

Federally-Funded Science as Engines of Regional Innovation and Prosperity: The Case of the National Labs

Susan Helper, Resem Makan, and Daniel Shoag*

Case Western Reserve University

July 2, 2025

Abstract

Can federal science funding spur local innovation and prosperity? After WWII, the U.S. built 16 national labs, mostly outside of existing innovation hubs. We find that counties with labs experienced lasting boosts in patenting by nearby, unrelated inventors compared to runners-up and synthetic controls. Spillovers appear in citation patterns and research area shifts. Newly digitized county-level data from 1937–1971 reveal large, heterogeneous economic gains. Matched census records show benefits accrued to both existing and new residents. These findings suggest science funding can shape innovation ecosystems and support broad-based local development.

JEL Codes: L81, N42, O31, O33, O38, R11.

Keywords: Innovation Ecosystem, Innovation Clusters, National Laboratories, R&D, Federal Investments, Place-Based Policies, Knowledge Spillovers.

*We thank participants at the NBER Place-based Policies and Entrepreneurship conference and the Case Western Reserve University Economics Brownbag for helpful comments. We also gratefully acknowledge the research assistance provided by Dawson Fishman, Megan Abel, Joanna Chiu, Alivia Michalski, Giuseppe Llovet-Nava, and John McCormick. And lastly, we thank the National Science Foundation (NSF) for funding this project.

1 Introduction

Urban economists like to quip that Silicon Valley isn’t innovative because it has a lot of silicon. Yet we still don’t fully understand how innovation clusters originate, even though they drive some of the most prosperous and dynamic regional economies in the country. Can government funding actively spark the creation of new innovation hubs, even in places far from the existing technological frontier?

Much of the existing literature looks backward, studying the origins of clusters that are already known to be successful. In contrast, this paper examines the establishment of multiple national laboratories without conditioning on whether they ultimately became successful innovation hubs. Sites for national labs were often chosen for reasons largely exogenous to their innovation potential; these choices were instead based on geopolitical, military, or logistical concerns. Using newly discovered data, we show that the creation of government-funded research labs successfully triggered local innovation takeoff and broader economic growth, even in regions that previously lacked innovation infrastructure. We find strong evidence that such interventions can indeed catalyze sustained innovation and economic spillovers, benefiting both pre-existing residents and new migrants.

Catalyzing innovation-based regional ecosystems that deliver broad economic and societal benefits has been a major focus of academic and policy discussions. For instance, [Gruber and Johnson \(2019\)](#) proposed to “jump-start America” by establishing competitive federal grants to help municipalities become new technology hubs. Partially in response to this work, the U.S. Congress over the past five years authorized \$80 billion for regions to “invest in clusters of technology, innovation, and competitiveness.”¹ These initiatives include Tech Hubs, RECOMPETE, and the Build Back Better Regional Challenge. Similarly, the NSF Engines program “aims to fund regional coalitions of partnering organizations to catalyze technology and science-based regional innovation ecosystems.”²

This activity is by no means limited to the United States. For example, the European Union has developed a methodology for “Regional Innovation Strategies for Smart Specialisation” over the last decade and continues to invest in “Innovation for place-based transformations”.^{3,4} A significant part of the ongoing 7-year, 94 billion euro “Horizon Europe”

¹Mark Muro, Robert Maxim, Joseph Parilla, and Xavier de Souza Briggs, *Breaking Down an \$80 Billion Surge in Place-Based Industrial Policy*, Brookings Institution, December 15, 2022. Available at: [Link](#)

²National Science Foundation, *Assessing Societal and Economic Impacts of Place-Based Innovation*, December 18, 2023. Available at: [Link](#)

³OECD, *How Have Place-Based Policies Evolved to Date and What Are They For Now?*, April 14, 2023. Available at: [Link](#)

⁴Bianchi Guida et al., *Innovation for Place-Based Transformations: Collection of Practices*, January 26, 2024. Available at: [Link](#).

program is devoted to building “excellence hubs” and a “European Innovation Ecosystems (EIE) programme that strengthens innovation ecosystems.”⁵ Individual nations continue to invest in such programs, such as the Catapult network in the United Kingdom, and the 800 clusters that make up the European Cluster Alliance.^{6,7}

A central question, however, remains: Do these efforts to foster innovation actually result in meaningful and sustained economic gains for the regions they target? Since these outcomes often take years to materialize, answering this question benefits greatly from examining a program with a multi-decade history. Our paper studies one of the few such large programs, the U.S. National Laboratories, most of which were established in the 1940s.

Built primarily in rural areas during the 1940s and 1950s, most of these labs—such as Los Alamos and Argonne—have remained prominent into modern times (see Figure 1 for the geographic distribution of the labs). Though most were constructed with the primary goal of securing American supremacy in nuclear technology, over the decades, they have also stressed their goals of fostering local economic development (Jaffe and Lerner, 2001). We focus on the period starting with the establishment of most of the labs in the 1940s, and continue through the 1970s, when the labs’ missions expanded and their budgets doubled due to the energy crisis.

While several studies have examined the effects of federal funding on local innovation and economic growth, most focus on government contracts awarded to existing frontier firms or research universities (Gross and Sampat, 2023; Kantor and Whalley, 2023). In contrast, the national laboratories represent a fundamentally different type of intervention: the direct federal creation of large-scale R&D infrastructure, built from the ground up in largely rural counties. These projects required not only new physical infrastructure but also the formation of entirely new organizations staffed with researchers and technical personnel. In this sense, they constitute investments at the extensive margin—bringing innovation capacity to places where it previously did not exist. The budgets for the labs were large, at over \$5 billion (in 2024 dollars) for the 8 labs operating in 1965 for which data is available. As of 2024, the total budget for the 17 current labs stood at \$19.6 billion.

In this paper, we investigate several types of impacts of the labs on local eco-systems:

- Innovation spillovers in the form of patents from non-lab entities in the same county; citations; changes in fields of inquiry; and informal interactions.
- Fiscal multipliers from the influx of federal dollars;

⁵European Commission, *Horizon Europe*. Available at: [Link](#)

⁶Innovate UK, *Innovate UK Catapult Network: Catapults at the heart of the UK’s innovation ecosystem*. Available at: [Link](#)

⁷European Clusters Alliance. Available at: [Link](#)

- Impacts on incomes of both movers and stayers. In addition, we look at the distribution of gains, for example as measured by changes in incomes to those who resided in the county both before and after a lab was established.

For each of our channels of impact, we compare counties that received lab investments with control counties determined by a) counties that were considered for a lab’s location, but did not receive a lab and b) synthetic controls (the construction of which is discussed further below).

Innovation Spillovers: Using both identified “runner-up” locations and a synthetic control approach, we find that the counties where the labs were established experienced a surge in patenting activity, an effect that has persisted for at least several decades after their founding. Figures A.11 and A.12 in the Appendix show that national lab counties were unique outliers in patenting growth, with many experiencing dramatic shifts in their relative position. For example, Anderson county in TN (site of Oak Ridge National Lab) rose from the bottom quintile of the U.S. patent distribution in 1940 to near the top 5% by 1975. Moreover, through archival research, we are able to distinguish between patents assigned to the labs themselves and those granted to other entities in the same counties. These non-lab patents co-move strongly with lab-assigned patents, which we interpret as evidence of knowledge spillovers from the labs to the broader region. Further supporting this interpretation, we find that non-lab patents shift their fields of innovation (as measured by international patent classification codes) toward those of the nearby lab, suggesting technological diffusion beyond the immediate research institution. In addition, we find that the closer a county is to a lab, the more likely it is to have patents citing the labs.

Economic Impact: To examine broader economic impacts, we introduce a novel dataset that allows us to analyze county-level economic outcomes such as retail sales and household income dating back to the 1930s. Using these newly digitized data, we find that the establishment of the labs led to significant increases in aggregate economic activity. These economic effects persisted into 1970 (the latest year for which we have data), indicating long-lasting regional benefits rather than temporary economic booms. For many of the labs, we observe multiplier effects much larger than those resulting from other forms of federal spending (eg, on physical infrastructure), again supporting the view that the lab investments played a significant role in generating a vibrant local innovation ecosystem.

For both patents and retail sales, we also observe significant heterogeneity in outcomes. To explore the sources of this variation, we use historical documents to obtain data on the operating costs of the labs. We find positive and statistically significant elasticities between lab operating costs and both patenting activity and retail sales. While acknowledging that the size of federal funding for the labs is likely in part endogenous to their perceived success,

the positive relationship between investment levels and observed economic outcomes suggests a meaningful impact of federal investment on regional development.

To further strengthen our analysis, we incorporate counterfactual locations for select labs, identified through historical documentation as serious contenders during the site selection process. Using these runner-up counties as control units, we observe trends that align with our synthetic control estimates. Counties that hosted the labs experienced greater long-term growth in both patents and retail sales, with divergence emerging particularly after the labs were established.

Distributional Impact: Additionally, leveraging US Census data linking individuals between 1940 and 1950, we investigate how prior residents of lab-hosting counties fared relative to those in runner-up locations. We find that their wages increased by 5% in the treated counties compared to the counterfactual locations, suggesting that the economic benefits of the labs extended beyond those directly employed by them, positively impacting the broader workforce. Moreover, college-educated and professional workers gained even more, seeing 25% and 14% respective rises in their wages.

1.1 Contribution to the Literature

Our first contribution to the literature is in highlighting the role of federal investment in fostering innovation clusters. A substantial body of qualitative research has demonstrated the importance of linkages between scientists and industry in creating environments conducive to innovation (e.g., [Porter and Stern, 2001](#)), while others have emphasized the role of large cities in facilitating agglomeration economies and attracting scientific talent ([Glaeser, 2010](#); [Kerr, 2010](#); [Chatterji et al., 2014](#); [Feldman and Francis, 2002](#)). We build on this literature by providing causal evidence that policy interventions can actively stimulate such agglomeration effects, even in regions with no prior history of innovation activity.

Recently, several papers have explored the relationship between government-sponsored R&D and private-sector innovation, while others focus on universities ([Cristelli, 2024](#)). Using defense-related R&D, [Moretti et al. \(2025\)](#) found significant complementarity between private and public R&D spending. Similarly, [Myers and Lanahan \(2022\)](#) found that government R&D grants yielded both patents by the recipient and spillover patenting. [Azoulay et al. \(2019\)](#) showed that NIH spending spurred private patenting, and again, [Gross and Sampat \(2023\)](#) found increased patenting due to World War II R&D. Another set of studies look at the role of public spending on universities. For example [Andrews \(2023\)](#) and [Russell et al. \(2024\)](#) find increases in local innovation and human capital accumulation in areas that received a public university, while [Babina et al. \(2023\)](#) find that cuts in federal research

funding to universities slow down publications. Our paper differs in that it looks at direct government provision of R&D, but like these papers, finds spillovers to the private sector. In particular, “little research has been done on the impact of national labs” (Howell, 2024), something we help to rectify in this paper.

While much of the literature has focused on the growth of clusters once they have been established (Saxenian, 1996; Moretti, 2021), relatively little is known about the long-term impacts of federal investments that aimed to create clusters. Our results reveal economic gains that significantly exceed traditional Keynesian effects, suggesting that the government innovation spending unleashes self-sustaining growth trajectories in treated areas, rather than providing merely short-term fiscal stimulus.

Thirdly, we contribute to the literature on place-based policies (Greenstone et al., 2010; Diamond, 2016). The most widely accepted rationale for such policies is to benefit the existing local residents (Kline and Moretti, 2014). Canonical spatial models predict that the impacts of policies to improve local incomes are dissipated over time by in-migration. In contrast, our findings suggest the possibility of generating persistent economic growth even in largely rural areas. While we document evidence for such a phenomenon, we also observe heterogeneity based on educational and occupational characteristics. This finding shows that the impact of national laboratories differs from the impact of other place-based interventions. For example Glaeser and Gottlieb (2009) show that many policies targeted towards less productive areas have been ineffective. Although we do not investigate general equilibrium effects in this paper or test whether there could have been more productive alternative uses of federal funds, we nonetheless find evidence consistent with improved outcomes in poorer regions.

2 Background on National Labs

Most studies of the impact of research institutions focus on universities. In this paper, we focus on the economic impact of U.S. national laboratories. This focus is useful for several reasons. The formation of a university involves a complicated mix of treatments over decades and even centuries. The national laboratory program, which is focused solely on research, is perhaps a more accurate approximation of government programs that focus on building innovation eco-systems. Although the laboratories do host post-docs, they do not house tens of thousands of students.⁸ Unlike universities, they are much more tied to federal funding and a federal agency (the Department of Energy). Understanding where these more targeted institutions can, nevertheless, have large spillovers is important for understanding how to

⁸According to the NSF, these labs as of Fall 2021 collectively hosted 3,357 postdocs ([link](#)).

craft ongoing interventions like the NSF Regional Engines program.

Figure 1: National labs are geographically dispersed



Notes: Lab name followed by founding year- (1) Pacific Northwest 1949, (2) Lawrence Berkeley 1933, (3) SLAC 1952, (4) Lawrence Livermore 1952, (5) Idaho Lab 1949, (6) National Renewable Lab 1977, (7) Los Alamos 1943, (8) Sandia 1952, (9) Ames 1947, (10) Argonne 1946, (11) Fermi 1967, (12) Oak Ridge 1943, (13) Savannah River 1951, (14) National Energy Tech 1911, (15) Thomas Jefferson 1984, (16) Princeton Plasma 1951, (17) Brookhaven 1947.

All but one of the 17 national laboratories are Federally Funded Research and Development Centers (FFRDCs).⁹ FFRDC's are "government-owned contractor-operated facilities (GOCOs)"; the rationale for this design is to give the labs insulation from both market and political pressures, and to enable attraction of talented personnel because they did not have to conform to civil service rules (Jaffe and Lerner, 2001; Mitre, 2015).¹⁰ Today, these are overseen by the U.S. Department of Energy (which was not founded until 1977).

The National Laboratory system emerged from the extraordinary scientific efforts of World War II, particularly the Manhattan Project, which was tasked with developing the first nuclear weapons.¹¹ Following the war, the U.S. government maintained these research institutions in an effort to continue advancing scientific knowledge and technology. During the Cold War, national labs played a pivotal role in nuclear research and development, for both nuclear weapons and nuclear energy. It appears that 14 of the 17 national labs were

⁹The exception is the National Energy Technology Laboratory (NETL) which is formally part of DOE. NETL is not included in our sample.

¹⁰MITRE, *FFRDCs-a Primer*, March 11, 2025. Available at: [Link](#)

¹¹Additional details on the history of the labs can be found in the respective websites for each of them. These websites include a page outlining their history and key dates (eg., [link](#) for Argonne National Lab).

originally created to develop nuclear weapons (or other kinds of advanced weapons).¹² Most came directly out of the Manhattan Project, with different labs working on different aspects of that work to produce an atomic bomb – Oak Ridge and Ames producing high concentration uranium, Hanford (now Pacific Northwest National Lab) producing plutonium, Los Alamos developing the actual bomb, and others (Argonne) working on the chemistry and metallurgy required. The labs also studied radiation and how radiation affected humans, instruments for measuring radiation, explosion physics, etc.

After World War II, several more labs were created to develop hydrogen fusion bombs (Livermore, Sandia, Savannah River, etc.), nuclear reactors for submarines (Idaho) and then for navy ships, and eventually for commercial use. After nuclear bomb testing was outlawed in 1963, it became even more important to be able to study nuclear reactions in the laboratory (Princeton Plasma Lab), through accelerators that smashed elemental particles into each other (Brookhaven, SLAC, Thomas Jefferson Lab, Fermilab), and using supercomputers that could simulate the reactions (many of the labs).

Historical records suggest that, while the labs were to engage in advanced research, they were to be located in relatively secluded areas because of the sensitive nature of their work (nuclear research). For example, when deciding where to set up Argonne National Lab, the siting committee felt it best to locate it in the Argonne Forest in DuPage IL, away from the bustle of the Greater Chicago area.¹³ Likewise, Los Alamos and Oak Ridge labs were built as top-secret missions and consequently needed to be as secluded as possible (Meade, 2014). Nonetheless there were also a few that were built on existing university campuses. For example Ernest Lawrence, a physics professor at UC Berkeley, helped build the Lawrence Berkeley National Lab on the same campus he worked in.¹⁴

As Cold War tensions eased and funding went down, the labs (with their thousands of

¹²The three labs that didn't follow this course are:

- National Energy Technology Laboratory (NETL), which grew out of research on coal mines and petroleum production dating back to 1910.
- National Renewable Energy Laboratory (NREL), which was established to focus on wind, solar, etc, and traces its origins to 1977.
- Lawrence Berkeley Laboratory, which was founded in 1931 to study radiation using a cyclotron (developed by Ernest Lawrence) and then did some of the theoretical work to develop the atomic bomb as well as developing medical radiation.

¹³For its 75th anniversary, the lab released on their website a series of writings of the lab's early days titled "Those days as we remember them." According to journalist reports of Christopher Kramer, Head of Media Relations at Argonne, "There was nothing out here but some farmland and forests back then [when the lab was founded]."

¹⁴Berkeley lab's website tells the story of Ernest Lawrence securing a building to build a radiation lab. Over time it would expand to areas beyond the campus (<https://history.lbl.gov/>.)

scientists and engineers) looked for other projects ([Tarter, 2018](#); [Johnson and Schaffer, 1994](#)). Some labs focused on one or another of these scientific aspects of weapons production and some developed new topics to research (medical radiation, cryptography, etc.) and began seeking contracts from other agencies of the US government and from commercial businesses. In 1964 Congress placed a spending cap on the funds that the Department of Defense could obligate to FFRDCS ([Dale and Moy, 2000](#)).

Therefore, by 1964 the focus of these labs broadened beyond nuclear research to encompass a wide range of scientific fields, including renewable energy, environmental science, and advanced computing. ([Westwick, 2003](#)) Today, the labs collaborate with universities, industries, and government agencies to drive technological advancements and stimulate economic growth. The labs developed the technology for CDs and DVDs, rechargeable lithium batteries, the cathodes most used in electric vehicle batteries, and many, many other technologies ([U.S. Department of Energy, 2023](#)). The research conducted at Argonne and other national labs has had far-reaching implications, impacting not only national security but also contributing significantly to economic growth and public health. These labs serve as hubs of innovation, fostering the development of advanced technologies and creating high-quality jobs in the surrounding regions. Through partnerships with various sectors, the labs help stimulate local economies by attracting skilled workers and catalyzing business activity.

These labs vary in size (both by location and over time). Typically, however, they represent significant infusions of resources into their local communities, especially when they were first established. Because of the danger and classified nature of their early work, the government often sought to place them in isolated locations. As their missions broadened, most of the labs have become more public-facing and are important parts of their local innovation ecosystems (though some argue that the labs are excessively “cloistered” ([Tartari and Stern, 2021](#); see also [Dale and Moy, 2000](#) and [Jaffe and Lerner, 2001](#)).

One example is Argonne National Laboratory, located in Lemont, Illinois. Established in 1946 as the first national lab in the U.S., Argonne evolved from the University of Chicago’s Metallurgical Laboratory, which was instrumental in the Manhattan Project. Initially, its mission centered on developing nuclear reactors for both peaceful and defense purposes. Argonne’s rural location was specifically chosen to facilitate safe testing of nuclear technologies (previously the testing was done underneath the University of Chicago’s football stadium, which was located in a populated area). Argonne had 2,727 employees in 1957, 2.5% of the total workforce of DuPage County. In 2022, it had 3,723 full-time employees and a budget of \$1.1 billion.¹⁵

¹⁵Argonne National Laboratory, *Annual Report*, p.99, 1958. Available at: [Link](#); Argonne National Laboratory, *Argonne: By the Numbers*. Available at: [Link](#).

Over the years, Argonne has expanded its research scope to include a broad array of scientific disciplines, such as physics, chemistry, biology, and engineering. Its collaborations with universities, industries, and government agencies have been instrumental in solving complex scientific challenges and driving innovations in various fields.

3 Data and Methodology

We utilize a rich collection of data from multiple sources, including archival documents. We describe this data, both publicly available and novel datasets that we collected in the first subsection below. The following subsection describes our strategies for causally identifying the labs’ impacts.

3.1 Data Sources

3.1.1 New Historical County-level Retail Sales and Income Data (1936-1970)

We are not aware of publicly available annual county-level data on economic activity for this period prior to this project. As part of the work for this paper, we identified novel data collected by the *Sales Management’s Survey of Buying Power* ([Sales and Management Magazine, 1972](#)) that are preserved in a handful of libraries across the United States. Starting in 1929 the series was published annually with the aim of “improving the accuracy and completeness and facility of arrangement of regional market data.”¹⁶ We obtained access to them at the Cleveland Public Library for the years 1936 to 1970. This series provides yearly county-level data on a number of economic variables including total retail sales and buying income per family. The construction of retail sales is based on the magazine’s own aggregation technique, using the Census of Business totals, the Department of Commerce’s estimates of retailers, bank debits, Federal Reserve reports of department store sales, and the Census of identical stores; the magazine claims its accuracy is further bolstered by corroboration with actual transaction tax records when available. “Buying power income” is defined as aggregate income (wages, salaries, dividends, interest, rents, entrepreneurial income, government payments) minus total taxes (both at the county level).¹⁷ To construct this variable, they use information from the Department of Commerce and the Bureau of Internal Revenue on income tax receipts plus other state information for states that do not levy income taxes. The magazine then reports buying income per-family by dividing this measure of total buying income by an estimate of total families at the county level.

¹⁶See Figure [A.2](#) in the Appendix for an image of a scan we took.

¹⁷For more details, see page 30 of the 1940 issue of the *Sales and Management Survey of Buying Power*.

The Magazine states that more details about their calculations can be obtained from the Superintendent of Documents in Washington, which we have been unable to do. To validate the accuracy of the Survey of Buying Power we correlate their measure of household income with data from the County Data Books ([United States. Bureau of the Census, 2012](#)). See Appendix Figure [A.10](#) for binned scatter plots of the two measures.

3.1.2 Exogenous Siting: Identifying Runner-up, Counterfactual Locations

In general, labs were sited based on rationales orthogonal to the quality of the local innovation eco-system. For example, ‘ample water and power supplies’ were a key criterion for siting the aptly-named Savannah River National Lab along the Savannah River ([Reed et al., 2013](#), pg 27). A site in rural DuPage County Illinois (in the Argonne Forest) was chosen for Argonne National Lab, because continuing to perform nuclear reactions under the University of Chicago football stadium was not considered safe for such a densely populated area. Seventeen sites were initially considered for the location of Brookhaven National Laboratory, but the list was eventually narrowed to one runner-up location (Monmouth, NJ) and the final site in Suffolk County, which was deemed “equally inaccessible to everybody” ([Crease, 1999](#)). As the scale of work increased, administrators sought even more isolated locations, such as Los Alamos in New Mexico,¹⁸ Oak Ridge in Tennessee,¹⁹ and Idaho National Lab.²⁰ In these locations initially there were hardly any residents (eg, 200 in Los Alamos County ([Hunner, 2007](#))). In Los Alamos and Oak Ridge, the Atomic Energy Commission built the towns from scratch, constructing houses and streets as well as labs.

For six labs we identify counterfactual locations using a variety of archival sources (see Figure [A.1](#)). These sources, which are detailed in section 2 (as well as in Appendix Table [A1](#)), give historical accounts of other locations that site scouts considered seriously before finalizing on the eventual ones (section A1 in the Appendix provides excerpts from these historical archives). The ultimate decisions often came down to arbitrary factors; for example press accounts attribute the Idaho Falls site’s selection over the town’s competitors to a cocktail party thrown for the official in charge. “Guest lists were carefully crafted to include the young wives in town who were ‘as winsome as possible,’” recounted the Idaho Statesman. The Ames National Laboratory in Iowa was founded based on the personal connections of Arthur Compton, a senior leader of the Manhattan Project working at the Metallurgical Lab in Chicago. “...when [in 1942] Compton turned to his former University of Chicago colleague Herbert McCoy for a recommendation of a rare-earth chemist to join the laboratory, McCoy

¹⁸Los Alamos: [Hunner \(2007\)](#). This book describes a number of accidents and near accidents that make clear the benefits of a remote site.

¹⁹Oak Ridge Lab: [Jones \(1985\)](#) pg 70.

²⁰Idaho National Lab: [Holl \(1994\)](#) pg 16.

enthusiastically suggested... Frank Spedding” (Goldman, 2008). Spedding happened to be a professor at Iowa State College and began work there instead, owing to his familiarity with the institute. A few years later, the Atomic Energy Commission officially created the Ames National Lab in the same town under the leadership of Spedding.

3.1.3 Patent Data

We source historical patent data from the HistPat database (Petralia et al., 2016), which has U.S. patent information dating back to 1836, including the county of residence of inventors, allowing us to examine geographical trends and the spatial diffusion of technological advances. In addition, we extract unstructured data from the *Official Gazette of the United States Patent and Trademark Office (USPTO)*. The Gazette includes the patent assignee name for every patent granted by the USPTO. This allows us to disaggregate patents in treated counties into lab versus non-lab categories, a critical step for measuring knowledge spillovers and assessing the broader impact of lab-based innovations. Complementary to these, we also utilize the Patstat data (De Rassenfosse et al., 2014), which provides detailed information on patent classifications and citations, offering further insights into the technological and innovation dimensions at a granular level.

Other data sources we use include Bergeaud and Verluise (2021) Gross and Sampat (2025), the USPTO’s *PatentsView* website, and the Visual Intellectual Property Search website of the National Labs. These are used primarily to identify patent citations and inventor locations for the later years (post 1975). We explain their use in more detail in the subsequent results section.

Finally, for our analysis of budgetary factors, we rely on the annually published Financial Reports of the Atomic Energy Commission which provide detailed accounts of operating costs during the labs’ earlier years.

3.1.4 Individual Level Panel Data from Linked Censuses

Lastly, to capture income dynamics at the individual level, we incorporate the 1940 and 1950 individual-linked Census data (Ruggles et al., 2024). This dataset is especially valuable because it tracks the same people across census years, thereby allowing us to control for individual-specific unobservable factors. The linking matches about 54 million individuals across the two census years.

3.2 Identification Strategies

Synthetic Control Method: Given the tractable number of treated counties and the aggregated nature of our data sources, we primarily employ the synthetic control method in our analysis. As outlined in [Abadie et al. \(2010\)](#), this method is particularly well-suited for evaluating “interventions that are implemented at an aggregate level affecting a small number of large units (such as a cities, regions, or countries), on some aggregate outcome of interest.” For each treated county hosting a lab, we construct a synthetic control using a donor pool comprised of other counties within the same state. This strategy enables us to effectively control for state-specific unobservables such as local policies, political dynamics, and broader economic trends that might confound our estimates.²¹

For our main analysis, we select predictor variables using lagged values of the outcome variable in question for 25 years prior to treatment at two year intervals, or when data doesn’t permit, to the earliest possible year ([Grier and Maynard, 2016](#); [Magness and Makovi, 2023](#)). Our findings are robust to many different constructions for the synthetic controls, for example using a common set of predictors (see Appendix Figure [A.8](#)), or using lagged outcomes for 15 years before treatment at two year intervals. The results are not sensitive to these choices—the change in patents for many treatment counties is very large. Figures [A.11](#) and [A.12](#) in the Appendix show that national lab counties were unique outliers in patenting growth, with many experiencing dramatic shifts in their relative position. For example, Anderson county in TN (site of Oak Ridge National Lab) rose from the bottom quintile of the U.S. patent distribution in 1940 to near the top 5% by 1975.

These lagged outcomes ensure that the pre-treatment trajectories of the treated and synthetic control units are closely aligned. Our results, however, remain robust to including county-level baseline wages and education levels as well as additional economic variables as predictors. We supplement this with additional inference-based methods to confirm the robustness of our findings. Instead of pooling all labs we report results for each individual lab. The small number of treated units affords us this approach while also allowing lab-specific visualizations. Our results are robust to using a consistent set of predictor variables across measures (see Appendix Figure [A.8](#)).²²

Runner-up Counties: As detailed in the previous subsection, we also leverage our identification of runner-up counties to use them as control locations. These were places that

²¹Los Alamos county was carved out of Sandoval county (and to a lesser extent from Santa Fe) in 1949. For our analyses, therefore, we will treat Sandoval county as the treated county and from 1949 onwards we merge Los Alamos with Sandoval.

²²Due to concern that metro-Chicago may be atypical in ways not captured by the synthetic controls approach, for Argonne we replicate our results using only other counties in the metro area as a counterfactual. The results, which are very similar, are in Appendix figure [A.4](#).

came close to being selected but narrowly lost out, and hence might serve as a cleaner set of controls. The site selection committees used a whole set of criteria to identify potential sites and hence these counterfactuals will likely alleviate the problem of unobservable confounders in our analysis. A few influential studies follow this approach for causal identification. For example, [Greenstone et al. \(2010\)](#) use runner-up plants as controls in their study of agglomeration spillovers. Other recent studies using similar runner-up strategies to study the effects of educational infrastructure include [Andrews \(2023\)](#) and [Howard et al. \(2024\)](#).

Difference-in-differences: In instances where individual-level or more disaggregated data is available, we complement the synthetic control approach with the difference-in-differences (DiD) method. For example we take advantage of the linked US Census between 1940 and 1950 so as to track the same individuals and analyze their wage gains from exposure to the labs. By integrating both aggregate and individual-level analyses, our approach provides a robust framework to assess the impacts of technological and economic interventions across diverse contexts and time periods.

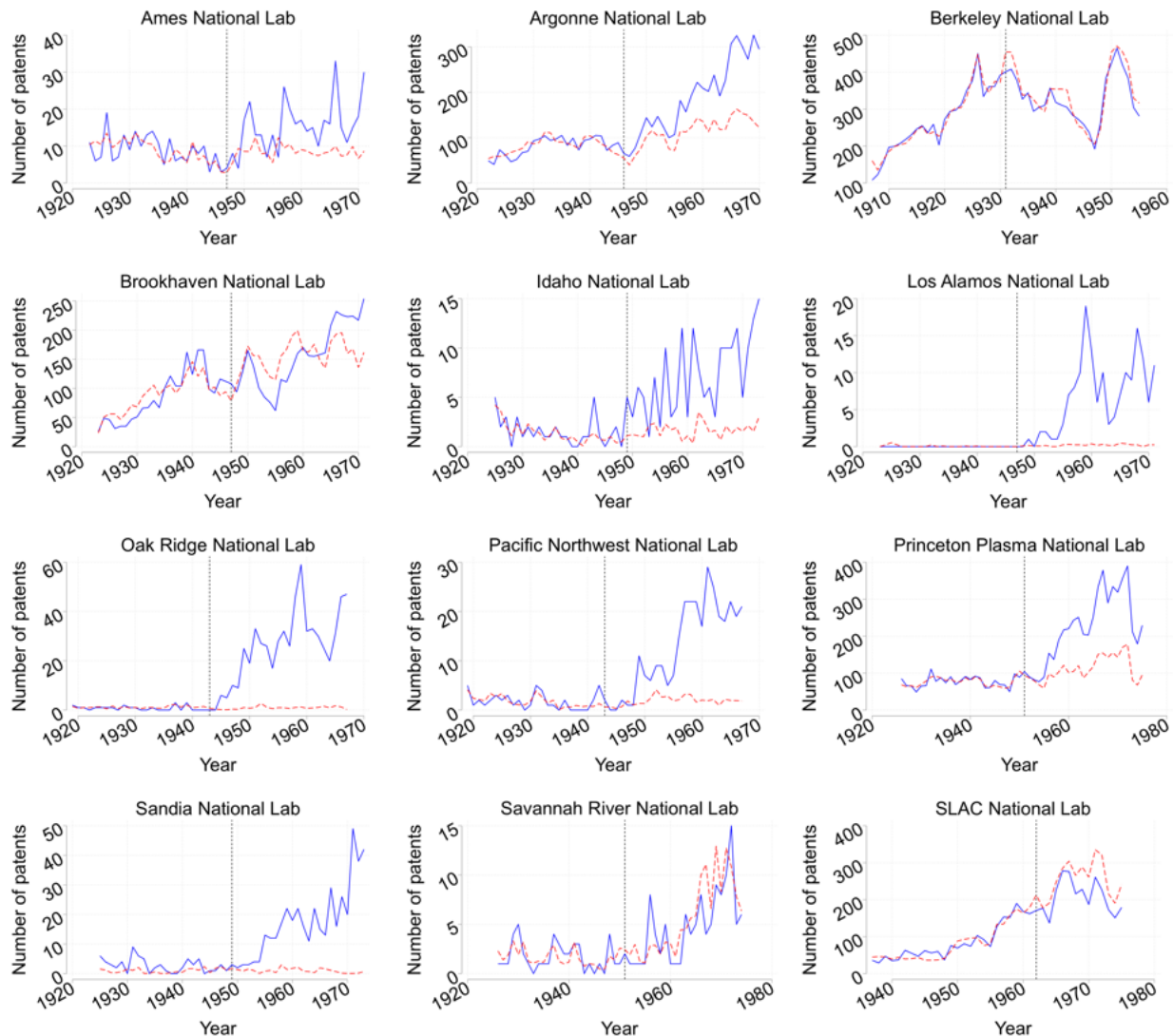
Due to data limitations, we restrict our sample to 12 labs only. One (NETL) was founded before our data range (1910). Two of them—NREL and Thomas Jefferson Lab—were founded in the 1970s and later, outside of our data range. Another two were founded in the same counties as an existing lab but in later years—Fermi Lab founded in DuPage county, IL of Argonne Lab and Lawrence Livermore Lab founded in Alameda county, CA of Lawrence Berkeley.

4 Results

4.1 Balance Checks

To ensure that our treatment and constructed controls are balanced at baseline, we compare the treated counties with the synthetic units (and weights) from the main results on a number of demographic and economic variables. Table [A2](#) in the Appendix shows strong balance between the two groups on traits not used in the construction of the controls. This result suggests the synthetic controls and weights do a fairly good job of creating comparable units with the treated ones, despite only using our lagged outcome variables as the predictors in the synthetic control. Similarly, Table [A3](#) compares the runner-up counties with their treated counterparts, and shows that runner-up and treatment counties have more or less identical labor force participation, wages, and racial compositions.

Figure 2: Time series of patents for treated counties (solid blue) and synthetic controls (red dashed)



Notes: Blue (solid) lines plot the time series of the treated county and the red (dashed) ones plot the synthetic controls. The vertical dashed line in each subfigure indicates the founding year of the labs.

4.2 Innovation Takeoff

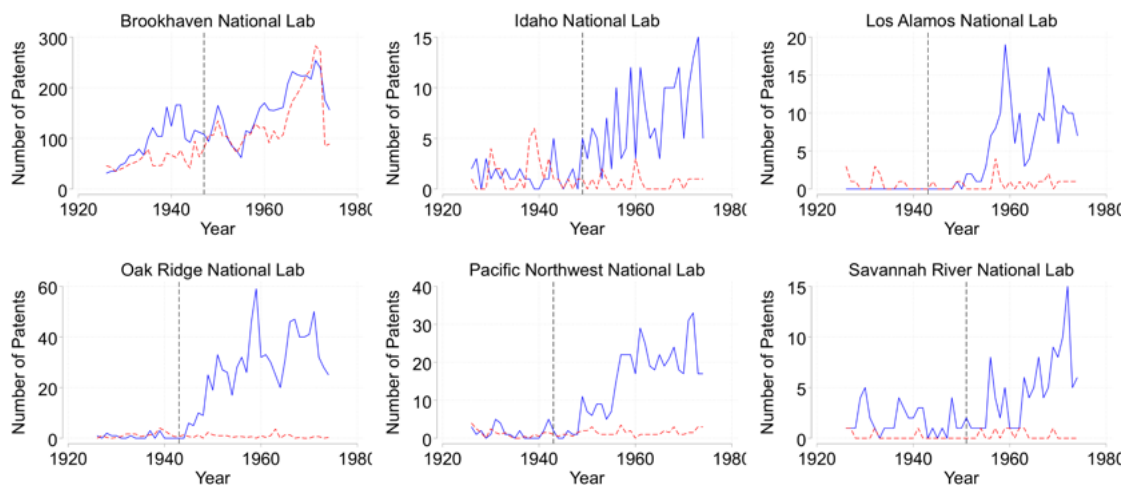
We first present our results focusing on patent outcomes. Our sample is restricted to inventors listed in the HistPat dataset.²³ Figure 2 illustrates the key findings using the synthetic control method. In each subfigure, the blue (solid) line represents the actual number of patents in the treated county, while the red (dashed) line shows the corresponding synthetic

²³Our results barely change, quantitatively speaking, when assignees are included as well.

control series constructed from a weighted combination of counties that did not host a lab. Notably, the synthetic control series tracks the treated county data quite well during the pre-treatment period, which lends credibility to our approach and sets the stage for analyzing post-treatment differences.

Examining the post-treatment period, we observe that, for two thirds of the treated counties, there is a clear uptick in the number of patents granted compared to those in the synthetic control counties. Even in cases where the divergence is less pronounced, the treated counties still show an upward trend in patent counts, suggesting that the establishment of labs may have a positive impact on local innovation activity.

Figure 3: Time series of patents for treated counties (solid blue) and runner-up counties (red dashed)



Notes: Blue (solid) lines plot the time series of the treated county and the red (dashed) ones plot the runner-up counties. The vertical dashed line in each subfigure indicates the founding year of the labs.

We obtain very similar results if using the identified runner-up counties in place of synthetic controls, as demonstrated in Figure 3.²⁴ The one exception is Brookhaven Lab whose patents do not appear to diverge over time. This likely arises due to the fact that its runner-up location (Monmouth county in New Jersey) also saw the establishment of other federal labs such as the Electronics Command (ECOM) at Fort Monmouth in 1962. The location also hosted important labs during the Second World War (Via and Rejan, 2010). Our results are also robust to using additional predictor variables including economic ones. Furthermore

²⁴Figure A.12 in the Appendix plots the time series of rank percentiles in patents for the treated and runner-up counties. While both groups ranked similarly prior to 1943, they start to diverge significantly starting in the mid 1940s as more labs get established.

we conduct inference tests which are reported in Table A4 in the Appendix and find significance for 8 of the 12 labs tested. In ten of the 12 treated counties, we obtain statistically significant estimates at conventional thresholds. As an additional robustness check we also use all counties in the treated plus adjacent states to construct the donor pool (see Figure A.9).²⁵

Ten years after establishment, patents typically increase, compared to control counties, by about 57% at the median. At the mean this number is 267% (driven primarily by Oak Ridge National Lab).

Lastly, for Brookhaven lab in Suffolk NY, we also have information on the number of publications during its early years. From about 195 publications to its name in 1950, this number explodes to 660 by 1960.²⁶

4.3 Innovation Spillovers

If labs indeed help to create innovation ecosystems in the places they are located, we should find that innovation by labs promotes innovation by other nearby actors. We investigate several types of innovation spillovers: 1) impacts on the numbers of patents from non-lab entities in the same county; 2) citations; 3) changes in fields of inquiry; and 4) informal interactions.

4.3.1 Disaggregating Lab vs. Non-Lab (External) Patents

To provide evidence of knowledge spillovers, we further disaggregate the patent data within treated counties into two categories: patents directly affiliated with the labs and those not linked to the labs. This disaggregation is achieved using documents from the *Official Gazette of the United States Patent Office*, which provides patent numbers and assignee names of all patents granted by the office. This information is published monthly. We identify all patents assigned to the Atomic Energy Commission—the parent organization overseeing the labs—from 1947 to 1974.²⁷ We then match them with the HistPat data using the unique patent numbers to identify their county locations, which we in turn interpret as a stochastic match to lab patents.²⁸

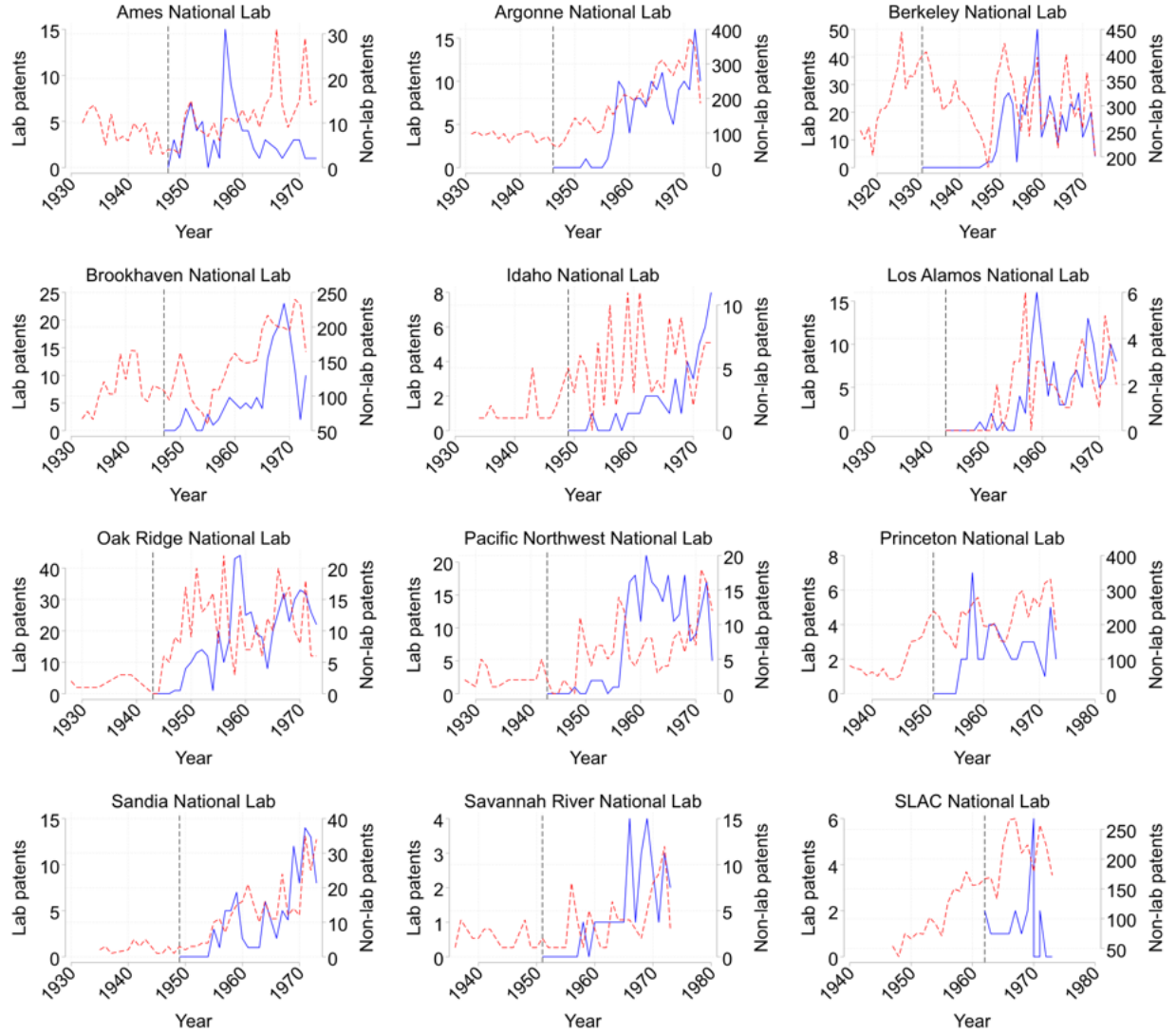
²⁵Section 4.6 of our paper delves a little into this heterogeneity, where we assess the role of operating costs as a measure of treatment dose to further understand the differential impacts across labs.

²⁶This information is taken from the lab’s annual report available on the Hathitrust online repository ([link](#)).

²⁷The Atomic Energy Commission was abolished in 1974 under the Energy Reorganization Act of 1974.

²⁸To get a sense of the accuracy of this matching process we validate it with a [document](#) (Argonne National Lab Patent Portfolio compiled by B.C Huguelet) obtained from the Office of Scientific and Technical Information that provides a list of all patents granted to Argonne Lab between 1959 and 1976. The method we use matches this record with a fairly high level of accuracy as shown in Figure A.13 in the Appendix.

Figure 4: Non-lab (external) patents rise after lab establishment



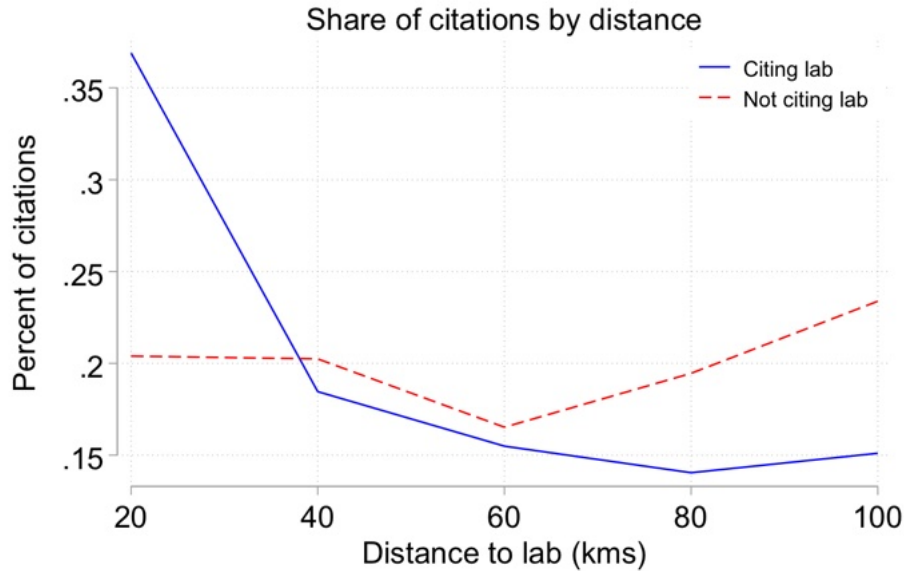
Notes: Time series of patents disaggregated by those granted to the lab (solid blue) vs non-lab (dashed red).

Figure 4 presents this disaggregated analysis. In each subfigure, the blue (solid) line depicts the time series of lab-associated patents, while the red (dashed) line represents non-lab patents. A clear pattern emerges from these plots: the two lines tend to move in tandem over time. This strong co-movement, while correlational in nature, suggests that lab scientists might be exerting an influence on the broader innovation ecosystem. In other words, the presence of a lab appears to stimulate not only in-house innovation but also indirectly boosts patenting activity among non-lab entities within the same county.

4.3.2 Spillovers over Space

To provide further evidence of knowledge spillovers we proceed as follows: first, for each of the 12 labs, we identify all *non-lab* patents within a 100 kilometer radius. We then code these patents into one of two categories: those that cite the labs and those that do not. Then for each of these two categories, we code patent locations into one of five 20 kilometer bins. This allows us to analyze the geographic distribution of the non-lab patents citing the labs versus those that do not within the radius.²⁹

Figure 5: External citations of lab patents cluster near lab locations



Notes: Data is divided into five 20 km bins. The y-axis measures the share of patents within each bin for each of the two categories. Data time period: 1932-2024; $n^{\text{citing}} = 43,957$, $n^{\text{not citing}} = 6,637,254$.

Looking at the red dashed line in Figure 5, we do not observe any discernible spatial trend for those patents that do not cite the labs. However, for those that do cite the labs (solid blue), we find that they are disproportionately close to the actual labs themselves.

²⁹To construct this dataset, we first identify lab patents using data from Gross and Sampat (2025) and the Visual Intellectual Property Search (VIPS) website of the national labs. The data from Gross and Sampat (2025) allows us to identify all patents belonging to the Department of Energy—the parent group that oversees the national labs—up till the year 2000. While not as precise as the method we employ in the earlier section (since the Department of Energy includes organizations beyond the Atomic Energy Commission), the advantage of the Gross and Sampat (2025) data is its extended time range beyond 1974 when the AEC closed down. For the succeeding years (2000 to 2024) we use information from the VIPS. Data from the USPTO’s *PatentsView* website gives geographical coordinates of patent inventors, and the Bergeaud and Verluise (2021) dataset gives information on patent citations.

We interpret this as evidence of knowledge spillovers from the labs to non-lab patents, since proximity to the lab would enable more frequent contact with lab scientists.³⁰

4.3.3 Spillovers in Technological Fields

We also provide additional evidence of spillovers by showing how the International Patent Classification (IPC) codes of non-lab patents shift towards those more commonly associated with the labs after their establishment.³¹ To analyse this we use linked data from Patstat (patent category) and HistPat (patent county locations) and identify non-lab patents in treated counties and compare them with patents in the runner-up counties to see if there was a shift towards categories that the labs patent in primarily. We run the following specification-

$$\text{ipc code}_{ict}^J = \alpha + \beta_1 \times \text{Treated}_c + \beta_2 \times \text{Post}_t + \beta_3(\text{Treated}_c \times \text{Post}_t) + \epsilon_{ict} \quad (1)$$

where ipc code_{ict}^J is a dummy variable that equals 1 if patent i from county c at time t belongs to category J , and $J = \{\text{Chemistry/Metallurgy, Construction, Electricity, Engineering, Human Necessities, Performing Operations, Physics, Textiles}\}$; Treated_c indicates if county c has a lab and Post_t equals 1 if the time period t falls after the establishment of a laboratory. For this regression we use the following labs and their respective runner-up locations: Idaho Lab, Los Alamos Lab, Oak Ridge lab, Savannah River Lab, Pacific Northwest Lab.

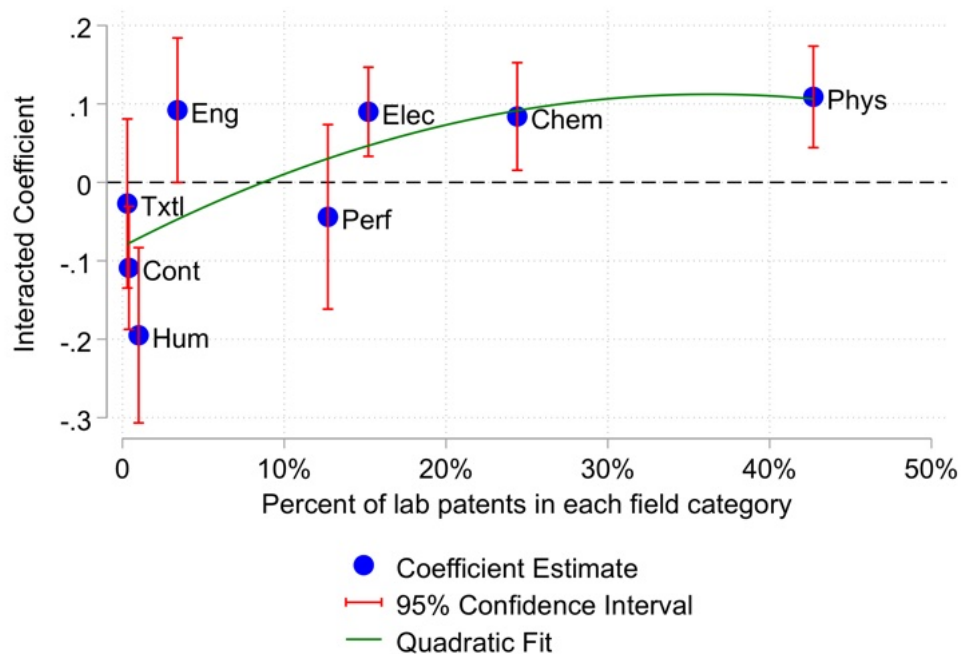
Our coefficient of interest is β_3 , which captures the relative shift in patent category for non-lab patents post a lab’s founding. Figure 6 plots the estimates for the 8 IPC categories. It is striking that for 3 of the 4 categories that the labs patent in significantly—physics, chemistry, electricity—we see that non-lab patents in treated counties see a relative increase in their share of these categories, while for the 3 categories that the lab minimally engages in—human necessities, construction, textiles—non-lab patents in treated counties fall or don’t change.

Lastly, to get a sense of the geographic spread of patents citing the labs, figure A.7 in the Appendix gives a visual representation of counties that cite all the lab patents from 1932 (founding year of the first lab in our study) to 2024.

³⁰In a recent work that measures knowledge spillovers, [Atkin et al. \(2022\)](#) find that face-to-face interactions between innovators significantly increase their probability of citing each other.

³¹The International Patent Classification categorises patents at various levels. The highest level comprises 8 categories: Chemistry, Metallurgy; Fixed Constructions; Electricity; Mechanical Engineering, Lighting, Heating, Weapons; Human Necessities; Performing Operations, Transporting; Physics; Textiles, Paper. While self-explanatory, for those interested, more details about these categories can be found on the [website](#) of the World Intellectual Property Organization.

Figure 6: Non-lab (external) patents in treated counties shift toward lab topic areas



Notes: Diff-in-diff coefficient plot for the 8 ipc categories (equation 1). The higher a lab’s share in a particular field, the more non-lab patents in treated counties shift their own fields. Legend: Phys (Physics), Chem (Chemistry and Metallurgy), Elec (Electricity), Perf (Performing Operations), Eng (Engineering), Ttxtl (Textiles and Paper), Const (Construction), Hum (Human Necessities). The sample includes non-lab patents in the following lab counties and their runner-up counties: Idaho Lab, Los Alamos Lab, Oak Ridge lab, Savannah River Lab, Pacific Northwest Lab.

4.4 Informal Interactions

The extent of innovation spillovers may seem surprising in the early years of the labs, when most were focused on nuclear weapons technology, which would seem to have few civilian spinoffs. In addition, security around the labs was tight, reducing (one might think) “ideas in the air.”³² In fact however, there was significant technology transfer. Some of this was due to labs’ work in the fundamental science behind nuclear technologies, science that had other applications. Eventually, some applications of this fundamental science (eg., in optics) led Sandia National Lab to become a leader in solar technology (Schrank, 2015). Another source of spillovers was extensive interaction with equipment suppliers. At Lawrence Livermore, at least since the 1960s there was significant interaction with the computer and laser

³²See Gross (2023) as an example of this effect.

industries, who developed equipment, instruments or other components needed for the labs’ experiments. Especially before the 1982 Stevenson-Wydler Act clarified the ownership of labs’ discoveries, frequently labs and their suppliers did not seek to patent their discoveries (Jaffe and Lerner, 2001). Thus, our measurement of both lab and non-lab patenting likely understates the true amount of innovative activity sparked by the labs.³³

In some cases, the innovation was only indirectly related to the labs’ missions. Some of the 1950s non-lab patents were for simple inventions such as arrow straightener, floor receptacle, or water cooler.³⁴ For example, according to his obituary, Harold Groves was a veteran who worked in Los Alamos but not as a scientist; “Harold, who was always inventing something, consulted with several scientists and built a ‘bow’ that would change his life.” A few years later, Harold left for Albuquerque to set up a bow business where he manufactured Groves Spitfire Bows.³⁵

Overall, these results offer compelling evidence that the establishment of labs has spurred an increase in innovative activities within their host counties, both directly through lab patents and indirectly through spillover effects on non-lab innovation.³⁶

4.5 Economic Effects

Above we showed that labs affect local patenting activity; did these innovative activities translate into broader economic benefits? Notably, several labs were originally established with a mandate to promote the economic well-being of the local community. Today, this principle remains a shared goal across all labs.³⁷ To rigorously assess these impacts, we adopt a three-pronged approach: first, we analyze aggregate economic outcomes; second, we investigate how variations in lab budgets correlate with these aggregate outcomes; and lastly, we examine effects at the per-capita level.

³³We introduce these examples to show that labs sparked interaction with local inventors, not that this interaction was optimally structured. As Tartari and Stern (2021), Traficante (2025), and Ham and Mowery (1995, 1998) show, labs could be frustratingly bureaucratic at times.

³⁴A few patent numbers of non-lab patents in Los Alamos county in the mid 1950s: 2876822 (Arrow runout tester and straightener), 2723535 (Portable refreshment cooler).

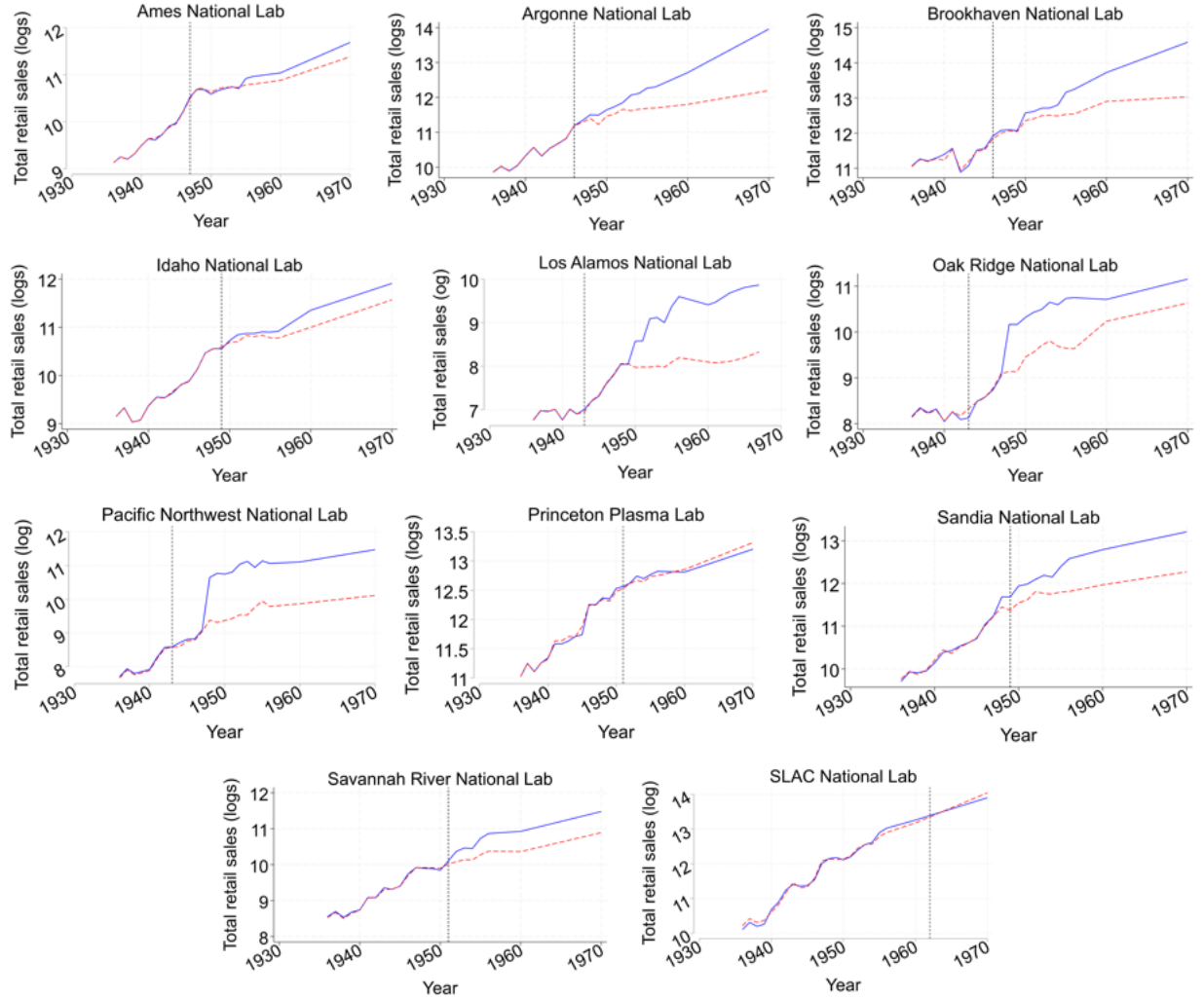
³⁵Details of Grove’s account can be found in this obituary written by his son in 1997.

³⁶In addition to such informal interactions, other spillovers might come in the form of spin-offs. For example, the Santa Fe Institute in New Mexico was founded by 8 people, 6 of whom were scientists at Los Alamos Lab located close by (Waldrop, 1993).

³⁷Contemporary evidence of this can be found in the economic mission outlined in most labs’ individual websites. For example, Idaho National Lab states that it “is committed to fostering small business growth and economic development not only in southeastern Idaho but throughout the state. Remarkably, for every job at INL, two jobs are generated in other industries, with nearly 12,600 other Idaho jobs tied to our operations.”

4.5.1 Retail Sales

Figure 7: Impact on retail sales



Notes: The sub-figures are plots using the synthetic control method. Blue (solid) lines plot the time series of the treated county and the red (dashed) ones plot the synthetic controls. The vertical dashed line in each subfigure indicates the founding year of the labs.

Figure 7 shows synthetic control plots for aggregate retail sales, derived from the Survey of Buying Power. This dataset spans from 1936 to 1971, providing a rich temporal perspective on economic performance at the county level. Given that Berkeley Lab was founded before the start of this dataset, we have excluded it from this segment of the analysis. The figure reveals several important patterns. For 9 out of the 11 cases examined, there is a noticeable increase in aggregate retail sales over the long run, typically manifesting around five years after the lab's founding. This delayed onset suggests that the economic benefits

associated with the lab’s establishment may require time to fully materialize, likely due to initial setup costs and the gradual diffusion of technological and managerial practices into the local economy.

It might seem confounding that some labs, like Argonne Lab in DuPage county IL, are located in close proximity to large cities like Chicago. As an additional robustness check we use the other 3 counties adjacent to Chicago metro area—Kane, Lake, Will—as a control group and find a similar divergence of DuPage county in its retail sales (Appendix figure A.4).

We also report inference tests for the retail sales estimates (Appendix Table A4). The results are somewhat mixed. For instance, the estimated treatment effects for Ames and Idaho appear statistically insignificant—even at the 10% level—despite visual evidence of post-treatment divergence in the corresponding event study plots. This discrepancy likely reflects a delayed treatment response, as discussed above, and that the inference procedure assigns zero effects in the immediate post-treatment years. As noted by Abadie (2021), however, lack of statistical significance in such settings does not preclude the presence of treatment effects “if the effect of an intervention is expected to arise gradually over time” and provided that the post-treatment window is sufficiently long.

Lastly, there is also heterogeneity in the magnitude and persistence of these effects. For instance, Argonne National Lab in Illinois shows a steadily widening gap between the treated county and its synthetic control, whereas Idaho National Lab experiences a divergence about six years after the lab’s founding and then the gap stabilizes over time.

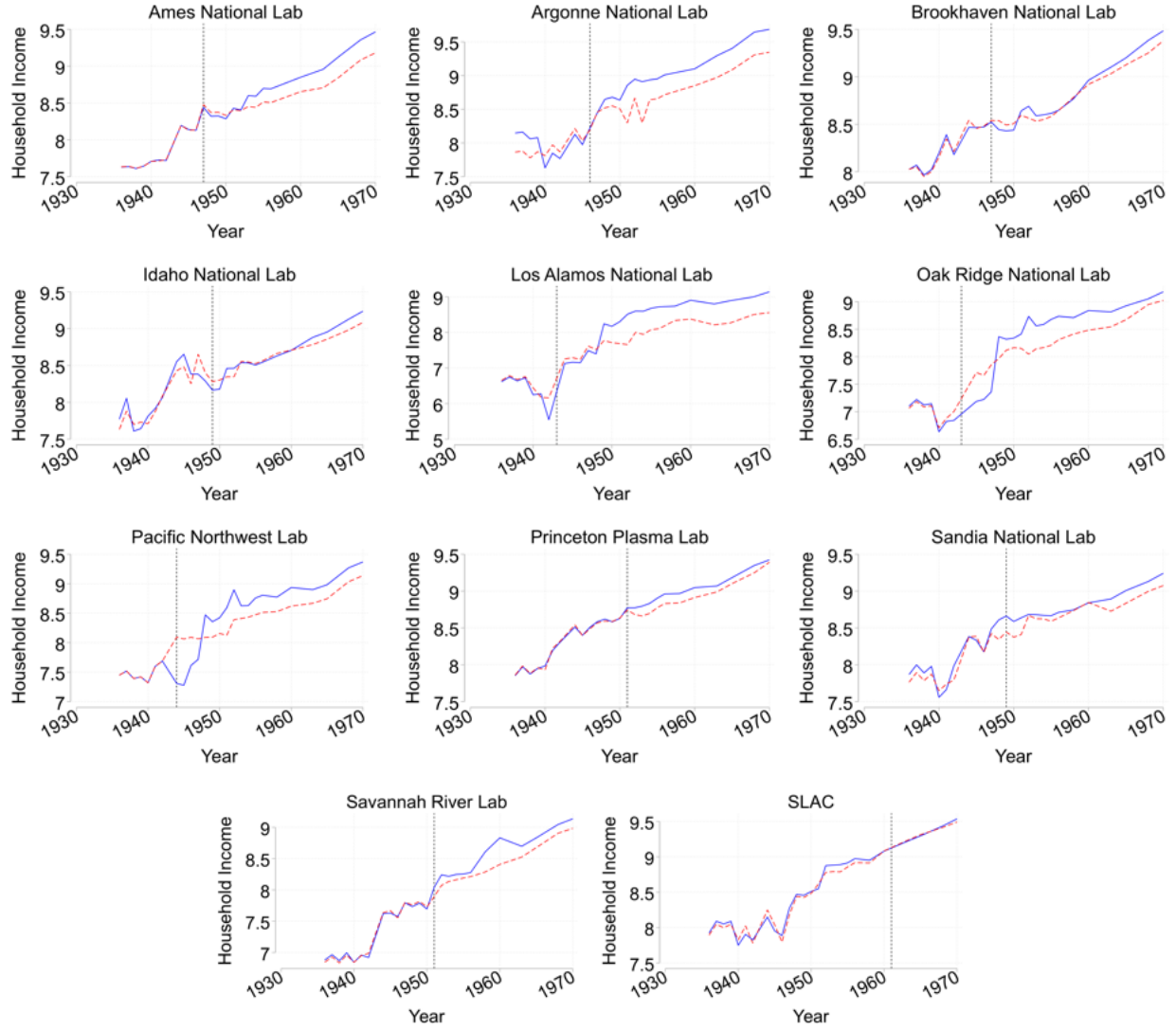
4.5.2 Household Income

Using additional county-level data from the Sales Management’s Survey of Buying Power (mentioned in section 3.1.1), we also look at trends in mean household income (defined by the survey as buying income per family).³⁸ Looking at Figure 8, for almost all labs we do see a long-run divergence in average household income. This suggests the labs had economic effects not just at the aggregate level (Figure 7) but that they also generated increases in living standards. While the aggregate changes suggest increased economic activity, the increases in per-family income are indicative of the average residents becoming better off. Figure A.5 plots the time series for the cases for which runner-up locations are identified. There is an initial divergence that then stabilizes about a decade after lab founding to about 25% higher household income on average.³⁹

³⁸The construction for the income per-family county estimates are outlined in section 3.1.1.

³⁹See Appendix Figure A.5 for additional results using the runner-up counties.

Figure 8: Impact on household income

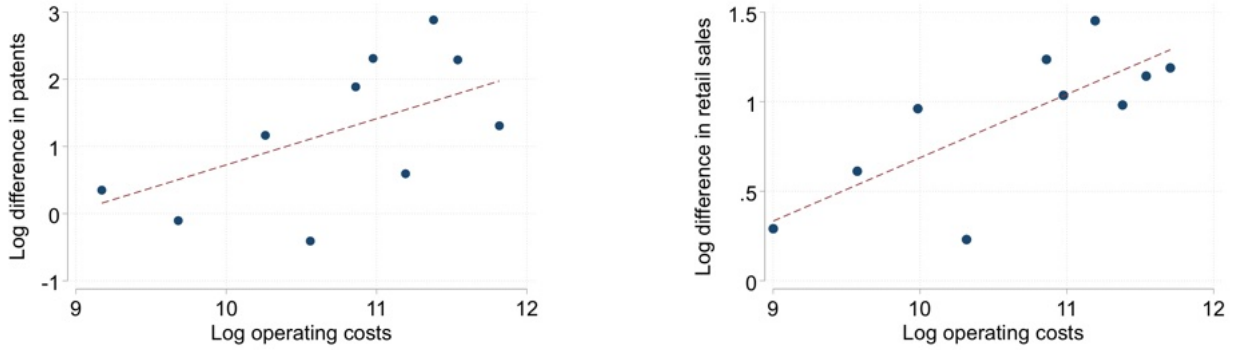


Notes: The sub-figures are plots using the synthetic control method. Blue (solid) lines plot the time series of the treated county and the red (dashed) ones plot the synthetic controls. The vertical dashed line in each subfigure indicates the founding year of the labs.

4.5.3 Dose-Response Relationship

To further understand the link between lab activity and economic performance, we utilize archival data on lab operating costs for selected years (1957, 1965, and 1970). This analysis, depicted in Figure 9, examines the correlation between a national lab's operating expenses and the logarithmic difference in aggregate retail sales between the treated county and its synthetic control. The results indicate a robust elasticity relationship: we estimate a regression coefficient of 0.4 (p-value = 0.001), suggesting that higher operating costs, which may

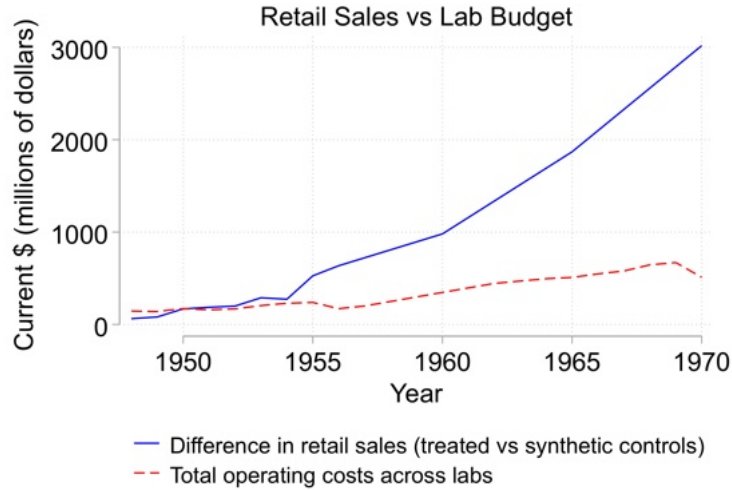
Figure 9: Patents and retail sales rise with lab operating budget



Notes: Binned scatter plots of patents (left) and retail sales (right) with respect to lab operating costs (both measured in logs).

proxy for a lab's scale or intensity of activity, are associated with larger economic expansion. For patents, the estimated coefficient is 0.6 ($p = 0.55$).⁴⁰

Figure 10: Trends in lab budget and economic activity



The multiplier effect of the spending grows over time to become much larger than that of a typical Keynesian stimulus. [Chodorow-Reich \(2019\)](#) summarizes a large literature on local multipliers and finds a preferred point estimate of 1.8, consistent with several other estimates

⁴⁰We also obtained annual reports for Brookhaven lab between 1950 and 1967 from the Hathitrust repository. This was the only lab for which we were able to obtain annual information on its budget and other activities such as publications and patenting output. Figure A.6 in the Appendix plots the time series of the lab's operating costs (black-dotted, left axis) and the following research activities: patent applications (blue-dashed), patents granted (black-dashed), and number of publications divided by 50 (red-solid). We do find that these three measures do move up with increases in the lab's spending, therefore likely reflecting a dose-response. For example, for every \$1 million in operating costs, the lab produces about 30 publications.

in the literature (Nakamura and Steinsson, 2014; Shoag, 2013; Fishback and Kachanovskaya, 2015; Clemens and Miran, 2012; Serrato and Wingender, 2016). However, over time, US national labs appear to develop significantly larger local multipliers. Taking the sum of retail sales in lab counties that is in excess of sales in the synthetic controls as an outcome, the volume of economic activity is initially 0.48 times total lab operating costs in 1948, rising to 2.2 times in 1955, 3.6 times in 1965, and exceeding 5 by 1970 (see figure 10).

These large multipliers align more closely with the higher estimates found in Jones and Summers (2020), Deleidi and Mazzucato (2021), and Ciaffi et al. (2024), which suggest that R&D spending generates disproportionately larger long-run effects. While macroeconomic estimates are primarily derived from time-series evidence⁴¹—making them potentially sensitive to specification choices and time windows (Boysen-Hogrefe, 2025)—our findings lend empirical credibility to the broader conclusion that direct R&D expenditure has significantly greater stimulative impacts than general government spending.

4.6 Income Effect on Prior Residents: Linked Individual Census Data

Table 1: Individual level wage regressions for stayers in the same county between 1940 and 1950

VARIABLES	(1) Wage change (logs)	(2) Wage change (logs)	(3) Wage change (logs)	(4) Wage change (logs)
Treated county	0.040** (0.020)	0.013 (0.020)	0.022 (0.021)	0.005 (0.021)
College $\times$ Treat		0.274*** (0.074)		0.252*** (0.076)
Professional $\times$ Treat			0.143** (0.061)	0.086 (0.063)
Observations	13,278	13,278	13,278	13,278
R-squared	0.026	0.028	0.027	0.028

Notes: The sample is restricted to male stayers in the same county between 1940 and 1950, and who were in the labor force in 1940 and under 65 in 1940. Robust standard errors in parentheses. All regressions control for 1940 baseline wages. College is a dummy variable that equals 1 if an individual has completed college. Professionals are industry types as defined by the IPUMS 1940 census. These include educational services, medical and other health services, legal, engineering, and miscellaneous professional services, charitable, religious, and membership organizations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

⁴¹Alternately, Dyevre (2023) uses an instrumental variable approach and Fieldhouse and Mertens (2023) use narratively identified R&D shocks to estimate productivity impacts.

Moving beyond aggregate county-level measures, we also explore the impact of lab establishment on individual wages. Leveraging the U.S. Census’ ability to link individuals across the 1940 and 1950 census rounds, we investigate how residents of treated counties fared in the decade following a lab’s founding. Between these census years, eight labs were established, including Ames National Lab, Argonne National Laboratory, Brookhaven National Laboratory, Idaho National Laboratory, Los Alamos National Laboratory, Oak Ridge National Laboratory, Pacific Northwest National Lab, and Sandia National Laboratories. By identifying counterfactual locations for four of these labs (Brookhaven, Idaho, Los Alamos, and Pacific Northwest), we construct 4 treatment clusters and 6 control clusters. We focus on “stayers”—individuals who remained in their respective counties in both census periods—to mitigate concerns that higher-income individuals might self-select into counties with labs. Though this movement of people is itself a lab effect, it, nonetheless, is interesting to explore the impact of the lab on those who might not have been endogenously induced to move. The sample is restricted to men who were in the labor force in both years and under 65 in 1940. The estimation follows the familiar form:

$$\Delta \text{wage}_{i,c,s} = \alpha + \beta \times \text{Treated}_c + \delta \mathbf{X}_i + \Gamma_s + \epsilon_{i,c,s} \quad (2)$$

where $\text{wage}_{i,c,s}$ denotes the log wage difference between 1950 and 1940 for individual i in county c in state s ; Treated_c equals 1 if county c received a lab between the two census rounds and 0 otherwise; $\mathbf{X}_i$ represents a vector of individual characteristics, including baseline wage, age and employment status in 1940; and Γ_s captures state fixed effects. Table 1 presents the results of our estimation. Column (1) indicates that treatment status is associated with a significant wage premium. On average, individuals residing in treated counties experienced a 4–5% increase in wages compared to those in counterfactual locations.

We further explore heterogeneity by certain baseline characteristics. Looking at columns 2 to 4 we find that the labs had differential impacts on the wages of states with a large boost for college educated workers as well as those in professional industries. For non-college educated individuals, we do observe wage gains of about 1.5%, though it is small and not statistically significant.

One concern about relocating a large number of highly educated scientists is that they might drive out existing residents for a variety of reasons, for example, by raising housing prices. Looking at the same census data between the years 1940 and 1950, we do not find such evidence. That is, prior residents of treated counties were not more likely to leave for another county after a lab’s founding than were residents of runner-up counties.

Lab histories provide examples of mechanisms behind the higher wages for existing resi-

dents when labs came in. Some residents were hired directly, as “carpenters, furnace stokers, and janitors” or lab technicians and secretaries; others contracted with the labs or did business with such contractors (such as the residents of San Ildefonso Pueblo near Los Alamos national lab, who rented reservation land to a construction company.⁴² Another mechanism by which labs affect local residents was through education spillovers. We owe the presence of one of our colleagues at Case Western, Prof. Jenny Hawkins, to this effect. She grew up in a community where girls did not think of college as accessible for them. However, she grew up in the vicinity of Idaho National Lab, which organized a Saturday conference to the labs exclusively for girls. When she learned what scientists did, she was intrigued, and wanted to be like them. She found her way to a BA in math at Idaho State University, and eventually to a PhD in economics. More directly, schools near the labs were often excellent and generously subsidized by the Atomic Energy Commission (Hunner, 2007; Schrank, 2015).

5 Conclusion

This paper examines the long-run effects of the National Laboratory System on local innovation and economic development. Leveraging a synthetic control approach, archival research, and counterfactual site comparisons, we document substantial and persistent differences in patenting activity, retail sales, and individual income growth between counties that hosted national labs and otherwise similar counties that did not. Our findings indicate that these labs were not only critical centers of scientific advancement but also played a broader role in fostering self-sustaining innovation clusters and regional economic growth.

Guzman et al. (2024) argue that the impact of place-based innovation policy interventions on an ecosystem should be judged based on whether it changes the ways in which “knowledge is distributed and translated within that ecosystem”. We believe that our counterfactual analysis shows that national labs, though not initially designed as a place-based policy, have indeed had this effect. Compared to counterfactual counties, lab-based innovations have for decades had spillover effects to non-lab inventors (as measured by their increased innovative activity, citations to lab patents and their changed fields of research, and archival reports of direct interaction). These benefits included economic improvements as well, with sustained increases in wages and retail sales, representing a multiplier effect of lab expenditure much greater than that of typical government spending programs.

The results highlight several key mechanisms driving these impacts. First, the labs appear to have generated substantial knowledge spillovers, as evidenced by the increase in non-lab

⁴²Not all the spillover effects were positive. Access to open space was restricted, and experiments “detonated blasts that at times scattered radioactive particles over surrounding areas” (Hunner, 2007).

patenting activity in treated counties, the co-movement between the numbers of lab and non-lab patents, and the observed shifts in non-lab patents toward the technological domains of the labs. Second, the economic benefits of the labs extended beyond direct employment effects, with significant wage increases for individuals residing in treated counties, even for those not directly affiliated with the labs, including non-college graduates. Third, we find a positive correlation between lab operating costs and economic outcomes, suggesting that continued federal investment in these research hubs reinforced their long-term impact.

Our study contributes to ongoing policy discussions on place-based innovation strategies. As policymakers around the world consider new investments in regional technology hubs—such as those proposed in the U.S. NSF Regional Engines program, and the European Innovation Ecosystems programs—our findings provide historical evidence that such investments can create durable economic and innovation clusters. The lessons from the National Laboratory System suggest that adequately-funded research institutions have the potential to catalyze long-term regional development, even in areas without preexisting innovation ecosystems.

Our study looks at the establishment of national labs – the extensive margin. In many cases, there was very little human activity in the region before the establishment of the lab.⁴³ As noted above, we find evidence that lab investments created a durable innovation eco-system. The absence of previous activity makes it easier to attribute the cause of the innovation to the establishment of the lab. However, this factor should not be interpreted as a finding that funds for innovation are most effectively spent in rural areas. It may be that the presence of complementary institutions (such as pre-existing universities or innovative firms) would increase multipliers even more and reduce the size of investment required to achieve takeoff. This possibility would be consistent with [Gruber and Johnson \(2019\)](#), who propose directing significant innovation spending to build technology hubs in cities that have already significant science prowess and with [Guzman et al. \(2024\)](#) who argue that “innovation ecosystem interventions...are more likely to succeed when they account for the current state of a given regional ecosystem”.

Future research could explore how modern national labs and similar research institutions interact with today’s innovation landscape, particularly in an era of increasing private sector R&D investment and evolving regional economic conditions. Further analysis of the specific conditions that enhance knowledge spillovers, firm creation, and commercialization of lab-generated innovations could provide additional insights for designing effective technology-based regional development policies.

⁴³For example, the population of Los Alamos County grew from 200 in 1943 to more than 12,000 in 1957, of whom almost half worked at the lab ([Hunner, 2007](#) p4, 30).

Taken together, our results suggest that large-scale, place-based scientific investments can have profound and lasting effects on local economies and benefit most of their residents. By fostering knowledge spillovers and stimulating economic growth, national labs have demonstrated that government-backed research institutions can serve as powerful engines of regional development.

References

- Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of economic literature*, 59(2):391–425.
- Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california’s tobacco control program. *Journal of the American statistical Association*, 105(490):493–505.
- Andrews, M. J. (2023). How do institutions of higher education affect local invention? evidence from the establishment of us colleges. *American Economic Journal: Economic Policy*, 15(2):1–41.
- Atkin, D., Chen, M. K., and Popov, A. (2022). The returns to face-to-face interactions: Knowledge spillovers in silicon valley. Technical report, National Bureau of Economic Research.
- Azoulay, P., Graff Zivin, J. S., Li, D., and Sampat, B. N. (2019). Public r&d investments and private-sector patenting: evidence from nih funding rules. *The Review of economic studies*, 86(1):117–152.
- Babina, T., He, A. X., Howell, S. T., Perlman, E. R., and Staudt, J. (2023). Cutting the innovation engine: how federal funding shocks affect university patenting, entrepreneurship, and publications. *The Quarterly Journal of Economics*, 138(2):895–954.
- Bergeaud, A. and Verluise, C. (2021). One century of innovation in europe and the us. Technical report.
- Boysen-Hogrefe, J. (2025). Is the supermultiplier currently nil?-a replication study of deleidi and mazzucato (2021). *Research Policy*, 54(3):105176.
- Chatterji, A., Glaeser, E., and Kerr, W. (2014). Clusters of entrepreneurship and innovation. *Innovation policy and the economy*, 14(1):129–166.
- Chodorow-Reich, G. (2019). Geographic cross-sectional fiscal spending multipliers: What have we learned? *American Economic Journal: Economic Policy*, 11(2):1–34.
- Ciaffi, G., Deleidi, M., and Mazzucato, M. (2024). Measuring the macroeconomic responses to public investment in innovation: evidence from oecd countries. *Industrial and Corporate Change*, 33(2):363–382.

- Clemens, J. and Miran, S. (2012). Fiscal policy multipliers on subnational government spending. *American Economic Journal: Economic Policy*, 4(2):46–68.
- Crease, R. P. (1999). *Making Physics: A Biography Of Brookhaven National Laboratory, 1946–1972*. University of Chicago Press.
- Cristelli, G. (2024). Funding the ivory tower: The effects of nsf institutional grants on universities and local innovation. *Working Paper*.
- Dale, B. C. and Moy, T. D. (2000). The rise of federally funded research and development centers. Technical Report SAND2000-2212, Sandia National Labs., Albuquerque, NM, and Livermore, CA (US).
- De Rassenfosse, G., Dernis, H., and Boedt, G. (2014). An introduction to the patstat database with example queries. *Australian economic review*, 47(3):395–408.
- Deleidi, M. and Mazzucato, M. (2021). Directed innovation policies and the supermultiplier: An empirical assessment of mission-oriented policies in the us economy. *Research Policy*, 50(2):104151.
- Diamond, R. (2016). The determinants and welfare implications of us workers’ diverging location choices by skill: 1980–2000. *American economic review*, 106(3):479–524.
- District, M., OF, M., Energy, D. o., and Engineers, U. S. A. C. o. (2020). *Manhattan District History: Book I - General; Volume I - General*. Manhattan District History. Nimble Books LLC.
- Dyevre, A. (2023). Public r&d spillovers and productivity growth. Working paper. Accessed: 2025-03-20.
- Feldman, M. P. and Francis, J. (2002). The entrepreneurial spark: Individual agents and the formation of innovative clusters. In *Complexity and Industrial Clusters: Dynamics and Models in Theory and Practice*, pages 195–212. Springer.
- Fieldhouse, A. J. and Mertens, K. (2023). *The returns to government R&D: Evidence from US appropriations shocks*. Federal Reserve Bank of Dallas, Research Department.
- Fishback, P. and Kachanovskaya, V. (2015). The multiplier for federal spending in the states during the great depression. *The Journal of Economic History*, 75(1):125–162.
- Glaeser, E. L. (2010). *Agglomeration economics*. University of Chicago Press.

- Glaeser, E. L. and Gottlieb, J. D. (2009). The wealth of cities: Agglomeration economies and spatial equilibrium in the united states. *Journal of Economic Literature*, 47(4):983–1028.
- Goldman, J. A. (2008). Frank speeding and the ames laboratory: The development of a science manager. *The Annals of Iowa*, 67(1).
- Greenstone, M., Hornbeck, R., and Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of political economy*, 118(3):536–598.
- Grier, K. and Maynard, N. (2016). The economic consequences of hugo chavez: A synthetic control analysis. *Journal of Economic Behavior & Organization*, 125:1–21.
- Gross, D. P. (2023). The hidden costs of securing innovation: The manifold impacts of compulsory invention secrecy. *Management Science*, 69(4):2318–2338.
- Gross, D. P. and Sampat, B. N. (2023). America, jump-started: World war ii r&d and the takeoff of the us innovation system. *American Economic Review*, 113(12):3323–3356.
- Gross, D. P. and Sampat, B. N. (2025). The government patent register: A new resource for measuring us government-funded patenting. *Research Policy*, 54(1):105142.
- Gruber, J. and Johnson, S. (2019). *Jump-starting America: How breakthrough science can revive economic growth and the American dream*. Hachette UK.
- Guzman, J., Murray, F., Stern, S., and Williams, H. (2024). Accelerating innovation ecosystems: The promise and challenges of regional innovation engines. *Entrepreneurship and Innovation Policy and the Economy*, 3(1):9–75.
- Ham, R. M. and Mowery, D. C. (1995). Improving industry-government cooperative r&d. *Issues in Science and Technology*, 11(4):67–73.
- Ham, R. M. and Mowery, D. C. (1998). Improving the effectiveness of public-private r&d collaboration: case studies at a us weapons laboratory. *Research policy*, 26(6):661–675.
- Holl, J. M. (1994). The national reactor testing station: The atomic energy commission in idaho, 1949-1962. *The Pacific Northwest Quarterly*, 85(1):15–24.
- Howard, G., Weinstein, R., and Yang, Y. (2024). Do universities improve local economic resilience? *Review of Economics and Statistics*, 106(4):1129–1145.
- Howell, S. T. (2024). Government intervention in innovation. *Annual Review of Financial Economics*, 16.

- Hunner, J. (2007). *Inventing Los Alamos: The growth of an atomic community*. University of Oklahoma Press.
- Jaffe, A. B. and Lerner, J. (2001). Reinventing public r&d: Patent policy and the commercialization of national laboratory technologies. *RAND Journal of Economics*, pages 167–198.
- Johnson, L. and Schaffer, D. (1994). *Oak Ridge National Laboratory: The First Fifty Years*. University of Tennessee Press.
- Jones, B. F. and Summers, L. H. (2020). *A calculation of the social returns to innovation*, volume 27863. National Bureau of Economic Research.
- Jones, V. C. (1985). *Manhattan, the Army and the atomic bomb*, volume 8. US Government Printing Office.
- Kantor, S. and Whalley, A. T. (2023). Moonshot: Public r&d and growth. Technical report, National Bureau of Economic Research.
- Kerr, W. R. (2010). Breakthrough inventions and migrating clusters of innovation. *Journal of urban Economics*, 67(1):46–60.
- Kline, P. and Moretti, E. (2014). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annu. Rev. Econ.*, 6(1):629–662.
- Magness, P. W. and Makovi, M. (2023). The mainstreaming of marx: Measuring the effect of the russian revolution on karl marx’s influence. *Journal of Political Economy*, 131(6):1507–1545.
- Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, 111(10):3328–3375.
- Moretti, E., Steinwender, C., and Van Reenen, J. (2025). The intellectual spoils of war? defense r&d, productivity, and international spillovers. *Review of Economics and Statistics*, 107(1):14–27.
- Myers, K. R. and Lanahan, L. (2022). Estimating spillovers from publicly funded r&d: Evidence from the us department of energy. *American Economic Review*, 112(7):2393–2423.
- Nakamura, E. and Steinsson, J. (2014). Fiscal stimulus in a monetary union: Evidence from us regions. *American Economic Review*, 104(3):753–792.

- Petralia, S., Balland, P.-A., and Rigby, D. L. (2016). Unveiling the geography of historical patents in the united states from 1836 to 1975. *Scientific data*, 3(1):1–14.
- Porter, M. E. and Stern, S. (2001). Innovation: location matters. *MIT Sloan management review*.
- Ramsey, N. F. (1966). Early history of associated universities and brookhaven national laboratory. brookhaven lecture series no. 55. Technical report, Brookhaven National Laboratory (BNL), Upton, NY (United States).
- Reed, M., Swanson, M., Tyson, J., and Gillett, T. (2013). Bringing it to form—a thematic study of svannah river sites’s separation processes, f and h areas. *New South Associate Technical Report*, 2202.
- Ruggles, S., Nelson, M. A., Sobek, M., Fitch, C. A., Goeken, R., Hacker, J. D., Roberts, E., and Warren, J. R. (2024). Ipums ancestry full count data: Version 4.0 [dataset]. minneapolis, mn: Ipums.
- Russell, L. C., Yu, L., and Andrews, M. J. (2024). Higher education and local educational attainment: evidence from the establishment of us colleges. *Review of Economics and Statistics*, 106(4):1146–1156.
- Sales and Management Magazine (1936-1972). *Survey of Buying Power*. Bill Brothers Publications.
- Saxenian, A. (1996). *Regional advantage: Culture and competition in silicon valley and route 128, with a new preface by the author*. Harvard University Press.
- Schrank, A. (2015). Green capitalists in a purple state: Sandia national laboratories and the renewable energy industry in new mexico. In *State of Innovation*, pages 96–108. Routledge.
- Serrato, J. C. S. and Wingender, P. (2016). Estimating local fiscal multipliers. Technical report, National Bureau of Economic Research.
- Shoag, D. (2013). Using state pension shocks to estimate fiscal multipliers since the great recession. *American Economic Review*, 103(3):121–124.
- Tartari, V. and Stern, S. (2021). More than an ivory tower: The impact of research institutions on the quantity and quality of entrepreneurship. Technical Report w28846, National Bureau of Economic Research.

- Tarter, C. B. (2018). *The American Lab: An Insider's History Of The Lawrence Livermore National Laboratory*. Johns Hopkins University Press.
- Traficante, D. (2025). Government research. *Yale Law Journal*.
- United States. Bureau of the Census (2012). County and city data book [united states] consolidated file: County data, 1947-1977. Version v2, published 2012-09-18.
- U.S. Department of Energy (2023). 75 breakthroughs by america's national laboratories. Accessed: 2025-03-20.
- Via, D. L. and Rejan, W. (2010). *A History of Army Communications and Electronics at Fort Monmouth, New Jersey, 1917-2007*. Government Printing Office.
- Waldrop, M. M. (1993). *Complexity: The emerging science at the edge of order and chaos*. Simon and Schuster.
- Westwick, P. J. (2003). *The National Labs: Science In An American System, 1947-1974*. Harvard University Press.

A Appendix

A.1 Sources for Identifying Runner-Up Locations

Lab Name	Sources
Brookhaven Lab	Ramsey (1966) , pp. 4 - 6
Idaho National Lab	Holl (1994) , pg. 16
Oak Ridge Lab	Jones (1985) , pg. 70
Los Alamos Lab	Link 1 , Link 2
Pacific Northwest Lab (earlier called Hanford Site)	District et al. (2020) , pp. 2.4 - 2.7
Savannah River Lab	Reed et al. (2013) , pg. 27

Table A1: Lab names and document titles/links of their respective runner-up sources

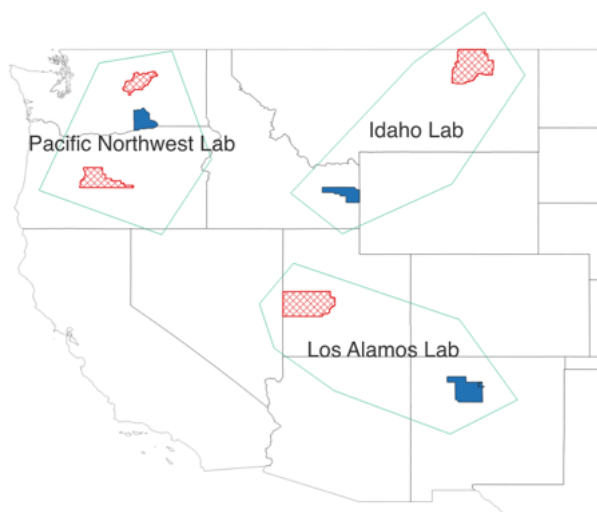
Below are some quotes of the respective lab siting committees with regard to their final decisions:

- **Brookhaven Lab:** *“With the additional restrictions applied by the Manhattan District there remained two out of the original seventeen sites provided the requirement for one hour driving time to New York City was relaxed. These were Camp Upton - the site of Irving Berlin’s World War I musical comedy, Yip, Yap, Yaphank - and Fort Hancock, on Sandy Hook peninsula near Red Bank, New Jersey..... The Site Committee, consequently, recommended with reservations the Camp Upton site..... George Kistiakowsky summarized the views of those present when he said that we could agree to this site on the basis of “equalization of disappointment.”*
- **Idaho Lab:** *“After a preliminary study of some 20 sites, the agency narrowed its search to two areas, the first located near Fort Peck, Montana, and the other at the U.S. Naval Proving Ground at Big Lost River, near Pocatello, Idaho. Both sites met the AEC requirement that the reactor testing station be located at least 50 miles from cities with populations of 50,000 or more.”*
- **Oak Ridge Lab:** *“...the entire group agreed that the Tennessee Valley seemed the best location..... although some of the scientists felt a site farther east in the Smoky Mountains, where the climate was not as warm...might prove more desirable.”*
- **Los Alamos Lab:** *“Kevin Roark, Los Alamos National Laboratory spokesman, said of the town’s [Oak City, Utah] consideration... ‘I don’t think the military was keen on*

Los Alamos.’... Major John Dudley of the Manhattan District Staff was assigned to survey the West and find potential sites for an atomic laboratory in October 1942..... ‘Dudley searched parts of California, Nevada, Utah, Arizona and New Mexico. His first choice for the laboratory site was Oak City, Utah.’....‘It was a delightful little oasis in south central Utah,’ Dudley wrote. ‘The railroad was only 16 miles away over a nice, easy road. The airport was not too distant. The water supply was good. It was surrounded by hills, and beyond there was mostly desert. However, I noticed one thing: If we took over this area we would evict several dozen families and we would also take a large amount of farm acreage out of production.’.... Because of the potential loss of farmland, Dudley recommended his second choice — Jemez Springs, N.M.’..... In the end, Dudley’s choice was overruled by J. Robert Oppenheimer, a physicist and the scientific director of the Manhattan Project. He favored Los Alamos.”

- **Pacific Northwest Lab:** ... Possible sites were physically inspected at two locations near Mansfield, WA,... in the vicinity of Grand Coulee Damns one near White Bluffs and Hanford, WA...one in the Deschutes River Valley of Oregon..... Many other possible locations were considered in some detail but were eliminated from consideration without inspection because of failure to meet one or more specific requirements.”
- **Savannah River Lab:** “Sixty-five sites were eliminated when progress in reactor design studies established that the minimum acceptable water supply was 400 c.f.s. By August 2, the list was pared down to seven sites. Members of the AEC, Army Corps of Engineers staff, and the Du Pont team, between August 6 and 17, chose these as candidates for a field inspection. Three local sites made it to this shortlist: two in South Carolina and one in Georgia. The site in Georgia was eliminated when it was learned that the Clark Hill reservoir would put a portion of the desired site under water and a site in northwestern South Carolina was considered too isolated. Site #5 in Aiken and Barnwell counties stayed in the running..... Site #5, a rural site along the Savannah River in South Carolina, was recommended to the Site Review Committee on November 13, 1950 as the final selection. In the words of Du Pont Engineer, C. H. Topping, it ‘more nearly meets the requirements than do the others.’”

A.2 Runner-up Locations



(a) Labs in the western states



(b) Labs in the eastern states

Figure A.1: Map of lab counties (blue) and runner-up counties (red, hashed). Los Alamos county in New Mexico was carved out of Sandoval county in 1949, and so for all our analysis we merge them into one.

A.3 Novel Data Collection

Figure A.2: A scan from the 1941 issue of the Sales and Management's Survey of Buying Power

WEST VIRGINIA—County Data—(Continued)

The "SM" symbols mark original, exclusive estimates by SALES MANAGEMENT.

COUNTY	POPULATION, 1940 (In Thousands)					RETAIL SALES				AUTO SALES 1940		IN-COME TAX RE-TURNS PER 1,000	EFFECTIVE BUYING INCOME, 1940  ESTIMATE					 MARKET CONTROLS	
						1939 U. S. Gov't.			1940				1940  Estimate				Dollars (in thousands)	% of U.S.A.	Per Family
	Total 1940	Ratio 1940 to 1930	% of U.S.A.	Fami- lies, Est'd	White Fami- lies, Est'd	Dollars (in thousands)	% of U.S.A.	Ratio 1939 to 1935	New Passen- ger Cars	Ratio 1940 to 1939									
Pleasants.....32	6.7	103	.005	1.7	1.7	1,224	.003	135	1,406	111	163	17	2,453	.003	1,469	1,469	.6	.003	60
Pocahontas.....31	13.9	96	.011	3.1	3.0	1,806	.004	118	2,075	105	85	9	3,921	.005	1,284	1,309	N. A.	.005	45
Preston.....30	30.4	105	.023	7.1	7.0	3,374	.008	122	3,877	298	132	7	6,731	.009	949	957	N. A.	.009	39
Putnam.....52	19.5	116	.015	4.4	4.4	2,144	.005	155	2,463	213	152	5	3,638	.005	820	820	N. A.	.005	33
Raleigh.....52	86.7	127	.067	18.9	15.6	20,174	.048	123	23,179	1,348	159	28	33,834	.046	1,786	1,983	5.3	.048	72
Randolph.....31	30.2	120	.023	6.8	6.7	5,946	.014	134	6,832	428	122	17	8,661	.012	1,265	1,279	1.8	.013	57
Ritchie.....32	15.4	99	.012	3.9	3.9	1,854	.004	111	2,130	171	109	11	4,329	.006	1,116	1,116	N. A.	.005	42
Roane.....32	20.8	107	.016	4.4	4.4	2,219	.005	103	2,550	200	143	11	4,491	.006	1,013	1,013	1.3	.006	38
Summers.....52	20.4	100	.016	4.7	4.3	2,751	.007	110	3,161	215	122	20	4,689	.006	1,003	1,046	1.8	.007	44
Taylor.....31	19.9	104	.015	4.9	4.7	3,258	.008	102	3,743	231	124	23	6,666	.009	1,372	1,390	1.4	.008	53
Tucker.....40	13.2	98	.010	3.0	3.0	1,724	.004	111	1,981	151	147	10	3,873	.005	1,280	1,280	N. A.	.004	41
Tyler.....33	12.5	98	.010	3.3	3.3	1,926	.005	98	2,213	119	95	20	4,306	.006	1,317	1,317	.9	.005	50
Upshur.....31	18.3	102	.014	4.6	4.5	2,530	.008	118	2,907	199	121	10	4,292	.006	938	951	N. A.	.006	43
Wayne (Huntington).....53	35.2	113	.027	8.5	8.5	2,179	.005	127	2,504	191	158	5	4,812	.006	563	563	2.6	.006	22
Webster.....31	18.1	127	.014	3.8	3.8	1,983	.005	111	2,278	145	113	9	3,453	.005	912	912	N. A.	.005	36
Wetzel.....33	22.3	100	.017	5.3	5.3	3,382	.008	100	3,886	314	125	16	6,922	.009	1,295	1,295	1.5	.009	53
Wirt.....32	6.5	102	.005	1.6	1.6	450	.001	153	517	24	86	3	1,009	.001	646	646	N. A.	.001	20
Wood.....32	62.4	110	.047	16.7	16.4	17,697	.042	121	20,333	1,066	133	36	35,535	.048	2,124	2,149	8.7	.045	96
Wyoming.....52	29.8	142	.023	6.2	5.6	4,990	.012	151	5,733	461	173	19	9,326	.013	1,509	1,598	N. A.	.013	57
STATE TOTAL.....	1,900.2	110	1.447	445.7	413.9	404,889	.963	122	465,203	29,828	140	29	753,807	1.016	1,692	1,762	117.7	1.008	70

A.4 Balance Checks

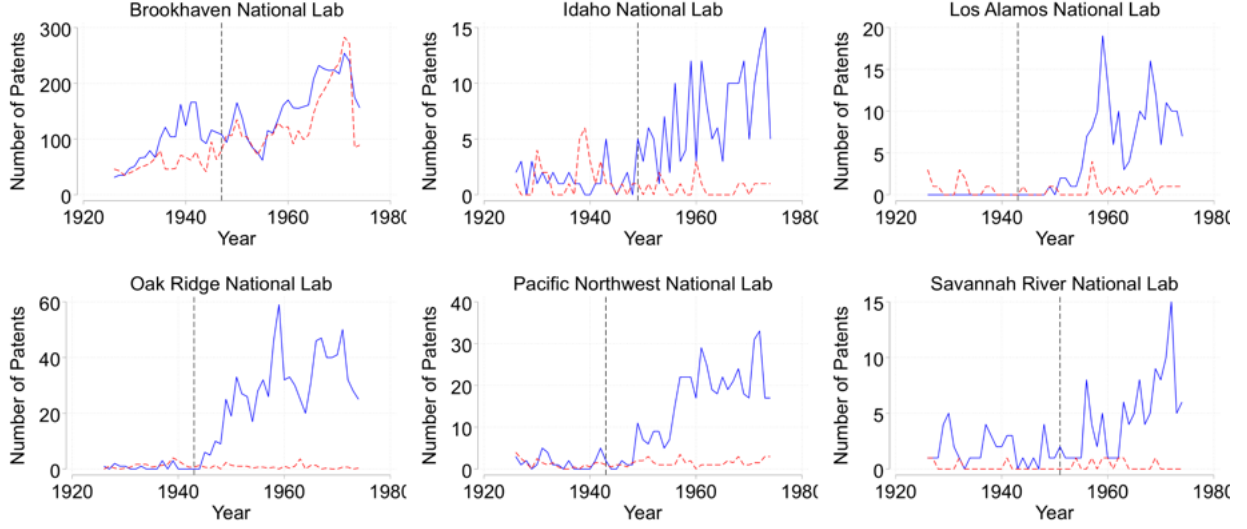
Table A2: Balance check (all treated vs synthetic Control): Data from the decennial census (IPUMS) aggregated to the county level. The sample consists of the following labs: Ames National Lab, Argonne National Lab, Berkeley Lab, Brookhaven, Idaho, Los Alamos, Oak Ridge, PNNL, Princeton, Plasma Savannah, SLAC, Sandia. Educational attainment is measured as in the IPUMS Database (ranges from 0 to 20). Share of farmers is total farmers divided by total employed.

Variables	Treated	Synthetic Control	p-val
Adult Population Age (1940)	39.8	37.7	0.403
Log population (1940)	11.03	11.15	0.821
Labor Force Participation Rate % (1940)	56.8	53.6	0.357
Educational attainment (1940)	11.8	11.0	0.392
Wages (current \$) (1940)	981	863	0.385
Share of farmers % (1940)	20.3	21.7	0.807
Share of manufacturing workers % (1940)	15.9	18.3	0.632
Share of whites % (1940)	92.3	87.1	0.454
Share of foreign-born % (1940)	16.9	15.3	0.732

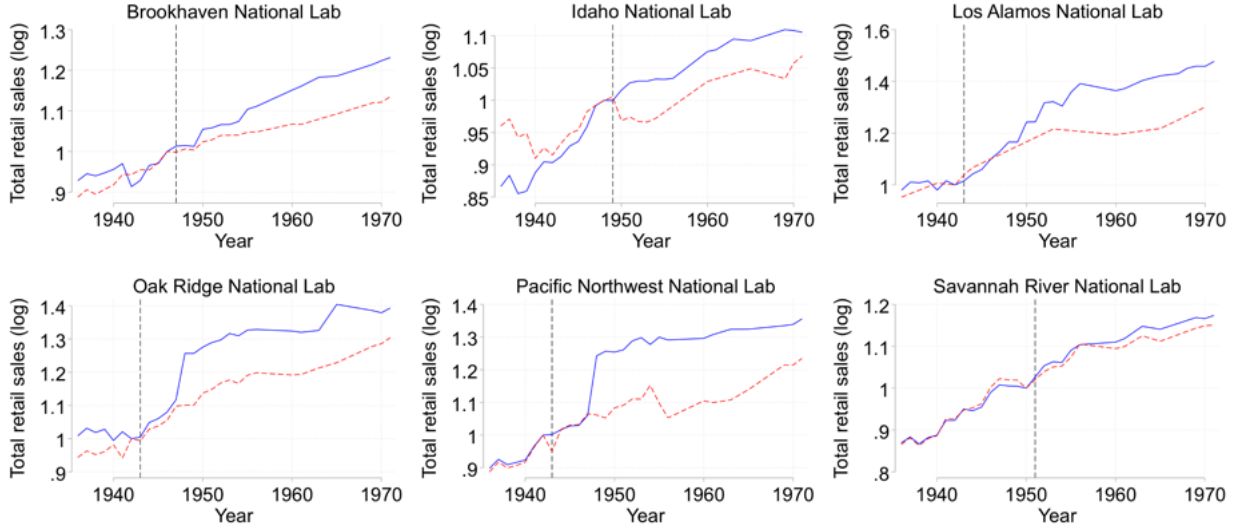
Table A3: Balance check (6 treated counties vs their respective runner-ups):

Variable	Treated	Runner-up	p-val
Adult Population Age (1940)	39.1	40.4	0.219
Log population (1940)	10.38	10.04	0.502
Labor Force Participation Rate % (1940)	57.0	55.5	0.740
Educational attainment (1940)	10.8	11.2	0.623
Wages (current \$) (1940)	718	714	0.977
Share of farmers % (1940)	31.1	40.1	0.420
Share of manufacturing workers % (1940)	11.9	15.4	0.619
Share of whites % (1940)	86.7	91.1	0.663
Share of foreign-born % (1940)	15.2	14.8	0.971

A.5 Time Series Plots of Patents and Retail Sales using Runner-up Locations as Controls



(a) Patents



(b) Retail Sales

Figure A.3: Time series of patents (a) and log aggregate retail sales (b). Blue solid lines indicate treated counties and the red dashed are the runner-up ones. For retail sales the values are normalized to equal 1 at treatment start year.

A.6 Inference: P-Values from the Synthetic Control Plots of Figures 2, 7, and 8

Table A4: P-values of synthetic control regressions. N/A for Berkeley lab since the retail sales series begins three years after its founding.

Lab	Patents	Retail Sales	Household Income
Ames	0.030**	0.316	0.109
Argonne	0.009***	0.031**	0.099*
Berkeley	0.087*	N/A	N/A
Brookhaven	0.021**	0.033**	0.833
Idaho	0.023**	0.756	0.627
Los Alamos	0.033**	0.000***	0.000***
Oak Ridge	0.010***	0.021**	0.012**
PNNL	0.052*	0.026**	0.000***
Princeton Plasma	0.300	0.850	0.700
Savannah	0.333	0.111	0.133
SLAC	0.072*	0.407	0.982
Sandia	0.000***	0.035**	0.758

A.7 Time Series of Retail Sales of Suburban Counties of the Chicago Metro Area

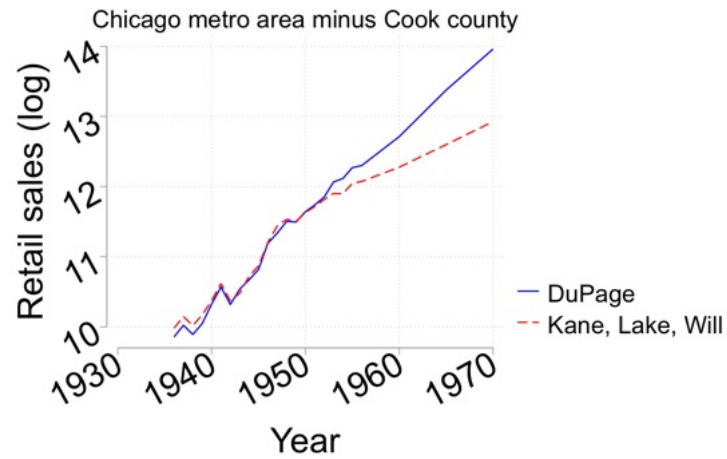
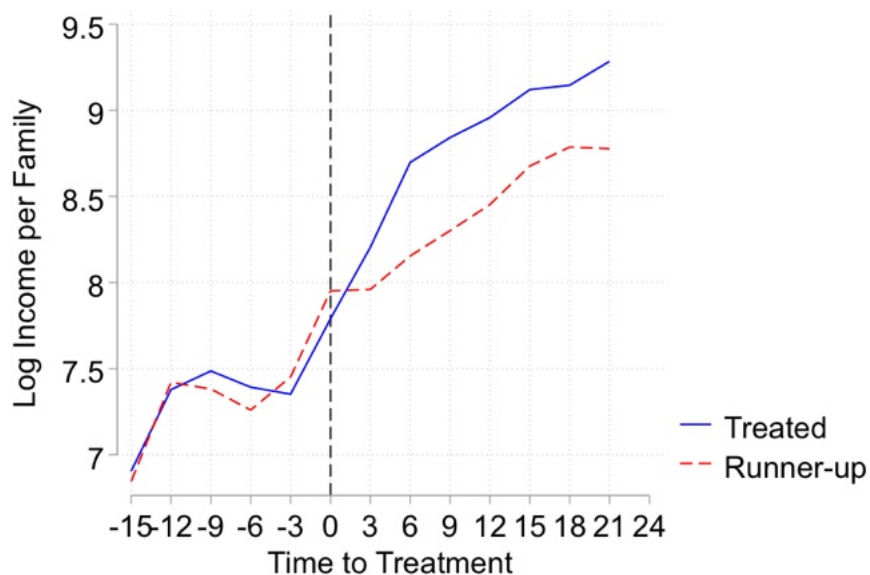


Figure A.4: Retail sales for counties adjacent to the Chicago metro area. Argonne Lab located in DuPage, IL. The red line is normalized so that it equals the blue line in 1940.

A.8 Time Series of Household Income (Treated vs Runner-up Counties)

Figure A.5: Household income rises for treated counties relative to the runner-ups



Notes: The sample includes the following counties and their runner-ups: Idaho Lab, Los Alamos Lab, Oak Ridge lab, Savannah River Lab, Pacific Northwest Lab, and Brookhaven Lab. The data is averaged at three-year intervals.

A.9 Budget Correlates of Brookhaven Lab in Suffolk County, NY

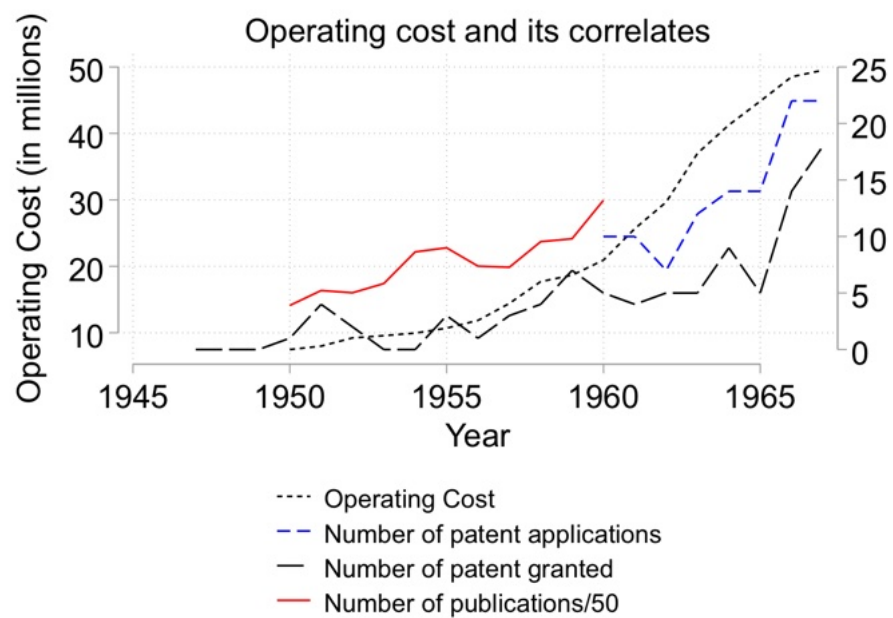


Figure A.6: Lab budget correlates over time for Brookhaven Lab in Suffolk county, NY

A.10 Regression Table for the Plots from Figure 6

$$\text{ipc code}_{ict}^J = \alpha + \beta_1 \times \text{Treated}_c + \beta_2 \times \text{Post}_t + \beta_3(\text{Treated}_c \times \text{Post}_t) + \epsilon_{ict}$$

Table A5: Diff-in-diff results of ipc-code changes in treated counties relative to runner-up counties

VARIABLES	(1) Physics (42.7%)	(2) Chemistry & Metallurgy (24.4%)	(3) Electricity (15.2%)	(4) Performing Operations (12.7%)	(5) Engineering (3.4%)	(6) Human Necessities (1%)	(7) Construction (0.4%)	(8) Textiles & Paper (0.3%)
Treated _c × Post _t	0.109*** (0.033)	0.084** (0.035)	0.090*** (0.029)	-0.044 (0.060)	0.092* (0.049)	-0.195*** (0.057)	-0.109*** (0.040)	-0.027 (0.055)
Observations	1,401	1,401	1,401	1,401	1,401	1,401	1,401	1,401
R-squared	0.051	0.043	0.012	0.009	0.017	0.017	0.028	0.039

Notes: The unit of observation is a patent. Each outcome variable is a dummy variable that indicates if the patent belong to the outcome IPC category. Post equals 1 if time period of patent grant is after lab's founding in the respective county and 0 otherwise. Percentages in parenthesis below the outcome variable names indicate the share of lab patents in each outcome category. Standard errors are two-way clustered at the county year level. *** p<0.01, ** p<0.05, * p<0.1

A.11 County Map of Non-Lab Patents Citing Lab Patents

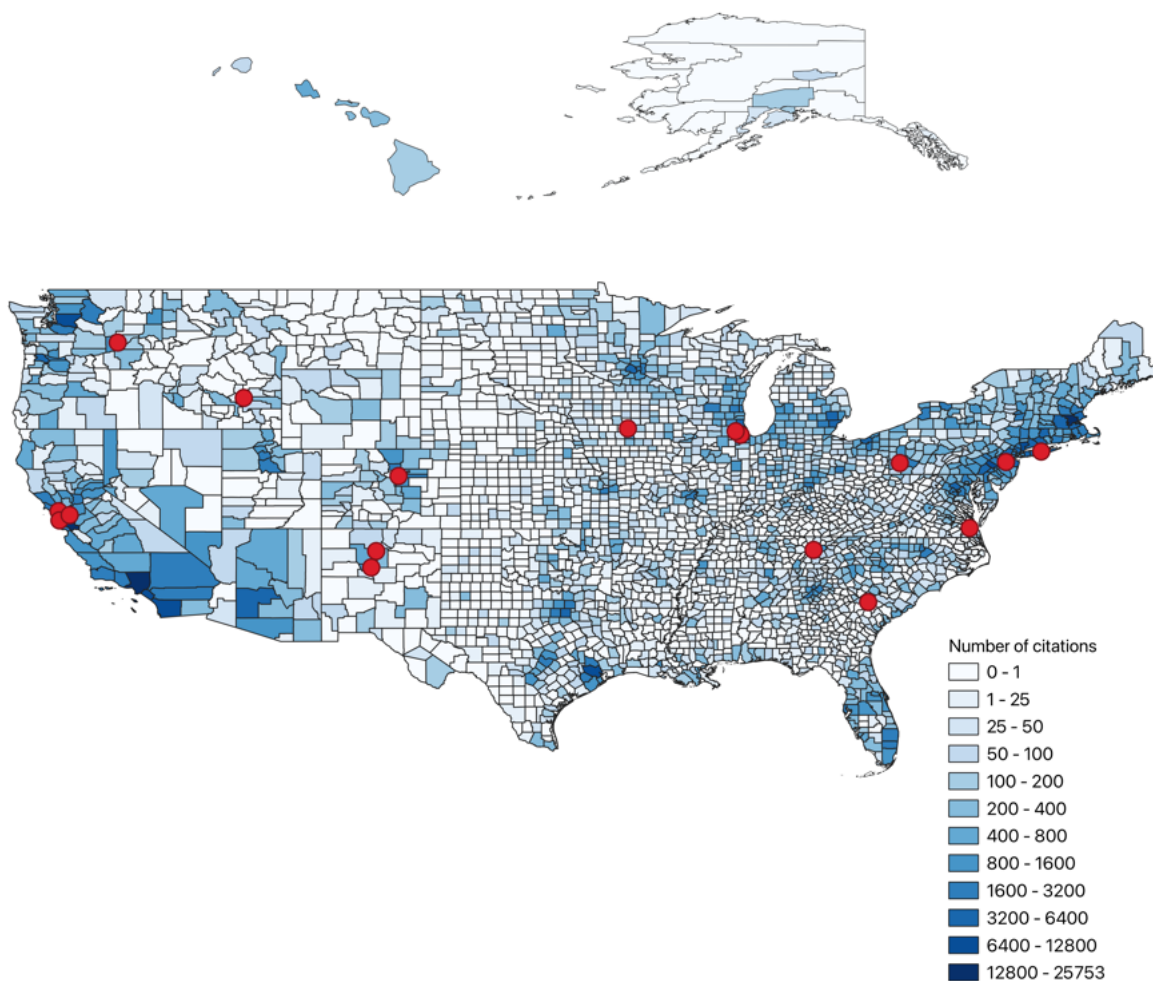
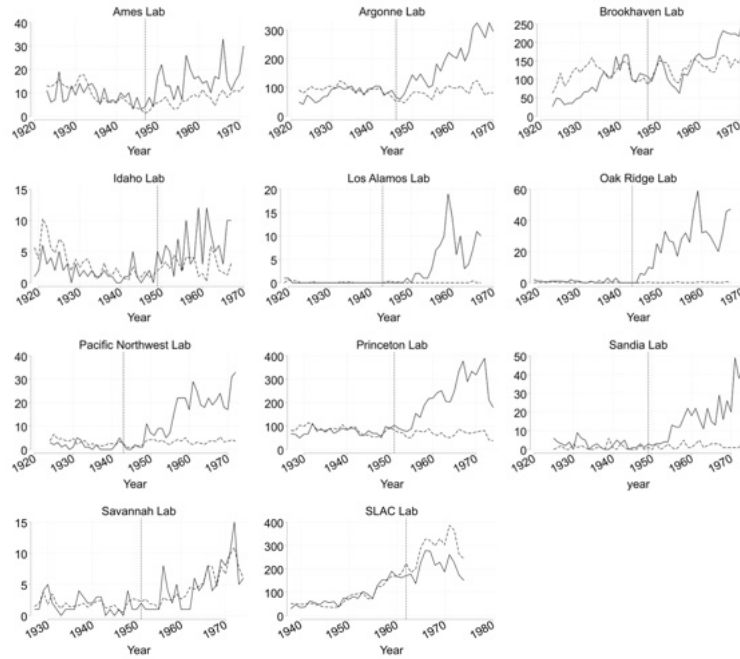
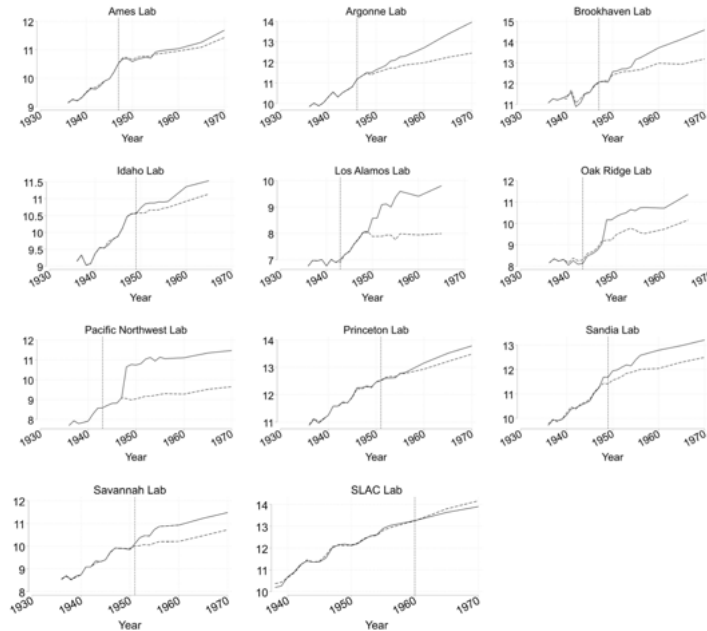


Figure A.7: This sample excludes patents assigned to the labs. Data period: 1932–2024. Red dots indicate lab locations.

A.12 Robustness to Using a Common Set of Predictor Variables



(a) On the y-axis is the number of patents.



(b) On the y-axis is the log of total retail sales

Figure A.8: Synthetic control plots using a common set of predictors for both patents and retail sales. This set includes lagged values of both patents and retail sales taken at two year intervals between 1936 and treatment year.

A.13 Robustness to Using Alternate Donor Pools

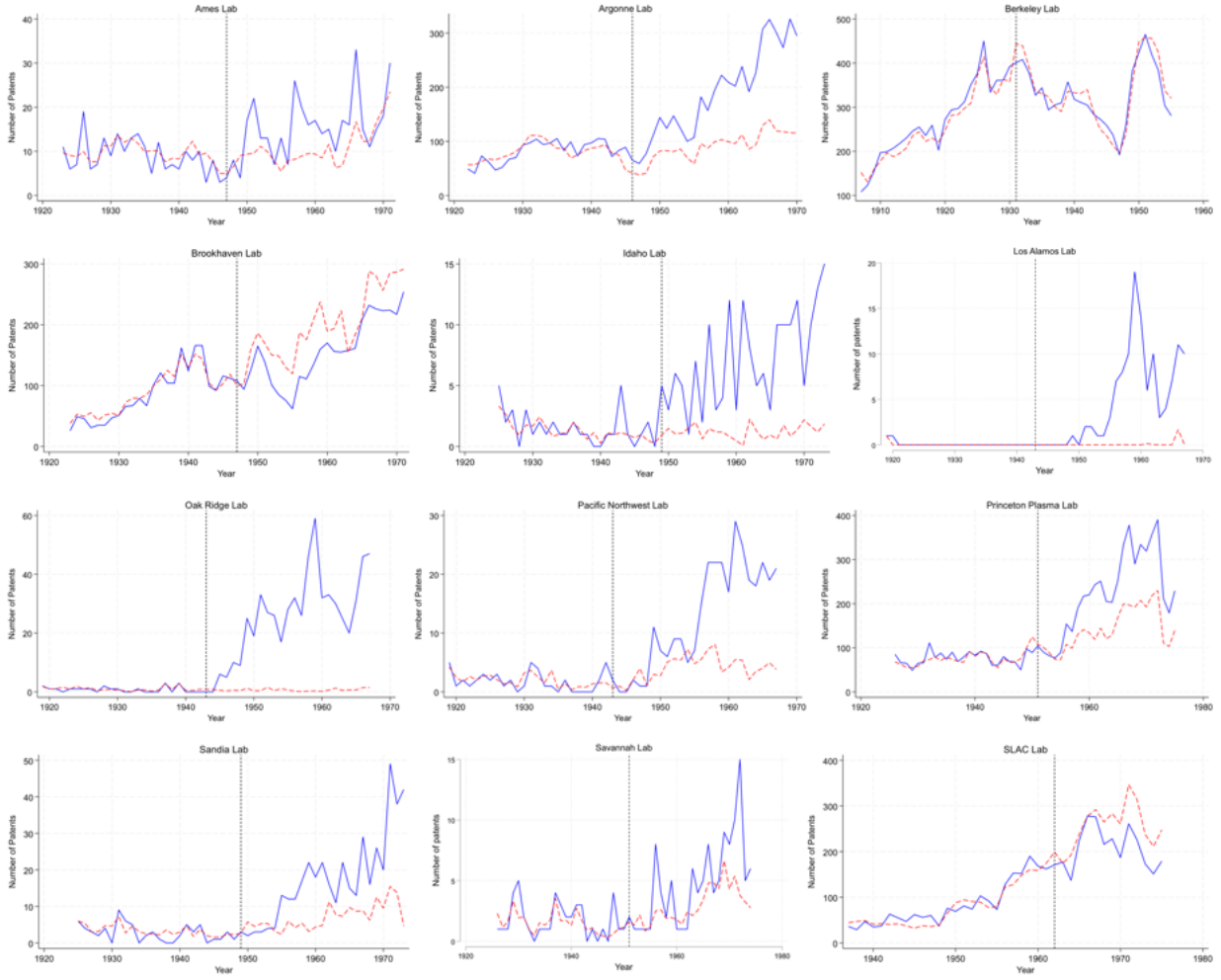
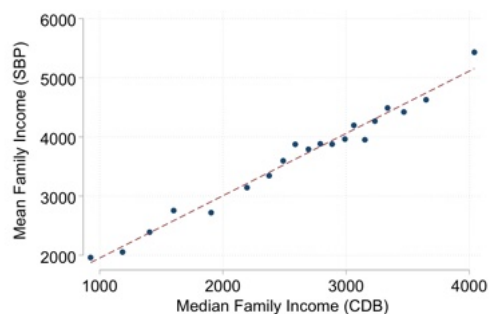
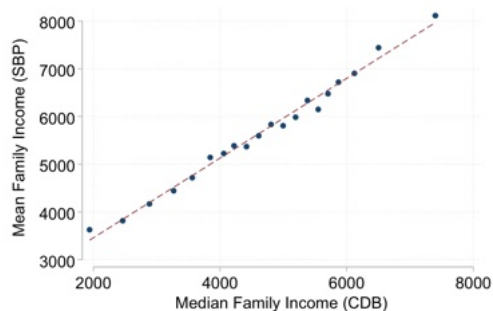


Figure A.9: Synthetic control plots for patents using counties in the treated states as well as those in adjacent states in the donor pool.

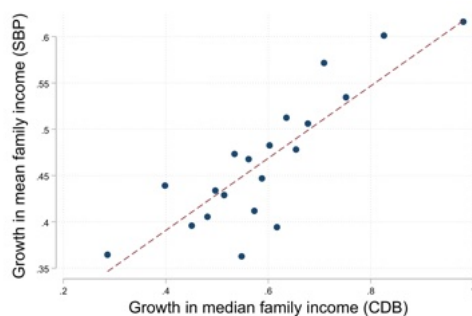
A.14 Validating Data from the Survey of Buying Power



(a) 1950: Binned scatter plot of mean family income from the Survey of Buying Power (SBP) and median family income from the County Data Books (CDB).



(b) 1960: Binned scatter plot of mean family income from SBP and median family income from CDB.



(c) 1950–1960: Binned scatter plot of income growth from SBP and CDB.

Figure A.10: Comparison of family income measures from the Survey of Buying Power (SBP) and County Data Books (CDB), 1950–1960.

A.15 Changes in Patents between Treated Counties and all other Counties in the Country

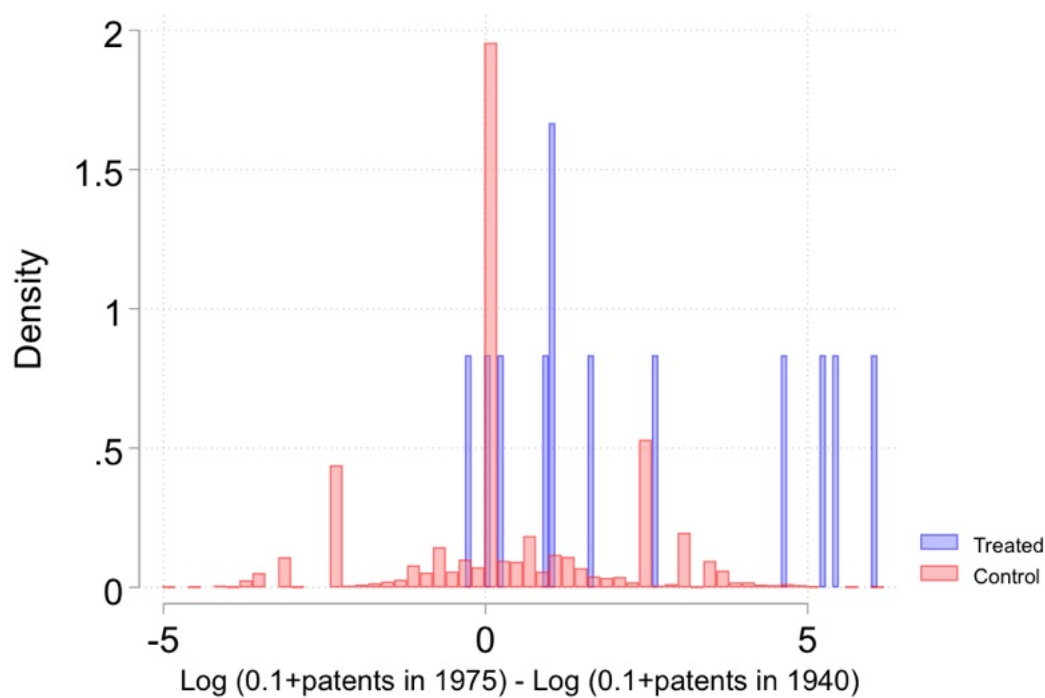


Figure A.11: Histogram of log changes in patents between 1940 and 1975. Treated counties in blue versus all other US counties in red.

A.16 Patenting Rank Changes (Treated versus Runner-up)

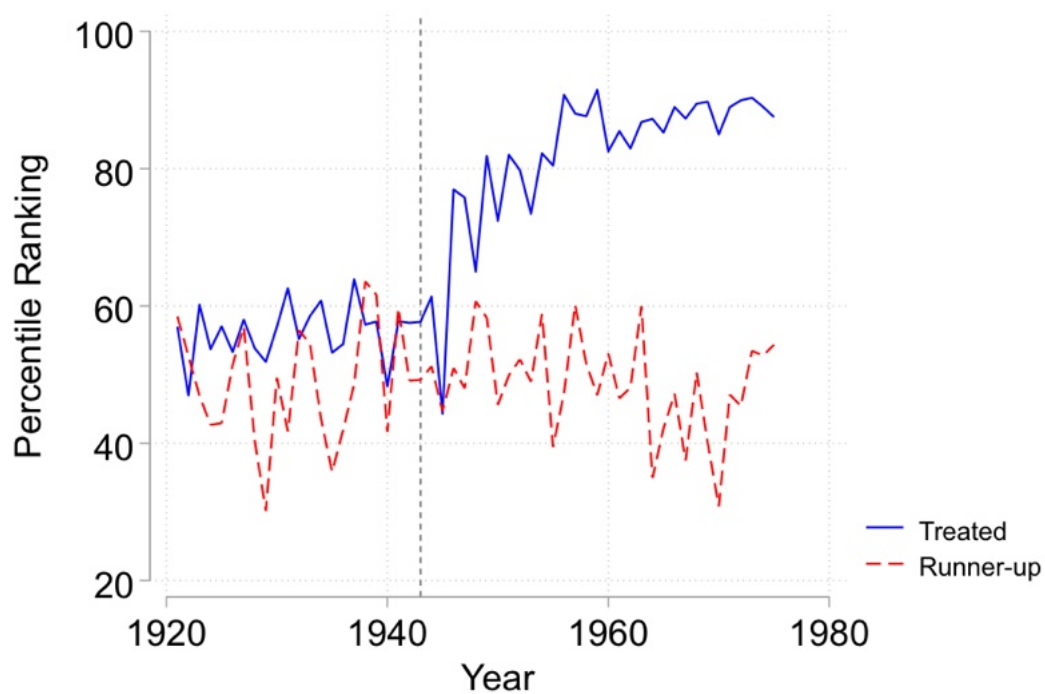


Figure A.12: The y-axis plots the percentile of national ranking in total annual patents. Dashed line is the year the first labs (Oak Ridge, Los Alamos, and Pacific Northwest) in the sample were founded. Others were founded in 1947 (Brookhaven), 1949 (Idaho Lab), and 1951 (Savannah River).

A.17 Validating Our Method to Identify Lab Patents

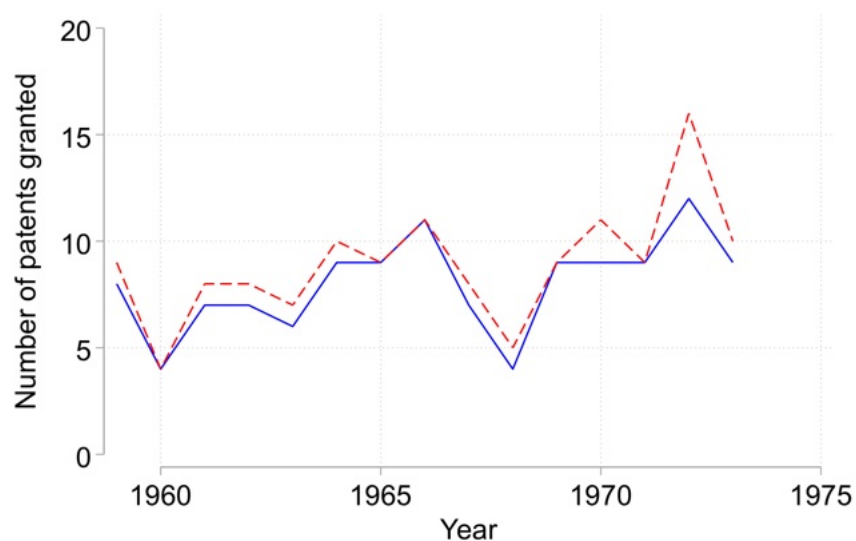


Figure A.13: The solid blue (dashed red) line indicates the number of patents assigned to Argonne Lab (the Atomic Energy Commission). Since the former listing is available only for Argonne Lab, for the remaining ones we identify lab patents as those assigned to their parent organization (the AEC). The former source ranges from 1959 to 1976 while the latter source ranges from 1946 to 1973.