew. As we explain in the paper, OSRD was the parent agency of two organizations, NDRC (which managed the technological research effort—e.g. radar, atomic fission, and more) and CMR (which managed the medical research effort—e.g., penicillin, antimalarials). NDRC grew to have into 19 core divisions and seven special sections and panels. These units covered a wide range of subjects and varied equally widely in scale. The table shows total contract authorizations only for 1943 onwards, when NDRC organized into this structure. The two largest divisions were Radar (14) and Rocket Ordnance (3), with the majority of funding going to MIT and CalTech, respectively, to support major research labs. NDRC also directed the atomic fission research program until it was transferred to the Army in mid-1943, which operated at a similar scale to the radar program while under OSRD.

CMR, in contrast to NDRC, was more contained with six divisions of roughly equal size (in dollars), and as we describe in (Gross and Sampat 2022c), operated very differently. Despite having less than one-tenth the budget of NDRC, CMR was nevertheless similarly important to the war effort, as infectious disease and other ailments had in previous wars killed more soldiers than battlefield wounds, making military medicine a key R&D priority.

Table A.2 illustrates the geographic concentration of OSRD research, listing the top 10 states with OSRD contracts (left panel) and OSRD patents (right panel). Massachusetts, California, New York, and New Jersey rank highly on both inputs and outputs, and together comprise around 65

[5]See https://digitalarchive.wilsoncenter.org/document/165247.

to 75% of both contract obligations and patents. Table A.3 lists the top 10 university and firm contractors. The major university contractors hosted large, central laboratories which led specific research programs, such as the Radiation Laboratory at MIT for radar (Gross and Roche 2023) and the Jet Propulsion Laboratory at CalTech for rockets and projectiles.

Table A.1: OSRD Divisions, Panels, and Special Sections (1941-1947) [reproduced from Gross and Sampat (2022c)]

National Defense Research Committee (NDRC)		Contract Authorizations	
Division/Section	Name/Description	($, '000s) (1943-1947)	
1	Ballistics	5,327.2	
2	Effects of Impact and Explosion	2,701.4	
3	Rocket Ordnance	85,196.5	
4	Ordnance Accessories	20,014.3	
5	New Missiles	12,881.2	
6	Subsurface Warfare	33,883.5	
7	Fire Control	7,711.7	
8	Explosives	11079.9	
9	Chemistry	4,698.2	
10	Absorbents and Aerosols	3,524.2	
11	Chemical Engineering	9,216.2	
12	Transportation Development	2,199.4	
13	Electrical Communication	2,073.9	
14	Radar	104,533.4	
15	Radio Coordination	26,343.0	
16	Optics	5,923.9	
17	Physics	7,655.3	
18	War Metallurgy	3,794.4	
19	Miscellaneous Weapons	2,416.1	*
AMP	Advanced Mathematics Panel	2,522.9	
APP	Applied Psychology Panel	1,542.5	*
COP	Committee on Propagation	453.0	*
TD	Tropical Deterioration	232.4	*
SD	Sensory Devices	272.5	*
S-1	Atomic Fission	18,138.2	*
T	Proximity Fuzes	26,400.0	*
Total		400,735.1	

Committee on Medical Research (CMR)		Contract Authorizations
Division	Name/Description	($, '000s) (1941-1947)
1	Medicine	3,873.3
2	Surgery	2,847.6
3	Aviation Medicine	2,466.5
4	Physiology	3,981.5
5	Chemistry	2,383.9
6	Malaria	5,501.9
–	Miscellaneous	3,635.3
Total		24,689.9

Notes: NDRC authorizations from January 1, 1943 onwards, except where noted below. CMR authorizations reported for the entire history of CMR.
*Authorizations for Division 19 from April 1, 1943; APP, from September 18, 1943; COP, from January 22, 1944; TD, from May 18, 1944; SD, from November 1, 1945. Authorizations for Sections S-1 and T are from June 27, 1940 onwards, with Section S-1 terminating in September 1943.

Table A.2: Top 10 states with OSRD contracts, by contract obligations [reproduced from Gross and Sampat (2022c)]

Top states by share of OSRD contracts				Top states by share of OSRD patents			
		OSRD contracts, 1941-1948				OSRD patents, 1941-1948	
Rank	County	Value	Share of total	Rank	County	Number	Share of total
1	Massachusetts	$147.9 mil.	32.0%	1	Massachusetts	597	21.4%
2	California	$97.3	21.1%	2	New York	516	18.5%
3	New York	$91.3	19.8%	3	New Jersey	509	18.3%
4	Illinois	$22.7	4.9%	4	California	247	8.9%
5	District of Columbia	$17.1	3.7%	5	Illinois	159	5.7%
6	Pennsylvania	$14.7	3.2%	6	Pennsylvania	113	4.1%
7	Maryland	$13.0	2.8%	7	Maryland	92	3.3%
8	New Jersey	$12.3	2.7%	8	Ohio	64	2.3%
9	Ohio	$8.6	1.9%	9	District of Columbia	61	2.2%
10	Michigan	$6.9	1.5%	10	Delaware	54	1.9%
	Total	$431.8	93.5%		Total	2412	86.6%

Notes: Table lists the top states by total obligations (left panel) and patents (right panel). Percentages measure each state's percent of total OSRD obligations/patents.

Table A.3: Top OSRD contractors, by contract obligations [reproduced from Gross and Sampat (2022c)]

Top 10 Universities			Top 10 Firms		
Contractor	Total oblg.	Pct. of total	Contractor	Total oblg.	Pct. of total
Massachusetts Inst. of Tech.	$106.8 mil.	23.1%	Western Electric Co.	$15.2 mil.	3.3%
California Inst. of Tech.	$76.6	16.6%	General Electric Co.	$7.6	1.6%
Harvard University	$29.1	6.3%	Radio Corp. of America	$6.0	1.3%
Columbia University	$27.1	5.9%	E. I. Dupont De Nemours & Co.	$5.4	1.2%
University of California	$14.6	3.2%	Monsanto Chemical Co.	$4.5	1.0%
Johns Hopkins University	$10.8	2.3%	Eastman Kodak Co.	$4.3	0.9%
George Washington University	$6.9	1.5%	Zenith Radio Corp.	$4.2	0.9%
University of Chicago	$5.7	1.2%	Westinghouse Elect. & Mfg. Co.	$3.9	0.8%
Princeton University	$3.6	0.8%	Remington Rand, Inc.	$3.7	0.8%
University of Pennsylvania	$2.9	0.6%	Sylvania Electric Products, Inc.	$3.1	0.7%
Total	$284.0	61.5%	Total	$57.8	12.5%

Notes: Table lists the top firms and universities with OSRD contracts by total obligations. Percentages measure each contractor's percent of total OSRD research spending.

B Additional Data Sources

B.1 Construction of U.S. patent datasets

B.1.1 Base data

The construction of the patent datasets used in this paper begins with the USPTO historical master file (Marco et al. 2015), which provides a master list of utility patents with grant dates, patent class/subclass (USPC), and two-digit NBER category (Hall et al. 2001). In building this paper's dataset, we restrict the sample to patents granted between January 1, 1920 and December 31, 1979—although most of the paper invokes only a subset of these, emphasizing the sample filed between 1930 and 1970. For all granted patents in this set, we obtain additional patent characteristics from the following sources:

- FreePatentsOnline.com (FPO): serial numbers, filing dates, and the network of forward and backward citations (front-page citations only)
- Derwent Innovation (2018) database (DI): assignee names[6]
- Petralia et al. (2016a) HistPat, Berkes (2018) CUSP, and Bergeaud et al. (2022) PatentCity datasets: inventor country, state, county[7]
- USPTO Historical Government Register: administrative data on government-funded invention (owned or licensed), collected since 1944[8]

The DI assignee names are (mostly) standardized and were later found to match those in Google Patents data, which are freely available through Google BigQuery. These data are mostly complete, but a small number of patents are missing filing dates and assignees. Table B.1 shows the number patents with missing data, by decade of grant. For the period sampled in this paper (1930-1970), approximately 2.3% of patents are missing a filing date and 2.3% missing an assignee (note: these percentages are calculated for patents granted between 1930 and 1970, whereas the paper uses the sample of patents known to have been filed between 1930 and 1970).

[6]Note that serial numbers, filing dates, and the network of patent citations were also retrieved from the Derwent database for comparison against the FPO data, as a validation exercise. The two data sources overwhelmingly agreed, and where they disagreed, spot checks revealed that FPO was consistently the more accurate of the two, and when there was an error in the FPO data, it typically reflected the occasional typographical error on the printed patent publication itself, such as two flipped digits, or a digit one unit off the correct value. Given their reliability, the data for this paper thus use serial numbers, filing dates, and citations from FPO.

[7]Also see Petralia et al. (2016), as well as Andrews (2019) for additional discussion of historical patent geography data. We evaluate the quality of these data, and use all three sources to produce a composite measure of inventor locations, below. We are grateful to the authors for sharing their data.

[8]We introduce these data, and compare them to Fleming et al. (2019), below.

Table B.1: Number of patents with missing data, by decade

		No filing date		No assignee data	
Decade of grant	Patents	Number	Percent	Number	Percent
1920-1929	414901	25738	6.2%	25918	6.2%
1930-1939	442842	11102	2.5%	11221	2.5%
1940-1949	307630	5470	1.8%	5546	1.8%
1950-1959	425985	12461	2.9%	12661	3.0%
1960-1969	567761	11203	2.0%	11363	2.0%
1970-1979	689027	2	0.0%	73	0.0%
Total	2848146	65976	2.3%	66782	2.3%

Notes: Table shows counts of patents with missing data, and their fraction of all patents, by decade.

Patented, OSRD-funded inventions are identified in the OSRD archival records by the serial number of the patent application. It is thus critical to have accurate data on serial numbers. We manually reviewed and validated the application-level data (serials and filing dates) from FPO for the period around World War II by checking patents with serial numbers or filing dates which are out of sequence. The important feature of the USPTO's application numbering system for our purposes here is that applications are organized into application "series", which span several years, and identified by a serial number within that series, generally issued in the order in which patent applications arrive at the USPTO, with serial numbers never exceeding six digits. Application series increment, and serial numbers reset, at the beginning of a year in which the serial numbers from the previous series are expected to surpass 1,000,000. Series 2 begins January 1, 1935 and ends December, 1947 and is the focus of this data cleaning effort. We take all patents identified by FPO as belonging to Series 2 and sort these patents by serial. We then look for patents where the previous and next serial have the same filing date but the given patent has a different filing date, and then manually validate the serial and filing date for these patents. Out of over 370,000 patents in Series 2, corrections were made to 279 serials and 188 filing dates. Although these corrections are valuable for matching patents to serials in OSRD records, the low error rate for this sample also indicates that such errors are not widespread in the data.

B.1.2 Harmonizing assignee names

Although the assignee names from DI are largely already standardized, closer examination reveals that there are still variants on individual assignee names (e.g., BELL TELEPHONE LABOR INC with >10,000 patents, and BELL TELPHONE LAB INC, BELL TEL PHONE LAB INC, and BELL TEIEPHONE LAB INC with 1 patent each). We undertake several procedures to further harmonize assignee names. We begin by sorting a list of assignees in alphabetical order, and for each assignee recording other nearby assignees up to 9 positions before/after in the sorted list. We then calculate the edit distance between the given assignee name and each of these nearby assignee names. When this edit distance is less than 25% of the length of the longer name in each pair, We flag that pair as a candidate for manual review. We then review all such matches for several categories of assignees, and standardize names when a match is found:

- Assignees with $\geq$15 patents between 1930 and 1960

- Assignees which were OSRD contractors
- Assignees identified as government agencies (see next section)
- Assignees identified as universities or hospitals (see next section)
- Assignees which were synthetic rubber manufacturers
- Assignees which were spinouts from Standard Oil

This process is repeated (because each round of harmonization may bring new assignees into the set with $\geq$15 patents between 1930 and 1960) until no new matches are found.

This harmonization is neither perfect nor exhaustive, but it is believed to be effective for the purposes of this paper. It is also worth noting that for the vast majority of assignee names which were standardized by this procedure, there was clearly a primary spelling for that assignee in the original DI data, with hundreds or thousands of associated patents in the case of large assignees, and at worst a handful of secondary spellings with one or two associated patents—such that the actual effects of both (i) performing this harmonization for the priority assignees above, and of (ii) not performing it for non-priority assignees, are likely minimal.

B.1.3 Determining assignee types

Assignees are then classified into four categories—firms, universities and hospitals, government agencies, and individuals—through a combination of rule-based and manual classification. We begin by classifying assignees as firms when the assignee name includes any of roughly 120 words which indicate firms (e.g., CO, CORP, INC, LTD, SPA, GMBH, etc., as well as technical words such as AERO, AUTO, CHEM, ENG, MACHINE, OIL, PROD, TECH, WORKS; full list available on request). We then manually classify remaining assignees with $\geq$15 patents between 1930 and 1960, as well as assignees whose name includes any of the following strings:

- COLLEGE, INST, UNIV, HOSP, RES FOUND
- US, CANADA, UK, FRANCE, GERMANY, SWITZERLAND, AUSTRALIA, JAPAN, ISRAEL, and assorted other countries
- ATOM (to identify international atomic energy commissions)

Assignees with >200 patents in the 1920-1979 period which are thus far unclassified are then classified as firms. Any remaining unclassified assignees are classified as individuals.

This classification procedure was developed over several years, and although—like the name harmonization—it is neither perfect nor exhaustive, random spot checks suggest it is overwhelmingly effective at categorizing assignees into the right bins. In total, 60.1% of patents with an assignee in the 1920-1979 sample are assigned to a firm, 0.2% to a university, 0.8% to a government agency, and 39.1% to an individual (numbers sum to >100% because 5% of patents have multiple assignees, and 0.2%

have assignees in multiple categories). Using administrative data, we will see below that the fraction we measure through names as assigned to a government entity is an undercount, primarily because the DI data sometimes undermeasure patent assignment.

B.1.4 Patent geography data

Measuring historical patents' inventor locations with completeness and accuracy is critical to our analysis. For modern, post-1976 patents, the USPTO provides inventor locations as part of the electronic record, but for pre-1976 patents, locations are only available from the text of the patent itself, presenting a formidable measurement challenge. Over the past few years, several researchers have invested in harvesting inventor and assignee locations from patent text for the universe of historical U.S. patents, typically rely on a mix of OCR with rule-based regex string parsing, machine learning, and manual correction (see Andrews 2019, for a summary). The most recent such effort has been produced by Bergeaud and Verluise (2022), which expands on prior work by measuring the location of historical patents issued by European patent authorities.

Because efforts to measure inventor locations from patent text are potentially susceptible to significant errors, we combine three sources—the Petralia et al. (2016a) HistPat, Berkes (2018) CUSP, and Bergeaud and Verluise (2022) PatentCity datasets—to develop and validate a composite measure of first inventor location in which we have high confidence, with the inventor's country, and if in the U.S., state and county. We begin by cleaning and harmonizing the inventor location data in each data source (country codes, state abbreviations, and county names). In some cases, FIPS codes are provided, but where needed, we assign FIPS codes to counties on state and name. We then restrict to first-listed inventors, calling their location the location of invention (a standard practice in research using patent data). We move forward with these data.

Our next step is to compare data sources, to evaluate how complete they are and how often they differ versus agree. Table B.2 provides summary statistics, including the rate at which they locate the patents in our sample, the rate at which they co-occur with and agree with other data sources. The simple takeaway is that CUSP and PatentCity are much more complete than HistPat, but any two sources agree on first inventor location for only 80% of patents.

Table B.2: Completeness and agreement of patent location data sources

	Overall	When HistPat located		When CUSP Located		When PatentCity located	
	Located	Located	Matches	Located	Matches	Located	Matches
Source	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HistPat	0.85	1.00	1.00	0.84	0.81	0.85	0.83
CUSP	0.93	0.93	0.81	1.00	1.00	0.94	0.85
PatentCity	0.94	0.94	0.83	0.94	0.85	1.00	1.00

Notes: Table summarizes the geolocation rates of patents by data source, and the pairwise rate of agreement across sources. For each row, the table shows the fraction of patents in our 1920-1979 sample for which it provides a first inventor location (Column 1). It then shows how often a location is provided when the column-wise data source also provides a location, and when so, the fraction of patents for which they agree (Columns 2-3, 4-5, and 6-7). Table illustrates the degree to which the data sources differ and we aim to reconcile.

These differences motivate our effort to aggregate these location measures to extract signal from the noise. To support this effort, we manually collected two ground-truth validation samples (patents for which we hand-coded their locations), against which we could benchmark the performance of different approaches to aggregation. One validation sample was generated from the USPTO's Index of Patents, an annual publication that lists all patents issued in a given year, along with inventor and assignee information. We selected two pages at random from each of the 1930, 1940, and 1950 editions and transcribed all patents therein, with approximately 350 patents in total.[9] In a second validation sample, we select 200 patents at random from each of the years 1930, 1940, 1950, 1960, and 1970 and hire workers on Mechanical Turk to extract inventor and assignee locations, which we then review for consistency. Through iterative comparisons to these validation samples, we ultimately arrived at an approach where we assign each patent in our sample a location as follows. Where a majority of our data sources agree, we assign a patent the consensus or majority location. This rule accounts for 90.6% of patents. When multiple sources provide a location but our sources disagree, we apply the following rules, in sequence:

1. If the PatentCity relevance score == 1, use PatentCity Location. Else:
2. If the HistPat accuracy score == 'High', use HistPat location. Else:
3. If the HistPat accuracy score == 'Medium', use HistPat location. else:
4. If CUSP has a county, use CUSP location. Else:
5. If PatentCity has a county, use PatentCity location. Else:
6. If CUSP has a state, use CUSP location. Else:
7. If PatentCity has a state, use PatentCity location. Else:
8. If CUSP has a country, use CUSP location. Else:
9. If PatentCity has a country, use PatentCity location. Else:
10. Leave as missing.

The end result is the assignment of a location to 99.9% of patents in our sample, whose data sources break down as shown in Table B.3. When compared against our validation samples, we find that 98% to 99% of patents where all three sources agree on a location have the correct location, and 90% to 93% of those where two of three sources agree on a location have the correct location. However, when our sources disgree, or only one sources provides a location, it is correct only 45% to 50% of the time. To limit potential mismeasurement, throughout the paper we restrict our analytical sample to patents where at least two sources agree on location. In Figure B.1 we show the share of patents with 3, 2, 1, and 0 data sources, by year, where we can see that between 80% and 95% of patents each year have agreement among 2+ location data sources.

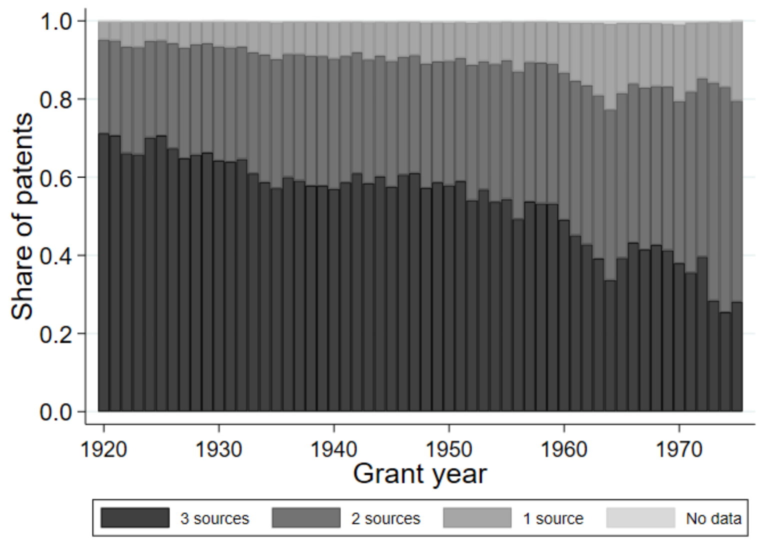
[9] The 1960 edition did not provide inventor locations.

Table B.3: Summary of final patent location measure

Source	Count	Percent	Cumulative
All sources (agreement)	1,600,150	56.2	56.2
2 of 3 sources (majority)	980,271	34.4	90.6
Single source (conflict)	265,040	9.3	99.9
No sources (no data)	2,685	0.1	100.0

Notes: Table summarizes the location data sources of all patents in our sample.

Figure B.1: Consensus across sources of patent geography data



Notes: Figure shows the annual fraction of granted U.S. patents from 1920 to 1975 for which we have a first inventor location where we have agreement (i) across all three data sources, (ii) across two sources, (i) no agreement across sources, and (iv) no data. Post-1976, USPTO began maintaining electronic records, such that inventor locations are broadly well-measured for this period.

In a final test, we also compare our data to administrative patent counts at the state-year level from the USPTO's 1977 Technology Assessment & Forecast (USPTO 1977).[10] Though accurately measuring counties is most crucial for our purposes in this paper, this comparison can be insightful as to whether our measurement is broadly on track. Figure B.2 plots state-year totals from each of our data sources (including our composite measure) against the USPTO state totals for the 1930 to 1960 period. All series are broadly consistent with each other and with administrative totals, but specific series seem to face measurement challenges in specific states (e.g., HistPat in WV, CUSP in FL, and PatentCity in RI, though it appears the USPTO data also have irregularities in RI). Our composite measure minimizes the RMSE against USPTO totals, being roughly 35% lower than that of PatentCity, 40% lower than HistPat, and 85% lower than CUSP.

[10]We thank Seamans et al. (2018) for pointing us to this source and sharing their data.

Figure B.2: State-year patent totals, HistPat vs. Administrative data, 1930-1960

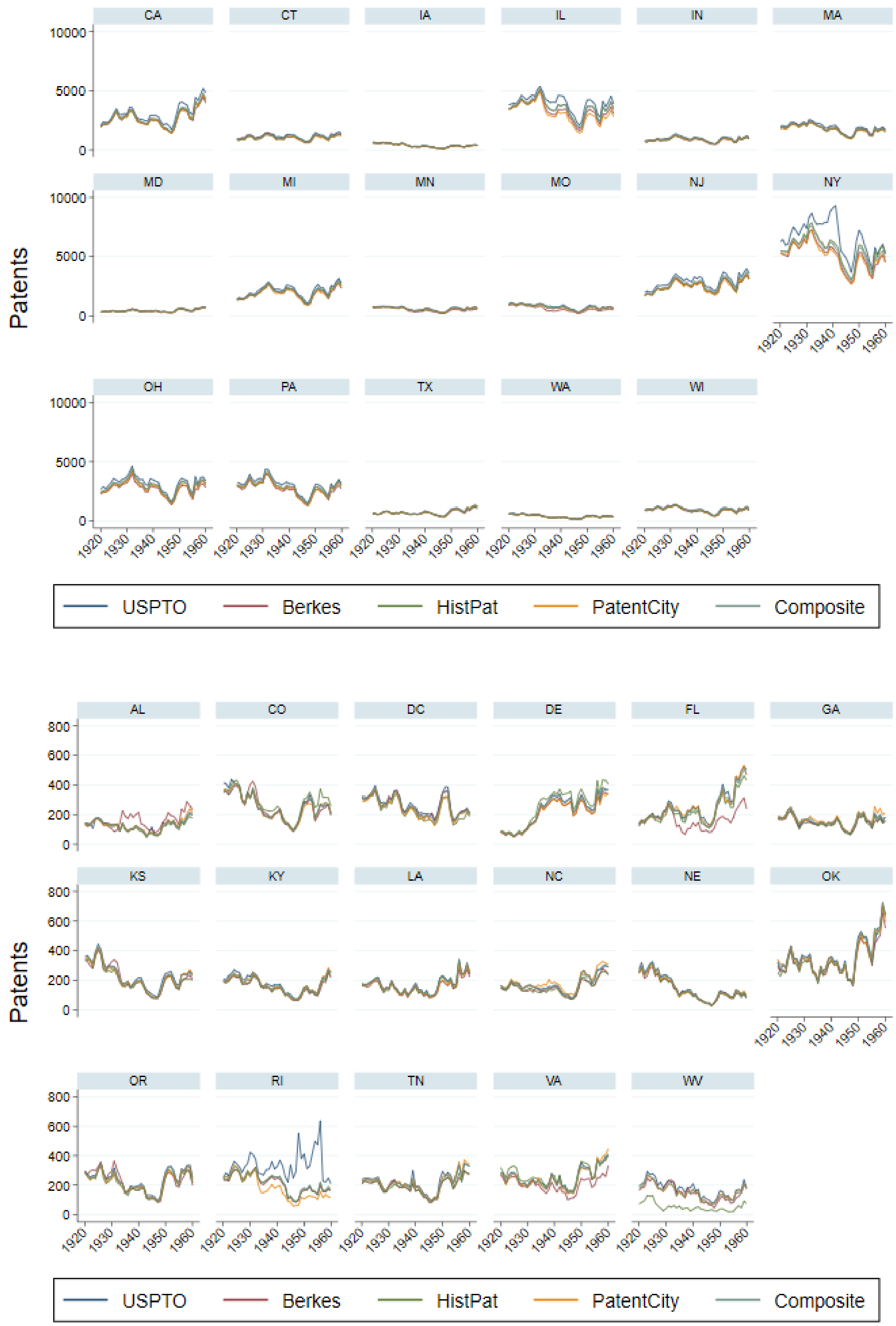
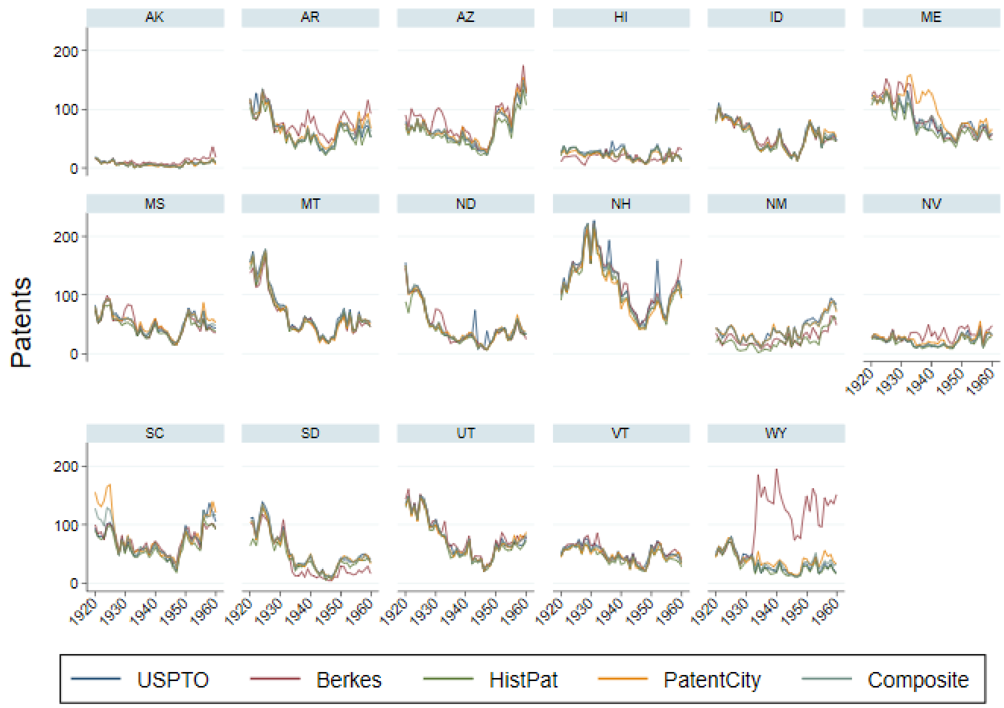


Figure B.2: State-year patent totals, HistPat vs. Administrative data, 1930-1960



Notes: Figure compares USPTO administrative totals of patent counts by state and year to those in each of our patent geography data sources (Petralia et al. 2016, Berkes 2018, Bergeaud and Verluise 2022), and to the composite measure we construct for this paper. Sample divided into the top third of states by average annual patents over the sampled period, middle third, and bottom third for ease of viewing.

Fixing county definitions

A final concern for location measurement is the fact that county definitions change over time, due to counties being combined, divided, or simply shifting borders—though most of these changes occur before 1940 (with the exception of independent cities in Virginia being carved out of, or merged into, their surrounding counties across most of the postwar period). To fix county boundaries across our sample period, we group up counties into the smallest stable units. We use two resources for tracking county boundary changes: the Atlas of Historical County Boundaries maintained by the Newberry Library, which provides a comprehensive list of county boundary changes for every state over the entire history of the U.S., and the U.S. Census Bureau's list of substantial changes to county boundaries since 1970. Note that we apply these changes to other county-level data sources as well, to ensure geographic consistency across all of our analysis.

B.2 Data on government-supported patents

A first-order question we wrestle with in the paper is to what degree the effects of World War II R&D we observe are driven by continued public investment in the same locations and technologies as those funded in the war, and (or) whether they occur organically, driven by Marshallian increasing returns to scale. To answer this question, we not only want to relate wartime government-funded R&D to postwar R&D, but also to compare places and technologies which were shocked by World War II and received more versus less postwar public research investment. Doing so requires comprehensive data on U.S. government (henceforth, USG) funded invention.

Recent efforts to comprehensively measure USG-supported patents have done so by algorithmically reading patent text for patent assignments to government entities and for government interest statements or other in-text mentions of government support (Fleming et al. 2019). With considerable effort, albeit also with the imprecisions of algorithmic measurement in a very large corpus, this work captures the set of patents where government interests can be discerned from the patent document. But this approach also bears important limitations that could result in a significant undercount, especially in the historical period, and present problems for our exercise. The first issue is that a large number of government-supported, patented inventions are produced by contractors and grantees in the course of supported work, who sometimes retain title to these inventions with the funding agency holding a paid-up license for government use. The Department of Defense, for example, has historically been a major funder of applied research and invention but has not taken title to patents, instead letting contractors have title while retaining a royalty-free license.[11] Though many such patents write government interest statements into their text, these are systematically required by agencies only after the Bayh-Dole Act of 1980, and even then, compliance and enforcement have been haphazard (Rai and Sampat 2012). Additionally, many patents by government employee-inventors have historically not been assigned nor acknowledge government employment, and are thus undetectable by reading and processing patent text. The text-based approach will thus tend to undermeasure USG-supported invention.[12]

In light of these measurement challenges, we chose to pursue administrative data on government-funded invention. Since 1944, USPTO has maintained a "Register of Government Interest in Patents", pursuant to Executive Order 9424 (18 Feb. 1944), which contains information on patents resulting from government grants and contracts. This Register has been used in research before: Watson and Holman (1964) study the so-called "Government Register" to report on the U.S. government patent portfolio, describing an index card series on which government interests were recorded. To our knowledge, it has not been revisited since.

We located these records at the U.S. National Archives (NARA) and arranged to have them scanned

[11] Watson and Holman (1964) note that individual agencies are usually either "title-policy" or "license-policy", and document that at least through the mid-1960s, more than 2/3 of federally-funded patents were licensed, not owned, by the agencies that funded the underlying R&D.

[12] As a more pedantic matter, as is we are able to identify roughly 1.5% more government-assigned patents in the Fleming et al. (2019) data than the authors identify, using the assignee data in their replication package, though this difference is too small to meaningfully alter our work.

and transcribed.[13] These records comprised 127,852 index cards, of which examples are shown in Figure B.3. The cards provide several pieces of information: identifying information (patent number and issue date, serial number and filing date, title), the assignor (i.e., contractor) and inventor, the sponsoring government agency (e.g., Army, Navy, Air Force, AEC, NASA), and the government interest (title vs. license, as well as Act of 1883 or U.S.C. 266, which are legal statutes which assign the government rights to employee inventions). Though the collection of these data began in 1944 under the E.O., the records include patents filed and/or issued as early as the 1890s, and as late as the early 1990s, when USPTO completed its transition to electronic records.[14]

We undertake several steps to clean and regularize these data, including: hand-checking the values of numeric fields with non-numeric characters, correcting errors in transcription as well as on the original cards; confirming that all identifying information is internally consistent, and manually resolving inconsistencies; and harmonizing government agency names and spellings, aggregating them up to modern cabinet-level departments where possible (e.g., Army, Navy, Air Force, War Department, NSA all become DOD; AEC becomes DOE; HEW, PHS, NIH all become HHS; etc.). The Government Register also identifies a number of OSRD patents, as the example in Figure B.3 illustrates, albeit far fewer than the OSRD records do, as many of the OSRD-funded inventions end up in these records marked as assigned or licensed to the armed services. We thus rely on OSRD's official, archival records to measure OSRD-funded invention, and on the Government Register to measure USG-funded invention in the wider population of patents.

[13] See NARA Record Group 241, "Records of the Patent and Trademark Office". The data are from records titled *Index to Patent Assignments by Government Licensees, January 1, 1890–December 31, 1955*. This title is a misnomer, as the records measure patents in which the U.S. federal government has an interest (i.e., title or license), and the records continue into the 1990s. See https://catalog.archives.gov/id/159071266.

[14] Analogous, modern data are recorded in the USPTO's Patent Assignment Dataset, where all assignments of interests (title, license, and more) are recorded. See Marco et al. (2015b). Conveyances of title and license can also be searched online at https://assignment.uspto.gov/patent/index.html#/patent/search.

Figure B.3: Example Government Register index cards

Pat. 2,416,718 March 4, 1947. Dept. Army
App. 460,328 Oct. 1, 1942. Bur.
Title: Pulse Generator
Assignor: Bell Telephone Laboratories, Incorporated
Inventor: Shockley, William
Liber:
File: Dept.14112 & Pub. 5927
Remarks:
Assignment
License X
Act of 1883
PO-283(b) (6-50) PAT'D
Department of Commerce U. S. Patent Office

Pat. 2,780,595 Feb. 5, 1957 Dept. ~~O.S.R.D.~~ AEC
App. 534,129 May 4, 1944 Bur.
Title: Nuclear Chain Reacting Systems
Assignor: Fermi, Enrico
Inventor: Same
Liber: U.S.12, p. 643;
File: Reel 131, Frame 082
Remarks: Outright
Assignment X
License
Act of 1883
PO-283(b) (6-50) PAT'D
Department of Commerce U. S. Patent Office

Pat. 2,540,654 Feb. 6, 1951. Dept. Navy
App. 16,998 Mar.25, 1948. Bur.
Title: Data Storage System.
Assignor: Engineering Research Associates, Inc.
Inventor: Cohen, Arnold A., Keye, William R. & Tompkins, Charles B.
Liber:
File: Pub.5209
Remarks:
Assignment
License x
Act of 1883
PO-283(b) (6-50) PAT'D
Department of Commerce U. S. Patent Office

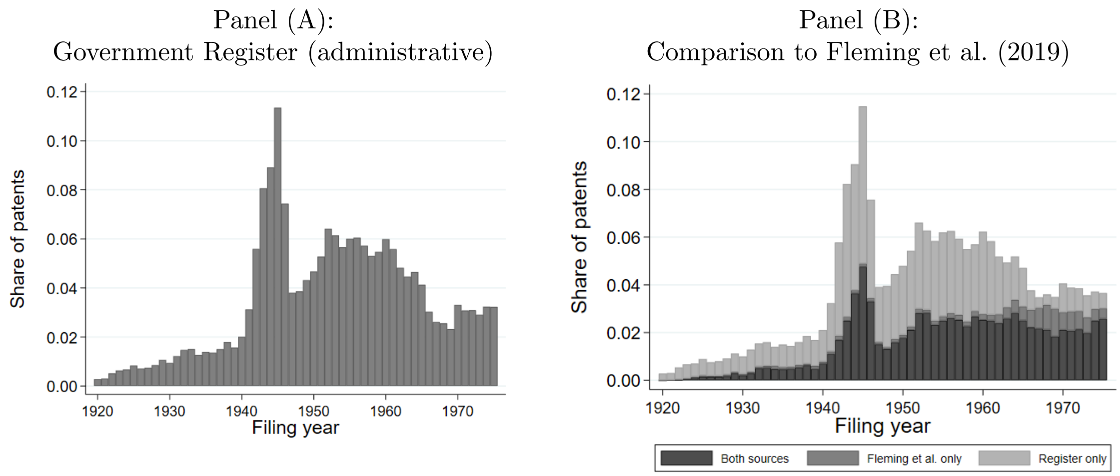
Pat. 2,744,042 - May 1, 1956 Dept. Air Force
App. 232,691 - June 21, 1951 Bur.
Title: Laminated Panels
Assignor: Goodyear Aircraft Corporation
Inventor: Pace, Henry A.
Liber:
File: Dept. 15265
Remarks:
Assignment
License X
Act of 1883
PO-283(b) (6-50) PAT'D
Department of Commerce U. S. Patent Office

Pat. 3309626 - Mar. 14, 1967 Dept. Army
S.N. 415,836-Dec. 3, 1964
Title: Microwave Limiter
Assignor: Higgins, Vincent J.
Inventor: Same
Reel: 1484 F. 679
File:
Remarks: Outright
Assignment: X
License:
U.S.C. 266 x
FORM PO-283(b) (11-63)
U.S. DEPARTMENT OF COMMERCE PATENT OFFICE

Pat. 4,267,953 May 19, 1981 Dept. N.A.S.A.
S.N. 122,967 FEB. 20, 1980
Title: METHOD for ALLEVIATING THERMAL STRESS DAMAGE in LAMINATES
Assignor: CHARLES A. HOFFMAN, JOHN W. WEETON, and NORMAN W. ORTH
Inventor: SAME
Reel: 3739 F. 927
File:
Remarks: Outright
Assignment: x
License:
U.S.C. 266
PTO-283
U. S. DEPARTMENT OF COMMERCE PATENT AND TRADEMARK OFFICE

In the figures below we illustrate what these data have to offer. Using the Register data, in Figure B.4, Panel (A) we first measure and plot the government-funded share of all U.S. patents by filing year, from 1920 to 1975, where we can see the USG share reaching its peak in World War II (note: when the series is extended into the 2000s, using modern data, we find that this share continues dropping). In Panel (B) we compare our data against those of Fleming et al. (2019), measuring what fraction of patents are in one, the other, or both sources. For most of the period we study, the Government Register data more than doubles the known number of government interest patents, with the Fleming et al. (2019) set fully subsumed by the Register data—though in the late 1960s and early 1970s, some patents begin to appear in Fleming et al. (2019) which are not present in the Register, potentially because it is less complete for these years.

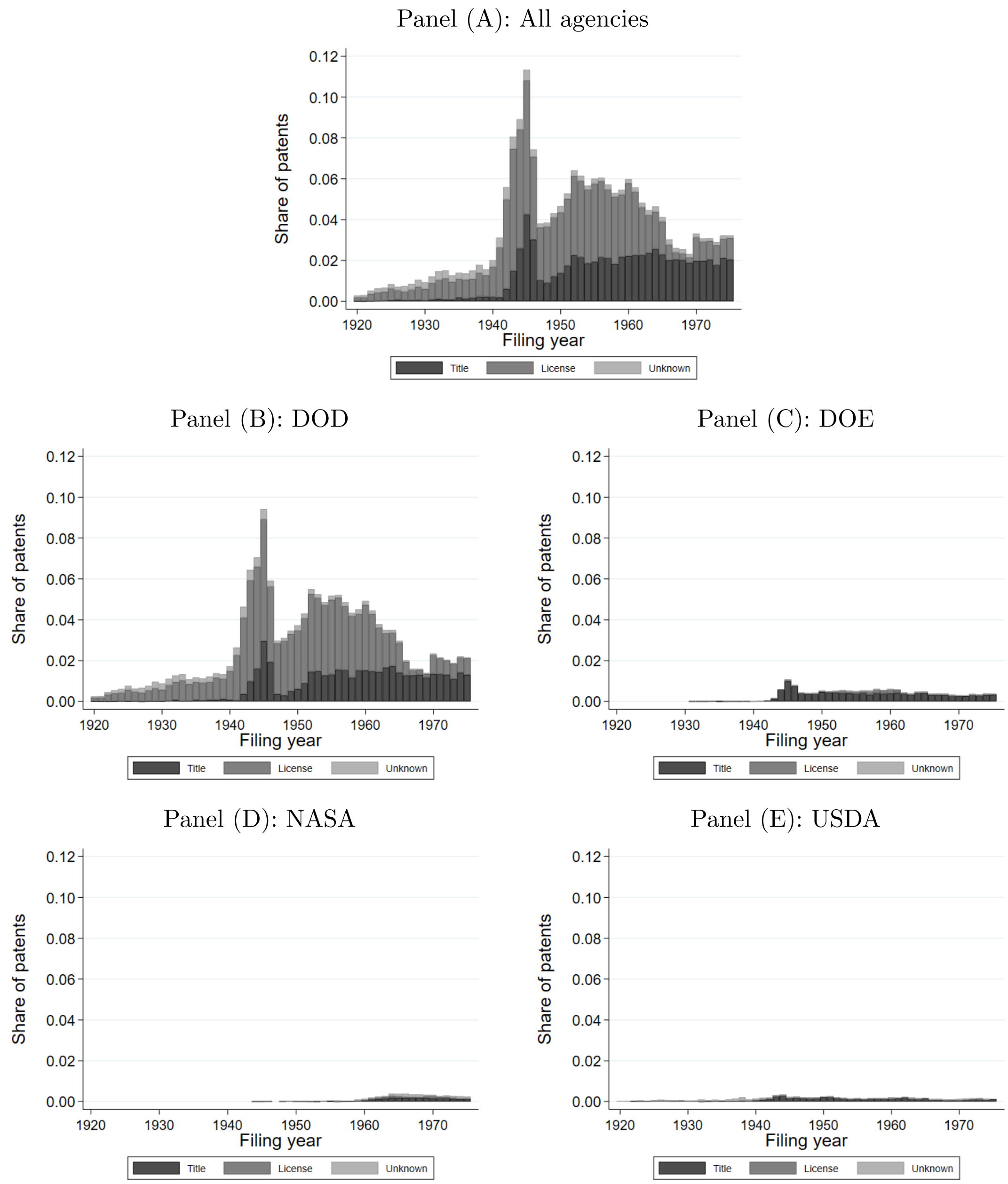
Figure B.4: Government-funded share of U.S. patent applications, 1920-1975



Notes: Figure shows the government-funded fraction of U.S. patents from 1920 to 1975 (Panel A) and compares the annual government share of patents in our newly-collected administrative data to Fleming et al. (2019) (Panel B).

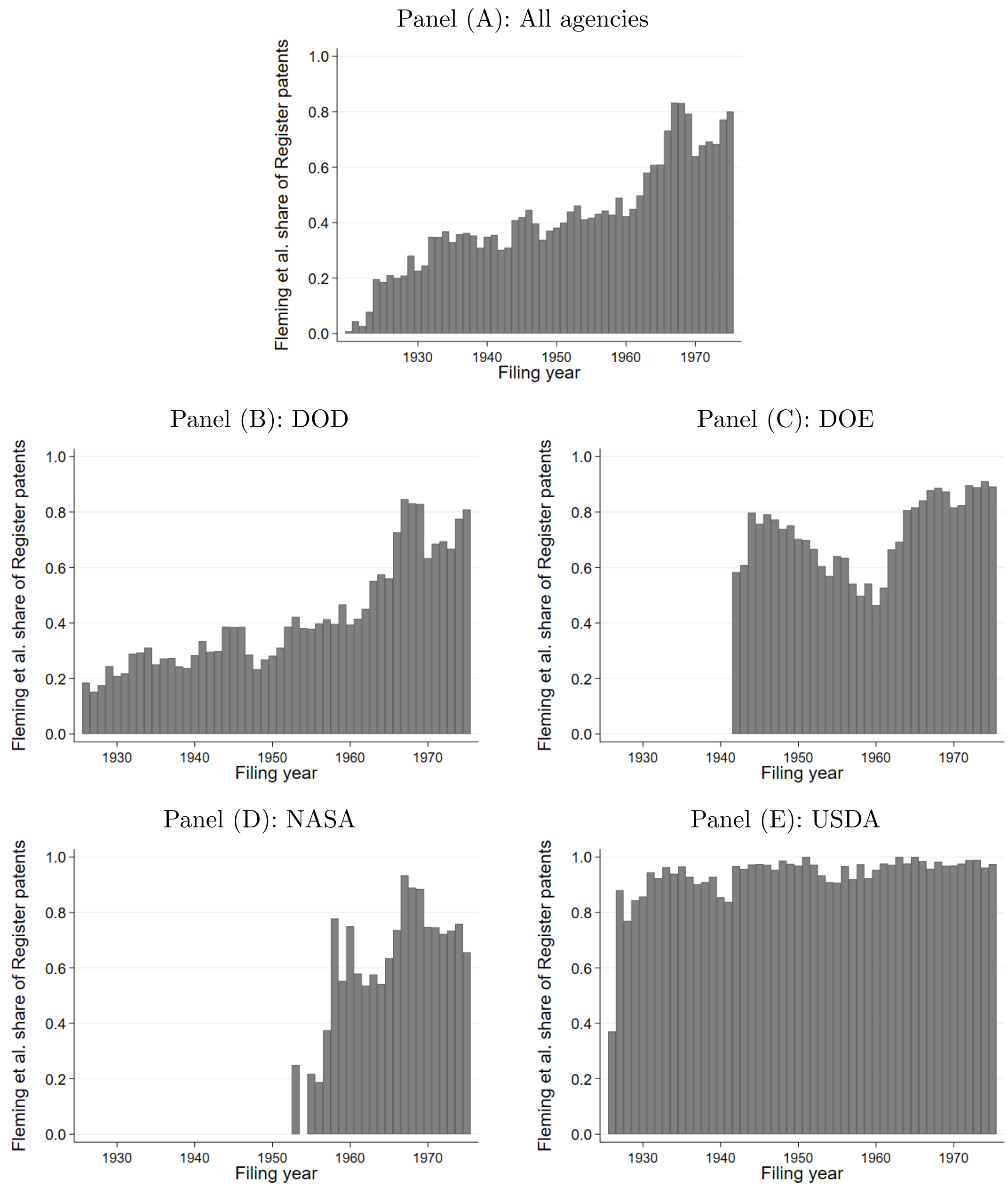
Figure B.5 examines the share of Register patents over time where the government has title, license, or an ambiguous interest, first overall (Panel A) and then for several of the larger R&D-funding agencies (Panels B to E). Here we see that license policy patents make up the vast majority of government-funded invention until the late 1960s, explaining the gap between the Register and Fleming et al. (2019) counts. We can also see that DOD is by far the driving force behind USG-supported invention: the next-largest agencies are only a small fraction of its size. In Figure B.6, we plot the share of Register patents identified as government assigned or supported (acknowledging), overall (Panel A) and by agency (Panels B to E). This share grows over time at DOD, fluctuates between 50% and 80% at DOE and NASA for most of the period, and is consistently near 100% at USDA. The completeness of the B.6 is largely driven by the degree to which each agency applies a title policy versus a license policy, and how this changed over time.

Figure B.5: Title vs. license policy share of U.S. patent applications, by agency, 1920-1975



Notes: Figure shows the government-funded fraction of U.S. patents from 1920 to 1975, overall (Panel A) and for the four highest patenting agencies (Panels B to E). Each subfigure shows the fraction of patents in our data that are title policy (i.e., government retains title) versus license policy (inventor allowed title, government retains paid-up license). License policy patents comprise two-thirds of government-funded invention but prior to these data could not be systematically measured.

Figure B.6: Share of patents captured by Fleming et al. (2019), by agency, 1920-1975



Notes: Figure shows the share of government-funded patents from 1920 to 1975 which appear in Fleming et al. (2019), overall (Panel A) and by agency (Panels B to E). These shares correlate with each agency's use of a title patent policy, both in the cross-section and over time, since title patents are assigned to the U.S. government and easily identified in modern data. DOD was historically a license policy agency but increasingly used title policy over time, while USDA has always been a title policy agency.

B.3 Construction of foreign patent dataset

We complement the U.S. patent data with foreign authority patent data. Specifically, we collect data on all utility patents granted by the U.S., British, and French patent authorities between 1920 and 1979 from the EPO PATSTAT database (EPO 2017). Much like the U.S. data, these data include grant dates and patent class (IPC), which are the main information used in this paper, as well as filing date, number of inventors and original assignees, the cross-jurisdiction patent family size, and the patent family's forward citations. In preparing these data, we restrict to patents from each patent authority (US, GB, FR) of inventions (as opposed to utility models in some jurisdictions, or design patents), and we restrict the U.S. patents in this dataset to those which are also in the USPTO dataset which we constructed and described above.

B.4 Other datasets

B.4.1 Historical U.S. County Business Patterns data

In the paper, we use U.S. County Business Patterns (CBP) data (U.S. Census Bureau 1980) to go beyond the patent record and study the effects of OSRD on local high-tech industries. The CBP measures establishments, employment, and wages at the level of counties and SIC industries, and was published at irregular intervals from 1946 to 1964 and annually thereafter. We collected data from several postwar CBP editions: 1947, 1959, 1970, and 1980. Early editions turned out to be too early and too aggregated for our purposes: too early because SIC 367 ("Electronic Components and Accessories", a key industry in relation to the OSRD shock) was only created by the 1957 SIC classification, and too aggregated because they have too few 3- and 4-digit SICs—the level at which more precise links between technology areas and industries can be drawn. This is the case even up to the 1970 CBP. The 1980 CBP, however, reports lower-level SICs more widely. For this reason, and because it (i) is based on the 1972 SIC classification, consistent with the USPTO crosswalk we use to connect patent classes and industries, and (ii) matches the vintage of D&B data we use to study firm creation (discussed below), 1980 is our preferred edition.

One challenge to working with the CBP is that it historically suppressed employment and wages in small county-industry cells, to avoid identifiable disclosures. In these cases, there are multiple means of resolving these missing values (e.g., Eckert et al. 2021). We impute employment in these cells using data on the distribution of establishments across size bins, which is provided unsuppressed for all county-industries. To do so, we assign each establishment in the size distribution an employment level equal to the midpoint of its bin, and add them together.[15] The correlation of these imputed values with reported values (where observed) is generally 0.8 or higher, although this correlation is in part driven by the skewed distribution of county size.

[15] These bins are as follows: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000-1499, 1500-2499, 2500-4999, 5000+. For firms in the upper, unbounded bin, we assign them an employment level equal to that lower bound. An alternative approach is to regress total employment (where observed) on the establishment size distribution, and use the estimated parameters to predict employment for all county-industry cells—though in practice we found this to be less reliable than the midpoint-based approach, because it is estimated (vs. imputed).

Given our use of a USPTO crosswalk that maps SICs and patent classes to common industry codes (USPTO 2007), it is useful to describe this in more detail as well. This classification has a total of 41 product codes (which we call industry codes, in this paper, for convenience) that group to the following 15, not mutually exclusive industry categories:

- R1: Chemicals and Allied Products
- R2: Chemicals, except Drugs and Medicines
- R3: Basic Industrial Inorganic and Organic Chemistry
- R4: All Other Chemicals
- R5: Primary Metals
- R6: Machinery, except Electrical
- R7: Other Machinery, except Electrical
- R8: Electrical and Electronic Machinery, Equipment and Supplies
- R9: Electrical Equipment, except Communications Equipment
- R10: Other Electrical Machinery, Equipment and Supplies
- R11: Communications Equipment and Electronic Components
- R12: Transportation Equipment
- R13: Motor Vehicles and Other Transportation Equipment, except Aircraft
- R14: Other Transportation Equipment
- R15: All Industries

Our focus in Section 5 is on the "Electrical and Electronic Machinery, Equipment and Supplies" category, which includes the following industries:

USPTO Code	Description	Crosswalked SICs
35	Electrical transmission and distribution equipment	361, 3825
36	Electrical industrial apparatus	362
38	Household appliances	363
39	Electrical lighting and wiring equipment	364
40	Miscellaneous electrical machinery, equipment and supplies	369
42	Radio and television receiving equipment	365
43	Electronic components, accessories and communications equip.	366-367

Industry 43 (SICs 366 and 367) was the category with the most associated OSRD patents, and the second-highest OSRD rate (behind ordnance and explosives). In light of their importance, it is also useful to describe some of the industries and products within these 3-digit SICs. The bullet list below provides the 4-digit subindustries and examples of products they manufacture, from the 1972 SIC classification manual. Where products are not listed, it is because the products approximately match the industry description.

- 366: Communications Equipment
  - 3661: Telephone and Telegraph Apparatus
  - 3662: Radio and TV Transmitting, Signaling, and Detection Apparatus

    * Aircraft control systems, Amplifiers, Antennas, Digital encoders, Electronic control systems, Inertial guidance systems, Laser systems, Linear accelerators, Microwave communication equipment, Radar equipment, Sonar equipment, Transponders

- 367: Electronic Components and Accessories
  - 3671: Radio and TV Receiving Type Electron Tubes, except Cathode Ray
  - 3672: Cathode Ray TV Picture Tubes
  - 3673: Transmitting, Industrial and Special Purpose Electron Tubes
  - 3674: Semiconductors and Related Devices
  - 3675: Electronic Capacitors
  - 3676: Resistors for Electronic Applications
  - 3677: Electronic Coils, Transformers, and Other Inductors
  - 3678: Connectors for Electronic Applications
  - 3679: Electronic Components (n.e.c.)
    * Antennas, Circuit boards, Magnetic recording tape, Oscillators, Relays

B.4.2 Historical firm creation from Dun & Bradstreet

We supplement these data with distinct data from Dun & Bradstreet (1980) (D&B), which has for two centuries collected data on U.S. firms for the purpose of assessing creditworthiness, making these data commercially available. Electronic records begin in roughly 1970, and modern D&B data cover millions of U.S. firms. These data are useful for our purposes because they measure firms' locations, 4-digit SIC industries, and founding years, enabling us to produce a measure of business creation by county, SIC, and year. An important caveat of these data is that our measurement is conditioned on both inclusion in the D&B sample (though this is very large) and survival to a given data year (this is more limiting, especially with the passage of time). Because it appears the D&B sample grew significantly over the 1970s, and in order to be able to include the 1970s in our analysis, we use the 1980 D&B data, balancing data quality against the survival of older cohorts. As with the CBP data, we focus our attention on firms in SIC 366 and 367, measuring the number of firms created in these SICs by county and decade.

B.4.3 Rosters of technical staff at OSRD-funded R&D labs

We also collect data on individuals who were at two major OSRD-funded R&D labs during the war: the MIT Radiation Laboratory (Rad Lab or RL), which was the epicenter of the Allied radar research effort during WW2, and the Harvard Radio Research Laboratory (RRL), which worked on radar countermeasures (i.e., stealth movement and enemy radar jamming). Both labs were large, employing thousands of scientists and engineers over the course of the war, and the Rad Lab was considered so successful that it became a model for post-war federally-funded research labs and is celebrated as an important part of the history of MIT and the broader region.

We use records from the Harvard and MIT university archives to compile rosters of technical staff from each of these labs. The MIT archive's collection of Rad Lab records contains three documents useful towards this end: (i) a list of former RL staff members published in June 1946, which lists the name, field, highest degree, year of degree, and years spent at the RL; (ii) the most reliable known address of former staff members, as of March 1946; and (iii) the post-war job (or grad school) placement of former staff members, as of January 1946. We digitize these data sources, harmonizing name formats in the process so that we can successfully link individuals across them. Although some individuals appear in only a subset of these records, for most we have complete records. From the Harvard archive, we observe only RRL staff member addresses, as of March 1946, without the ancillary information on educational background or post-war job placement. We supplement this information by collecting data on all pre-, mid-, and post-war patents by these individuals, which we can use to study the effects that these individuals might have had on local inventive activity after the war in the fields where they were active.

B.4.4 Universities and PhD student production across the 20th century

We also collect data on historical PhD graduates of U.S. universities, which we use to identify major universities. We collect two sources to do so: a National Academy of Sciences report on doctorate production in U.S. universities (NAS 1963), which covers the 1920-1962 period, and the NSF Survey of Earned Doctorates (NSF 2022), which covers 1958+. We then count PhD graduates by university, field, and decade, and identify universities with the most postwar (1950-1969) graduates in the physical and biological sciences. We also borrow a measure of leading institutions from the NAS (1963) report. See Appendix C for further discussion.

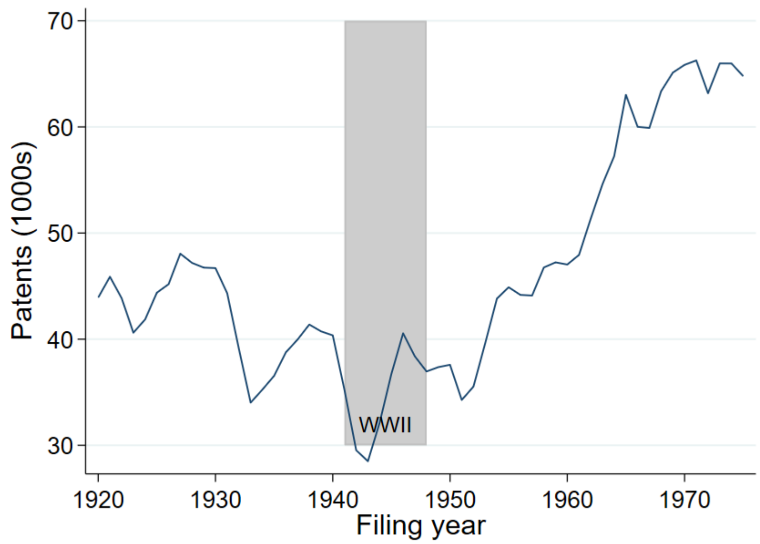
B.4.5 Population data, shapefiles for mapping, etc.

Where we normalize cluster patenting by county population, we use data from Forstall (1996) (obtained in 2018 from the U.S. Census Bureau's website, at an address which no longer functions), which we interpolate across census decades for an annual measure. Where we map OSRD patenting or other variables, we use the 2000 TIGER/Line shapefile from Manson et al. (2022), filtered to the continental United States, as a base layer. As we noted earlier, county-level variables are grouped to their smallest stable geographic units throughout the paper.

C Supplementary Results

C.1 U.S. patenting in the 20th century

Figure C.1: Aggregate U.S. patenting, 1920 to 1975



Notes: Figure shows the time series of U.S. patents, by filing year, 1920 to 1975.

C.2 Top OSRD-supported technology fields

Table C.1: Top 10 technology areas with OSRD patents (denominator: all patents)

NBER	Description	Patents from OSRD contracts	Pct. of patents from OSRD, 1941-48	Max pct. OSRD in any year, 1941-48
44	Nuclear, X-rays	194	12.5%	24.8%
21	Communications	671	6.9%	16.6%
46	Semiconductor devices	15	5.4%	12.1%
42	Electrical lighting	241	4.2%	10.0%
22	Computer hardware/software	65	4.1%	8.5%
43	Measuring, testing	187	3.1%	6.8%
41	Electrical devices	308	2.5%	6.5%
45	Power systems	163	1.7%	4.2%
31	Drugs	27	1.7%	6.4%
49	Misc. (elec)	93	1.6%	3.7%

Notes: Table lists the top 2-digit NBER technology subfields (Hall et al. 2001), ranked by the fraction of 1941-1948 patents which were OSRD-funded, and the maximal fraction of OSRD-funded patents in any year.

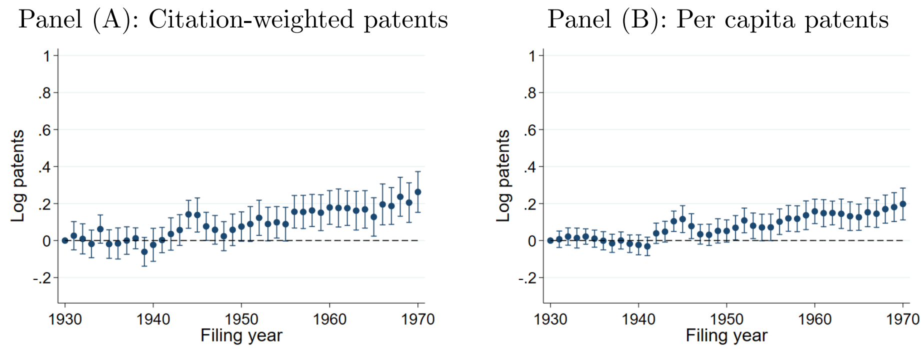
Table C.2: Top 10 patent classes with OSRD patents (denominator: all patents)

USPC	Description	Patents from OSRD contracts	Pct. of patents from OSRD, 1941-48	Max pct. OSRD in any year, 1941-48
376	Induced nuclear reactions	62	33.9%	81.8%
367	Acoustic wave systems/devices	95	20.4%	41.0%
102	Ammunition and explosives	174	16.6%	39.4%
343	Radio wave antennas	104	12.6%	33.9%
380	Cryptography	29	12.0%	21.4%
250	Nuclear energy	120	12.0%	23.8%
342	Directive radio wave systems/devices (radar)	200	10.9%	21.9%
333	Wave transmission lines and networks	108	10.5%	20.0%
327	Misc. electrical devices, circuits, and systems	88	10.3%	25.8%
708	Electrical computers	15	9.4%	22.2%

Notes: Table lists the top patent classes ranked by the fraction of 1941-1948 patents which were OSRD-funded, and the maximal fraction of OSRD-funded patents in any year.

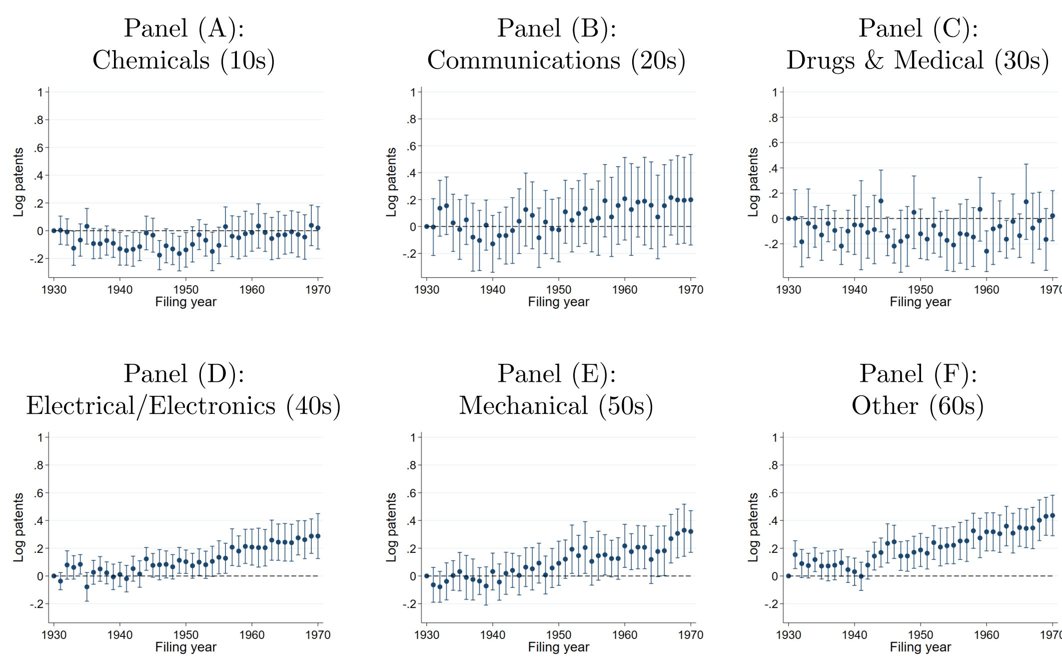
C.3 Additional results

Figure C.2: Effects of OSRD on citation-weighted patents and per-capita patents



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting on citation-weighted patents and per-capita patents. The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure C.3: Effects of OSRD on cluster patenting, 1930-1970, by technology area



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting, splitting the sample into high-level technology categories (Hall et al. 2001). The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure C.4: Effects of OSRD on cluster patenting, 1930-1970, omitting individual states

Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting, omitting individual states from the estimation sample. The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

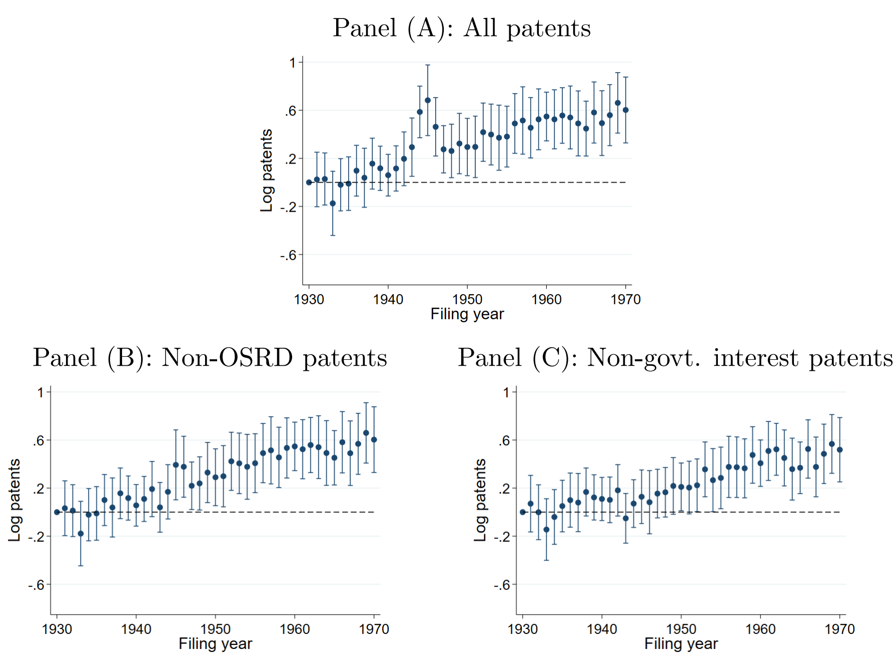
C.4 Alternative treatment measure: OSRD intensity quartiles

The following figures re-estimate our agglomeration results using a categorical treatment measure. We group clusters (county-categories) in four quartiles of treatment intensity (fraction of 1941-1948 patents OSRD-funded, conditional on any), and estimate changes in cluster patenting over time by treatment quartile, relative to a reference category of clusters without any OSRD-funded invention. Concretely, the specification we estimate here and elsewhere is:

$$Ln(Patents)_{ict} = \sum_{q=1}^{4} \sum_{t=1931}^{1970} \beta_{qt} \cdot \mathbb{1}(\text{Treatment quartile } q) \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict}$$

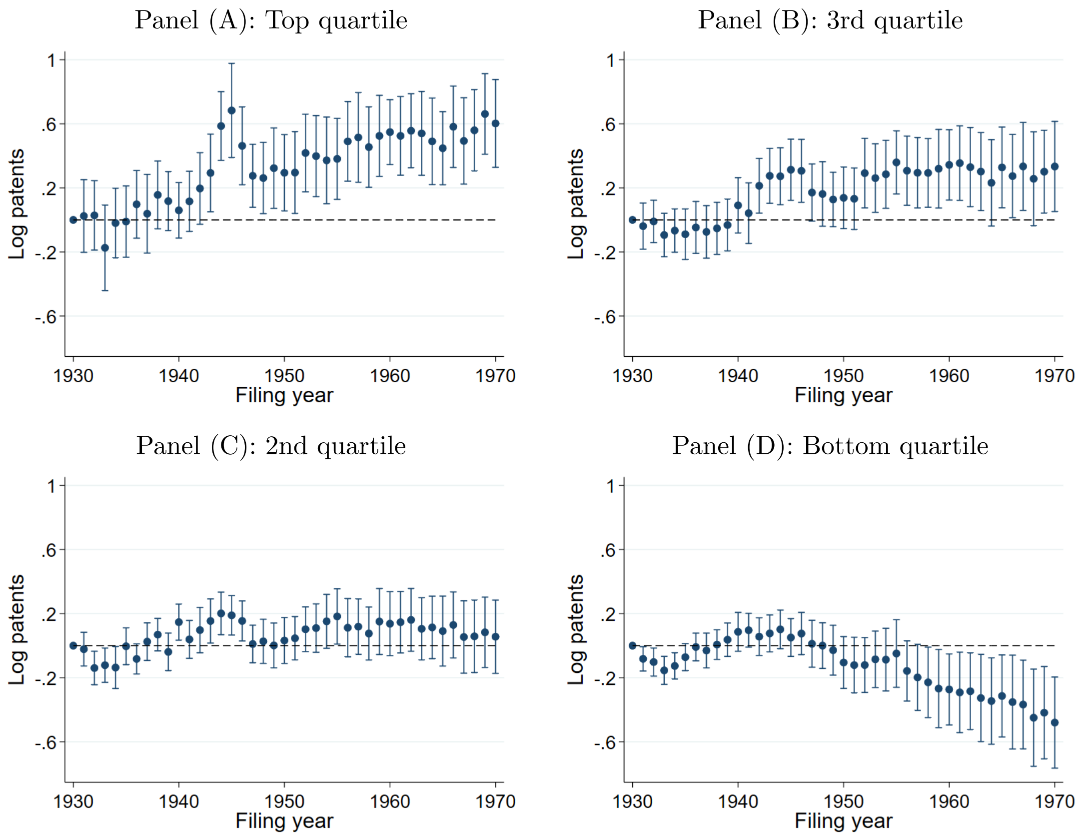
where i indexes counties, c indexes patent categories, and t indexes years, and the sample runs from 1930 to 1970, with standard errors clustered at the county level. Figure C.5 presents our key result for the top quartile of treated clusters, reproducing Figure 4 of the paper with this alternative treatment measure. Figure C.6 presents estimates for all four treatment quartiles, where the effect of the World War II shock can be seen to diminish in treatment intensity. Our preferred treatment measure for this paper is continuous, rather than categorical, because continuous measure preserve power (whereas categorical measures slice the sample into smaller cells, with wider confidence bands, as can be seen in these figures).

Figure C.5: Effects of OSRD on cluster patenting, 1930-1970, top treatment quartile



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure C.6: Effects of OSRD on cluster patenting, 1930-1970, by treatment intensity quartile



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the quartile of treatment intensity, conditional on treatment (the fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded, conditional on any), with parameters across all four panels estimated jointly (in one regression) relative to a reference group of county-categories without any OSRD patents. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

C.5 Correlation of OSRD and postwar government-funded patenting

Table C.3 estimates the relationship of World War II OSRD patenting to postwar government-funded patenting across county-categories. The outcome variable is measured as the government-funded share of 1950-1969 patents, in levels (Column 1), logs (Columns 2 and 3), and relative to the median, conditional on non-zero (Columns 4 and 5). The explanatory variable is measured as the OSRD-funded share of 1941-1948 patents, in levels, logs, and quartiles. The table shows path dependence in the local intensity of government-funded invention.

Table C.3: Correlation of OSRD patenting and postwar govt-funded patenting across clusters

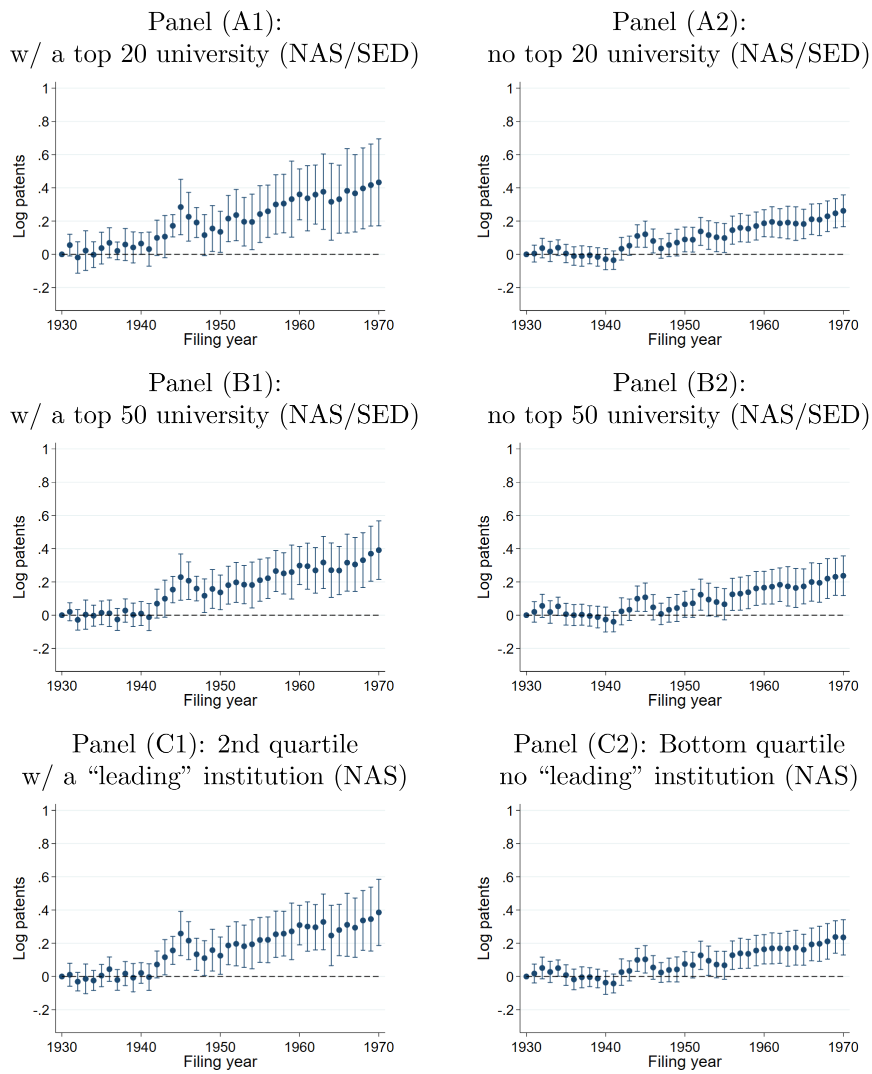
	USG rate, 1950-1969			Rel. to median	
	(1)	(2)	(3)	(4)	(5)
	Level	Log+1	Log	Above	Below
Wartime OSRD rate, 1941-1948	0.370***				
	(0.071)				
Ln(1 + Wartime OSRD rate)		0.415***			
		(0.065)			
Ln(Wartime OSRD rate)			0.463***		
			(0.040)		
Wartime OSRD rate in top quartile				0.417***	0.095***
				(0.045)	(0.036)
Wartime OSRD rate in 3rd quartile				0.349***	0.262***
				(0.049)	(0.043)
Wartime OSRD rate in 2nd quartile				0.251***	0.466***
				(0.045)	(0.043)
Wartime OSRD rate in bot. quartile				0.063*	0.672***
				(0.038)	(0.039)
N	14521	14521	606	14521	14521
R^2	0.02	0.03	0.30	0.04	0.06
Y Mean	0.04	0.04	-2.48	0.10	0.17

Notes: Table relates county-category postwar government-funded patents to wartime OSRD patents. The OSRD rate measures the OSRD-funded share of county-category patents between 1941 and 1948, and the USG rate measures the government-funded share of county-category patents between 1950 and 1969. All columns include county-category and year fixed effects. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. SEs clustered by county in parentheses.

C.6 Differential effects in clusters with major universities

The following figures examine whether the effects of the OSRD shock vary in counties with vs. without a major university. As we explain in Section 4 of the paper, we measure major universities in two ways. First, we use a National Academy of Sciences report, and the NSF Survey of Earned Doctorates, to measure PhD graduates in the physical and biological sciences from 1950 to 1969 and identify the top 10, 20, and 50 universities by PhDs granted in these fields. Second, we borrow a measure of "40 leading institutions" from the National Academy report (which, according to the report, is ranked in terms of their total PhD production from 1920 to 1962). When we control for these measures, our results are unchanged. However, as Figure C.7 shows, we find effects of OSRD that are roughly twice as large in clusters with a major university.

Figure C.7: Effects of OSRD on cluster patenting, 1930-1970, by university presence



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patents in county-categories with and without a top university, by various measures. See text for definitions. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

C.7 Aggregate outcomes

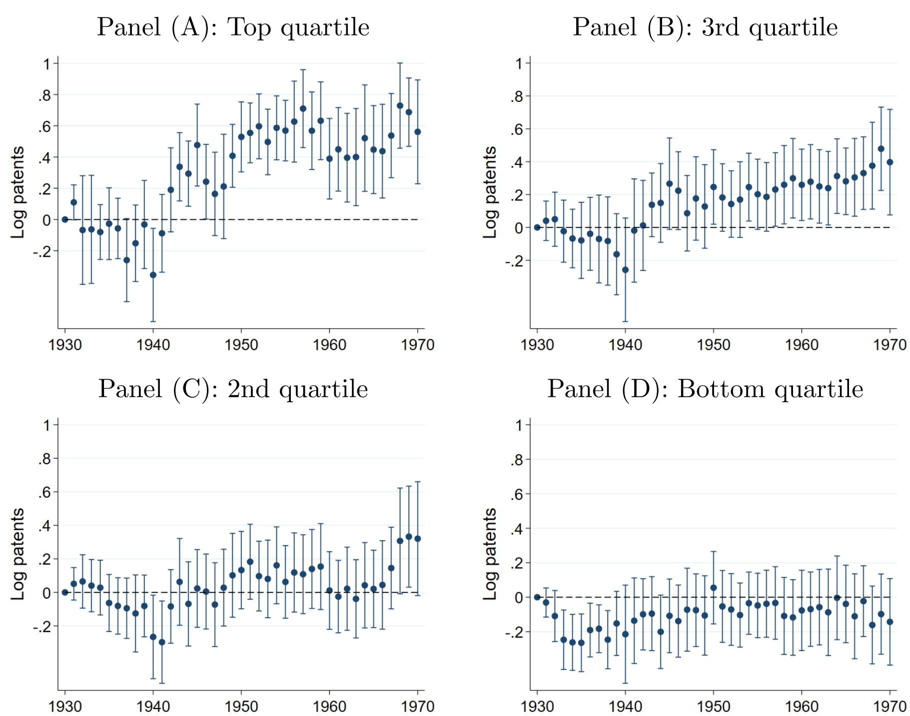
The following figures present annual estimates of the effects of World War II R&D on the direction of U.S. invention, disaggregating the simple difference-in-differences presented in Figure 9 in the body of the paper. We estimate the following specification:

$$Ln(Patents)_{ict} = \sum_{q=1}^{4} \sum_{t=1931}^{1970} \beta_{qt} \cdot \mathbb{1}(\text{Country } i = \text{US}) \cdot \mathbb{1}(\text{Class } c \in \text{quartile } q) \cdot Year_t$$
$$+ \alpha_{ic} + \delta_{it} + \gamma_{ct} + \varepsilon_{ict}$$

where i, c, and t index countries, technology classes, and years, the latter terms represent interacted fixed effects, and standard errors are clustered at the country-class level.

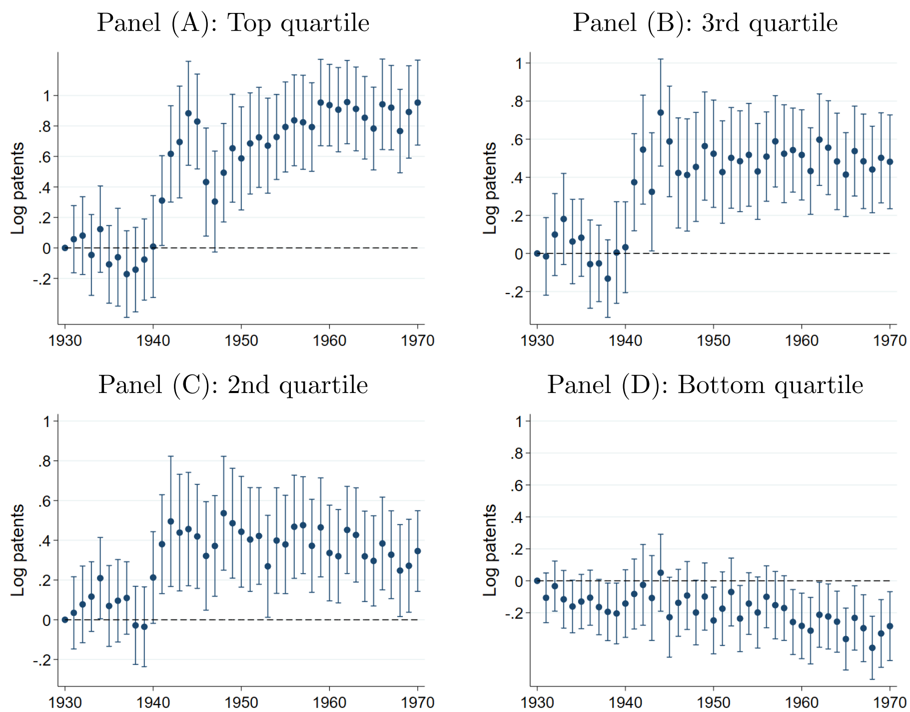
Figure C.8 presents the estimates for patenting at the USPTO vs. foreign patent offices. Figure C.9 does so for USPTO patents of U.S. versus foreign inventors. In both cases, the effect of the World War II shock is visible but diminishes in treatment intensity.

Figure C.8: Patenting at the USPTO versus UK/FR patent offices, by quartile of treated patent classes (relative to untreated classes), 1930-1970



Notes: Figure shows annual difference-in-differences estimates of the effects of the OSRD shock on patenting at USPTO versus UK and FR patent offices, in technology classes (IPC classes) in each quartile of OSRD treatment, as measured by the fraction of U.S. patents in those classes between 1941-1948 which were OSRD-funded, versus those without OSRD treatment. Error bars represent 95% confidence intervals, computed from SEs clustered at the country-class level.

Figure C.9: Patenting at the USPTO by domestic versus foreign inventors, by quartile of treated patent classes (relative to untreated classes), 1930-1970



Notes: Figure shows annual difference-in-differences estimates of the effects of the OSRD shock on USPTO patents with U.S. versus foreign inventors, in technology classes (USPCs) in each quartile of OSRD treatment, as measured by the fraction of U.S. patents in those classes between 1941-1948 which were OSRD-funded, versus those without OSRD treatment. Error bars represent 95% confidence intervals, computed from SEs clustered at the country-class level.

D Examining key specifications

D.1 Theoretical underpinnings

Our main specification is motivated by Romerian classes of endogenous growth models (e.g., Romer 1990), where the flow of innovation is proportional to the stock.

To see this more clearly, let A_t represent a cluster's stock of varieties at the end of period t. Innovation, $\Delta A_t = A_t - A_{t-1}$, can be written $\Delta A_t = gA_{t-1}$, where $g > 0$ is the growth rate (which is, in turn, a function of R&D inputs). Iterating, and letting A_0 be the stock of varieties in a base period (such as 1940, just before the World War II R&D investment), we get $\Delta A_t = g(1+g)^{t-1}A_0$. The OSRD shock, in this case, can be interpreted as a windfall φ to the stock of local innovation or inventive capabilities in a particular field. Innovation in treated clusters will then follow a process $\Delta A'_t = g(1+g)^{t-1}(A_0 + \varphi)$, but in untreated clusters it follows ΔA_t.

We seek to compare innovation in treated and untreated clusters, which we will henceforth equate with patenting. Observe that the ratio of treated and untreated clusters' patenting at time t is $\Delta A'_t / \Delta A_t = (1 + \varphi/A_0)$. Taking logs, we have that $\ln(\Delta A'_t) - \ln(\Delta A_t) = \ln(1 + \varphi/A_0)$, which indicates a constant difference at each post-treatment period t in log patents across treated and control clusters. This difference, in turn, is a function of OSRD-funded patents normalized by the size of the cluster (φ/A_0). We can turn this into a specification for a regression by attaching a β to $\ln(1 + \varphi/A_0)$. If untreated clusters are the omitted category against which treated clusters are compared, we can sweep $\ln(\Delta A_t)$ into a fixed effect. If we then want to estimate β across a panel of clusters, we can add cluster ic fixed effects (where i and c index counties and technology categories, respectively). Our model is then $\ln(\Delta A'_t) = \beta \cdot \ln(1 + \varphi/A_0) + \alpha_{ic} + \delta_t$.

This model can thus be translated into an estimating equation which can be used to test whether OSRD had a long-run effect—and more generally, whether the data are consistent with endogenous growth. If $\hat{\beta} > 0$, it suggests the OSRD shock had a Romerian effect, and if $\hat{\beta} \approx 1$, the data match the assumptions of Romer (1990) exactly. When we estimate this model as specified, we get $\hat{\beta} \approx 1$, reinforcing a Romerian interpretation of the data. We can also estimate time-varying parameters β_t, to evaluate whether the effects of this windfall change over time.[16]

The specification we estimate in the paper approximates the model above, but also includes a few differences. We measure φ/A_0 as the OSRD share of a cluster's 1941 to 1948 patents, rather than normalizing by pre-war patents.[17] We also replace $\ln(1+X)$ with $\ln(X)$, which allows estimated

[16] Time-varying parameters can be motivated in a variety of ways. For example, recombinant innovation is one reason why log patenting in differently-endowed clusters may diverge over time (Weitzman 1998). Complementarities are another. To motivate time-varying effects of endowment differences in a simple, mechanism-agnostic way, we can augment this model by defining $A_t = (1+g)^t A_0^{\beta_t}$, where β_t is a time-varying scaling parameter on initial stocks (e.g., $\beta_t = t\beta$). This leads to an estimating equation with $\beta_t \cdot \ln(1 + \varphi/A_0)$.

[17] Our choice to use cluster patents from 1941 to 1948 as the denominator allows the fraction to be interpreted as the intensity of a cluster's mid-1940s engagement in the war effort, relative to its overall size at that time. We have performed the analysis with both 1930s patents and 1941-1948 patents in the denominator, and the choice is not material to the results since the two measures are very correlated (ρ=0.91).

parameters to be interpreted as elasticities. Though these choices slightly decouple the specification from the underlying theory, they also simplify the empirical interpretation. As we show in the next subsection, this does not materially affect our main takeaways.

Formally, our estimating equation is thus as follows:

$$Ln(Patents)_{ict} = \sum_{t=1931}^{1970} \beta_t \cdot Ln(\text{OSRD rate})_{ic} \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict} \tag{D.1}$$

where ic and t index clusters and years, respectively.

D.2 Alternative approaches

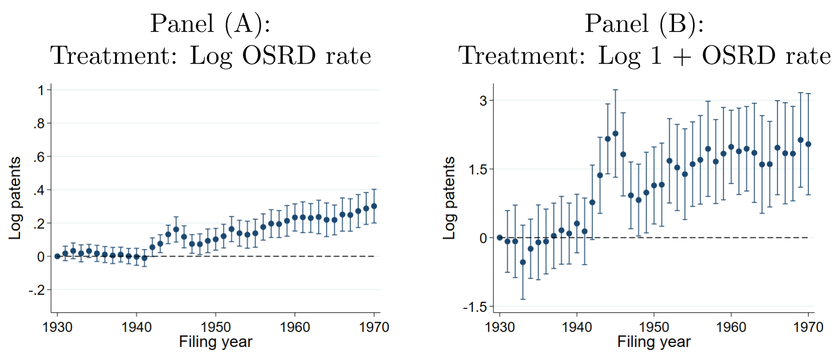
D.2.1 Treatment: Log 1 plus OSRD rate

Following the derivation in Section D.1 above, we could consider replacing $Ln(\text{OSRD rate})_{ic}$ in our main estimating equation with $Ln(1 + \text{OSRD rate})_{ic}$:

$$Ln(Patents)_{ict} = \sum_{t=1931}^{1970} \beta_t \cdot Ln(1 + \text{OSRD rate})_{ic} \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict} \tag{D.2}$$

This would have the added benefit of eliminating zeros in the argument, such that this object is defined for many more cluster years, but it would challenge elasticity interpretations, since natural logarithms are not scale independent (Mullahy and Norton 2022, Chen and Roth 2023). Figure D.1 presents the results when we do so. In the left panel we present the β_t parameters from Equation (D.1), as a reference point, and in the right panel the β_{1t} parameters from Equation (D.2). The results show a similar pattern, but larger magnitudes.

Figure D.1: Effects of OSRD on cluster patenting, 1930-1970



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable in Panel (A) measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. The independent variable in Panel (B) measures the log of 1 + the fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

D.2.2 Treatment: Level OSRD rate

We could alconsider replacing $Ln(\text{OSRD rate})_{ic}$ with $(\text{OSRD rate})_{ic}$ in levels:

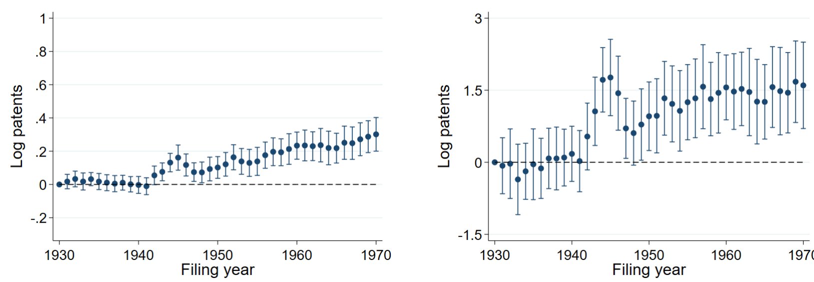
$$Ln(Patents)_{ict} = \sum_{t=1931}^{1970} \beta_t \cdot (\text{OSRD rate})_{ic} \cdot Year_t + \alpha_{ic} + \delta_t + \varepsilon_{ict} \tag{D.3}$$

In this case the treatment measure will have more skew (which natural logs previously compressed), but on the other hand may permit more straightforward interpretation of the parameter (as semi-elasticities; e.g., a 10 percentage point increase in the OSRD rate yields a $0.1\beta_t$ increase in patenting). Figure D.2 presents the results when we do so. In the left panel we present (again) the β_t parameters from Equation (D.1), and in the right panel the β_{1t} parameters from Equation (D.3). The results show (again) a similar pattern, but larger magnitudes.

Figure D.2: Effects of OSRD on cluster patenting, 1930-1970

Panel (A): Treatment: Log OSRD rate

Panel (B): Treatment: Level OSRD rate



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable in Panel (A) measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. The independent variable in Panel (B) measures the level of the fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

D.2.3 Separating OSRD and total 1941-1948 patents

An alternative approach is to measure the treatment as a cluster's OSRD-funded patents. The interpretation of marginal effects would in this case answer a somewhat different—and arguably slightly narrower—question, but a valid one nonetheless. Moreover, in doing so, one would want to control for total cluster patenting during the years OSRD was active, so as to not confound OSRD clusters with generally-inventive clusters, which may correlate.

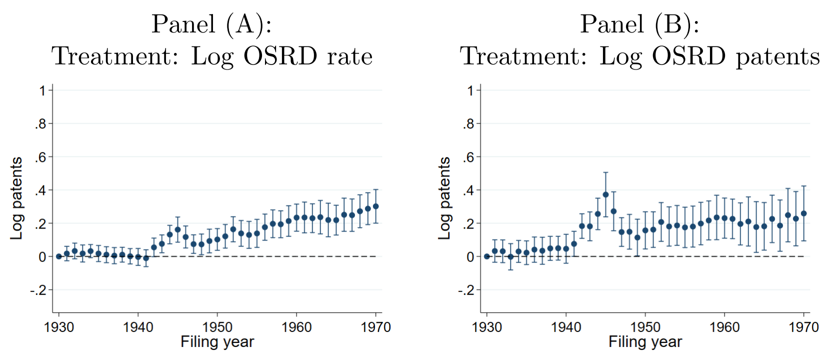
In this appendix, we examine an alternative specification, where we continue to measure logged cluster-year patenting as the outcome variable, but we replace clusters' log OSRD rate with their log OSRD patents as a measure of the shock, as well as log total 1941-1948 patents as a control.

The specification we estimate is accordingly the following:

$$Ln(Patents)_{ict} = \sum_{t=1931}^{1970} [\beta_{1t} \cdot Ln(\text{OSRD patents})_{ic} \cdot Year_t \\ + \beta_{2t} \cdot Ln(\text{1941-48 patents})_{ic} \cdot Year_t] + \alpha_{ic} + \delta_t + \varepsilon_{ict} \tag{D.4}$$

These two constructions are mechanically very nearly the same, since $Ln(\text{OSRD rate}) = Ln(\text{OSRD patents}) - Ln(\text{1941-48 patents})$, but this new specification differs in that it permits the parameters on the two objects to vary (β_{1t} and β_{2t}, versus β_t). That the specifications are similar does not imply they must yield the same results, and indeed a parameter restriction like this (in Equation 1) could have a large impact on its estimated value. Figure D.3 presents the results from each, where in the left panel we present (again) the β_t parameters from Equation (D.1), and in the right panel the β_{1t} parameters from Equation (D.2). The results are statistically and quantitatively similar across specifications, reflecting in the end their close relation.

Figure D.3: Effects of OSRD on cluster patenting, 1930-1970



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable in Panel (A) measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. The independent variable in Panel (B) measures the log number of U.S. patents in each county-category between 1941-1948 which were OSRD-funded, controlling for log total patents in 1941-1948. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

E Alternative interpretations: OSRD or war demand?

One potential threat to this paper's conclusions is the question of whether the OSRD effect we estimate may be attributable to other causes.[18] The absence of pre-trends reassures us that OSRD investments did not coincide with local technological or commercial possibility, which was unlikely to spontaneously arise. But it does not rule out the possibility of contemporaneous shocks in the same technologies and locations, especially due to broader war-related causes. This can be a threat to identification if, for example, OSRD R&D coincided with other applied R&D investments during the war, or an attribution error if OSRD displaced war-induced innovation in the same technologies, performed in the same places, that would have taken place by other means. For example, the same firms involved in OSRD research may have made these investments on their own, in the course of fulfilling military supply contracts. Or these firms might have contracted with the same universities OSRD worked with. Or a different agency (especially the military branches) might have funded R&D in the same technologies and regions if OSRD had not.

To a casual reader these differences may not seem problematic. We measure the World War II R&D shock through OSRD records, but a shock is a shock, and maybe OSRD is just an instrumentality: we could view it as a proxy for whatever R&D investments took place in World War II, regardless of the means. We do not find this view satisfactory, as it's not sufficiently discerning of mechanisms. In particular, government demand spilling in upstream R&D (demand-pull)—which one might view as either a potential confounder or a counterfactual to the OSRD-led research effort—is fundamentally different than the technology-push mechanism we attribute our results to, and understanding which was at play is essential to the generalizability of our findings.

In this appendix, we set out to more fully evaluate alternative-to-OSRD explanations. To reiterate the concern, it is that even without OSRD funding, the technologies and places OSRD funded may have seen R&D surge during the war. This could be because:

1. War supply contractors would have funded this R&D, had it not been funded by OSRD (e.g., in the course of serving a procurement contract, or in bidding for future ones).
    (a) The war equipment suppliers may have performed this R&D themselves—and in the same technologies and locations that OSRD funded.
        - If war equipment suppliers were also the main OSRD R&D performers for a given technology, then their spill-in R&D investments in this counterfactual may have naturally taken the same geographic distribution OSRD R&D did.
        - If war equipment suppliers were not the principal OSRD R&D performers, but war production was co-located with OSRD R&D, that implies these firms had facilities in 'OSRD places' where this counterfactual R&D could occur, which might for this reason also take the same geographic distribution as OSRD R&D did.

[18] We thank an anonymous reviewer for posing questions which prompted the analysis in this appendix.

- If war equipment suppliers were not the principal OSRD R&D performers, and war production was not co-located with OSRD R&D, these firms could have still in principle set up R&D operations for the same technologies in the same places where OSRD did—even if their existing R&D facilities were elsewhere (or nonexistent—though we would argue it's unlikely that firms with no R&D experience would be able to scale up R&D operations during and for the war effort).

(b) The war equipment suppliers may have subcontracted to firms and universities in the same technologies and locations that OSRD funded.

2. Another agency (especially procuring agencies, like the War and Navy Departments) may have funded the requisite R&D—maybe contracting for R&D in the same technology areas, with the same firms and institutions, and in the same locations.

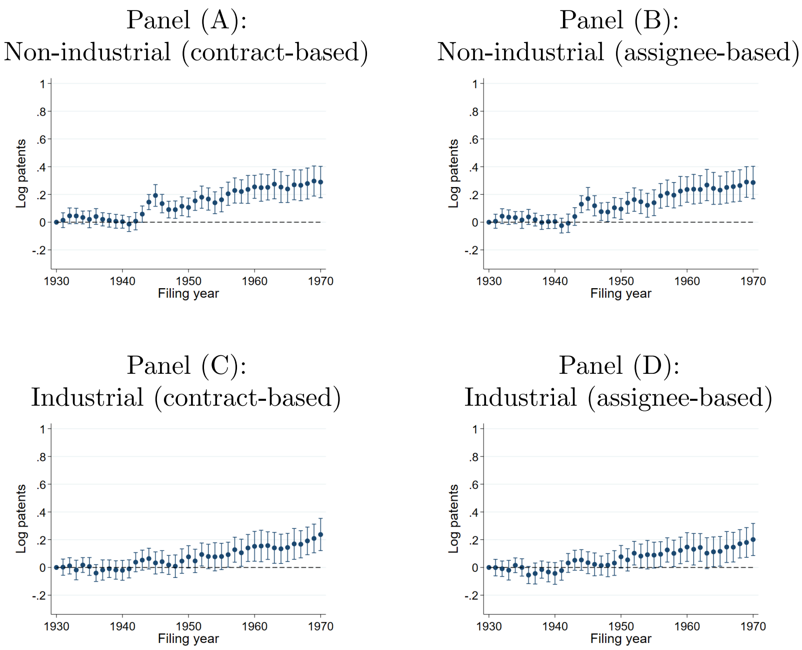
The remainder of this appendix will follow this sequence. First we evaluate whether war equipment suppliers were likely candidates to replace OSRD R&D. Supposing they were, and that they would perform this R&D themselves, we will then explore how likely it is that the geographic pattern would match that of OSRD R&D. We also discuss the prospects that in this counterfactual, war equipment suppliers might contract out the R&D in a pattern similar to what OSRD did. Finally, supposing that firms would not be R&D sponsors, we evaluate the likelihood that other agencies could replace OSRD as a similar-impact R&D funder. This analysis will use a mix of old and new data sources and combine empirical and qualitative evidence.

Were war equipment suppliers were likely candidates to replace OSRD R&D?

Across a broad set of indicators, this seems unlikely. The first piece of evidence is that only 25% of OSRD obligations, and 45% of OSRD-funded patents, were spent with or produced by firms. What really powered OSRD's work was a collection of new wartime central laboratories which led major projects, like the MIT Rad Lab (radar), Johns Hopkins Applied Physics Laboratory (proximity fuses), CalTech Jet Propulsion Laboratory (rockets), and others at other institutions like Harvard, Columbia, GWU, and so on—not to mention Manhattan Project research, development, and enrichment sites. We think this is work that firms were unlikely to replace on their own in the absence of a coordinated, government-led wartime R&D effort.

Some additional robustness checks reinforce the importance of non-industrial R&D to our results. In Figure E.1, we re-estimate our main specification (Equation 1 in the paper) using only non-industrial OSRD-funded patents in our treatment measure. We measure non-industrial OSRD patents in two ways: those produced under non-firm contracts, and those without a firm assignee. For comparison, we also estimate Equation (1) with a firm-only treatment measure. Panels (A) and (B) estimate the effects of non-industrial OSRD patent intensity, and Panels (C) and (D) the effects of industrial OSRD patent intensity. The effects are present for all treatment measures, but larger in magnitude for the non-industrial treatment measures.

Figure E.1: Variation in estimated effects by treatment sector



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the log fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded, and produced in the given sector. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

One might still conjecture that non-industrial and industrial OSRD-funded R&D were co-located, and that the latter is what really mattered—such that when the treatment is measured by non-industrial R&D only, Equation 1 is confounded by co-occurring industrial R&D that then enters the error term. We will return to the question of geography momentarily. Beyond this, one might also conjecture that if universities and university-based, government-funded central labs had not performed this R&D, firms may have, driven by war demand.

To evaluate this question more fully, we contacted the authors of Li and Koustas (2019), who collected microdata on major war supply contracts (i.e., those with value >$50,000 in 1945 dollars) from postwar publications of the Civilian Production Administration. These data report the vast majority of World War II military equipment purchases at the individual contract level, and include the firm, product description, value, contract date, and more.

The war supply data offer an interesting and useful comparison to the OSRD R&D contract data. The first thing we note is that their portfolios were quite different. It is well known that war supply was concentrated in heavy equipment like aircraft, warships, tanks, and cargo vehicles and vessels (trucks, oil tankers, etc.)—whereas OSRD research was more heavily allocated to specific warfighting technology which was novel and high-impact, like radar, rocketry, atomic fission, proximity fuses, and such—which were relatively low cost compared to tanks and fighter planes. Accordingly, the major war supply contractors were broadly quite different from OSRD contractors. We show this in Tables E.1 and E.2, which list the top 15 war supply firms, OSRD firms, and war supply categories, by their share of war supply and OSRD contracts.

Though the firms in the left and right halves of Table E.1 are generally different, a few firms show up in both sets, like General Electric (GE), Western Electric, Westinghouse, and Douglas. Douglas had no OSRD patents (that we know of), but we can take a deeper dive into the three others (GE, Western Electric, Westinghouse), however, which were the largest electrical firms of this era and important OSRD contractors. To get a better understanding of these firms, Table E.3 lists their top products supplied under war production contracts, and Table E.4 their top production locations. Even for these firms, the focus of war production is (mostly) different than the technology their OSRD-funded R&D focused on, and the locations of their war production are likewise (mostly) different than the locations of their OSRD patents. This is especially true for Western Electric and Westinghouse (whereas GE performed most of its R&D and production in the same, Schenectady location). These locations were generally not important OSRD hubs.

Table E.1: Top 15 firms by war supply and OSRD contract value

War supply contracts				OSRD R&D contracts			
Rank	Firm	Percent	Cum. Pct.	Rank	Firm	Percent	Cum. Pct.
1	Ford Motor Co.	2.6%	2.6%	1	Western Electric Co.	3.4%	3.4%
2	Douglas Aircraft Co.	2.0%	4.6%	2	General Electric Co.	1.7%	5.1%
3	Wright Aeronautical Corp.	1.9%	6.5%	3	Radio Corp. of America	1.3%	6.4%
4	Chrysler Corp.	1.9%	8.4%	4	E. I. Dupont De Nemours & Co.	1.2%	7.6%
5	Cons. Vultee Aircraft Corp.	1.8%	10.2%	5	Monsanto Chemical Co.	1.0%	8.6%
6	General Electric Co.	1.7%	11.9%	6	Eastman Kodak Co.	1.0%	9.6%
7	Curtiss Wright Corp.	1.6%	13.6%	7	Zenith Radio Corp.	0.9%	10.5%
8	Western Electric Co.	1.6%	15.1%	8	Westinghouse Elect. & Mfg. Co.	0.9%	11.4%
9	Lockheed Aircraft Corp.	1.4%	16.6%	9	Remington Rand, Inc.	0.8%	12.2%
10	Bethlehem Steel Co.	1.4%	18.0%	10	Sylvania Electric Products, Inc.	0.7%	12.9%
11	United Aircraft Corp.	1.3%	19.3%	11	Standard Oil Dev. Co.	0.7%	13.5%
12	General Motors Corp.	1.1%	20.4%	12	Erwood Sound Co.	0.6%	14.1%
13	Packard Motor Car Co.	0.9%	21.3%	13	Douglas Aircraft Co.	0.5%	14.7%
14	Glenn L. Martin Co.	0.9%	22.2%	14	Budd Wheel Co.	0.4%	15.1%
15	Westinghouse Elec. & Mfg. Corp.	0.8%	23.0%	15	Gulf Research & Dev. Co.	0.3%	15.4%

Notes: Table lists the top 15 firms with war supply contracts and OSRD R&D contracts, alongside their share of total contracts. War supply data from Li and Koustas (2019).

Table E.2: Top 15 products by war supply contract value

Rank	Product	Percent	Cum. Pct.
1	Bomber Airplanes	7.5%	7.5%
2	Airplane Engines	6.3%	13.7%
3	Fighter Airplanes	2.1%	15.8%
4	Trucks	1.7%	17.5%
5	Communication Equip.	1.4%	18.9%
6	Cargo Vessels	1.4%	20.3%
7	Airplane Engines	1.3%	21.6%
8	Aviation Gasoline	1.3%	22.9%
9	Destroyers Ships	1.3%	24.2%
10	Cargo Ships	1.2%	25.4%
11	Medium Tanks	1.1%	26.5%
12	Pursuit Airplanes	1.1%	27.6%
13	Ordnance Equipment	1.1%	28.7%
14	Airplane Prop Assemblies	1.0%	29.7%
15	Airplane Parts	0.9%	30.6%

Notes: Table lists the top 15 product categories for war supply contracts. Data from Li and Koustas (2019).

Table E.3: Supplied products of principal electrical equipment firms

General Electric				Western Electric				Westinghouse			
Rank	Product	Percent	Cum. Pct.	Rank	Product	Percent	Cum. Pct.	Rank	Product	Percent	Cum. Pct.
1	Communication Equip.	8.9%	8.9%	1	Communication Equip.	28.2%	28.2%	1	Communication Equip.	13.2%	13.2%
2	Turbosuperchargers	8.3%	17.1%	2	Radio Sets	9.6%	37.8%	2	Machine Guns	8.5%	21.8%
3	Fire Control Systems	8.1%	25.3%	3	Radar Equipment	7.0%	44.7%	3	Ordnance Material	6.9%	28.6%
4	Radio Equipment	4.4%	29.7%	4	Radio Equipment	6.2%	51.0%	4	Torpedoes	4.9%	33.6%
5	Internal Comb. Eng.	4.0%	33.7%	5	Radio Parts	4.1%	55.1%	5	Radio Equipment	3.8%	37.3%

Notes: Table lists the top 5 products supplied under war production contracts by principal electrical equipment firms. Data from Li and Koustas (2019).

Table E.4: Manufacturing locations vs. patent locations of principal electrical equipment firms

War supply manufacturing locations

General Electric				Western Electric				Westinghouse			
Rank	Location	Percent	Cum. Pct.	Rank	Location	Percent	Cum. Pct.	Rank	Location	Percent	Cum. Pct.
1	Schenectady, NY	42.8%	42.8%	1	Hudson, NJ	48.6%	48.6%	1	Baltimore, MD	25.8%	25.8%
2	Onondaga, NY	11.7%	54.6%	2	Cook, IL	34.6%	83.2%	2	Delaware, PA	18.3%	44.0%
3	Essex, MA	9.1%	63.7%	3	Baltimore, MD	7.4%	90.7%	3	Macomb, MI	8.5%	52.6%
4	Fairfield, CT	7.4%	71.1%	4	New York, NY	7.4%	98.1%	4	Allegheny, PA	8.3%	60.9%
5	Allen, IN	7.4%	78.4%	5	Passaic, NJ	0.7%	98.8%	5	Hampden, MA	8.0%	68.9%

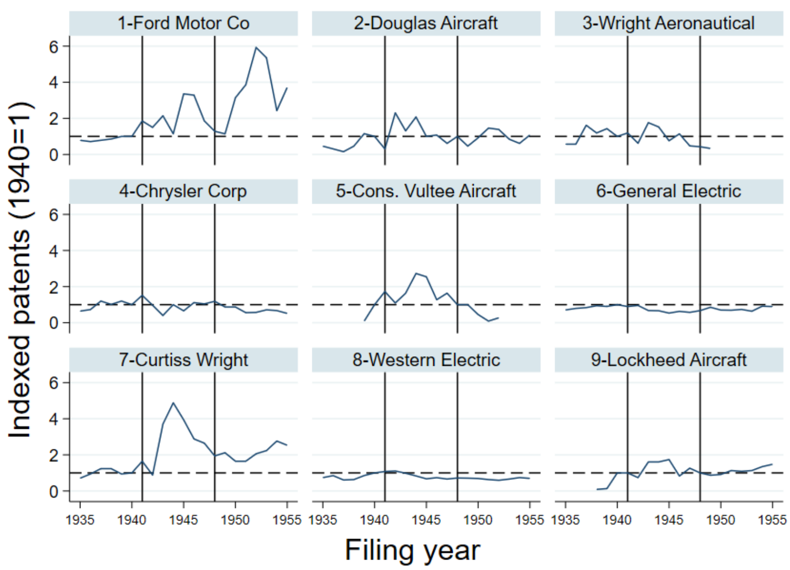
OSRD patent locations

General Electric				Western Electric (/ Bell Labs)				Westinghouse			
Rank	Location	Percent	Cum. Pct.	Rank	Location	Percent	Cum. Pct.	Rank	Location	Percent	Cum. Pct.
1	Schenectady, NY	75.5%	75.5%	1	Essex, NJ	19.1%	19.1%	1	Essex, NJ	57.1%	57.1%
2	Fairfield, CT	5.7%	81.1%	2	Morris, NJ	18.7%	37.7%	2	Allegheny, PA	20.6%	77.8%
4	Cuyahoga, OH	3.8%	84.9%	3	Union, NJ	16.0%	53.7%	4	Baltimore, MD	4.8%	82.5%
4	Rensselaer, NY	3.8%	88.7%	4	New York, NY	8.9%	62.6%	4	Montgomery, MD	4.8%	87.3%
				5	Westchester, NY	8.6%	71.2%	5	Mercer, PA	3.2%	90.5%

Notes: Table lists the top 5 manufacturing locations for war production by principal electrical equipment firms in Panel (A), and top 5 OSRD patent locations for these firms in Panel (B). War supply data from Li and Koustas (2019).

Figure E.2 provides one last piece of evidence: we link top war suppliers to the patent data to measure their patenting around the war years. The time series in this figure are indexed to 1940, which is normalized to one. Despite the massive military demand these firms served, their patenting patterns over this period were very mixed. A couple of the major aircraft manufacturers had elevated patenting during the war (especially Curtiss Wright, and to a lesser degree Consolidated Vultee/Convair), but not all (e.g., more modest increases for Douglas, Lockheed). The electrical firms had materially lower patenting for the duration of the war. As we work further down the supplier list we continue to see that besides aircraft manufacturers, major war suppliers saw little to negative changes in patent filings—including most automakers, shipbuilders, steel producers, Du Pont (also an OSRD contractor), and others. One takeaway of this evidence is that war supply contracts did not necessarily spill in R&D by the same firms.

Figure E.2: Patents filed 1935 to 1955 for top war supply contractors (indexed to 1940)



Notes: Figure shows annual patenting between 1935 and 1955 for top war supply firms, indexed to 1940. The dashed horizontal line marks parity (index=1). Solid vertical lines mark 1941 and 1948, to visually demarcate the war years.

Broadly, we think this evidence collectively suggests against counterfactual (a), that war equipment suppliers were likely candidates to replace OSRD R&D.

Suppose they were. Would in-house R&D have followed the same geographic pattern?

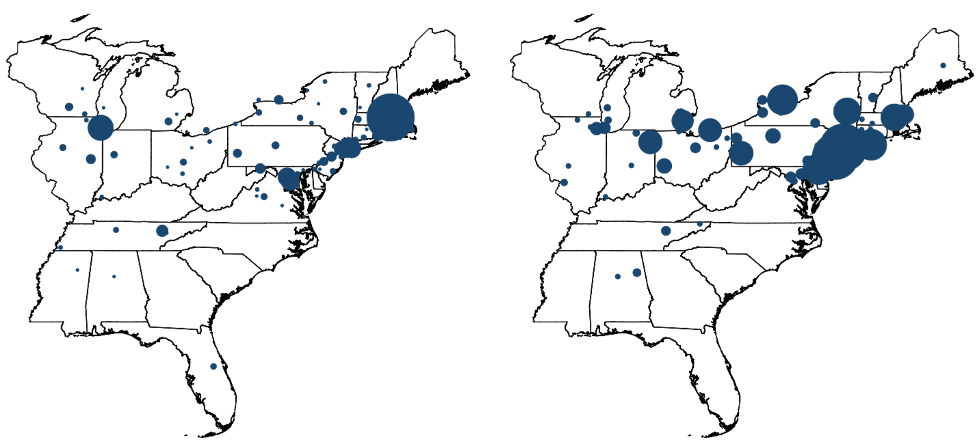
In any case, let us suppose that firms may have replaced OSRD R&D (in the same clusters) in its absence. We might then ask whether this firm R&D was likely to follow the same geographic distribution. Here, again, the evidence we will show suggests it would not. The first reason is that the major war equipment suppliers and OSRD industrial R&D performers were generally different (Table E.1). However, that does not rule out that the OSRD industrial R&D performers could have picked up the slack that OSRD would have left behind.

A second piece of evidence is that industrial and non-industrial OSRD-funded patents were generally in different places. Figure E.3 illustrates this, mapping industrial and non-industrial OSRD patents based on the contractor's sector (Panels A and B). For visualization purposes we restrict these maps to states east of the Mississippi River, to make them easier to compare side-by-side. The difference in their geographic distribution is—to us—visually apparent.

Figure E.3: Geography of industrial and non-industrial OSRD patents
(contract-based definitions; zooming into eastern states for easier viewing)

Panel (A):
Industrial OSRD patents

Panel (B):
Non-industrial OSRD patents



Notes: Figure maps counties with industrial and non-industrial OSRD-funded patents, using contract-based definitions. Bubble sizes proportional to each county's total number of OSRD patents. Maps restricted to eastern states (where a large majority of OSRD-funded invention was produced) for ease of visualization.

Regression evidence indicates that these differences are present at the cluster (county x technology) level as well—even conditional on subject matter. Table E.5 regresses clusters' (level and log) count of industrial OSRD patents on non-industrial OSRD patents, conditional on technology area (NBER category) fixed effects. We also do so for a given cluster's rank in industrial and non-industrial OSRD patents. The specification we estimate is the following:

$$\text{Industrial OSRD patents}_{ic} = \beta \cdot \text{Nonindustrial OSRD patents}_{ic} + \alpha_c + \varepsilon_{ic}$$

where i indexes counties, c indexes patent categories, and α_c are NBER category FEs. Industrial and non-industrial OSRD patenting appears to negatively correlate in space. This is a natural result, in our view, because fundamentally different work was done by non-industrial and industrial contractors: whereas the former were more involved in basic and applied research, design, and early prototyping, the latter were more heavily engaged in late-stage development and engineering. Oral histories describe how this happened in practice: for example, in one, a Rad Lab researcher explained this division of labor and the handoffs between them, where "People from General Electric and Westinghouse would come up to the Rad Lab and get the designs ... and then they would go back and [make] modifications" (quotes from oral history with Theodore Saad conducted in 1991 by Andrew Goldstein, available at the IEEE History Center).[19]

Table E.5: Clusters' industrial vs. non-industrial OSRD patents

	OSRD firm patents (def. 1)			OSRD firm patents (def. 2)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Count	Log count	Rank	Count	Log count	Rank
Nonfirm OSRD patents	-0.020***			-0.020***		
	(0.007)			(0.006)		
Log nonfirm OSRD patents		0.053			0.002	
		(0.097)			(0.100)	
Nonfirm OSRD patents rank			-0.503***			-0.392***
			(0.029)			(0.024)
N	690	115	690	690	128	690
R^2	0.07	0.21	0.36	0.07	0.13	0.31

Notes: Table estimates the relationship of industrial and non-industrial OSRD patents at the county level, using contract-based (columns 1-2) and assignee-based (columns 3-4) definitions. In columns (1) and (3) we measure these in levels; in columns (2) and (4) we rank clusters in their number of industrial and non-industrial patents and correlate ranks. All columns include tech. category fixed effects. *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Robust SEs in parentheses.

The evidence we have presented thus far indicates that industrial and non-industrial OSRD-funded R&D was performed in difference places. What about OSRD-funded R&D and war production? If the R&D were physically co-located with production, war equipment suppliers conceivably may have taken up some of this R&D in the same places. To evaluate this question we borrow data from ICPSR 2896 (Haines 2010), which provides county-level war supply contract value, in total and for combat equipment specifically (which comprised $\approx$2/3 of supply contracts), and which also provides county-level war facilities spending. Because there is no straightforward way to crosswalk product categories in the war supply microdata (from Li and Koustas 2019) to technology areas in the patent data, we will restrict our attention here to county-level analysis (rather than using Li and Koustas (2019)'s data for county-category level analysis).

In Table E.6, we correlate (logged) war supply contracts with county-level measures of OSRD treatment. Columns (1) and (2) estimate total war supply contracts as the outcome; Columns (3) and (4), combat equipment contracts; and Columns (5) and (6), war facilities spending. Odd-numbered columns measure treatment as the log OSRD rate, and even-numbered columns as the log number of OSRD patents, conditional on log total 1941-1948 patents (a related but slightly different specification, which we discuss further in Appendix D).

[19]See https://ethw.org/Oral-History:TheodoreSaad.

Table E.6: County-level war supply contracts and OSRD treatment intensity

	War supply contracts		Combat equipment		Facilities spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(OSRD rate, 1941-48)	-0.921***		-0.828***		-0.524***	
	(0.138)		(0.159)		(0.116)	
Ln(OSRD patents, 1941-48)		-0.235**		-0.213*		-0.175
		(0.118)		(0.120)		(0.108)
Ln(Patents, 1941-48)		1.315***		1.501***		0.926***
		(0.102)		(0.147)		(0.129)
N	160	160	144	144	135	135
R^2	0.27	0.64	0.15	0.55	0.12	0.37

Notes: Table estimates the relationship of county-level log war supply contracts (from ICPSR 2896) and the county-level log OSRD rate (columns 1 and 3) and county-level log OSRD patents (columns 2 and 4). *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels, respectively. Robust SEs in parentheses.

We find that war supply contracts and OSRD activity correlated negatively in space.[20] In other words, "war supply places" and "OSRD places" (to borrow the language of Kantor and Whalley 2022) were different. These results are consistent with broader understanding, such as the observation by Garin and Rothbaum (2022) that "Concerns about supply chain security and production bottlenecks led the military to insist that ... plants built to supply the war effort be built outside of established manufacturing hubs in less-congested inland locales"—a departure from the geographic distribution of OSRD activity. The U.S. R&D and manufacturing base were more generally not fully coincident in the late 1930s, contributing to this divide.

Between industrial and non-industrial OSRD R&D having different geographic distributions, and war supply contracts and OSRD R&D also having different geographies, we think this evidence largely rules out counterfactual case (a)(i)—that firms might have replaced OSRD R&D following the same geographic pattern—though not fully, since we have not yet ruled out that in the counterfactual, firms would have set up R&D operations where non-firm OSRD R&D took place. Though difficult to evaluate, this counterfactual also seems unlikely. The MIT Rad Lab, for example, was staffed by researchers who migrated in from around the country, as we show in concurrent research (Gross and Roche 2023). This feature of OSRD—which we have seen for other large OSRD research projects as well—would seem difficult for a firm to reproduce.

Would these firms have instead contracted out R&D, as OSRD did?

This is another alternative we can consider, though it is a pretty intricate counterfactual which would require a lot of pieces to come together: firms would need to not only finance the R&D, but also find partners in the same places, negotiate contracts, coordinate efforts, and more. Based on our view of OSRD through recent work (e.g., Gross and Sampat 2022c), we do not think this is a likely counterfactual. Mobilizing U.S. science and technology for war was a complex policy and organizational problem, and for many reasons (including reasons related to OSRD's breadth, complexity, and centralized administration) not something that atomistic firms would be able to

[20]We find similar, albeit statistically weaker, patterns for facilities spending.

reproduce on their own—not least without the weight of the federal government, let alone the relationships and administrative diplomacy of Vannevar Bush.

On these grounds, we would rule out counterfactual case (a)(ii).

Would another agency have funded this R&D?

The last alternative we can consider for a no-OSRD counterfactual is that other government agencies (like the War Department or the Navy) might have served the same functions. For the purposes of this paper, this would largely be the same story, just by other means. But even this counterfactual, in our view, is unlikely. The War and Navy Departments were not set up to do what OSRD did—at least not as well. OSRD enjoyed a different and much more flexible institutional arrangement, operating somewhat outside of the scope of traditional government, with relatively little attachment to existing structures, little internal politics or bureaucracy, and little external red tape. Most importantly, OSRD conducted no intramural research—whereas the military had active intramural research programs (e.g., at the Army Signal Corps and Naval Research Laboratory), which were the locus of its R&D activity during the war, and their wartime jockeying for influence suggests would have continued to be even if given resources with which to scale. OSRD's distinctive position allowed it to engage a considerably different (and then-novel) administrative model in the way of R&D policy (see Gross and Sampat 2022c). Moreover, OSRD was not itself distracted by the operation of the war effort, but rather mobilized alongside it.

We thus think history suggests against counterfactual case (b).

The evidence in review

Collectively, we think this evidence suggests against the hypothesis that OSRD's R&D activity and impacts would have been reproduced by other means in a no-OSRD counterfactual. This includes a demand-driven version the World War II shock, where military demand spills in R&D in the same technologies and regions. This is not to say that all of OSRD's work or outputs would have been absent in its absence, but rather that the scale, scope, geography, and impacts of any alternative arrangement would almost necessarily have been different.

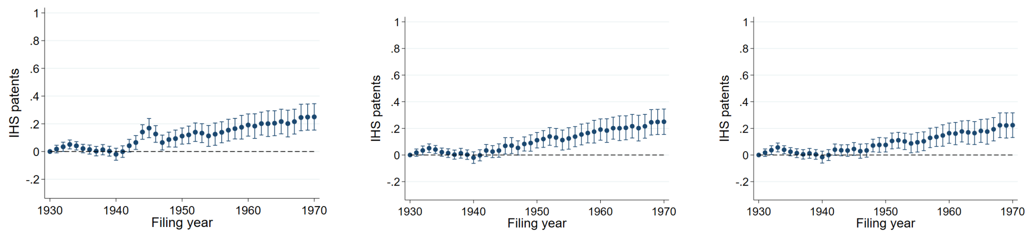
If nothing else, we can observe that military orders followed the technology, rather than vice versa. This R&D was ex-ante uncertain, and the form or extent of its military applications often not yet known. OSRD's work was underway long before orders were placed or ideas proven to work—and well before the U.S. entered the war in December 1941.

F Alternative outcome measures

This appendix reproduces our main results on the postwar agglomeration of U.S. invention, replacing logged outcome measures with the inverse hyperbolic sine (IHS) transformation. Figures F.1 to F.5 reproduce Figures 4 to 8 from the body of the paper.

Figure F.1: Effects of OSRD on cluster patenting, 1930-1970

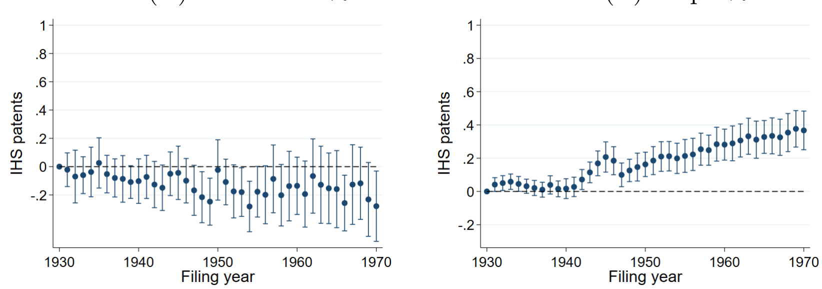
Panel (A): All patents | Panel (B): Non-OSRD patents | Panel (C): Non-govt. interest pats.



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the IHS fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

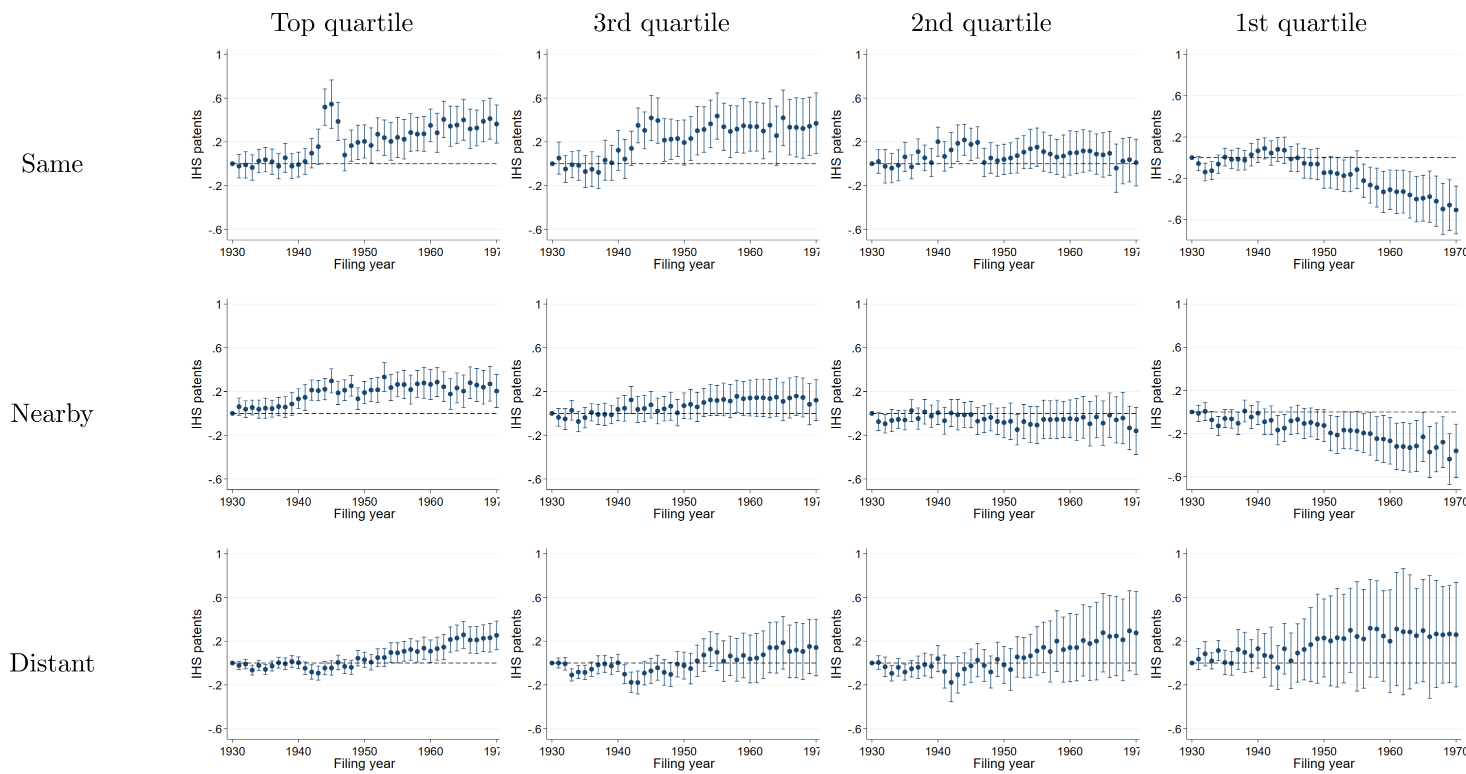
Figure F.2: Effects of OSRD on cluster patenting, for clusters in counties in the bottom 95% versus top 5% of 1930s patenting

Panel (A): Bottom 95% | Panel (B): Top 5%



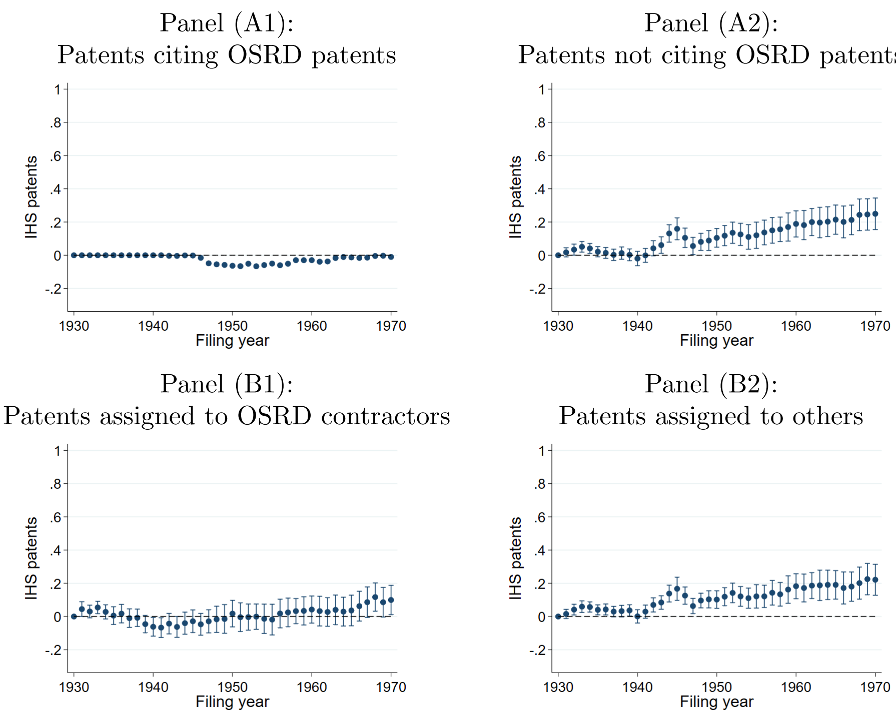
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting, for counties in the bottom 95% and top 5% of 1930s patenting (i.e., existing technology clusters). Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure F.3: Effects of OSRD on cluster patenting, 1930-1970, cross-technology area spillovers
horserace regression of treatment in (i) same technology area, (ii) nearby technology areas, (iii) more distant technology areas



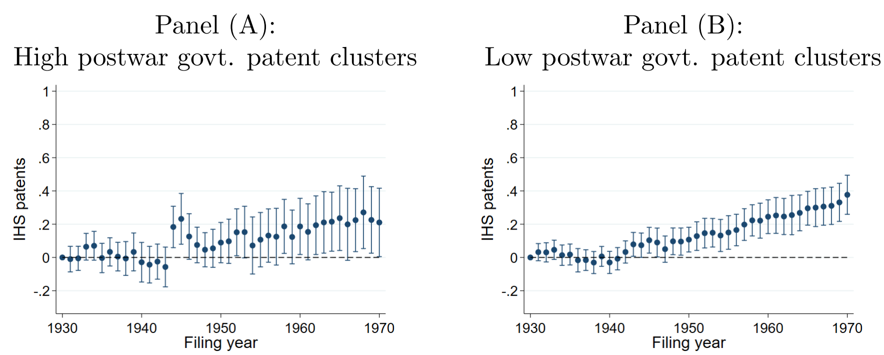
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patenting. The independent variable measures the quartile of treatment intensity, conditional on treatment (the fraction of U.S. patents in each county-category between 1941-1948 which were OSRD-funded, conditional on any), of three types: (i) in the given county-category (top row); (ii) in the same county and proximate technology categories (same 1-digit NBER category, per Hall et al. (2001); middle row); and (iii) in the same county and more distant technology categories (other 1-digit NBER categories; bottom row). Parameters across all panels are estimated jointly (in one regression) relative to a reference group of county-categories without any OSRD patents. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure F.4: Effects not explained by OSRD's direct impacts on local invention



Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category (i) patents citing versus not citing OSRD patents, and (ii) patents assigned to OSRD contractors versus others, as an exploration of the direct impacts of OSRD on postwar invention in the treated clusters. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

Figure F.5: Effects not explained by sustained government investment in local invention



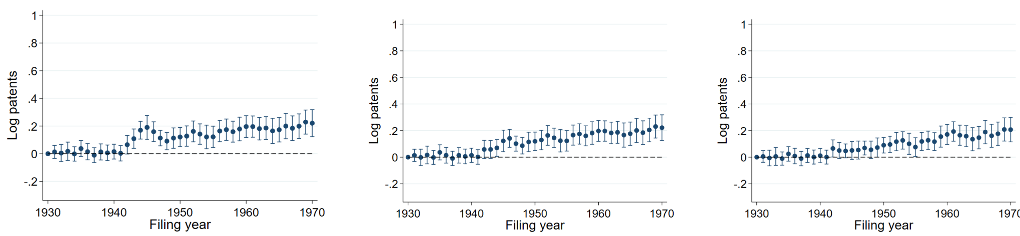
Notes: Figure shows annual estimates of the effects of the OSRD shock on county-category patents in county-categories with above and below median postwar (1950-1969) government-funded patent rates, as an exploration of the role of sustained public R&D investment as an explanation for persistence. Error bars represent 95% confidence intervals, computed from SEs clustered at the county level.

G CBSA-level analysis

This appendix reproduces our main results on the postwar agglomeration of U.S. invention, aggregating counties up to core-based statistical areas (CBSAs), geographic units consisting of one or more counties around an urban center tied together by modern commuting patterns. Though we believe counties to be a preferred unit of analysis for the period we study—most of which preceded the postwar development of regional transportation systems—CBSA-based robustness checks can test whether the results are sensitive to the choice of geographic units. Figures G.1 to G.5 reproduce Figures 4 to 8 from the body of the paper at the CBSA-category level.

Figure G.1: Effects of OSRD on cluster patenting, 1930-1970

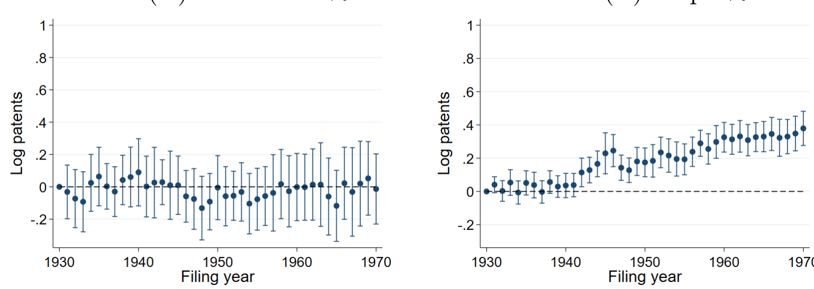
Panel (A): All patents | Panel (B): Non-OSRD patents | Panel (C): Non-govt. interest pats.



Notes: Figure shows annual estimates of the effects of the OSRD shock on CBSA-category patenting. The independent variable measures the log fraction of U.S. patents in each CBSA-category between 1941-1948 which were OSRD-funded. Error bars represent 95% confidence intervals, computed from SEs clustered at the CBSA level.

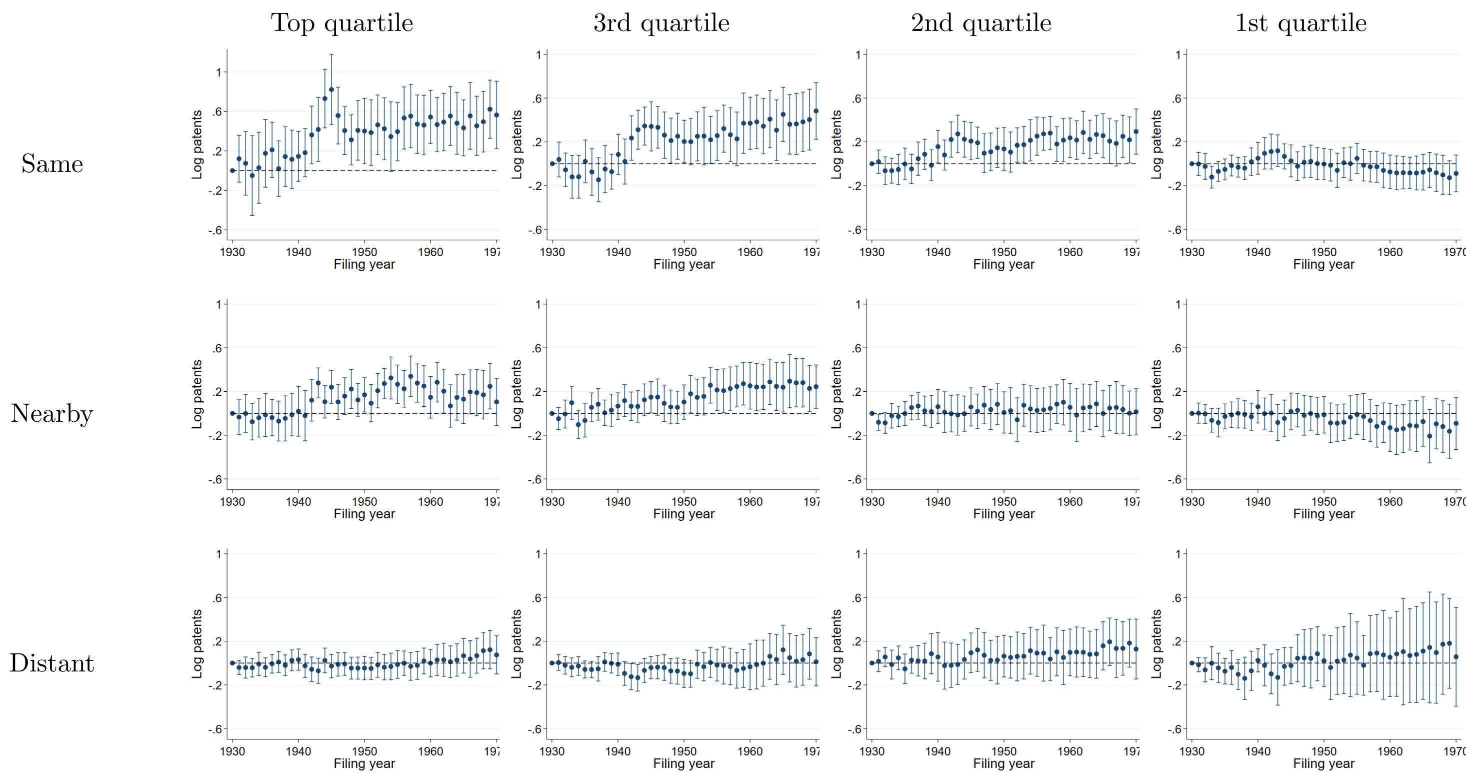
Figure G.2: Effects of OSRD on cluster patenting, for clusters in CBSAs in the bottom 95% versus top 5% of 1930s patenting

Panel (A): Bottom 95% | Panel (B): Top 5%



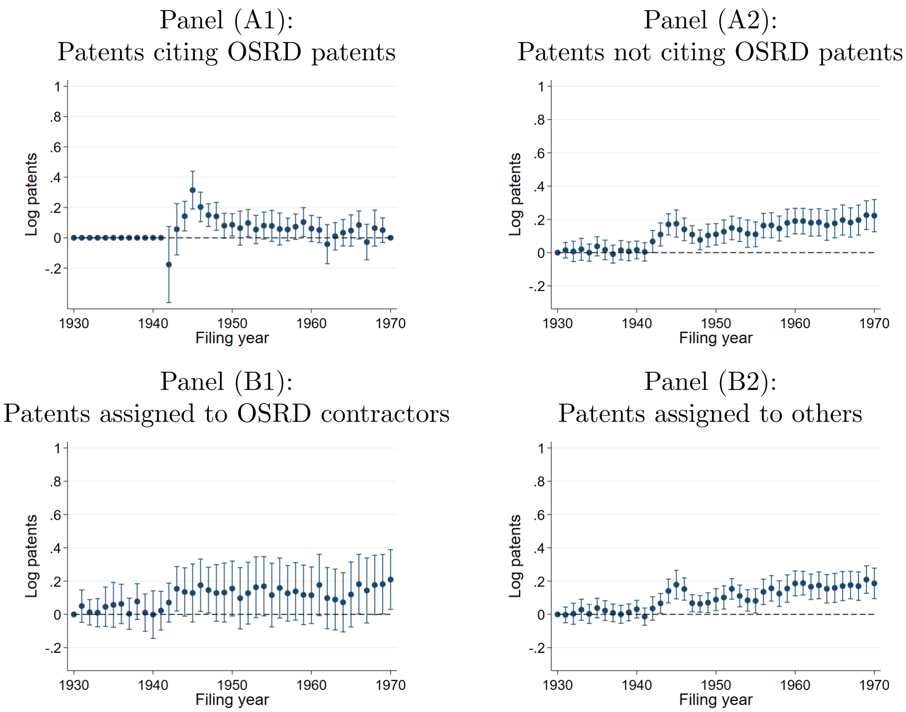
Notes: Figure shows annual estimates of the effects of the OSRD shock on CBSA-category patenting, for CBSAs in the bottom 95% and top 5% of 1930s patenting (i.e., existing technology clusters). Error bars represent 95% confidence intervals, computed from SEs clustered at the CBSA level.

Figure G.3: Effects of OSRD on cluster patenting, 1930-1970, cross-technology area spillovers
horserace regression of treatment in (i) same technology area, (ii) nearby technology areas, (iii) more distant technology areas



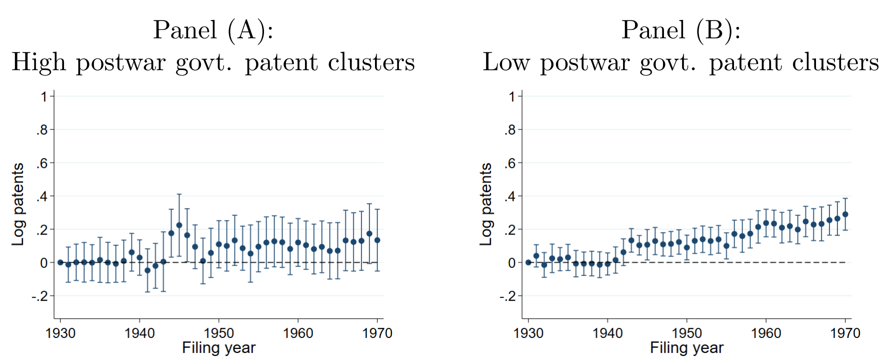
Notes: Figure shows annual estimates of the effects of the OSRD shock on CBSA-category patenting. The independent variable measures the quartile of treatment intensity, conditional on treatment (the fraction of U.S. patents in each CBSA-category between 1941-1948 which were OSRD-funded, conditional on any), of three types: (i) in the given CBSA-category (top row); (ii) in the same CBSA and proximate technology categories (same 1-digit NBER category, per Hall et al. (2001); middle row); and (iii) in the same CBSA and more distant technology categories (other 1-digit NBER categories; bottom row). Parameters across all panels are estimated jointly (in one regression) relative to a reference group of CBSA-categories without any OSRD patents. Error bars represent 95% confidence intervals, computed from SEs clustered at the CBSA level.

Figure G.4: Effects not explained by OSRD's direct impacts on local invention



Notes: Figure shows annual estimates of the effects of the OSRD shock on CBSA-category (i) patents citing versus not citing OSRD patents, and (ii) patents assigned to OSRD contractors versus others, as an exploration of the direct impacts of OSRD on postwar invention in the treated clusters. Error bars represent 95% confidence intervals, computed from SEs clustered at the CBSA level.

Figure G.5: Effects not explained by sustained government investment in local invention



Notes: Figure shows annual estimates of the effects of the OSRD shock on CBSA-category patents in CBSA-categories with above and below median postwar (1950-1969) government-funded patent rates, as an exploration of the role of sustained public R&D investment as an explanation for persistence. Error bars represent 95% confidence intervals, computed from SEs clustered at the CBSA level.

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