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THE PUBLIC ORIGINS OF AMERICAN INNOVATION

by Andrea Gazzani*, Joseba Martinez*, Filippo Natoli* and Paolo Surico*

Abstract

We study the macroeconomic effects of government-funded and privately funded innovation on postwar US productivity and economic growth. Using newly digitized data that allow us to distinguish innovations by funding source and ownership, we document systematic differences in how public and private innovation translate into aggregate outcomes. Government-funded but privately owned patents—though accounting for only about 2 per cent of total patenting—explain roughly 20 per cent of medium-term fluctuations in total factor productivity and GDP growth and are associated with strong spillovers to business-sector R&D and investment. Privately funded patents also contribute to aggregate fluctuations, but with smaller effects, while publicly owned patents display muted average impacts despite being disproportionately represented among highly disruptive innovations, particularly in health and biotechnology. Across federal agencies, innovations funded by the NIH and NSF exhibit the strongest links to subsequent productivity growth, and research institutes and universities outperform for-profit firms in converting public funding into aggregate gains. Taken together, our results highlight how the institutional design of public support for innovation shapes medium-term productivity dynamics and plays a central role in sustaining US economic growth.

JEL Classification: E32, E22, O41.

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"New impetus must be given to research in our country. Such impetus can come promptly only from the Government. We cannot expect industry adequately to fill the gap. Industry will fully rise to the challenge of applying new knowledge to new products. The commercial incentive can be relied upon for that. But basic research is essentially noncommercial in nature. It will not receive the attention it requires if left to industry."

– Vannevar Bush (1945a, Chapter 3, p. 16)

1 Introduction[1]

In 1944, as the war was nearing its end, President Roosevelt asked the chief science advisor and coordinator of U.S. scientific research efforts during World War II, Vannevar Bush, to recommend how the U.S. government could support scientific research in the postwar era. Roosevelt's objective was to sustain the scientific momentum generated during wartime and ensure that scientific progress would benefit public health, economic growth, and national security in peacetime.

Bush's reply laid the foundation for postwar American innovation. His vision rested on three pillars defining complementary roles: (i) the government funds research in areas of public interest; (ii) universities and research institutes preserve the intellectual freedom necessary for major discoveries; and (iii) the private sector translates new knowledge into commercial applications. Bush (1945a)'s recommendations led to the creation of the National Science Foundation (NSF), the expansion of the National Institutes of Health (NIH), and the emergence of an innovation ecosystem characterized by close interaction between government, academia, and industry.

In this paper, we assess the macroeconomic impact of the postwar American innovation model through the lens of Bush (1945a)'s architecture. Leveraging the detailed categorization in Gross and Sampat (2025) of the universe of U.S. patents granted since 1950, we construct

[1] We are grateful to Juan Antolin-Diaz, Pierre Azoulay, Katharina Bergant, Antonin Bergeaud, Steve Davis, Gary Dushnitsky, Andrea Galeotti, Luca Gambetti, Yuriy Gorodnichenko, Pierre-Olivier Gourinchas, Daniel Gross, Sergei Guriev, Òscar Jordà, Divya Kirti, Karel Mertens, Stelios Michalopoulos, Silvia Miranda-Agrippino, Kyle Myers, Nicholas Nelson, Marcel Olbert, Fabio Panetta, Elias Papaioannou, Dimitris Papanikolaou, Lucrezia Reichlin, Jim Stock, Ludwig Straub, Chris Tonetti, Emil Verner, Heidi Williams, Jonathan Yiangou, Ekaterina Zhuravskaya, and seminar participants at the BI Norwegian Business School, Harvard University, Boston College, Brown University, IMF, EIEF, CEPR Paris Symposium 2025, French Ministry of Finance, German Ministry of Finance, UK DSIT, European Commission and DIW for very useful comments and suggestions. Paolo Surico gratefully acknowledges financial support from the Economic and Social Research Council (Grant ES/Y002490/1).

novel time series of innovation activity that distinguish between patents that are: (i) funded by the government but privately owned; (ii) privately funded and owned; (iii) funded and owned by the public sector.

Our empirical strategy complements the two dominant approaches in the innovation and business-cycle literature. Micro studies using patent-level data exploit cross-sectional variation that identifies partial-equilibrium elasticities, but do not capture the general-equilibrium effects that are likely to shape macroeconomic outcomes. Macro analyses using national statistics estimate the economy-wide effects of technology shocks, but cannot disentangle the underlying transmission channels masked at the aggregate level. Our approach offers a third, complementary way: we exploit granular patent data in a bottom-up framework that aggregates innovation by funding source, agency, and innovator type into time series suitable for macroeconomic analysis. This allows us to quantify aggregate effects while tracing their heterogeneous transmission.

After documenting patterns of patent composition by funding source, we link aggregate outcomes to movements in innovation activity that are not confounded by patenting in other groups, R&D spending, or broader macroeconomic dynamics, including GDP, stock prices, and identified fiscal and monetary policy shocks. Controlling for a rich set of business-cycle indicators ensures that the remaining variation reflects fluctuations specific to innovation rather than aggregate conditions. The dynamic correlations we uncover exhibit the hallmark of technological disruption, moving quantities and prices in opposite directions (Miranda-Agrippino et al., 2025).

Our analysis uncovers several new empirical regularities. Publicly funded but privately owned patents display the strongest medium-term associations with GDP and TFP growth: although only 2% of total patents, they account for roughly 20% of aggregate fluctuations and sizable spillovers to private investment, R&D spending, real wages, and consumption. Privately funded patents exhibit weaker comovements, while government-funded and owned patents show insignificant average correlations. However, this average effect masks important heterogeneity: fully public patents include a relatively large share of highly disruptive innovations, whose estimated effects exceed those of other categories. Overall, our results suggest that the returns of government-funded innovation could be twice as large as those of fully private innovation.

Turning to federal agencies, industries, and research fields, a clear ranking emerges. Among government-funded but privately owned patents, NIH and NSF support the most successful innovations in terms of their medium-term associations with TFP, GDP, and business-sector R&D, followed by the Department of Energy and NASA. The contribution of the Department of Defense is statistically significant but smaller. Among publicly funded and publicly owned patents, innovations in healthcare and biotechnology, especially those supported by NIH, are associated with far larger medium-term gains in GDP and TFP than fully private patents.

Regarding the primary actors, research conducted by non-profit organizations is more strongly associated with a large and sustained rise in aggregate productivity than innovation by for-profit entities, with universities and research institutes performing best on a per-patent basis. Among private firms, start-ups—and to a lesser extent venture capital-backed firms—are more strongly linked to subsequent TFP and GDP growth than established companies, but only when backed by public funding: absent government support, their productivity advantage disappears.

Taken together, our findings are consistent with Bush (1945a)'s vision of an ecosystem in which the public sector leads investment in basic research—primarily through universities and research institutes—while the private sector specializes in commercialization. Government funding supports high-risk, high-spillover research that would otherwise be underprovided, crowding in private R&D and capital investment by start-ups and venture capital-backed firms. In this ecosystem, government-funded but privately owned innovations emerge as the main conduit through which fundamental research translates into sustained productivity growth. This interpretation aligns with the classic insights of Nelson (1959) and Arrow (1962) on the role of government in knowledge production. Appendix C formalizes this intuition in a simple growth framework and uses our empirical estimates to quantify the implied social returns to innovation.

Concrete examples illustrate the outsized impact that government-funded but privately owned innovations can have on the economy. NIH support enabled Fire and Mello's discovery of RNA interference (patented in 2003). NSF funding at Stanford supported the research that produced PageRank (patented in 1998), the core algorithm underlying Google's search engine. DARPA- and NSF-backed advances in signal processing led to Qualcomm's CDMA patent (1992), foundational to modern mobile communications. More recently, federal funding contributed to breakthroughs such as induced pluripotent stem cells, CAR-T therapies, and CRISPR–Cas9 genome editing, illustrating how public funding paired with private ownership can generate large social returns.

At the same time, public funding has also supported unsuccessful projects. The Aircraft Nuclear Propulsion program (1946–1961) absorbed substantial resources without producing a viable technology. NASA's X-33 reusable spaceplane and DARPA-funded early autonomous aerial systems were abandoned as technically and economically unfeasible, while Department of Energy support for firms such as Solyndra and Fisker Automotive resulted in high-profile bankruptcies. Together, these examples show how selective attention to celebrated successes like Google or salient failures like Solyndra may yield very different conclusions. This motivates our approach, which moves beyond anecdotal evidence to quantify the average macroeconomic effects of government-funded innovation across the full distribution of outcomes.

Related Literature. A set of influential empirical studies using patent-level data, such as Acemoglu et al. (2016), Cohen et al. (2016), Kogan et al. (2017), Kline et al. (2019), Azoulay et al. (2019), Kelly et al. (2021), Myers and Lanahan (2022), Gross and Sampat (2023), Kalyani et al. (2025) and Bergeaud et al. (2025) levers sharp exogenous variation from event studies to identify the direct, partial equilibrium effects of technological progress on firm-level or sectoral outcomes. We complement and generalize the findings from this important strand of research by eliciting the *aggregate* connection between innovation, productivity and GDP in the U.S. economy, paying particular attention to the role of government funding and private ownership.

A long-standing tradition in macro —from Blanchard and Quah (1989) to Galí (1999), Christiano et al. (2003), Francis and Ramey (2005), Basu et al. (2006), Fernald (2012), and recently Miranda-Agrippino et al. (2025), Aghion et al. (2025)— studies the effects of technology shocks on long-run output using time series drawn solely from national accounts. While we also focus on aggregate fluctuations, we exploit rich patent-level data to construct new time series of innovation activity disaggregated by funding source and ownership. This enables us to shed light on both the transmission channels and the underlying drivers of technical progress.

A growing literature explores how fiscal policy can foster productivity. Janeway (2012), Mazzucato (2013), Antolin-Diaz and Surico (2025), Fieldhouse and Mertens (2023b), Dyèvre (2024), Fornaro and Wolf (2025) focus on public R&D, while Bloom et al. (2019), Akcigit et al. (2021), Akcigit et al. (2022), Dechezleprêtre et al. (2023), Cloyne et al. (2025) analyse tax incentives. We contribute to these efforts by studying the medium-term impact of publicly funded innovation, linking different federal agencies, industries and innovators —such as universities, research institutes, start-ups and VC-backed firms— to aggregate productivity.

Structure of the Paper. Section 2 describes the patent data and the empirical framework used to isolate unanticipated variation in innovation activity. Section 3 reports the main results across the three patent groups, while Section 4 provides a comprehensive sensitivity analysis to alternative identification strategies and empirical models. Section 5 studies the role of basic research in publicly versus privately funded innovation. Section 6 examines federal agencies, industries and research fields to shed light on underlying mechanisms. Section 7 explores the role of research institutes, universities, start-ups and incumbents. Section 8 concludes, while the appendices contain additional analyses and selected case studies.

2 Data and Empirical Framework

This section describes the data and econometric framework used in the empirical analysis. We first present the main data sources and summarize the key characteristics of the three innovation categories, which combine information on government interest and patent ownership. We then examine the role of federal agencies in supporting public-interest innovation and conclude by outlining the time-series approach and identification strategies used to link government-funded innovation to macroeconomic outcomes.

2.1 Patent Classification by Government Interest

Our analysis draws on the *Government Patent Register* (GPR) compiled by Gross and Sampat (2025), which combines information on government interest and assignees for all U.S. patents granted since 1890. The GPR classifies patents into three categories based on government involvement: (i) patents funded by the government but assigned to a private (non-federal) entity, labeled *public–private* ("license" in GPR);[2] (ii) patents both funded and owned by private entities, labeled *private–private*; and (iii) patents funded and owned by the government, labeled *public–public* ("title" in GPR).[3] The GPR also identifies the federal agency funding each patent. By combining multiple administrative sources (see Table 1 in Gross and Sampat, 2025), the GPR reduces measurement error arising from incomplete reporting of government interest.[4]

Our sample covers 1950–2015. Before 1950, *public–private* patenting is sparse, key macroeconomic controls are unavailable at quarterly frequency, and after 2015 patent registration delays become severe.[5] Throughout, we use the filing date to time patents, following Miranda-Agrippino et al. (2025), as it provides the earliest observable indication of innovative activity and mitigates anticipation concerns.[6]

Other Data Sources. We complement the GPR patent data with several sources. Assignee characteristics are provided by *PatentsView*, while measures of patent *importance* and *reliance on science* used in Section 5 are drawn from Kelly et al. (2021) and Marx and Fuegi (2020, 2022). We also incorporate market-valuation measures from Kogan et al. (2017), extended to non-listed firms following Kline et al. (2019). Sectoral analyses rely on USPTO CPC Master Classification Files, information on start-ups and venture capital-backed firms comes from Ewens and Marx (2024), and aggregate variables rely upon Antolin-Diaz and Surico (2025). Appendix A reports data sources and variable construction.

[2] Universities and research institutes are prominent assignees in this category.

[3] "Title" patents list a government agency as assignee, implying agency ownership, sometimes alongside private entities.

[4] A residual "unknown" category arises from conflicting government-interest records, particularly after 1980, following the digitization of patent records and the Bayh–Dole Act. We classify these cases using a transparent rule: patents indicating government license rights or private development are treated as *public–private*, while the remainder are classified as *public–public*. Appendix A details this procedure and shows that excluding these cases does not affect our results.

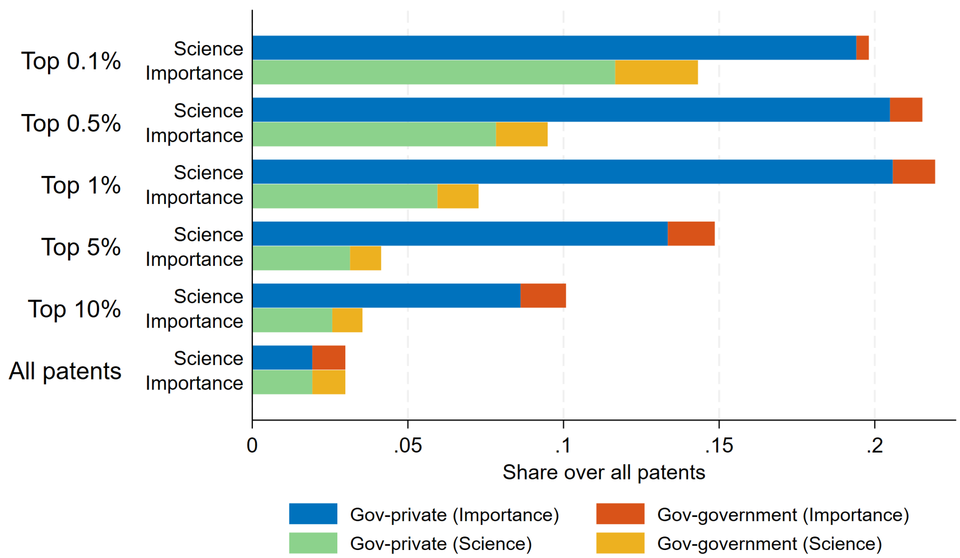
[5] Although the GPR extends to 2020, post-2015 patent counts decline sharply due to reporting lags.

[6] Patent applications at the US Patent office are not immediately public upon filing, but typically become publicly available after an intermediate period, while examination and eventual grant can take several years. Because the filing date marks the moment when the underlying invention is formally disclosed to the patent office and legally established, it constitutes the most appropriate timing variable, as it mitigates concerns related to anticipation effects.

2.2 Descriptive Statistics

The GPR database covers over 7 million granted patents (Table A1). Patents with no public interest account for about 97% of the total; among the remainder, 2% are government-funded but privately owned (*public–private*) and 1% are both funded and owned by the government (*public–public*). While the number of *public–public* patents has remained broadly stable, *public–private* patents have trended upward, partly reflecting the Bayh–Dole Act of 1980, which allowed small businesses and non-profits to retain ownership of federally funded inventions (Figure A1). Publicly funded patents also tend to be more disruptive and more reliant on basic science than privately funded patents, consistent with the government's role in supporting fundamental research.[7]

Figure 1: Patents *Importance* and *Reliance on Science*



Note. Share of public interest patents for different levels of basicness from Kelly et al. (2021) and of reliance on science, measured by the number of citations of scientific papers from Marx and Fuegi (2020, 2022). The bottom bar reports the unconditional share of public patents to total patents. Sample: quarterly data 1950:Q1-2015:Q4.

In Figure 1, we examine the composition of disruptive patents. Although all publicly funded innovation accounts for only about 3% of all patents, their share rises sharply among the most disruptive ones. Government-funded innovation represents over 9% (22%) and 14% (20%) of the top 0.5% and top 0.1% most disruptive patents, respectively, based on the

[7] Our results are robust to pooling all publicly funded patents into a single category (Appendix B) and to controlling for major institutional changes such as TRIPS in 1995. Following Kelly et al. (2021), *importance* weights forward and backward textual similarity, while *reliance on science* measures cited scientific publications (Marx and Fuegi, 2020, 2022).

importance indicator of Kelly et al. (2021) (the reliance on science of Marx and Fuegi, 2020, 2022).[8] In Section 5, we show that more disruptive patents are linked to larger subsequent gains in GDP and TFP.

Across federal agencies, the Department of Defense (DoD) accounts for the largest volume of public-interest patents, followed by NIH, DoE, NSF, and NASA (Table A1, Panel D), but funding structures differ markedly. NIH and NSF primarily fund privately owned innovations, whereas NASA, DoD, and DoE retain larger public–public shares. Over time, DoD's public-ownership share declined from nearly 100% in 1950 to about 20% in 2015, while NIH and NSF became increasingly prominent after the 1970s (Figure A1, Panel C). Appendix A reports additional statistics, and Appendix D provides illustrative examples.

2.3 Time-series Approach

Our goal is to provide novel macroeconomic correlations between GDP, aggregate productivity and innovation originating from (i) *public-private*, (ii) *private-private*, and (iii) *public-public* patents. To achieve this, we use local projections (LP; Jordà, 2005) and a rich set of controls that could otherwise confound the association between patent activity and macroeconomic conditions (Miranda-Agrippino et al., 2025). In our baseline specification, we estimate a set of regressions for each horizon h:

$$\Delta_h y_{t+h} = \alpha_h + \beta_h x_t + \boldsymbol{\gamma}_h \mathbf{w}_t + \upsilon_{h,t}, \qquad h = 0, 1, ..., H \tag{1}$$

where $\Delta_h y_{t+h} = y_{t+h} - y_{t-1}$ is the outcome of interest expressed in long difference to mitigate the small sample bias in LPs (Jordà and Taylor, 2025), α is a constant, x_t is the number of granted patents that are filed in quarter t for each of the three categories, and β_h captures the dynamic effects of our driving variable or the Impulse Response Function (IRF) at the horizon h. The vector $\mathbf{w}_t$ contains a set of controls, including four lags of y_t, x_t, GDP, TFP, investment, stock prices, the T-bill, public and private R&D spending, and patent filing in the other groups. These variables capture the business cycle, expectations on future economic conditions, and monetary policy, among others. As developing innovations takes time, the

[8] This share approaches 10% among patents narratively classified as historically important by Kelly et al. (2021).

information set spanned by the lags of our rich set of controls helps us to isolate unanticipated changes in x_t.

In Table 1, we test for any possible remaining endogeneity in our implicit shock $\varepsilon_t = x_t \perp \mathbf{w_t}$.[9] Panel A reports the results for the main patent categories, while Panel B focuses on individual agencies. We reject the null that the control set has no predictive power for patenting activity in the three funding–ownership groups, x_t, although the relevance of macro controls varies across agencies. Second, using the test for sufficient information proposed by Forni and Gambetti (2014), we cannot reject the orthogonality of ε_t to neither forecasters' projections nor to the macroeconomic shocks identified by early contributions on government spending (Ramey and Zubairy, 2018), taxes (Romer and Romer, 2010; Mertens and Ravn, 2013) and monetary policy (Romer and Romer, 2004).[10] In Appendix B1, we further show that —unlike R&D expenditures— patent applications are virtually a-cyclical, thereby fulfilling our desire of using a driving variable that is unrelated to business-cycle conditions.[11]

Our baseline estimates rely on conditional correlations between GDP, TFP, and innovation, controlling for key macroeconomic dynamics. This approach is intentionally transparent and easy to interpret. Yet, to ensure that our findings are not driven by this specific choice, we assess their robustness using several state-of-the-art time-series strategies. In Section 3.1, we present the baseline results, while in Section 4, we show that our main findings remain virtually unchanged using instead a wide range of alternative identification strategies, including instrumental variables (based upon the measures proposed by Fieldhouse and Mertens, 2023b; Miranda-Agrippino et al., 2025), the narrative identification of legislative and regulatory changes (in the tradition of Romer and Romer, 1989, 2010; Ramey and Shapiro, 1998), the max-share variance (as in Uhlig, 2003), among many other specifications.

[9] In the words of Montiel Olea et al. (2025): *"In an LP, we are estimating impulse responses with respect to a shock that is defined as the residual from projecting the impulse variable on the control variables."*

[10] We employ an extension of the monetary policy series until 2007 from Coibion et al. (2017). Furthermore, we cannot reject the orthogonality of ε_t to factors extracted from the FRED-QD large, quarterly macroeconomic database.

[11] We employ LPs rather than VARs as baseline model because we are interested in studying the medium-run effects of perturbations that exert delayed effects. In this setup, extrapolating VARs from the first autocovariance moments in the data may lead to severe biases (Plagborg-Møller and Wolf, 2021; Montiel Olea et al., 2025), although in Section 4 we will verify that our baseline estimates are not overturned using a VAR. Inference is based on Newey and West (1987) standard errors.

Table 1: The Sufficient Information Test of Forni and Gambetti (2014).

Panel A: *p-values from F-test of joint significance — by patent type*

	Test for controls' explanatory power	*Test for implied patent shocks' orthogonality*			
Variable	(i) LP specification	(ii) Military spending shocks	(iii) All shocks	(iv) SPF	(v) Shocks + SPF
Total patents	0.001	0.897	0.976	0.154	0.384
Private-private	0.001	0.834	0.976	0.164	0.402
Public-private	0.008	0.507	0.996	0.580	0.909
Public-public	0.038	0.787	0.564	0.766	0.614

Panel B: *p-values from F-test of joint significance — by agency*

	Test for controls' explanatory power	*Test for implied patent shocks' orthogonality*			
Variable	(i) LP specification	(ii) Military spending shocks	(iii) All shocks	(iv) SPF	(v) Shocks + SPF
DoD	0.000	0.514	0.558	0.598	0.182
NASA	0.167	0.498	0.895	0.098	0.825
NIH	0.014	0.557	0.809	0.270	0.771
NSF	0.638	0.310	0.409	0.175	0.318
DoE	0.161	0.237	0.682	0.942	0.587

Note. Column (i) reports p-values for the F-test of joint significance on the coefficients associated to the set of controls from our baseline local projection model, excluding patents' own lags and the constant. Columns (ii)–(v) report p-values from an orthogonality test where the implied shocks ε_t are regressed on external information (contemporaneous and two lags). "Military spending shocks" are from Ramey and Zubairy (2018). "All shocks" also include the monetary policy shocks of Romer and Romer (2004) updated using Coibion et al. (2017), personal and corporate income tax changes from Mertens and Ravn (2013) following Romer and Romer (2010). SPF stands for Survey of Professional Forecasters: one- and four-quarter-ahead forecasts for the unemployment rate, the GDP deflator, real non-residential investment, and real corporate net profits, as in Miranda-Agrippino et al. (2025).

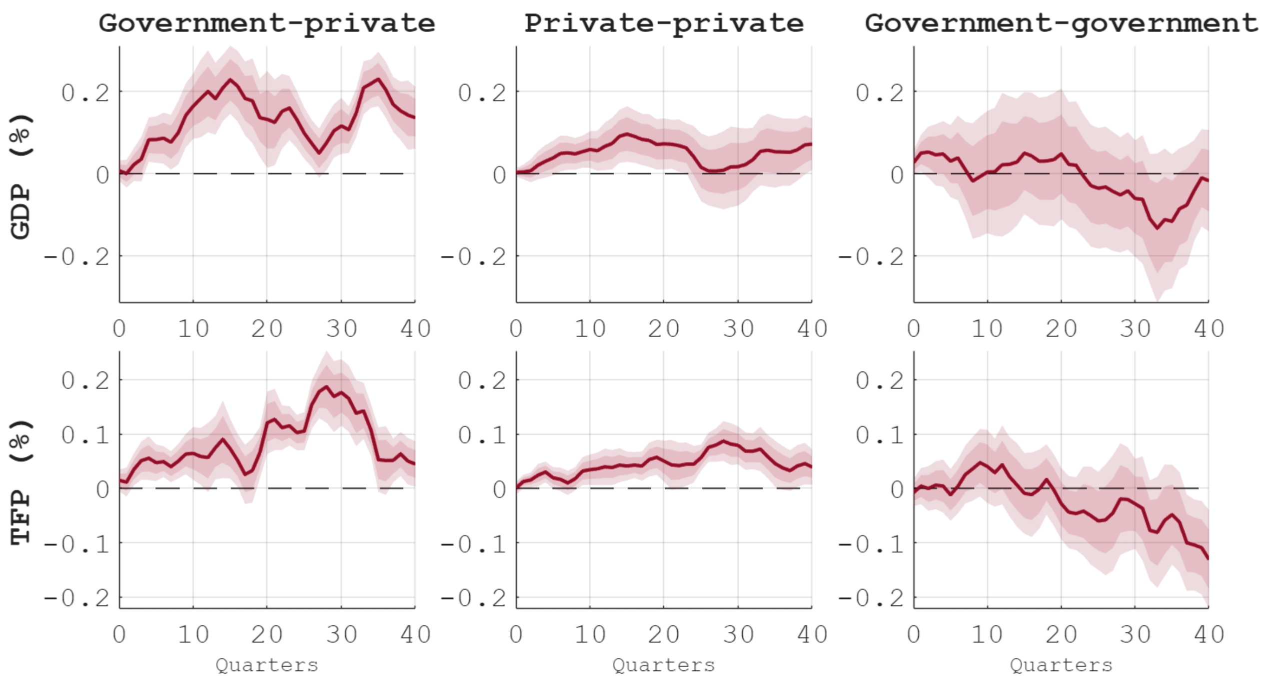
3 The Macro Impact of Publicly Funded Innovation

This section examines the macroeconomic effects of government-funded versus privately funded innovation using the empirical framework presented in equation (1) and the patent classification described in Section 2.1. We begin by estimating the dynamic responses of GDP and TFP, and then turn to the effects on private R&D expenditure, capital investment, wages, and consumption. A variance decomposition quantifies the contribution of government-funded innovation to short-term and medium-term fluctuations in GDP and TFP. We conclude with back-of-the-envelope calculations comparing the output and private R&D multiplier of public and private spending on innovation. The next section presents alternative identification strategies—including instrumental-variable and narrative approaches—and additional empirical specifications that corroborate these results.

3.1 Main results

In this section, we use local projections to estimate the dynamic association between innovation activity and several key macroeconomic variables, using the patent categorization presented in Section 2.1. The first column of Figure 2 records the responses of GDP (top row) and TFP over a 40 quarters horizon to an unanticipated increase in public-private patents, while the second (third) column refers to their private-private (public-public) counterpart. Shaded areas represent 68% and 90% confidence bands, respectively. To account for differences in group size, shocks are normalized so that each corresponds to a 1% increase in total patents on impact.

Figure 2: The Dynamic Effects of Innovation on GDP and TFP



Note. The figure displays the dynamic effects of innovation shocks in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita private GDP and (log) TFP . The estimation by local projections follows eq.(1). The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes four lags of the patent group shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

Three main results emerge from Figure 2. First, public-private patents exhibit the largest medium-term effects on both output and productivity. The responses are delayed—consistent with the gradual diffusion of new knowledge—and highly significant, peaking at around 0.2% after 8 to 9 years. Second, while privately funded innovations also have statistically significant effects, their impact on GDP and TFP is smaller and does not exceed 0.1%.[12] Third, patents

[12] Two bootstrap-based tests (Sup-Wald and Cramér–von Mises) reject the null of equal effects between public-private and private-private patents for both GDP and TFP. Appendix B3 reports the differences in IRFs across the two groups, which are economically large and highly statistically significant.

funded and owned by the public sector display, on average, no significant positive effects. As we will show in Section 5, however, this average masks substantial heterogeneity: the most disruptive public-public patents are associated with the largest responses of aggregate output and productivity.

In Figure 3, we extend the analysis to investment, consumption, and wages. The ranking across patent categories mirrors that in Figure 2. More specifically, in Panel A, we show that an unanticipated rise in public-private patent activity is followed by a sustained expansion in private R&D expenditure (first row) and private capital investment (second row). By contrast, the spillovers to investment from purely private innovation are small and statistically insignificant. In Panel B, we report the effects on standards of living. Only public-private patents are associated with large, persistent, and statistically significant increases in real wages (third row) and real consumption (fourth row). These responses stand in contrast to the weaker and less persistent effects of private-private patents and the insignificant average associations for patents funded and owned by the public sector.

3.2 Contribution to Aggregate Fluctuations and Economic Growth

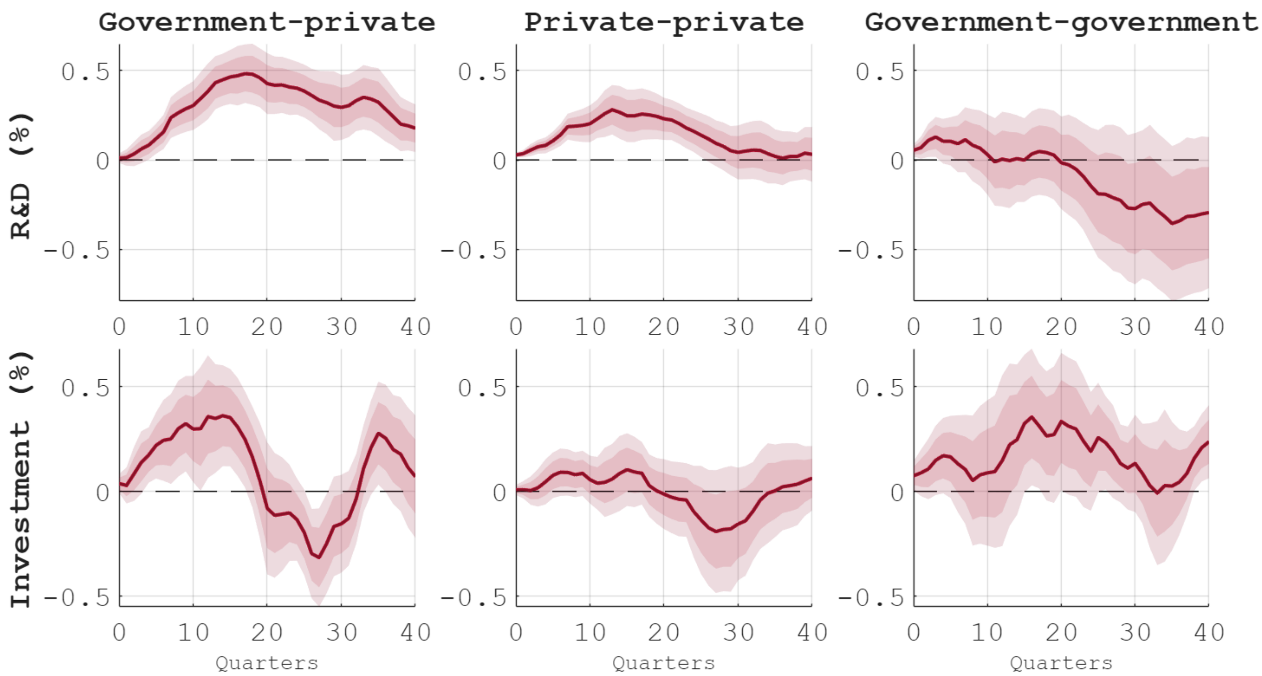
The previous section showed that public–private innovations are most strongly associated with medium-term movements in aggregate productivity and output. We now quantify the contribution of unanticipated surges in government-funded but privately owned patenting to aggregate fluctuations and growth using the R^2 decomposition for local projections proposed by Gorodnichenko and Lee (2020). We conduct two exercises: a forecast error variance decomposition that measures the share of output and productivity forecast variance explained by these shocks at each horizon, and a historical decomposition of TFP growth at an eight-year horizon ($h = 32$), capturing their contribution to medium-term productivity growth beyond business-cycle frequencies.[13]

In Figure 4, we report the share of forecast error variance in GDP (top row) and TFP (bottom row) explained by each innovation shock. Public–private innovation shocks (left

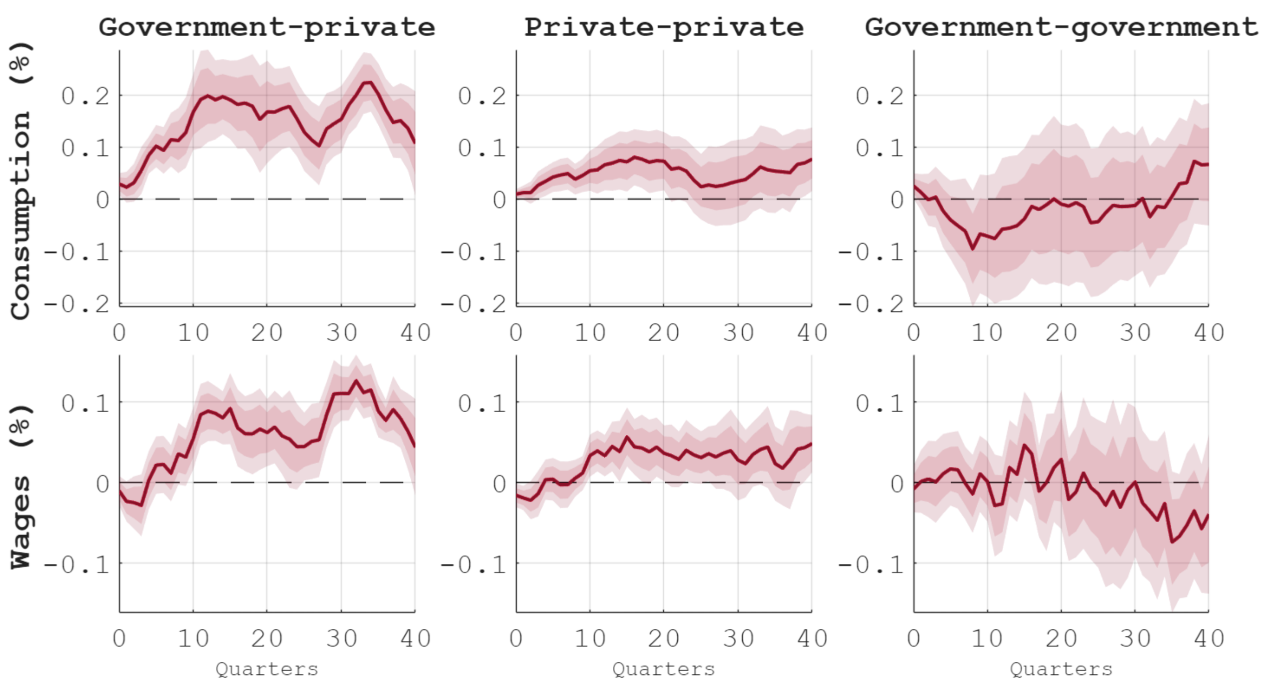
[13]Eight years is a standard choice in the empirical macro literature when focusing on frequencies beyond the business-cycle (Christiano and Fitzgerald, 2003). The historical decomposition combines shocks implied by the local projection model with estimated impulse responses following Gorodnichenko and Lee (2020). In Appendix F, we report a formal and detailed explanation of this procedure. We are not aware of other applications of LP methods that either estimate a conventional historical decomposition or generalize it to different horizons/frequencies.

Figure 3: The Dynamic Effects of Innovation on Firms and Households

(a) Private R&D and Investment



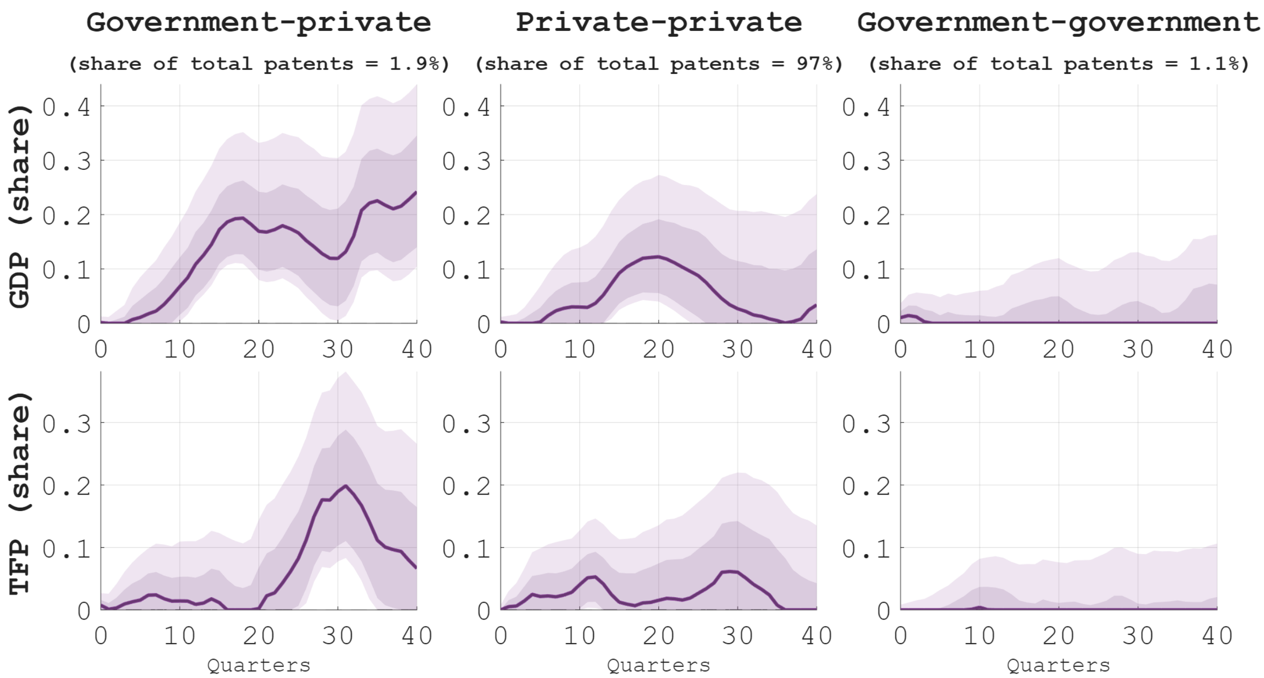
(b) Real Wages and Consumption



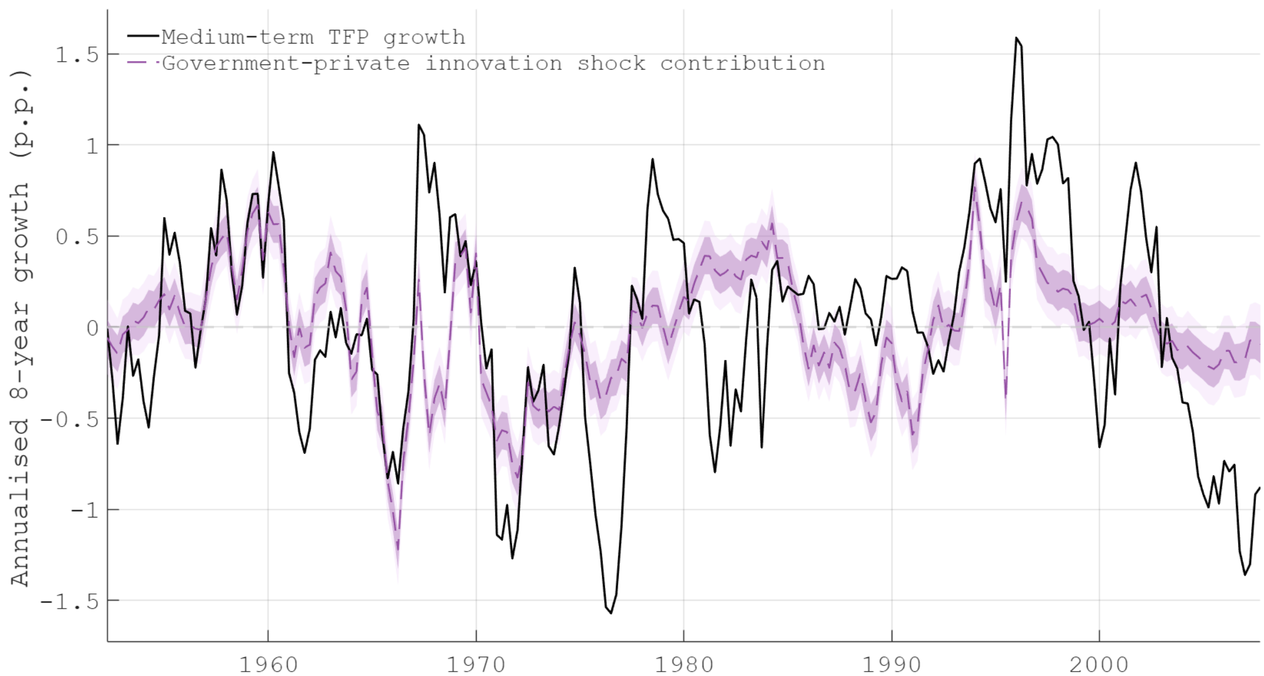
Note. The figure displays the dynamic effects of innovation shocks in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita private R&D and (log) real per-capita investment (panel a) and (log) real wages and (log) real per-capita consumption (panel b). The estimation by local projections follows eq.(1). The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes four lags of the patent group shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

Figure 4: Forecast Error Variance Contribution and Historical Decomposition

(a) Forecast Error Variance Contribution



(b) Historical Decomposition of the Medium-Term Component of TFP growth



Note. Panel (a) displays the forecast error variance contribution of innovation shocks in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita GDP expenditure and (log) TFP (by row). The estimation by local projections is based on the R^2 method in Gorodnichenko and Lee (2020). The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals. Panel (b) displays the historical contribution of public-private innovation shocks to the medium-term component of the TFP growth rate (data as solid black line). The purple line (bands) represents the point estimate (68% and 90%) contribution of the public-private innovation shocks. The estimation by local projections is also based on the econometric framework in Gorodnichenko and Lee (2020). Inference is based on 2000 bootstrap replications with small-sample adjustment. Sample: quarterly data 1950:Q1-2015:Q4.

column) account for about 20% of the medium-term variance in GDP and TFP growth, while contributing little at short horizons; private innovation shocks (middle column) play a smaller role and peak at business-cycle frequencies; and fully public innovation shocks (right column) explain a negligible share at all horizons.[14] In Panel B, we show that public–private shocks also dominate low-frequency productivity dynamics: a historical decomposition of TFP growth at an eight-year horizon ($h = 32$) reveals that these shocks closely track major medium-term swings in postwar productivity, including the strong growth of the 1950s, the resurgence of the 1990s, and the slowdown of the 2000s.[15]

Counterfactual Exercise. In Appendix F2, we show that if the medium-term contribution of government–private innovations in the 2000s had continued at its 1990s peak, the level of TFP in 2007 would have been 5.4% to 10% higher.[16]

3.3 Innovation Multipliers: A Back-of-the-Envelope Calculation

Our baseline results show that public-private innovations generate larger macroeconomic effects than fully private patents, but they are not expressed in monetary units. We therefore construct back-of-the-envelope innovation multipliers in three steps. First, we estimate the average cost of privately and publicly funded patents by dividing the cumulative real R&D by the number of patents in each sector over the entire sample. Because R&D expenditure cannot be allocated across government-funded patent categories, we pool all publicly funded patents for this exercise.[17] Using national accounts data deflated by the GDP deflator, the historical average cost is \$25.1 million per publicly funded patent and \$0.82 million per privately funded patent.

Second, we rescale the impulse responses to obtain the real-dollar effects associated with one additional patent in each category. Third, we compute multipliers at 6- and 32-quarter horizons by dividing these dollar responses—averaged over the relevant horizon—by the corresponding average patent cost.[18] Because patent shocks are dated at filing, while R&D

[14] In the robustness analysis of Section 4.2, we obtain similar results using orthogonalized local projections ('LP Cholesky').

[15] In contrast, public-private innovation shocks explains little of the short-run component of TFP growth, h=6 (Appendix F).

[16] These results complement existing explanations for the post-2005 productivity slowdown (e.g. De Ridder, 2024).

[17] Appendix Figure B4 shows that pooling government-funded patents does not affect our main results.

[18] As already noted in the context of the historical decomposition of Section 3.2, the horizons of 6 and 32 quarters are standard choices in the empirical macro literature to delimit business-cycle frequencies (Christiano and Fitzgerald, 2003).

expenditures precede patenting by several years, we follow earlier studies and apply an additional discount to account for R&D–patenting lags (Li et al., 2017; Dyèvre, 2024). The estimates in this section assume a 15-year lag, but we have verified robustness to 10- and 20-year lags.

Table 2 reports the resulting multipliers. Rows distinguish privately and publicly funded innovation; the first column reports average patent costs, while the remaining columns report GDP and private R&D multipliers over 6- and 32-quarter horizons. At the 6-quarter horizon, the GDP multiplier of publicly funded innovation is insignificant and only marginally higher than its private-sector counterpart.[19] At the 32-quarter horizon, however, both GDP multipliers become statistically and economically significant, with their difference widening markedly: government-funded innovation generates roughly twice the GDP impact of privately funded patents. Notably, our estimated medium-term impact of roughly $8 for every dollar of public funding is in line with the GDP multiplier of government R&D spending reported by Fieldhouse and Mertens (2023b), De Lipsis et al. (2023), CBO (2025) and DSIT (2025), despite very different data, methods, and identifications.[20] In Appendix C, we provide a structural interpretation of these multipliers by developing a theoretical mapping from our estimated impulse responses into aggregate and agency-level social returns.

Turning onto spillovers in the last two columns, government-funded innovation generates substantially larger effects on business-sector R&D, with the 32-quarter multiplier between 49 and 98 cents per dollar, consistent with the evidence for France in Bergeaud et al. (2025), and the cross-country estimates reported by Moretti et al. (2025). Overall, the gap between the effects of the two funding sources widens with the forecast horizon, and despite their higher average cost, in the medium-term, government-funded patents deliver about twice the GDP and private R&D impact per dollar than fully private innovations.

[19] While the point estimate of 2.28 lies toward the upper end of available evidence (Ramey, 2011; Auerbach and Gorodnichenko, 2012), differences in the underlying object of analysis—total government purchases, defense spending and public investment *versus* government support for innovation—limit the comparability of our estimates with the fiscal multiplier literature.

[20] Our goal is to assess how variation in the flow of ideas funded by the government versus the private sector maps into subsequent aggregate productivity and output. Existing work typically proxies public innovation using government R&D spending. We complement this approach by measuring the flow of ideas directly through government- and privately- funded patents, which allows us to exploit the granularity of patent data to uncover heterogeneity across research fields, industries, and innovator types for both public and private innovation. By contrast, government R&D aggregates across these margins but has the advantage of a direct dollar-based interpretation. We view the two approaches as complementary and mutually informative.

Table 2: Back-of-the-Envelope Innovation Multipliers at 6- and 32-quarter Horizons

		GDP MULTIPLIER		PRIVATE R&D MULTIPLIER	
funding source	*cost per patent*	*6 quarters*	*32 quarters*	*6 quarters*	*32 quarters*
private	0.82M$	1.95	4.72	0.15	0.35
		[0.0, 3.9]	[1.2, 8.2]	[.10, .20]	[.21, .48]
government	25.1M$	2.28	8.86	0.25	0.73
		[-0.3, 4.8]	[4.6, 13]	[.17, .33]	[.49, .98]

Note: The estimated IRFs are expressed as cumulative changes in the level of the target variables because local projections are specified in long differences. Innovation multipliers are constructed by averaging these cumulative responses of GDP or private R&D (in real dollars, evaluated at end-of-sample prices) following a unit patent shock over the relevant horizon window ($h = 1, \ldots, 6$ or $h = 1, \ldots, 32$ quarters) and scaling by the unit cost of patents. The assumed R&D-to-patent lag is $L = 15$ years. Each entry is computed as $\mathcal{M}_H = \frac{1}{H}\sum_{h=1}^{H} \frac{\Delta X_h^{disc}}{Cost\ per\ patent}$, where $H \in \{6, 32\}$ and ΔX_h denotes the cumulative IRF at horizon h for either GDP or private R&D. Discounted cumulative responses are defined as $\Delta X_h^{disc} = \Delta X_h(1+r)^{-(L+h/4)}$, with $r = 0.04$ and $L = 15$ years. Numbers in brackets report 68% confidence intervals.

4 Sensitivity Analysis

The baseline results in the previous section are obtained using local projections estimated by OLS, controlling for a rich set of aggregate variables to address potential confounding and reverse causality. While this specification already absorbs a wide range of macroeconomic forces— including lags of GDP, TFP, capital investment, stock prices, a short-term interest rate, R&D expenditure, and patenting activity in other categories—concerns may remain about residual endogeneity in innovation shocks. We therefore subject our findings to an extensive sensitivity analysis. We begin by adopting instrumental-variable local projections to explicitly address endogeneity, using instruments for government-funded and privately funded innovation drawn from recent empirical studies. Then, we move to implementing fourteen alternative identification strategies and empirical specifications proposed in the time-series literature to isolate unanticipated movements in innovation activity and trace their dynamic effects. Across all these exercises, the qualitative ranking and quantitative magnitude of our results remain remarkably stable, providing reassurance that our findings are not driven by a particular identification or modeling choice.

4.1 Instrumental Variables

Isolating exogenous variation in innovation activity is challenging, given the long and uncertain lags between research funding, patenting, and macroeconomic outcomes. To address potential endogeneity concerns directly, in this section we adopt an instrumental-variable strategy that draws on well-established sources of exogenous variation used in the recent macroeconomic literature.

For each category of government-funded innovation, we exploit the narrative measures of federal R&D appropriations constructed by Fieldhouse and Mertens (2023a) and studied in Fieldhouse and Mertens (2023b). These authors document substantial heterogeneity across agencies and long, distributed lags between government appropriations and patenting activity. To mirror this structure, we use agency-specific R&D appropriation series and allow their effects to operate through lags of up to 40 quarters. This yields a rich set of 240 instruments that capture both the agency dimension and the slow-moving transmission of public R&D into innovation outcomes.

The resulting "many instruments" environment raises well-known concerns about overfitting and weak first stages. We address this issue using regularization, implementing ridge regressions following Carrasco (2012). Rather than selecting a small subset of instruments, ridge shrinks the contribution of weak or redundant instruments toward zero, stabilizing the first stage while preserving the information content of the full instrument set.[21] As a robustness check, Section 4.2 shows that imposing smooth lag restrictions across appropriations—using an extended Almon-type structure in the spirit of Barnichon and Mesters (2020)—yields very similar results.

Private innovation requires a different identification strategy. We draw on the technology shock series constructed by Miranda-Agrippino et al. (2025), who orthogonalize patent applications to their own lags, identified macroeconomic shocks, and professional forecasters' expectations. In their framework, this series is used as an instrument for stock prices in order to isolate the technological component of a forward-looking variable related to news. In contrast, our objective is to study technology shocks rather than technology news. Accordingly, we use their orthogonalized patent series directly as an instrument for privately funded patenting, with stock prices included as controls in our LP-IV specification. This allows us to isolate variation in patenting activity that is plausibly unrelated to contemporaneous macroeconomic conditions, or expectations, and to trace its dynamic association with

[21] The ridge penalty parameter is chosen in a data-driven way, subject to a conservative lower bound on shrinkage that limits effective first-stage complexity and guards against overfitting.

aggregate outcomes.

In Figure 5a, we report the LP-IV estimates following Stock and Watson (2018). First-stage diagnostics indicate strong instruments.[22] The results closely mirror the baseline OLS findings of Figure 2. Government-funded but privately owned patents generate the largest medium-term increases in GDP and TFP, peaking at roughly 0.25% and 0.2%, respectively. Fully private innovations also raise output and productivity, albeit more modestly, while fully public patents exhibit weak and imprecise responses. Despite the efficiency loss inherent in IV estimation, the qualitative ranking across patent categories and the quantitative magnitudes remain remarkably stable relative to Figure 2, reinforcing the interpretation that our baseline controls effectively isolate exogenous variation in innovation activity.[23]

4.2 Alternative Approaches

In Figure 5b, we evaluate the robustness of our baseline findings across a broad set of alternative time-series identification strategies and empirical specifications. These exercises address four potential concerns: sensitivity to instrument choice, dependence on timing restrictions, the influence of outliers, and the role of the information set used to identify innovation shocks.

External-instrument robustness (LP-IV). We begin by assessing the robustness of the LP-IV results to alternative instrument constructions based on the narrative R&D appropriations shocks of Fieldhouse and Mertens (2023b). In addition to the ridge-regularized specification, we implement an Almon-type smooth-lag restriction in the spirit of Barnichon and Mesters (2020) ("Almon LP-IV"), which disciplines the first stage by imposing smoothness across lags.[24] We also consider narrative identification strategies that isolate large institutional changes plausibly unrelated to contemporaneous macroeconomic conditions (Friedman and Schwartz, 1963; Hamilton, 1985; Romer and Romer, 2010). Using institutional events that affect patenting (Appendix E), we implement two variants: a narrative LP-IV based on the quarterly change in filings attributed to the event, and a sign-restricted narrative LP-IV

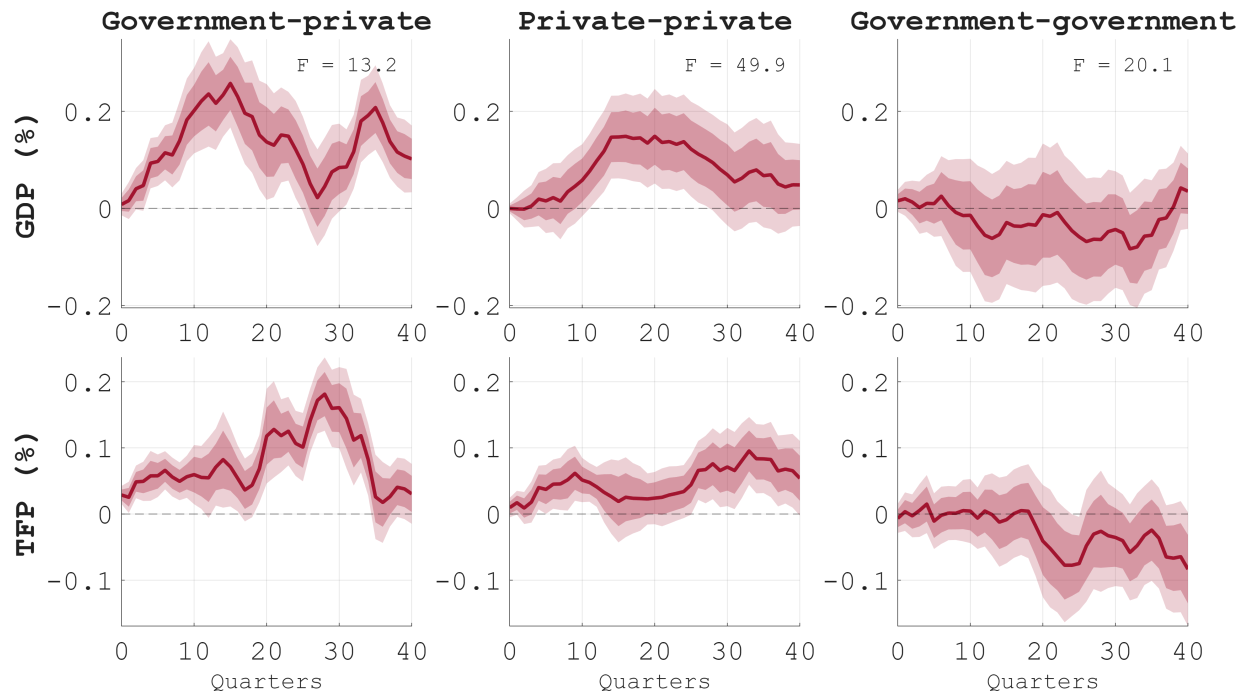
[22] For specifications with multiple instruments, we report first-stage F-statistics adjusted for instrument dimensionality.

[23] This interpretation is consistent with Appendix B1, which shows that patent applications are largely acyclical.

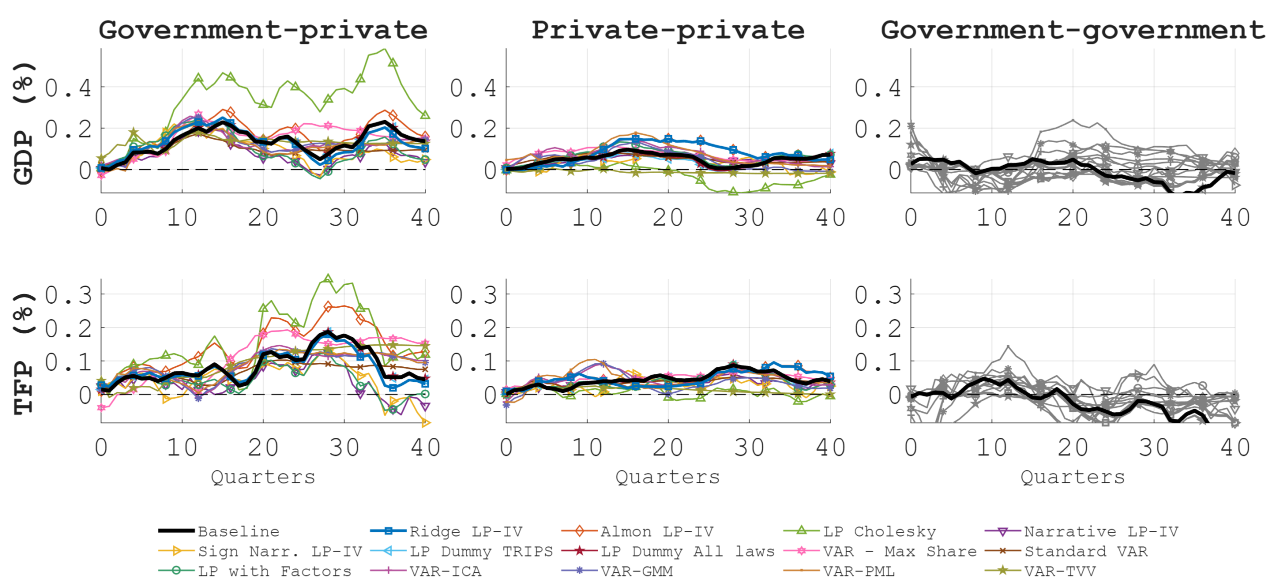
[24] Results are stable across polynomial orders; higher-order polynomials improve first-stage fit given the sparsity of appropriation shocks and the long, uneven R&D-to-patent transmission. Results are also robust under weak-IV robust inference.

Figure 5: LP-IV Estimates and Alternative Approaches

(a) LP-IV



(b) Alternative Time-series Strategies



Note. Panel (a) displays the dynamic effects of innovation shocks identified through a LP-IV approach in each category of patents (government-private, private-private, government-government) on (log) real per-capita private GDP and (log) TFP. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals respectively, computed from Newey and West (1987) standard errors. Panel (b) displays the point estimates from our baseline specification and 14 alternative time series approaches. The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes four lags of the patent group shocked and the dependent variable, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. Sample: quarterly data quarterly data 1950:Q1-2015:Q4. Grey lines indicate impulse responses that are statistically insignificant at the conventional level for the vast majority of forecast horizons.

using only event timing and direction (Romer and Romer, 1989; Ramey and Shapiro, 1998). Both approaches yield impulse responses closely aligned with the baseline.[25]

Alternative identification strategies. Our baseline LP relies on timing restrictions analogous to a recursive ordering. We examine the sensitivity of the results to alternative or weaker identifying assumptions. First, we adopt a more conservative timing scheme by controlling for contemporaneous movements in other patent categories when identifying a shock to a given category ("LP Cholesky"), thereby isolating innovations orthogonal to both past and contemporaneous fluctuations in remaining groups. Second, we identify innovation shocks in a VAR using the max-share criterion (Uhlig, 2003), which selects the shock that explains the largest share of patent forecast error variance over a two-year horizon and relaxes recursive impact restrictions ("VAR–Max Share"). Third, we exploit higher-order moments of reduced-form residuals using Independent Component Analysis, GMM-based identification, and pseudo–maximum likelihood ("VAR-ICA"; "VAR-GMM"; "VAR-PML"; Hyvarinen, 1999; Himberg et al., 2004; Keweloh, 2021; Gouriéroux et al., 2020). We also consider identification through time-varying volatility (TVV; Lewis, 2021; Rigobon, 2003).[26] Across all these approaches, the implied impulse responses are close to the baseline, indicating that the results are not driven by a particular contemporaneous restriction.

Outliers. To rule out the influence of exceptional spikes in patenting activity, we reestimate the baseline LP specification including dummies for major institutional episodes (e.g. TRIPS "LP Dummy TRIPS", and also Bayh–Dole, AIA "LP Dummy All laws") and obtain nearly identical dynamics.

Information set. Finally, we assess robustness to expanding the information set. We estimate (i) a standard VAR(12) "Standard VAR" with Cholesky identification and longer lag structure, and (ii) a factor-augmented "LP with Factors", which includes as additional controls the first two principal components of the large, real-time, macroeconomic quarterly dataset 'FRED-QD' maintained and hosted by the Federal Reserve Bank of St. Louis for

[25] First-stage diagnostics are strong in both cases.

[26] Details, including non-Gaussianity diagnostics, outlier handling, and dimensionality constraints are reported in the Appendix.

macroeconomic analyses (McCracken and Ng, 2020). In both cases, the estimated responses closely match the baseline.

Summary. Across our baseline model, the LP-IV estimates and the additional fourteen specifications presented in this section, the results consistently point to a strong and persistent medium-term association between aggregate productivity and government-funded but privately owned innovation, with smaller aggregate effects for fully private patents.

5 The Role of 'Basic' Innovation

In Section 3, a clear ranking emerged across patent categories: the macroeconomic effects of innovation publicly funded and privately owned are more significant, both statistically and economically, than those generated fully within the private sector, which in turn are larger than those produced by the public sector only. In this section, we aim to examine the distribution of patents within each sector in order to identify more disruptive and fundamental research for each category.

The notion of importance or fundamentalness relates to the concept of "basic" research emphasized by Bush (1945a) and the innovation literature. As the classification of 'basic' research in R&D expenditure data is ultimately subjective and thus exposed to significant measurement errors, in this section, we rely on two complementary indicators based on patents: i) the measure of 'importance' developed by Kelly et al. (2021), and ii) the measure of 'reliance on the science' constructed by Marx and Fuegi (2020, 2022). In Section 6, we will zoom on federal agencies such as NIH and NSF, while in Section 7, we focus on research institutes and universities. Each dimension (i.e. text similarity, citations of scientific papers, agencies and players) covers a different aspect of "basic" research and together paint a fuller picture of its contribution.

As discussed in Section 2, the measure of importance or fundamentalness in Kelly et al. (2021) is a function of both forward and backward patent similarity, with the former (latter) receiving a positive (negative) weight in the importance measure. Accordingly, a patent with high textual similarity to later patents, relative to its similarity to preceding patents, is considered more disruptive. The intuition for the metric developed by Kelly et al. (2021) is that pathbreaking innovations are more likely to move away from existing knowledge (i.e. less backward similarity) and are also more likely to influence future knowledge (i.e. more forward similarity).[27]

Given this background, in Panel A of Figure 6, we divide each patent category into two additional groups: top 25% (blue solid lines) and bottom 75% (orange dashed lines), using the measure of importance in Kelly et al. (2021).[28] Three major results emerge. First, as expected, the top 25% most disruptive patents in each category have a larger impact on GDP and TFP than the bottom 75%, with the gap between sub-groups in each category that tends to grow with the forecast horizon. Second, patents funded and owned by the government, in the last column, are characterized by the most striking heterogeneity, with the top 25% most disruptive patents in this category associated with the largest medium-term effects on output and productivity in the whole economy. Third, in sharp contrast, the bottom 75% of least important patents has small and insignificant traces, which turn even negative in the case of public-public innovation. In summary, patents that are funded and owned by the government represent a relatively higher share of the most disruptive innovations in terms of medium-term impact on GDP and TFP. In Appendix D2, we provide examples of patents in each category.

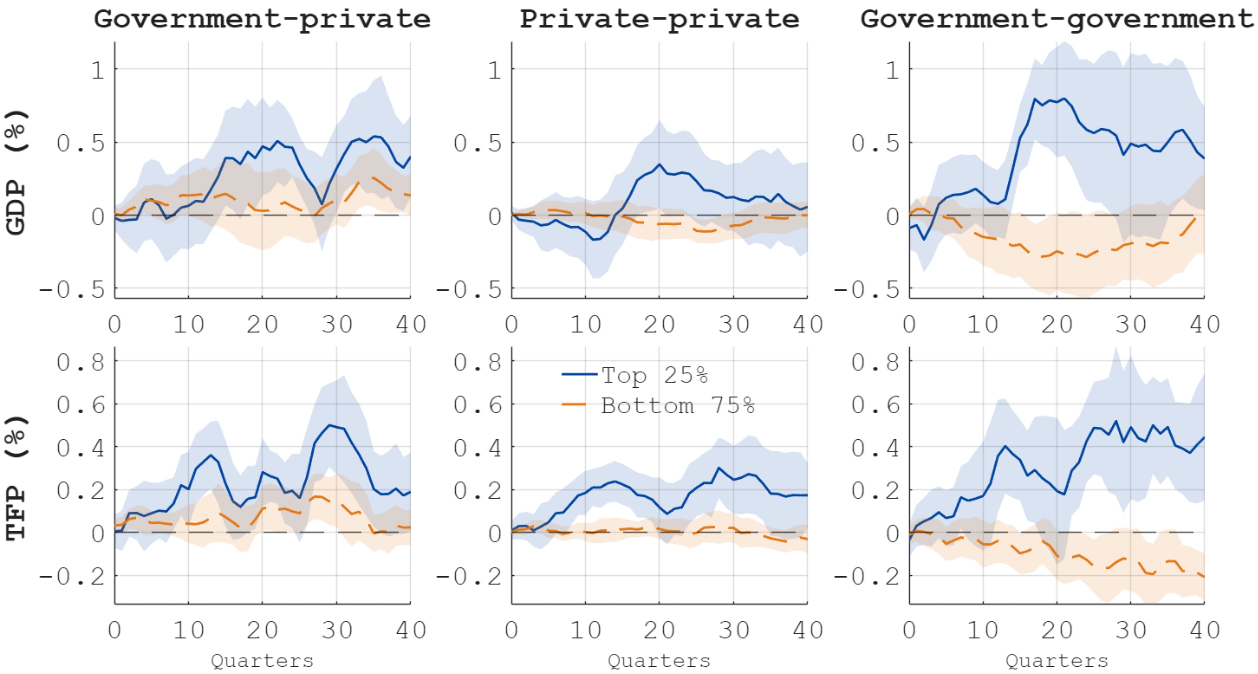
The indicator of reliance on science by Marx and Fuegi (2020, 2022) captures the number of scientific paper citations contained in a patent. Patents citing more scientific articles are thus considered more science-based, providing a proxy for the "basicness" of the underlying research. Panel B of Figure 6 replicates the exercise in Panel A by splitting patents into those with high- versus low-scientific reliance (i.e. top decile versus bottom 90%). According to this measure, correlations with GDP and TFP are somewhat stronger among the most science-based patents for both government–private and private–private collaborations. Furthermore, and consistent with the main result in Panel A, the heterogeneity is most pronounced for fully public innovations (in the third column): patents more reliant on science are associated

[27] A main reason to favor the measure of Kelly et al. (2021) over Kogan et al. (2017) is that the latter only refers to patents owned by listed firms and thus excludes government-owned patents. In Section 7, we show that the most impactful innovations are owned by research institutes, universities, start-ups and VC-backed firms, which are unlikely to be listed. For robustness and sake of completeness, in Appendix G3, we show that similar results are obtained using as indicator of importance the patent value metric in Kogan et al. (2017) extended beyond listed firms following the strategy proposed by Kline et al. (2019).

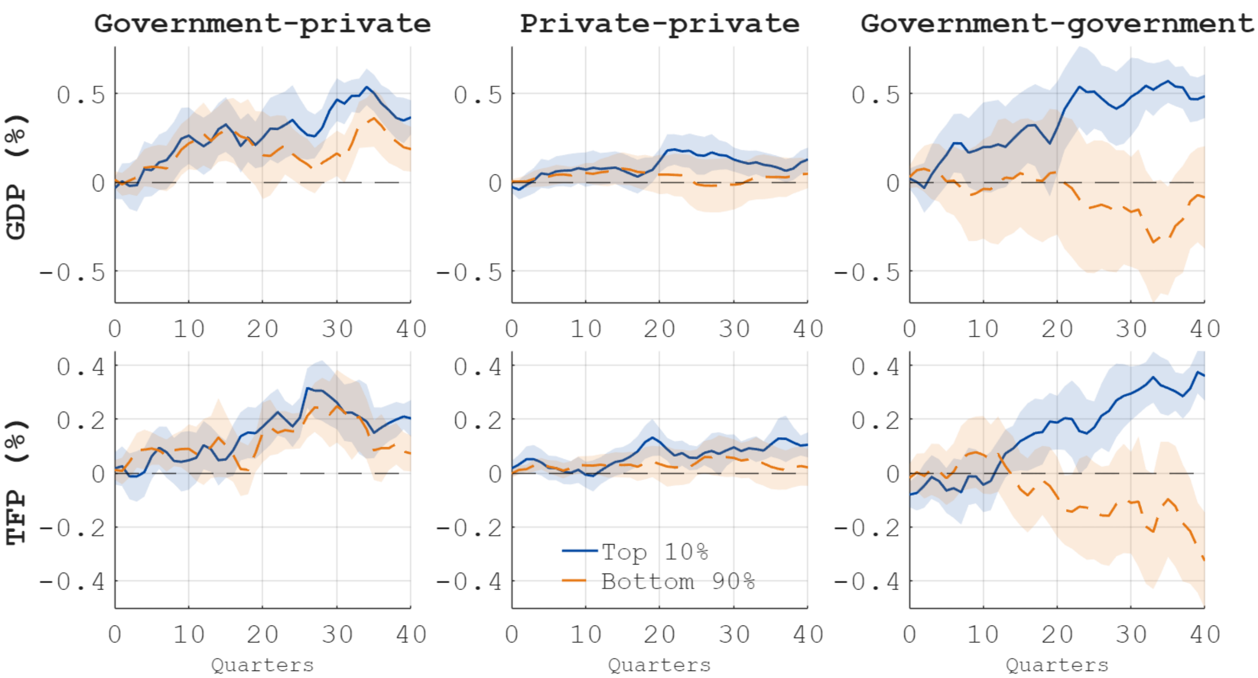
[28] We use the five-year window for patent similarity in Kelly et al. (2021) by category in the whole sample. We obtain similar results employing the ten-year window instead.

Figure 6: The Dynamic Effects of the Most *Important* and *Reliant on Science* Innovations

(a) Importance



(b) Reliance on Science



Note. *Panel (a) represents the dynamic effects of innovation shocks to the top quartile of patents ranked by the Kelly et al. (2021) five-year patent similarity measure versus other patents in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row). Panel (b) displays the results of the same exercise performed by using the reliance on science measure by Marx and Fuegi (2020, 2022). The estimation by local projections follows eq.(1). The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for top 25% (bottom 75%) important or top 10% (bottom 90%) reliant on science patents, respectively. The corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.*

with the largest increases in TFP and GDP growth. By contrast, the remaining 90% of less science-based patents appear largely inconsequential for GDP, and even negatively associated with productivity.

Finally, in Appendix Figure G4, we show that the strong positive association between macroeconomic outcomes and the most fundamental fully public innovations remains robust when we adopt a 25–75 percentile split of the 'reliance on science' measure proposed by Marx and Fuegi (2020, 2022). With this more balanced cutoff, the heterogeneity across the other two patent groups becomes less pronounced, possibly reflecting a more even distribution of this measure within each group relative to the importance index developed by Kelly et al. (2021) (see also the statistics in Table A1). In Appendix Figure G5, we further corroborate these findings by comparing —within each group— patents that cite at least one scientific publication to those that cite none, obtaining qualitatively similar results.

6 On the Mechanism

In the previous sections, we documented a prominent role for publicly-funded/privately-owned innovations in driving productivity and prosperity in the post-WWII U.S. economy, with significant spillovers to business investment and R&D. In this and the next section, we explore the mechanisms through which these dynamics have unfolded. More specifically, this section focuses on federal agencies, industries, research fields, and innovation spillovers. In the next section, we quantify the contributions of the different players, including research institutes and universities, start-ups, VC-backed companies, and incumbents.

6.1 Federal Agencies and Industries

The innovation architecture designed by Bush (1945a) led to the establishment of the National Science Foundation (NSF) in 1950 and to a sizable expansion of the National Institutes of Health from 1947. Together with other federal agencies, Bush (1945a) believed this was the primary mean through which government should support 'basic' research in colleges, universities and research institutes.[29] In this section, we group public patents by five main federal agencies or departments: NIH, NSF, NASA, Department of Energy (DoE), and Department of Defense (DoD), which –according to Table A1– account for 98% of government-funded patents.[30] To construct private-sector counterparts to federal agencies, we assign patents to industries based on CPC codes that capture the main technological domains relevant to each industry, except for university-related patents, which are identified by classifying assignee names (Appendix H).

In the top and bottom rows of Figure 7, we present the point estimates of the dynamic effects on GDP and TFP, respectively, of an unanticipated increase in patenting by either federal agencies or industries in the private sector. The first and third columns refer to public-private and public-public innovations, respectively. In the second column, we report the findings for industries that most closely match the main industry in which each federal agency or department mainly operates.[31] Coloured (grey) lines refer to point estimates that are (not) statistically significant at the 68% confidence level. In a few instances, the response of total patents is negative on impact; accordingly, only for Figures 7a and 7b, we normalize the IRFs across agencies, industries and research fields such that each innovation shock has a maximum impact of 1% on total patents over the forecast horizon, following Fieldhouse and Mertens (2023b).

Three main results emerge from Figure 7a. First, NSF and NIH innovations lead to the largest medium-term gains among the public-private patents of the first column, with peaks around 0.3% for TFP and 0.5% for GDP, in line with the counterfactual analysis on NIH funding cuts in Azoulay et al. (2025). The other federal agencies and departments produce relatively smaller effects, which, however, are still sizable. Second, fully private innovations in the second column exhibit muted heterogeneity, particularly in TFP responses. Third, in

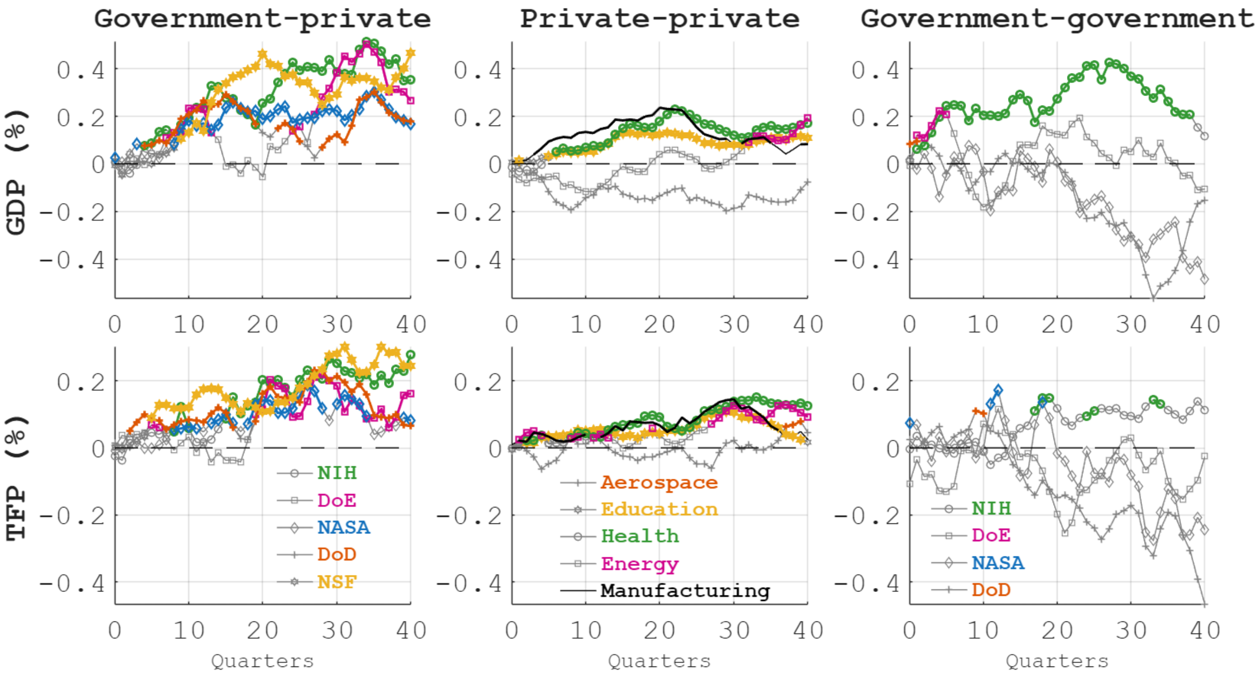
[29]In the letter to President Truman summarizing the main findings of his report, (Bush, 1945b) writes: *"The Government should foster the opening of new frontiers and this is the modern way to do it. [...] The effective discharge of these new responsibilities will require the full attention of some overall agency devoted to that purpose. There is not now in the permanent Governmental structure receiving its funds from Congress an agency adapted to supplementing the support of basic research in the colleges, universities, and research institutes, both in medicine and the natural sciences, adapted to supporting research on new weapons for both Services, or adapted to administering a program of science scholarships and fellowships. Therefore I recommend that a new agency for these purposes be established."*

[30]The Department of Education Organization Act of 1979 (Public Law 96-88) established the U.S. Department of Health and Human Services (HHS) as the primary federal agency responsible for public health, social services, medical research, and Medicare and Medicaid administration. Since its inception in 1980, the vast majority of HHS patents have been funded by the NIH. Accordingly, we will refer to patents by all federal health agencies over the full sample as 'NIH'.

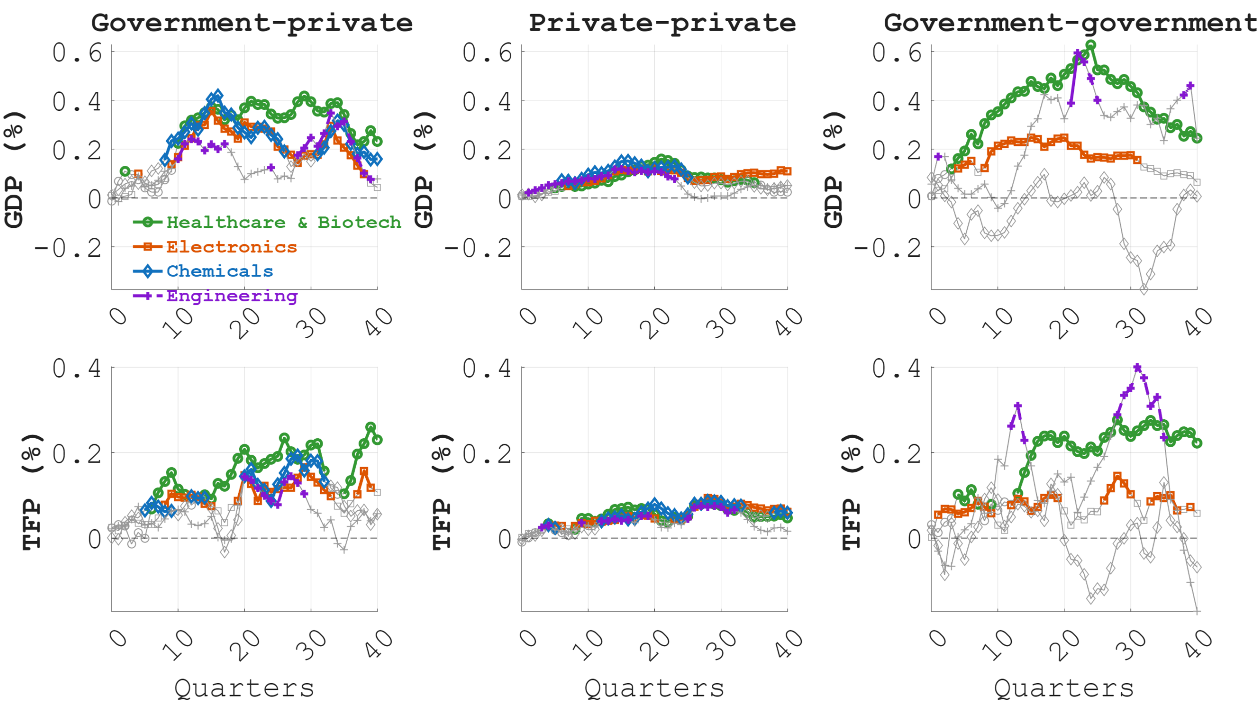
[31]In Appendix H, we bridge federal agencies, research fields, and industries using CPC codes. Due to data limitations in PatentsView, the sample for the 'Education' sector in the second column of Figure 7 begins in 1976.

Figure 7: The Effects of Innovation by Federal Agencies and Research Fields

(a) Federal Agencies and Industries



(b) Research Fields



Note. The figure displays the dynamic effects of innovation shocks in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row) by agency-sectoral breakdown (panel a) and research fields (panel b). The estimation via local projections follows Eq. (1). The size of the shock is normalized such that the peak response of total patents is 1%. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents not belonging to the shocked group. All variables except the T-bill are in logs. Colored (gray) lines denote (no) significance at the 68% level according to Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4 (except for 'University' in the second column, 1975q1-2015:Q4).

contrast, we observe the largest heterogeneity among patents that are funded and owned by the government in the third column, consistent with the notion that the public sector pursues 'high-risk/high-reward' innovations (Section 5). Within those, NIH and DoD stand out as the most and least impactful agencies/departments, respectively. In the next section, we return to this result by examining the healthcare research field, showing that government-funded patents systematically outperform private-funded innovations in terms of their impact on GDP and TFP.

Finally, as documented in Appendix Table K3, funding agencies differ substantially in the composition of the public–private patents that they support. Federal agencies with higher estimated impacts tend to fund a larger share of patents that involve non-profit organizations such as research institutes and universities. Furthermore, among for-profit participants, the best performing agencies support a higher share of young firms. Anticipating the evidence presented in Section 7 that innovations by non-profit entities are, on average, more impactful than innovations by for-profit companies, and that public–private patents assigned to startups are the most impactful within the for-profit sector, these compositional differences are consistent with the ranking of impact across agencies documented in this section.

6.2 Research Fields

In the previous section, we have shown that NIH and NSF support innovations with the largest economic impact. In this section, we shed light on why: are these agencies special, or do they happen to fund work in research fields whose innovations tend to have stronger effects on GDP and TFP? To answer this important question, we look at the composition of each agency's patents by research field. In Appendix Figures H1 and H2, we report the share of all pooled patents by research field for the players under investigation, namely the main federal agencies and the private sector in this section, and research institutes and universities in the next section. While each player has historically patented innovations across a broad range of fields, four specific fields account for at least 40% of all patents granted to each player in the post-WWII period. Such fields are: Healthcare & Biotechnology, Electronics, Chemicals, and Engineering. Accordingly, we focus on patents in these four research fields to explore potential differences in the effectiveness of publicly versus privately funded innovation within each of them.[32]

In Figure 7b, we replicate the setting and format of Figure 7a. Coloured lines represent all the significant point estimates at the 68% confidence level, with each research field displayed with a different pattern and a different colour. The main finding of the exercise in this panel is that among government-funded patents, the green lines with squares for 'healthcare & biotechnology' appear to outperform the other research fields, especially among public-public innovations. This contrast is all the more striking when set against the additional result (in the second column) showing that, among private patents, the 'healthcare & biotechnology' field is associated with little advantage in productivity or output growth relative to the other research fields.

The much smaller GDP and TFP effects of private innovations in healthcare and biotechnology, relative to public patents, align with a large empirical literature showing that the incentives of profit-maximizing firms often limit their contribution to aggregate productivity and economic growth. Three channels are central. First, strategic patenting —through common practices such as 'patent thickening' and 'evergreening'— is used to block competitors and extend market exclusivity without meaningful technological progress (Frakes and Wasserman, 2025; Dwivedi et al., 2010).[33] Second, a substantial share of private R&D in pharmaceutics is directed toward drugs that enhance longevity and quality of life among older patients, who are less likely to participate in the labor force (Benmelech et al., 2021). Third, private firms disproportionately target large markets, so technological change is steered toward the most profitable areas rather than the most productivity-enhancing innovations (Boldrin and Levine, 2008; Acemoglu and Linn, 2004; Moen-Vorum, 2025).

6.3 Innovation Spillovers

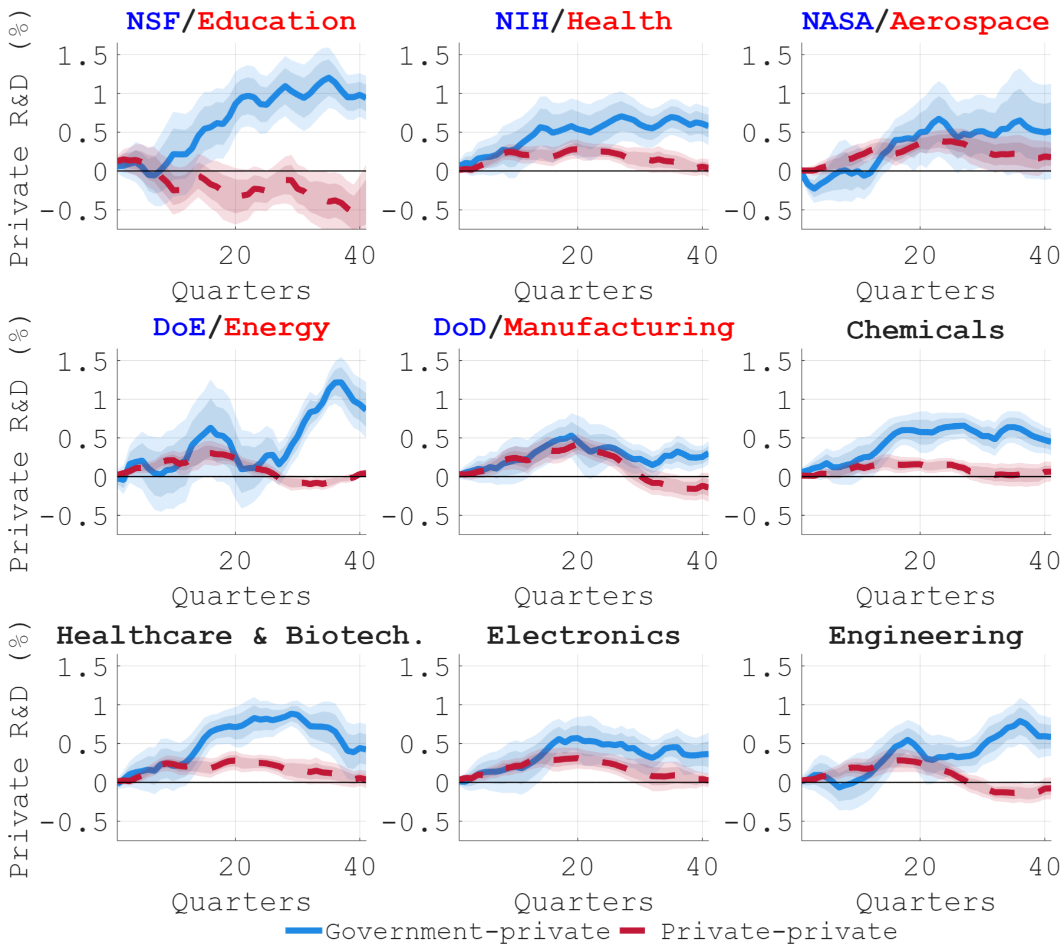
In Section 3.1, we have shown that public-private patents generate substantial spillovers by stimulating a significantly larger response of investment in the private-sector. In this section, we explore this result further and examine the contributions of government-funded

[32] Appendix Table H2 shows the mapping between CPC codes and fields of knowledge.

[33] More specifically, 'patent thickening' refers to the practice of building large patent portfolios to raise rivals' litigation or licensing costs, while 'evergreening' denotes the strategy of obtaining later patents on minor drug modifications —such as new formulations, doses, or uses— to prolong market exclusivity beyond the original patent term.

and privately-funded innovations to driving R&D spillovers across federal agencies, industries, and research fields.

Figure 8: The Effects of Innovation on Private R&D by Agencies, Industries and Fields



Note. The figure displays the dynamic effects of innovation shocks in public-private (solid blue lines) and private-private (dashed red lines) patents on (log) real private R&D per capita, by agency and technology field. The estimation by local projections follows eq.(1). The size of the shock is normalized such that the peak response of total patents is 1%. The set of controls includes four lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

In Figure 8, we report the response of business-sector R&D expenditure to innovation shocks that raise patenting activity in a single federal agency, industry, or research field. Blue lines and bands correspond to public–private innovation, while red dashed lines and shaded areas refer to private–private patents. The first row shows results for NSF, NIH, and NASA, paired with their closest private-sector counterparts—universities, healthcare and biotechnology, and aerospace, respectively. In the second row, the first and second panels report results for the Department of Energy and the Department of Defense (public–private patents) and for the energy and manufacturing sectors (private-only patents), mirroring the groups in Figure 7a. The remaining panel in the second row and all panels in the third row compare R&D spillovers from public–private versus fully private innovation across the research fields of Chemicals, Healthcare and Biotechnology, Electronics, and Engineering, corresponding to Figure 7b.

A few findings emerge from Figure 8. First, publicly funded but privately owned innovations lead systematically to larger spillovers towards the rest of the economy than fully private patents, for most agencies and industries. Second, very sizable differences in the medium-term responses of private R&D are recorded in the 'Education', 'Health' and 'Energy' sectors, driven by the NSF, the NIH and the Department of Energy.[34] In particular, NSF-funded patents stimulate subsequent scientific research and product development substantially more than NIH, in line with the evidence provided by Akcigit et al. (2020) and Williams (2013), respectively. Third, the gap between public-private patents and fully private innovation is smaller (but still significant) for 'Chemicals' and 'Engineering', while it is modest in 'Electronics', DoD/'Manufacturing' and NASA/'Aerospace', consistent with a larger impact of public R&D outside NASA and the Defense sector after WWII, as reported by Kantor and Whalley (2025) and Fieldhouse and Mertens (2023b), respectively.[35] In Appendix I, we further show that government-funded patents with higher innovation-network centrality are associated with larger gains in aggregate productivity and output, representing further evidence of substantial spillovers from government funding to the rest of the economy.

7 Who are the Main Innovators?

In the previous section, we identified NSF and NIH as the agencies that develop innovations with the largest medium-term impact on TFP and GDP. Furthermore, we have contrasted the higher performance of public-public patents in 'healthcare & biotechnology' relative to

[34] Interestingly, while NSF-funded patents crowd-*in* private R&D, university patents with no public funds crowd-*out* private R&D. The former finding chimes with Lerner et al. (2025) who report significant commercial spillovers from university-based research. The latter result is consistent with Arora et al. (2023), who argue for the rivalrous and excludable nature of public science. Our evidence, however, qualifies their finding and suggests it may hold only for *privately funded* university innovation. The results of significant private R&D spillovers from Department of Energy patents is in line with Myers and Lanahan (2022).

[35] The significant spillovers to private R&D in Figure 8 chimes with the evidence in Fleming et al. (2019) that the number of corporate patents citing government-funded innovations has increased dramatically since the mid-1960s.

the far smaller productivity gains associated with their solely private counterparts. In this section, we split the data along another dimension: the players. We start with the non-profits vs for-profits divide, and then zoom in on research institutes and universities among the former group, and on start-ups and VC-backed firms for the latter. The sources of data for this section are *PatentsView* for research institutes or university patent assignees and Ewens and Marx (2024) for start-ups or VC-backed companies, which both start in 1976.

7.1 Non-profit vs. For-profit Organizations

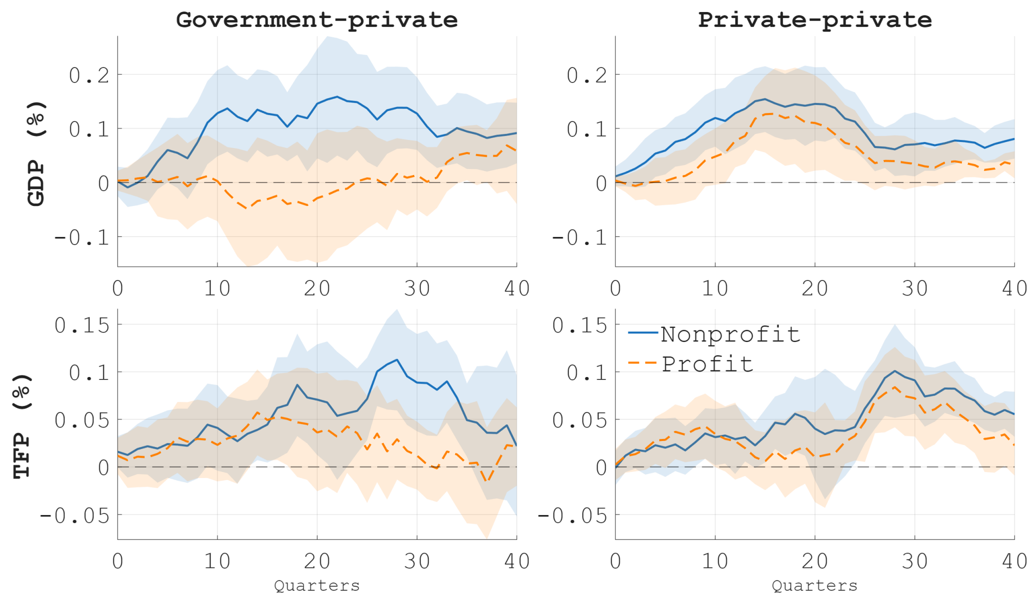
In each category, we separate patents into two sub-groups, depending on whether the organization is for-profit or non-profit. As there is no heterogeneity along this dimension among public-public patents, we exclude this category from the analysis in this section. The estimates are in Figure 9, which reports the effects of public-private sponsorship (left column) and solely private innovations (right column) on GDP (top row) and TFP (bottom row). Blue solid lines and associated 90% confidence bands illustrate the effects of innovation by non-profit organizations, while orange broken lines and shaded areas refer to patents owned by for-profit businesses.

Our estimates suggest three main takeaways. First, among public-private patents (left column), non-profit organizations produce innovations that have significantly larger and more persistent effects on GDP and TFP over the medium term. Second, in contrast, the impact of patents funded by the government and owned by for-profit entities is never statistically different from zero. Third, on the other hand, there is no discernible heterogeneity between patents produced by for-profit and non-profit companies in the private sector (right column). In Section 7.2, we will focus on research institutes and universities within the non-profit sector, while in Section 7.3, we will consider start-ups and VC-backed for-profit companies.

7.2 Research Institutes and Universities

In his report, Bush (1945a) envisioned a central role for 'basic' research, defined as *"research performed without thought of practical ends"* and for the *"general knowledge and understanding of nature and its laws"*. In the letter to President Truman presenting the report, Bush

Figure 9: The Effects of Innovation by For-profit vs Non-profit Organizations



Note. The figure compares the dynamic effects of innovation shocks in each category of patents (public-private, private-private; by column) across profit and non-profit sectors on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row). The estimation by local projections follows eq.(1). The size of the shock is normalized so as to increase total patents by 1% on impact. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for the non-profit (profit) patents, while the corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: 1976:Q1-2015:Q4.

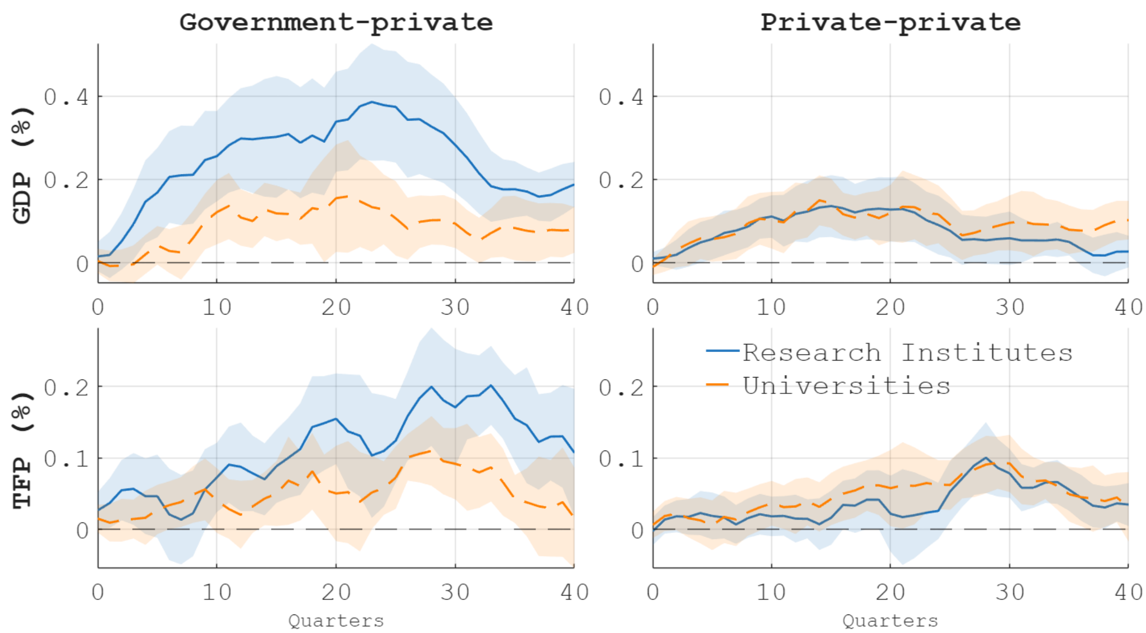
(1945b) writes: *"It is only the colleges, universities, and a few research institutes that devote most of their research efforts to expanding the frontiers of knowledge. [...] These institutions provide the environment which is most conducive to the creation of new scientific knowledge and least under pressure for immediate, tangible results".*[36] Bush's vision has been reflected in the sustained commitment of higher education institutions and research laboratories to basic research.

In Appendix Figure J1 Panel A, we show that most of the post-WWII U.S. R&D spending has involved later-stage innovations, such as applied research and experimental development, driven by the private sector. However, the weight of 'basic' research has grown over time, reaching almost 20% in 2010. In Panel B, we show that the federal government accounts for the lion's share of funding sources, financing an average of 60% of annual basic R&D spending since the 1950s; after including universities' own sources, non-business funds committed to basic R&D have averaged around 70%. As for the composition of federally funded basic

[36] In Bush (1945a), he adds: *"The responsibility for basic research in medicine and the underlying sciences, so essential to progress in the war against disease, falls primarily upon the medical schools and universities."*

R&D, Appendix Figure J1 Panel C makes it clear that universities and research institutes account for about 70% of the government budget. Accordingly, in this section, we single out research institutes and universities -the bulk of the non-profit world- as primary drivers of 'basic' research.[37]

Figure 10: The Effects of Innovation by Research Institutes and Universities



Note. The figure compares the dynamic effects of innovation shocks for public-private and private-private patents across research institutes and universities on (log) real per-capita GDP and (log) utilization-adjusted TFP. The estimation by local projections follows eq.(1). Shock size normalized such as to increase total patents by 1% on impact. Controls includes 4 lags of the dependent variable and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for the research institutes (universities), while the corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: 1976:Q1-2015:Q4.

In Figure 10, we report the aggregate effects of innovation by universities (orange dashed lines) and research institutes (blue solid lines) by source of funding and ownership. It is worth noting that Gross and Sampat (2025) classify all research institutes and universities as "private" entities. Accordingly, differences across columns reflect whether innovation undertaken within the same institutional sector is funded by the government or by private sources. In the terminology of Bush (1945a), the estimates in the left column correspond to 'basic' research that is government-funded and carried out by universities and research institutes. By contrast, the right column captures innovation by the same institutions but funded under

[37]Looking at research institutes and universities to proxy for 'basic' research compares favorably with alternative metrics based on citations (Section 5) or patent textual analysis. First, the binary classification of these institutions is less prone to the measurement errors typically associated with the specific definition of 'basic' research using patent descriptions or R&D data. Second, to the extent that research institutes and universities might also engage in 'applied' research, the estimates in this section could be interpreted as a lower bound for the actual impact of 'basic' research on TFP and GDP.

private sources.

The estimates in Figure 10 lead to three main findings. First, research institutes funded by the government (left column) make the largest contribution to the economy with persistent and significant effects that reach a peak in excess of 0.4% after six years for GDP and in excess of 0.2% after eight years for TFP, following a 1% increase in total patents. Second, patents developed by universities using government funds (left column) have a relatively smaller but still largely significant aggregate impact, around 0.2% for output and 0.1% for productivity over the medium-term. Third, when the funds come from private sources (right column), research institutes and universities produce innovations that have smaller and less significant effects, consistent with the event study in Babina et al. (2023). Together with the results in Sections 5 and 6.1, we conclude that 'basic' research in universities and research institutes funded by NIH and NSF is a fundamental driver of post-WWII American innovation.

7.3 Are start-ups and venture capital-backed firms special?

In the final part of this section, we turn our attention to the for-profit world and single out the possible special role of start-ups and VC-backed firms. To this end, we rely on the classification of patents by these two actors in Ewens and Marx (2024). The estimates for these two groups are displayed in Figures 11. In Panel A (B), start-ups (VC-backed firms) are blue solid lines and 90% confidence bands, while other firms are shown as orange broken lines and shaded areas.[38]

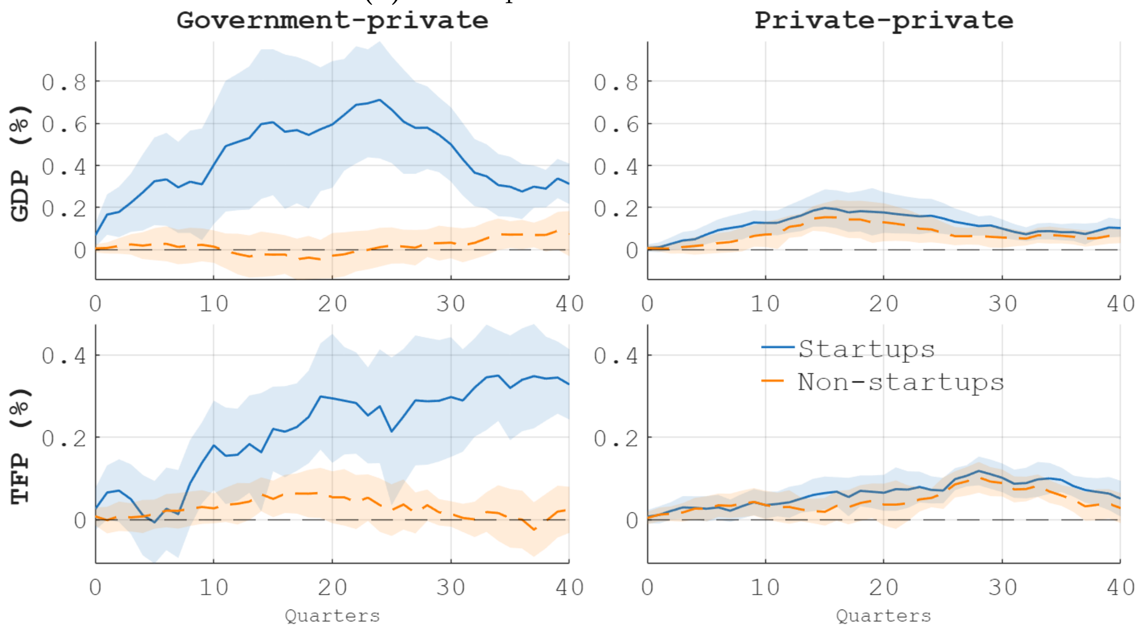
When government-funded (left column), the difference between start-ups and incumbents could not be starker: the innovation by the former have persistent effects that are very significant, both statistically and economically, with peaks around 0.6% and 0.3% for GDP and TFP, respectively. In contrast, when the source of funds is private (right column of Figure 11), the gap between the effects generated by the two groups of firms is negligible. In other words, start-ups are far more innovative than incumbent companies but *only* when funded by the government.

In Panel B, we repeat the same exercise of Panel A but for VC-backed (blue solid lines

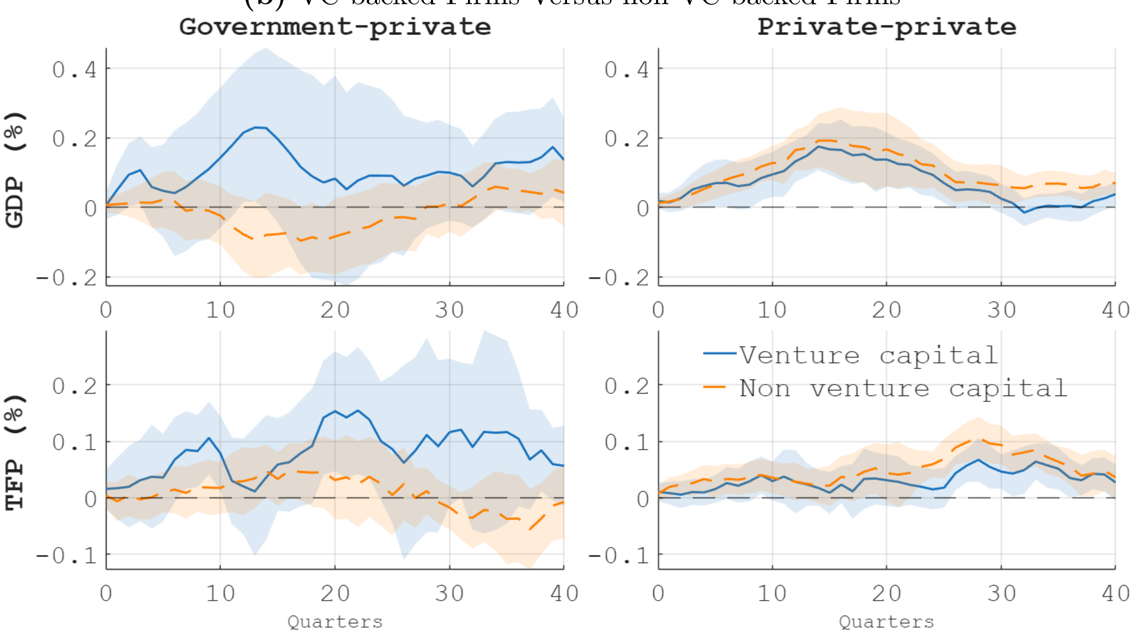
[38]Start-up status and VC backing may overlap. "Other firms" denotes non-start-ups in Panel A and non-VC-backed firms in Panel B, so the panels should be interpreted as two separate comparisons rather than a single decomposition.

Figure 11: The Effects of Innovation by Firms' Characteristics

(a) Start-ups Versus Incumbents



(b) VC-backed Firms Versus non-VC-backed Firms



Note. The figure compares the dynamic effects of innovation shocks in each category of patents (public-private, private-private; by column) across start-ups versus established firms (Panel A) and VC-backed versus non-VC-backed firms (Panel B) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row). The estimation by local projections follows eq.(1). The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for the startups (established) firms in Panel A and venture capital (non-venture capital) in Panel B, while the corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: 1976:Q1-2015:Q4.

and 90% confidence intervals) and non-VC-backed firms (orange broken lines and shaded areas). There is some evidence that, when government-funded (left column), VC-backed firms produce more growth-enhancing innovations than other companies; but the magnitudes are smaller than for start-ups and the confidence intervals of the two groups overlap. In contrast, there is virtually no heterogeneity in the effects of privately funded patents (right column). Finally, VC-backed firms with government support tend to outperform their fully private counterparts, reminiscent of the findings by Beraja et al. (2024) for China and in line with those in Li (2025) on the role of venture capitalists in U.S. public–private innovation.

Summary. This section highlights three key findings. First, basic research—exemplified by innovations generated in universities and research institutes financed by taxpayers—produces the strongest and most durable effects on U.S. aggregate TFP and GDP. Second, government-funded patents developed by start-ups, and to a lesser extent by VC-backed firms, yield larger macroeconomic gains than those owned by established business-sector companies. Third, in the absence of government support, these heterogeneities vanish, leaving no systematic differences in the aggregate impact of innovation on output and productivity.

8 Conclusions

Technological progress is often credited to private ingenuity, but our analysis highlights the role of government support in shaping the trajectory of American innovation. Although patents funded by the U.S. government represent only a fraction of overall activity, they are associated with a disproportionate share of medium-term fluctuations in aggregate productivity over the postwar period. This link operates primarily through public funds channeled to universities and research institutes, which emerge as the most powerful correlates of TFP and GDP growth. Their innovations, unconstrained by short-term commercial goals, coincide with the strongest spillovers to private R&D and investment, laying the groundwork for transformative technologies.

Our findings contribute to the macroeconomic literature by identifying a novel source of aggregate technology shocks: government-funded but privately owned innovation. They also reinforce the classical insight of Nelson (1959) and Arrow (1962) that markets underprovide basic research. The institutional architecture envisioned and strengthened by Bush (1945a) —most notably the NIH and NSF— has been central in sustaining U.S. technological leadership. From a policy perspective, our evidence points to the enduring importance of funding basic research in universities and research institutes. Such investments crowd in private-sector activity, generate general-purpose technologies, and shape the medium-term cycles of productivity and economic growth that ultimately underpin the global frontier of knowledge and living standards.

This paper takes a first step toward understanding how government support influences the direction and macroeconomic impact of technological progress. The framework we develop opens the door to new research avenues on the interaction between public policy and innovation. Cross-country comparisons —from South Korea's technological ascent to China's state-led innovation drive and Europe's productivity slowdown— can shed light on how institutional context shapes these dynamics. While we focus on the funding source–ownership structure divide, many other forms of heterogeneity may also play a central role in shaping macroeconomic outcomes: for instance, how universities and research institutes serve as springboards for start-up entrepreneurs and their innovation; the macroeconomic impact of green and brown technologies, and whether any differential effect may depend on public versus private funding; the extent to which private investment in frontier technologies such as AI complements or substitutes public research and affects its macroeconomic influence; how inventors' demographics, origins, and networks shape aggregate outcomes. Finally, our findings reveal institutional forces and players largely absent from leading theories of endogenous growth. Bringing these actors into the core of macroeconomic analysis can lay the foundations for a deeper understanding of how public support and private ingenuity drive technological transformation and standards of living in the long-run.

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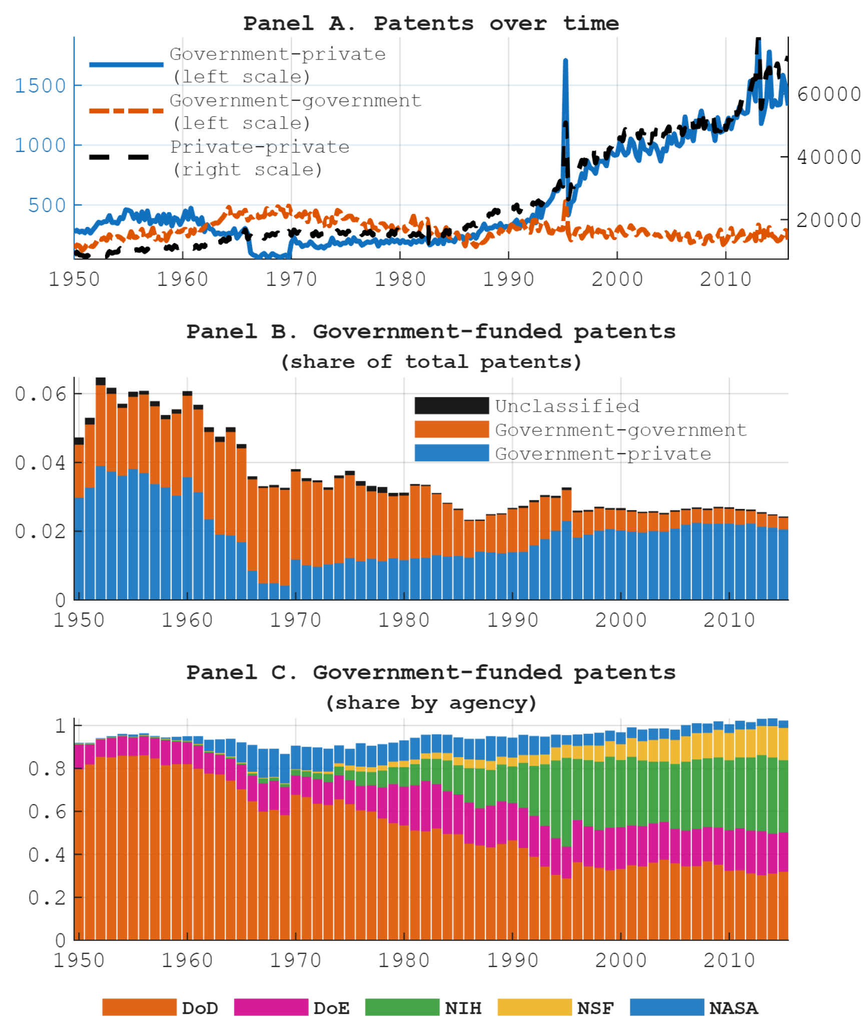
Online Appendix

A Data Sources and Definitions

This Appendix provides further details on the data, its sourcing and the transformations of the key variables used in the paper's empirical analysis.

A1 Descriptive Statistics

Figure A1: The Evolution of Patenting Activities by Funding Entities and Ownership



Note. Panel A reports the quarterly total number of patents by government interest over time (GPR database - Gross and Sampat (2025). Panel B displays public interest patents over time as share of the total number of patents. Panel C represents the breakdown of public interest patents over time by federal agencies. The shares may sum to more than 1 because several agencies may fund the same patent.

Table A1: Descriptive Summary of Patent Types and Importance

Panel A: Publication Type Breakdown			
	Priv–priv	Pub–pub	Pub–priv
Number of Patents	7,000,953	76,601	139,191
Share of Total	97.0%	1.1%	1.9%

Panel B: Importance by Public Interest Type

Statistic	Priv–priv	Pub–pub	Pub–priv
Median	0.17	0.15	0.18
Skewness	0.91	1.59	1.50
Kurtosis	7.49	11.78	11.56

Panel C: Reliance on Science

Statistic	Priv–priv	Pub–pub	Pub–priv
Mean	2.67	3.85	23.15
Median	0.00	0.00	3.00
75th percentile	1.00	1.00	25.00
90th percentile	4.00	7.00	70.00
95th percentile	10.00	19.00	107.00

Panel D: Agency Breakdown

Agency	Patents	Pub–pub share	Pub–priv share
Department of Defense	106,574	43.0%	55.1%
National Institutes of Health	47,830	10.4%	84.0%
Department of Energy	35,439	37.6%	60.5%
National Science Foundation	14,670	≈0%	93.8%
NASA	12,869	56.1%	36.8%

Panel E: Government Interest by Assignee Type

Assignee type	Patents	Pub-share	Share of govt-funded
Research institutes	153,956	8.7%	8.4%
Universities	90,785	52.9%	30.1%
Start-ups	131,572	1.5%	1.2%
VC-backed assignees	410,959	1.6%	4.1%
Federal agencies	42,147	100.0%	26.4%

Note: Panel A is the patent distribution of the government interest classification in the GPR database of Gross and Sampat (2025). Panel B shows the importance distribution in Kelly et al. (2021) by patent category. Panel C shows the reliance on science distribution in Marx and Fuegi (2020, 2022) by patent category. Panel D reports the distribution of public interest patents across main federal agencies; the last two columns do not sum to 100 due to a small group of patents that Gross and Sampat (2025) leave 'unclassified'. Panel E reports for the sample 1975-2015 the total number of patents produced by entity types, together with the shares of government-funded patents within each assignee type (Pub-share) and their (%) contribution to the number of total government-funded patents (Share of govt-funded; they do not sum to 100 because not all possible actors are included). Government-funded patents in Panel E include both pub-pub and pub-priv. Data on startups and venture capital is available since 1975 from Ewens and Marx (2024).

Additional details on patent dynamics and composition. The patents assigned to *public-private* or solely private display an upward time trend, which partly reflects legislative changes. Enacted to encourage the commercialization of inventions arising from federally funded research, the Bayh–Dole Act of 1980 introduced a uniform patent licensing policy across federal funding agencies under which small businesses and non-profit institutions could retain ownership of patents that benefited from public funding while the government retained a license for use. This primarily affected innovations developed by research institutes and universities, some of which may have been classified as public-public rather than public-private without the Act. Moving to shares, we observe that the incidence of solely public patents has been progressively falling over time (Figure A1, Panel B), while the proportion of *public-private* patents has stayed roughly constant with only mild variations over the years. In 1995, the number of patent applications surged due to the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS).

Importance and reliance on science distributions. In Panel B of Table A1, we report that *public-private* patents tend to be more disruptive than *private-private* ones, followed by *public-public* patents. However, their distribution reveals that the importance of public interest patents is heavily skewed to the right and is leptokurtic. In Panel C, we report summary statistics for the number of scientific publications cited in each patent group. Publicly funded innovations emerge as the most exposed to academic publications, especially at the top end of the distribution. These patterns are consistent with the notion that the government typically funds research that is more basic or fundamental relative to the research financed and developed solely by the private sector.

Agency heterogeneity. The innovations of most federal agencies tend to be associated with a majority of private ownerships with government funds. NASA, DoD and—to a lesser extent—DoE display a much higher share of *public-public* patents, while the NIH and the NSF mainly fund innovations that are eventually developed outside the federal government. As revealed by Panel C of Figure A1, patents funded by NASA increased between the 1960s and 1980s, as a result of the Moonshot race with the USSR; since the 1990s, however, they have started to play an increasingly minor role.

Assignee type breakdown. Finally, in Panel E of Table A1, we describe the data employed in Section 7. We combine information on government funding, both for private and public ownerships, with the patents' assignee type, including research institutes, universities, startups, and venture capital-backed companies. Within each assignee type (under the heading 'Pub-share'), more than half of university patents are funded by the government; this share drops to about 9% for research institutes and sits around 1.5% for startups and venture capital companies. On the other hand, universities and federal agencies are the main contributors to the total number of government-funded patents (in the 'Share of govt-funded' column), which is far higher than the shares for research institutes, VC-backed firms, and startups.

A2 Government Patent Registry Database

Gross and Sampat (2025) constructs the Government Patent Register database by combining historical administrative records with several modern data sources to create a comprehensive measure of U.S. government-funded patents. The core of the database is the digitization of the historical U.S. Patent and Trademark Office (USPTO) Register of Government Interest in Patents ("historical GPR"), which the authors digitized and cross-validated against Google Patents. To supplement the historical GPR and extend the data through 2020, the authors integrated several modern sources:

USPTO Patent Assignment Dataset (UPAD). They identified government-interest patents by searching for conveyance text referencing "Executive Order 9424" or "Confirmatory License" and by systematically identifying all federal agencies listed as assignees in the dataset. The authors then manually classified these transactions as conveying either *title* or *license* to the government.

PatentsView Government Interest Statements. The authors used the government interest statement data from PatentsView. Finding occasional imprecision in the existing agency identification, they developed a new approach using a large language model (GPT-4) to extract the specific funding agencies from the text of the interest statements.

Government Assignee Data. They identified government-assigned patents using assignee data from Fleming et al. (2019) for the pre-1976 period and from PatentsView for 1976 onwards.

Gap-filling using Fleming et al. (2019). For the pre-1976 period, the authors identified a set of patents that appeared in the Fleming et al. (2019) data as having an interest statement but were not in the historical GPR. Using a semi-automated process involving GPT-4 and manual review, they isolated the true positives from this sample and extracted the funding agency, adding 818 additional patents to their data.

The final dataset is the union of all patents identified through these sources. The unique feature of the GPR is the classification of government-funded patents into *title* and *license*. In the former, the federal government is the owner of the patent, whereas in the latter, the government retains licensed use of the patent because it funded its development. The method creates a more complete accounting of government-funded patents than previously available, as many patents, particularly the *license* ones from the mid-twentieth century, can only be identified via the historical GPR.

Imputing Unclassified Patents in GPR

The GPR contains a residual category marked as "unknown", primarily arising from multiple records with discordant government-interest information. The size of this group increased after 1980, due to the introduction of digital records and the adoption of the Bayh–Dole Act. Although our main results are unaffected if we exclude these ambiguous cases from the analysis, for completeness, we categorize unknown patents into public-private and public-public. To do so, we apply a straightforward strategy: any indication of a license right for the government or any involvement of private parties in the innovation's development signals joint *public-private* efforts; the remaining cases are classified as *public-public*.

Specifically, to classify patents with unclassified government interest (code 3) in the GPR database, we distinguish between public-public patents (code 1), which are patents developed entirely within government agencies with government retention of title, and public-private patents (code 2), which are patents developed with private sector involvement where contractors/grantees retain title with government license.

We first classify patents based on the `assignee_type` field from PatentsView. Patents with `assignee_type = 6` (U.S. federal government agency) are classified as public-public, while those with `assignee_type = 2` (U.S. company organization) or `assignee_type = 3` (foreign company organization) are classified as public-private.

For remaining unclassified patents, we apply regular expression searches to the government interest statement text (`gi_statement`), converted to lowercase. Patents are classified as public-public if the government interest statement contains any of the following phrases: `"assigned to the united states"`, `"assigned to the uṡȧ"`, `"title to this invention (is|has been) vested"`, or `"owned by the (u?s?|government)"` where `?` allows for optional periods (in Stata). Patents are instead classified as public-private if the statement contains `"nonexclusive"` (indicating nonexclusive license to government) or `"license"` (indicating contractor/grantee retention of title).

Finally, when a patent has multiple government interest records with conflicting classifications, we identify duplicate patent IDs with different government interest codes and retain the public-private record when both public-private and public-public records exist. This prioritization reflects the principle that any private sector involvement classifies the patent as public-private.

A3 Additional Patent Data Sources

Importance. We employ the measure of patents' importance from Kelly et al. (2021), which is the ratio of forward to backward textual similarity, computed using natural language processing techniques. We use the variable `lqsim05` (importance based on a 5-year window) in our baseline analysis and `lqsim010` (importance based on a 10-year window) in our robustness analysis. In the baseline, we define dummy groups based on percentiles computed within each category. In Appendix G, we report that similar results hold when computing percentiles over the whole distribution of patents.

Reliance on Science. We employ the measure of reliance on science from Marx and Fuegi (2020, 2022), which counts scientific citations in patents both in the title and in the body of the patent. We rely on the measure that aggregates papers' citations across title and text.

In Appendix G, we report that similar results hold when computing different percentiles or considering papers' citations as a dichotomous variable.

Innovation Network We construct a measure of innovation network centrality at the US Patent Classification (USPC) level using the citation flow measure of Acemoglu et al. (2016) (available online). In defining the citation network, we follow the analysis in Acemoglu et al. (2016) and exclude self-citation (citations within USPC categories), so our centrality measure is the dominant left eigenvalue of the citation flow network with the leading diagonal set to zero. Finally, we crosswalk the centrality measure from USPC to CPC codes using the USPTO-provided statistical mapping. See I for further details.

Startups and VC. The startup and venture capital-backed flags for patents' assignees are based on data constructed by Ewens and Marx (2024).[39] The patent-level dataset provides assignees' founding year. Following Ewens and Marx (2024), we assign a patent-level startup flag in cases when the patent filing date is 3 or fewer years from the foundation. The VC-backed flag is directly provided by Ewens and Marx (2024) as a dummy equal to 1 if the assignee has received venture capital at any point in its life, and 0 otherwise.

A4 Macroeconomic variables

Our primary source for macroeconomic variables is Antolin-Diaz and Surico (2025). We measure economic activity using log Real GDP per capita, and its main private components also in per-capita logs: Private Consumption, sourced from BEA NIPA data (1947-2015), and Private Investment, which is based on unpublished BEA estimates from 1901 onwards and interpolated to a quarterly frequency. Research and Development (Total R&D) comes from FRED `Y694RX1Q020SBEA` and is expressed in (log) per capita terms by dividing it by the FRED series `CNP16OV` (civilian noninstitutional population). We similarly transform the FRED series `Y006RC1Q027SBEA` for Private R&D. The GDP deflator is the FRED series `GDPDEF`. For productivity, we use Total Factor Productivity (TFP), calculated as the Solow residual from a Cobb-Douglas production function (with a capital share $\alpha = 0.28$) and

[39] The dataset used in Ewens and Marx (2024) is shared through foundingpatents.com

subsequently adjusted for capacity utilization. The aggregate price level is measured by the logarithm of the GDP Deflator, and we include Wages using the FRED series `COMPRNFB`, also in logs. Finally, the model includes two financial variables: the short-term interest rate series from Ramey and Zubairy (2018) and stock prices, sourced from R.J. Shiller website (series `Real price`) and expressed in logs.

B Additional Results

This Appendix presents additional results on the cyclicality of patents applications in each of the three patent categories, on the explicit difference in IRFs across patent groups, a historical decomposition and a counterfactual scenario that elicits the contribution of public-private innovation partnerships to aggregate productivity and output.

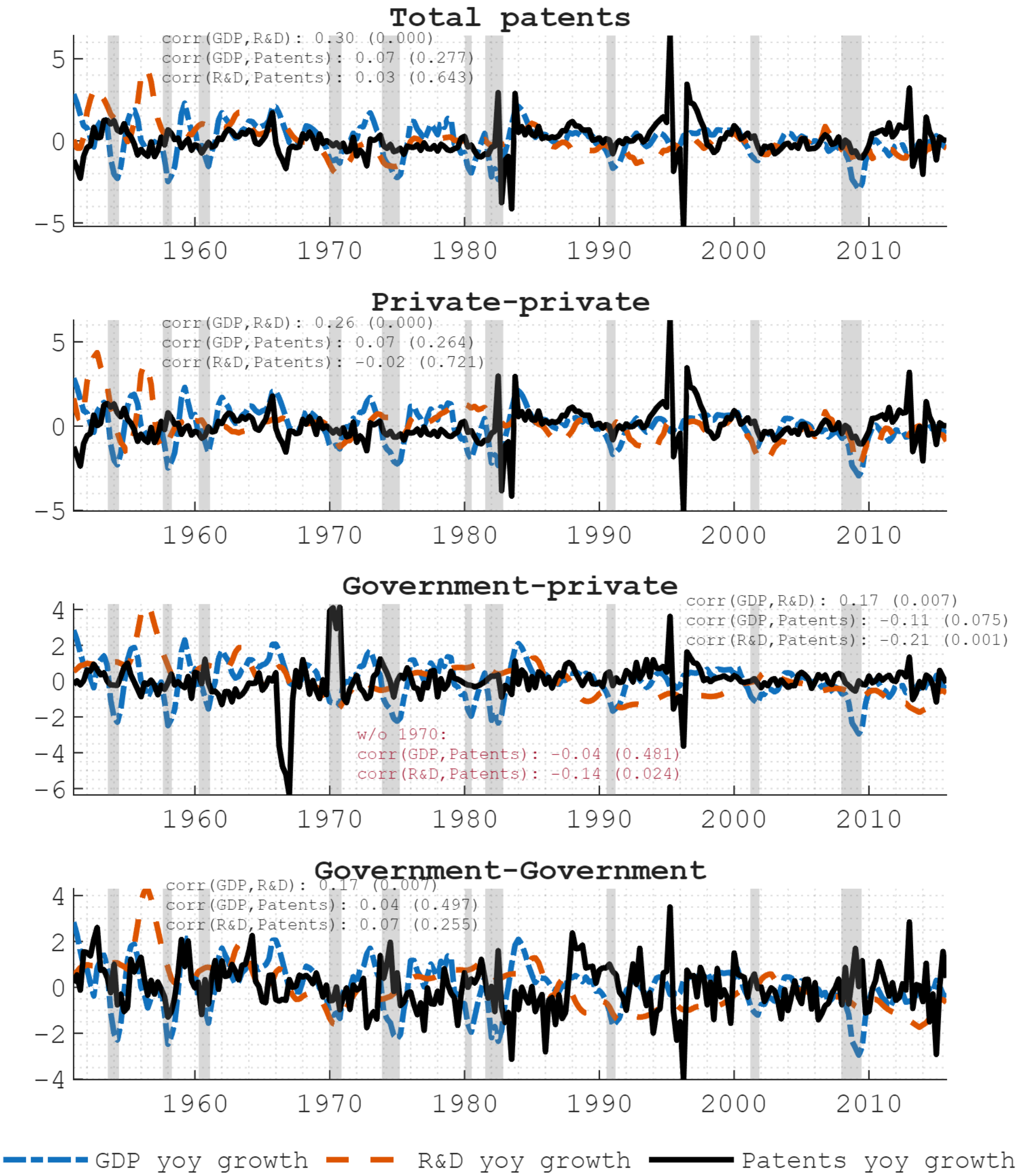
B1 Patent Filing Cyclicality and Effects of Total Patents

In this section, we show that, unlike R&D expenditure, patent filings tend to not exhibit much business-cycle cyclicality, neither economically nor statistically. This holds for all patents as well as government-interest patents. In Figure B1, we report the contemporaneous correlation between these variables and real GDP. The only possible exception are Government-private patents in the third panel. However, while patenting activity in this group is somewhat negatively correlated with GDP, driven by the 1970 recession, the coefficient is small and the significance marginal. Figure B2 plots the effects on key macroeconomic aggregates of estimating the empirical model described in Section 2 using total patents as the right-hand side variable. In line with previous literature (Miranda-Agrippino et al., 2025), an innovation shock measured from total patents has the properties of a standard technology shock, increasing GDP and TFP while lowering prices.

B2 Macroeconomic Impact of Total Patenting Activity

In Figure B2, we show that the dynamic effects of our shocks to patenting activity generate response of main macroeconomic indicators that align with a technology shock interpretation,

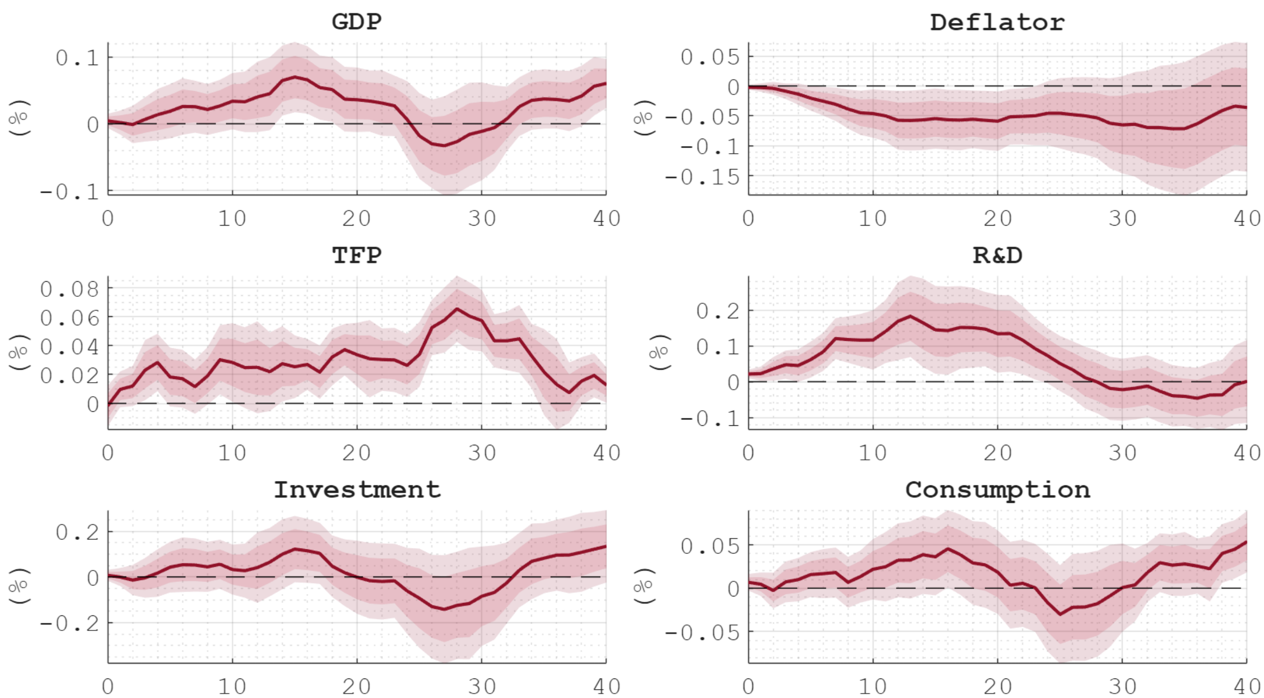
Figure B1: Patent filing cyclicality



Note. The figure displays the growth rates of real per-capita GDP, RD expenditure, and the number of patents filed in each category (total, public-private, private-private, and public-public), along with their contemporaneous correlations (p-values in parentheses). The figure shows that, unlike R&D expenditure, patent filings do not exhibit strong cyclical behavior.

especially the negative conditional correlation between prices and quantities in the first row.

Figure B2: Macroeconomic effects of a patent shock - all patents

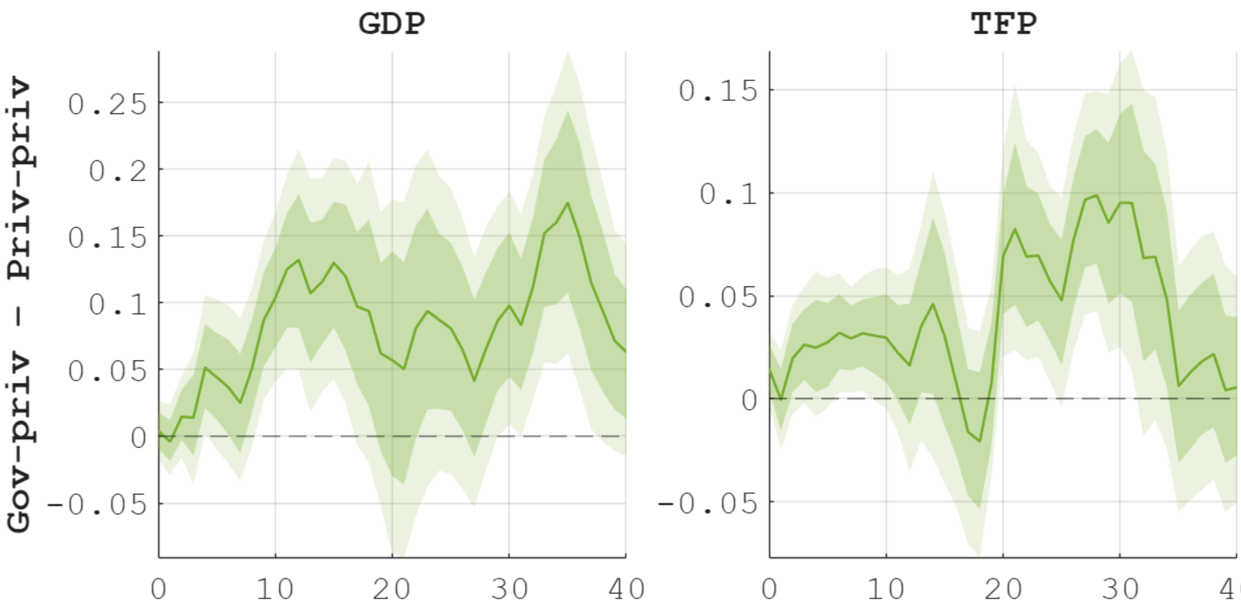


Note. The figure displays the dynamic effects of an aggregate innovation shock on (log) real per-capita GDP, (log) utilization-adjusted TFP, (log) real per-capita private R&D expenditure, (log) real per-capita private investment, (log) real wages, and (log) real per-capita consumption. The shock is an unanticipated increase in the total number of patents, normalized to increase total patents by 1% on impact. The estimation by local projections follows eq.(1). The set of controls includes 4 lags of total patents, real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, and real per-capita R&D expenditure. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4

B3 Are the effects of government-private and private-private patents different?

To explicitly assess the statistical difference between the effects of patenting in government-private and private-private groups, we rely on wild bootstrap with the same multiplier across the three local projection equations. Both the Sup-Wald test and the Cramér-von Mises test reject the equality of the estimated response of GDP and TFP. Figure B3 explicitly report the difference between the estimated response across the two patents group. The delta is economically sizable and highly statistically significant.

Figure B3: Difference between Government-private and fully private effects



Note. The figure displays the differential effects of government-private and private-private shocks on (log) real per-capita GDP and (log) utilization-adjusted TFP. The shock is an unanticipated increase in the number of patents by category, normalized to increase total patents by 1% on impact. The estimation by local projections follows eq.(1). The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from wild bootstrap standard errors. Sample: quarterly data 1950:Q1-2015:Q4

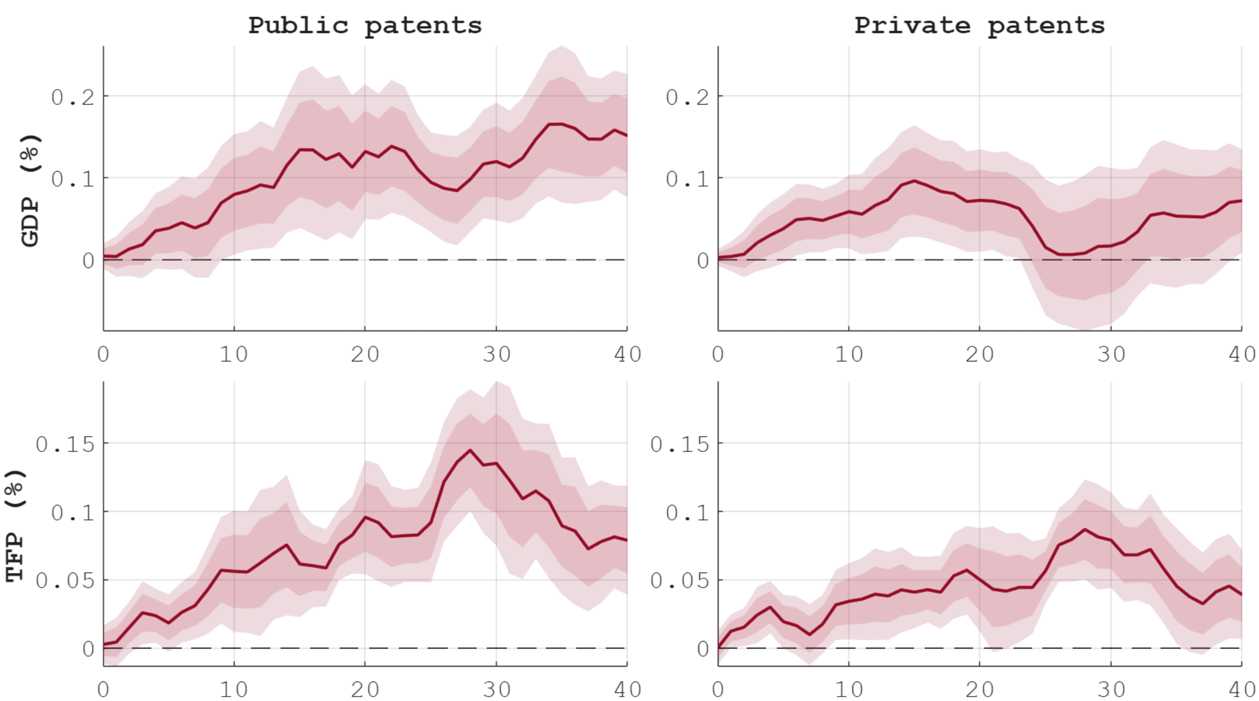
B4 The Bayh–Dole Act

A significant legislative change in patenting occurred in 1980 with the Bayh–Dole Act. The Act changed the rules for patents funded by the federal government and harmonized regulations across agencies. Before the Bayh-Dole Act, the federal government typically retained ownership of inventions arising from its funded research. However, the policies were fragmented across agencies. The Act was intended to increase the incentives for universities and research centers to participate in federally funded projects and patent the resulting research, with the government retaining a license to the patent and acknowledgments of funding. Our time series approach captures the increased patenting incentives introduced by the Act.

Additionally, the Act also led to the reclassification of the ownership of government-funded patents from the government to contractors (universities, firms, etc.). To assess whether classification affects our results, we consolidate the two types of government-funded patents into a single category. Figure B4 - which corresponds to Figure 2) - provides very similar insights to our baseline specification: the boost that government-funded patents provide to

GDP and TFP is twice as large as the stimulus coming from privately-funded patents. Figure B5 - which corresponds to Figure 7a) - is also consistent with the results in the main text: NIH, HHS, and DoE shocks lead to large gains to both GDP and TFP, while the contribution of DoD and NASA is smaller or not statistically significant.

Figure B4: Effects on GDP and TFP - grouping government-funded patents



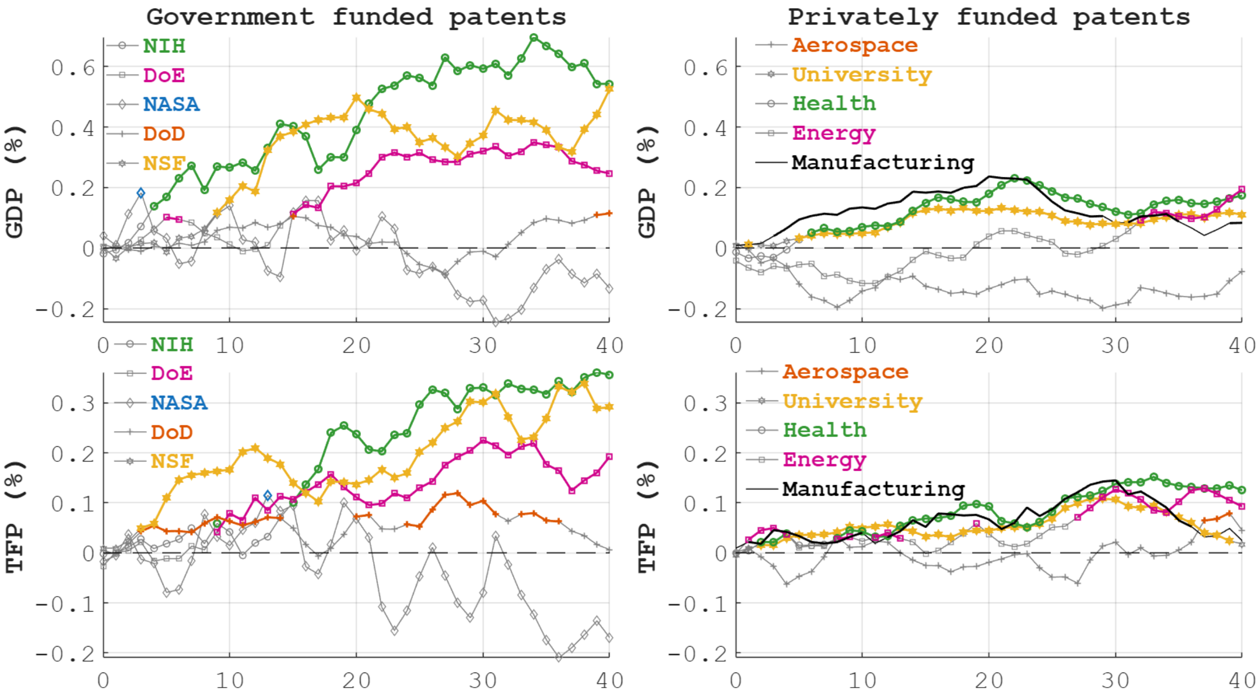
Note. The figure displays the dynamic effects of innovation shocks in each category of patents on (log) real per-capita GDP and (log) utilization-adjusted TFP. This is a robustness check of the baseline results in Figure 2. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The set of controls is the same as in the baseline specification. The solid line represents the point estimate, while the shaded areas report 68% and 90% confidence intervals computed from Newey-West standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

B5 Controlling for Major Institutional Events

Several patent changes occurred in the US patent law between 1950 and 2015. Our patent series exhibits three significant spikes associated with such changes (see Figure A1). The baseline results are unaffected if we dummy out the significant spike associated with TRIPS or all three events (Figure 5b). Below, we provide a short description of these changes.

Creation of the Court of Appeals for the Federal Circuit (1982). In 1982, the establishment of the Court of Appeals for the Federal Circuit significantly enhanced patent protection by improving judicial consistency and favoring patent holders during infringement

Figure B5: Federal Agencies breakdown - unique government-funded category



Note. The figure displays the dynamic effects of innovation shocks in each category of patents (government-funded, privately-funded; by column) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row) by agency-sectoral breakdown. The estimation by local projections follows eq.(1). The size of the shock is normalized such that the peak response of total patents is 1%. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. Colored (gray) lines denote (no) significance at the 68% level according to Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4 (except for 'University' in the second column, 1975q1-2015:Q4).

cases. This judicial shift increased patenting incentives, leading to a substantial increase in filings.

Implementation of the TRIPS Agreement (1995). The introduction of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) in 1995 standardized international patent regulations (following the GATT Uruguay Round agreements), significantly enhancing transparency and discouraging strategic patenting behaviors. International harmonization under TRIPS (Uruguay Round) and associated U.S. implementation created a sharp timing incentive: applicants rushed filings to exploit grandfathering provisions and the pre-deadline regime, producing a mechanical spike across categories (Bertolotti, 2022).

Enactment of the America Invents Act (2013). Implemented in March 2013, the America Invents Act introduced a crucial shift in patent law by transitioning from a "first-to-invent" to a "first-inventor-to-file" priority system. This reform aimed to simplify and accelerate the patenting process, motivating inventors to disclose innovations promptly and thereby increasing patent application filings around the period of its enactment.

C Mapping Empirical IRFs to Social Returns

In this appendix, we develop a tractable model that captures the key features of public-to-private knowledge spillovers. The model provides a structural interpretation of the empirical impulse responses of R&D, TFP, and GDP following a public innovation breakthrough.

By mapping the model to our empirical impulse responses, we show how to estimate key parameters in the computation of the social return to R&D. Despite following very different empirical approaches, we find comparable estimates of returns to public R&D to Fieldhouse and Mertens (2023b). We also provide novel estimates of the strength of agency-specific spillovers to private R&D, diffusion lags, and social returns.

The estimates reveal substantial heterogeneity in public R&D spillovers across agencies, with NSF having the highest and DOD the lowest. The diffusion rates tell a complementary story: DOD exhibits the fastest knowledge diffusion and NSF the slowest. This pattern is consistent with the interpretation that agencies like NSF fund more basic research, which private firms take longer to absorb and commercialize, but ultimately generates larger spillovers. Taken together, our estimates suggest that the return to public R&D is 3.5 times larger at NSF than at DOD.

C1 A Semi-Endogenous Growth Model with Public R&D Spillovers

The economic environment is summarized in Table C1. Final output is produced according to $Y_t = A_t^{\sigma} L_{Y,t}$, where A_t is the stock of knowledge, $L_{Y,t}$ is labor devoted to production, and $\sigma > 0$ governs the elasticity of output with respect to knowledge.[40]

Table C1: The Model

	Equation	
Final output	$Y_t = A_t^{\sigma} L_{Y,t}$	(1)
Knowledge	$\dot{A}_t = R_t - \delta_A A_t$	(2)
Private R&D	$R_t = \chi L_{R,t} A_t^{\phi} \prod_{j=1}^{J} S_{j,t}^{\psi_j}$	(3)
Accessible public ideas	$\dot{S}_{j,t} = \lambda(G_{j,t} - S_{j,t})$	(4)
Raw public ideas	$\dot{G}_{j,t} = \omega_j \tau A_t - \delta_G G_{j,t}$	(5)
Government budget	$\sum_{j=1}^{J} \omega_j = 1$	(6)
Population	$L_t = L_0 e^{nt}, \quad L_t = L_{Y,t} + L_{R,t}$	(7)

Knowledge accumulates through R&D and depreciates at a rate δ_A. Private R&D output R_t depends on R&D labor $L_{R,t}$, the existing knowledge stock A_t raised to the power ϕ, and accessible public knowledge from J government agencies. The parameter $\phi < 1$ governs the rate at which "ideas are getting harder to find" (Jones, 2022), while $\psi_j \geq 0$ captures the spillover elasticity from agency j's public knowledge. Define $\Psi \equiv \sum_j \psi_j$ as the total public-knowledge elasticity.

Public knowledge dynamics involve two stocks for each agency j. Raw public ideas $G_{j,t}$ arrive at rate $\omega_j \tau A_t$ and depreciate at rate δ_G. The term A_t reflects a "standing on shoulders" effect whereby public researchers build on existing knowledge. This formulation can be derived from a more primitive specification where the arrival rate depends on government

[40] We adopt a semi-endogenous growth framework because it delivers persistent level effects of innovation without (likely counterfactual) permanent growth effects and, as shown below, captures the key dynamic features of the empirical impulse responses in a parsimonious and tractable way.

expenditure $E_{j,t}$, but there is an offsetting congestion effect from the scale of the economy Y_t. The parameter τ represents public R&D intensity, and ω_j is agency j's share of the total, with $\sum_j \omega_j = 1$.

Raw public knowledge diffuses gradually into the "accessible" stock $S_{j,t}$ at a common rate λ. This diffusion process captures the time it takes for private researchers to learn about and absorb public breakthroughs. The distinction between raw and accessible knowledge is central to the model, as it generates the hump-shaped impulse responses that we document empirically.

It can be shown that on a balanced growth path where all knowledge stocks grow at rate g, the equilibrium growth rate is

$$g = \frac{n}{1 - (\phi + \Psi)} \tag{C1}$$

where n is the rate of population growth, and $\phi + \Psi < 1$ such that there are diminishing returns to the reproducible knowledge inputs at the aggregate level.

Long-run growth depends on population growth n and the knowledge elasticities ϕ and Ψ, but not on the level of R&D effort or public R&D policy. Increasing public R&D intensity τ or reallocating spending across agencies $\{\omega_j\}$ affects the *level* of all knowledge stocks but does not affect the long-run growth rate. This semi-endogenous property reflects diminishing returns: as knowledge accumulates, it becomes progressively harder to generate new ideas, so faster idea production today is offset by harder discovery tomorrow. In the long run, growth is pinned down by the rate at which new researchers enter the economy.

From the production function $Y_t = A_t^\sigma L_{Y,t}$, per-capita output grows at rate $g_y = \sigma g$, so the TFP elasticity σ scales the effect of knowledge accumulation on aggregate output.

C2 Theoretical Impulse Responses

We now derive the model's impulse responses to match with our empirical estimates. The thought experiment traces out the dynamic effects of a single public idea from agency j arriving at time $t = 0$. This isolates the propagation of a public research breakthrough through the economy growing along a balanced growth path (BGP).

Let $\tilde{x}_t \equiv x_t e^{-gt}$ denote the detrended level of any variable that grows at rate g on the

BGP, and let $\hat{x}_t \equiv (\tilde{x}_t - \bar{\tilde{x}})/\bar{\tilde{x}}$ denote the percent deviation from the BGP. All impulse responses below are expressed in terms of $\hat{x}_t$.

Raw public knowledge. The shock is a unit increase in raw public knowledge of agency j at $t = 0$, so $\hat{G}_{j,0} = 1$. In detrended form, raw public knowledge therefore obeys $\dot{\tilde{G}}_{j,t} = -(\delta_G + g)\tilde{G}_{j,t}$, so the impulse response is

$$\hat{G}_{j,t} = e^{-(\delta_G+g)t} \tag{C2}$$

Accessible public knowledge. Detrended accessible knowledge evolves according to $\dot{\tilde{S}}_{j,t} = \lambda\tilde{G}_{j,t} - (\lambda + g)\tilde{S}_{j,t}$. Linearizing around the BGP and imposing $\hat{S}_{j,0} = 0$ yields

$$\hat{S}_{j,t} = \frac{\lambda + g}{\lambda - \delta_G}\Big(e^{-(\delta_G+g)t} - e^{-(\lambda+g)t}\Big), \qquad \lambda \neq \delta_G \tag{C3}$$

The response is hump-shaped: it initially rises as knowledge diffuses from G_j to S_j, then decays as both stocks depreciate relative to trend.

Private R&D. Private R&D is given by $R_t = \chi L_{R,t} A_t^{\phi} \prod_k S_{k,t}^{\psi_k}$. Log-linearizing around the BGP (with a constant R&D labor share) yields $\hat{R}_t = \phi\hat{A}_t + \sum_k \psi_k \hat{S}_{k,t}$. Since only agency j is shocked,

$$\hat{R}_t = \phi\hat{A}_t + \psi_j\hat{S}_{j,t} \tag{C4}$$

Stock of knowledge. The stock of knowledge evolves as $\dot{A}_t = R_t - \delta_A A_t$. In detrended form and linearized around the BGP,

$$\dot{\hat{A}}_t = (\delta_A + g)(\hat{R}_t - \hat{A}_t) \tag{C5}$$

Substituting equation (C4) gives

$$\dot{\hat{A}}_t = -\mu\hat{A}_t + (\delta_A + g)\psi_j\hat{S}_{j,t}, \qquad \mu \equiv (\delta_A + g)(1 - \phi) \tag{C6}$$

Because $\phi < 1$ in the semi-endogenous model, $\mu > 0$ and the stock of knowledge is mean-reverting.

Solving equation (C6) with $\hat{A}_0 = 0$ yields

$$\hat{A}_t = (\delta_A + g)\psi_j \int_0^t e^{-\mu(t-u)} \hat{S}_{j,u} \, du \tag{C7}$$

For the generic case $\lambda \neq \delta_G$, $\mu \neq (\lambda + g)$, and $\mu \neq (\delta_G + g)$, the closed-form solution is

$$\hat{A}_t = (\delta_A + g)\psi_j \frac{\lambda}{\lambda - \delta_G} \left[\frac{e^{-(\delta_G+g)t} - e^{-\mu t}}{\mu - (\delta_G + g)} - \frac{e^{-(\lambda+g)t} - e^{-\mu t}}{\mu - (\lambda + g)} \right] \tag{C8}$$

The stock of knowledge rises gradually, peaks later than R&D, and eventually decays back to the BGP due to the diminishing returns effect.

Output and TFP. Final output is $Y_t = A_t^{\sigma} L_{Y,t}$. With $L_{Y,t}$ on its BGP,

$$\widehat{\text{TFP}}_t = \sigma \hat{A}_t, \qquad \hat{Y}_t = \sigma \hat{A}_t \tag{C9}$$

Figure C1 illustrates the theoretical impulse responses for two contrasting agency types: a high-spillover agency and a low-spillover agency.

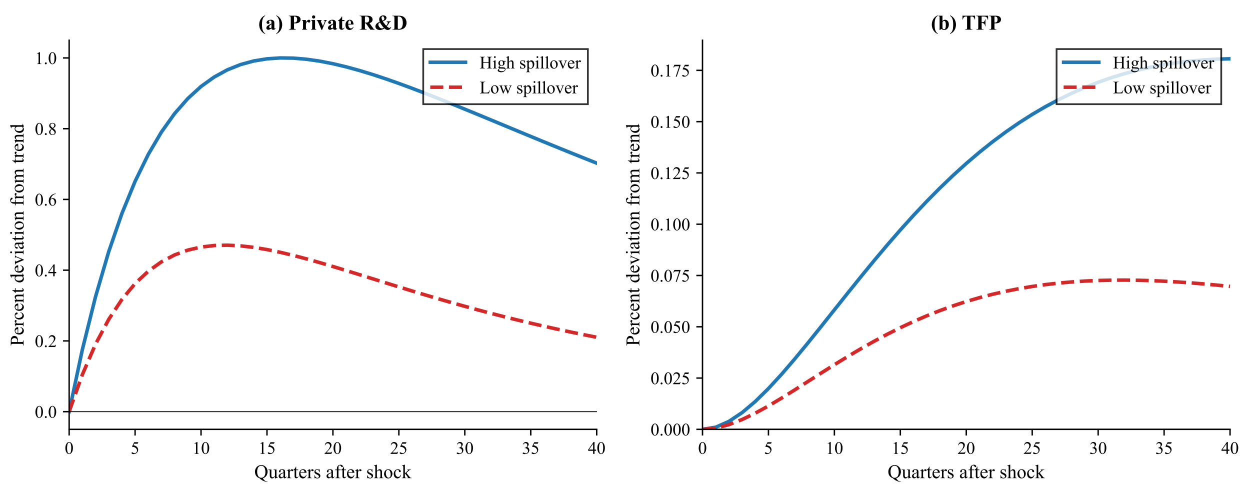


Figure C1: Theoretical Impulse Responses to a Public Research Breakthrough

Note. Panel (a) shows the response of private R&D to a shock in raw public knowledge, computed from equation (C4). Panel (b) shows the TFP response, computed from equation (C9). The calibration for the low- and high-spillover agencies corresponds to the estimates for DOD and NSF in Tables C3 and C4. Other parameters: $\sigma = 0.26$, $\phi = -2$, $\delta_G = 5\%$, $\delta_A = 15\%$, $g = 2\%$ annual.

C3 Estimating Model Parameters

We now show how to estimate the key model parameters using our empirical impulse responses. Three parameters are of particular interest: the TFP elasticity σ, which governs how strongly knowledge accumulation translates into aggregate productivity gains; the diffusion rate λ, which determines how quickly public innovation becomes accessible to private researchers; and the spillover elasticities ψ_j, which determine which types of public innovation are most complementary to private R&D.

We calibrate three parameters. First, we set the depreciation rate of the stock of knowledge to $\delta_A = 15\%$ annually, following the Bureau of Economic Analysis methodology for R&D capital stocks. Second, conjecturing that basic innovation is less subject to creative destruction than applied innovation, we set the depreciation rate of public knowledge to $\delta_G = 5\%$ annually, motivated by our paper's evidence that public innovation tends to be more basic than private R&D. Third, we set $\phi = -2$, following Jones (2022).

C3.1 Estimating σ

The TFP elasticity σ can be recovered by regressing the empirical TFP impulse response on the model-implied knowledge stock. From the model, the TFP response is $\widehat{\text{TFP}}_t = \sigma \hat{A}_t$, where knowledge accumulates according to the log-linearized dynamics:

$$\hat{A}_{t+1} = (1 - \delta_A)\hat{A}_t + (g + \delta_A)\hat{R}_t \tag{C10}$$

Starting from $\hat{A}_0 = 0$, we use the empirical R&D impulse response to construct the model-implied knowledge stock via perpetual inventory. We then estimate σ by OLS regression of the TFP impulse response on this constructed knowledge stock:

$$\widehat{\text{TFP}}_t = \sigma \hat{A}_t + \varepsilon_t \tag{C11}$$

Table C2 reports the resulting estimates of σ under alternative assumptions about the annual depreciation rate δ_A.

Table C2: Estimates of the TFP Elasticity σ: OLS Regression Estimator

	Depreciation rate (annual)				
	5%	10%	15%	20%	30%
$\hat{\sigma}$	0.42	0.30	0.26	0.24	0.23

Note. Estimates based on OLS regression of the TFP impulse response on model-implied knowledge stock following a public-private patent shock. The knowledge stock is constructed via perpetual inventory using the empirical R&D impulse response. The balanced growth rate is set to $g = 2\%$ annual.

C3.2 Estimating λ

Although the model assumes a common diffusion rate λ across all agencies for tractability, we can estimate agency-specific diffusion rates from the empirical IRFs. The timing of each agency's peak R&D response provides information about how quickly private researchers absorb public knowledge from that agency.

From equation (C4), the R&D response is $\hat{R}_t = \phi \hat{A}_t + \psi_j \hat{S}_{j,t}$. The peak occurs where

$$\frac{d\hat{R}_t}{dt} = \phi \frac{d\hat{A}_t}{dt} + \psi_j \frac{d\hat{S}_{j,t}}{dt} = 0 \tag{C12}$$

Given an observed peak time $\hat{t}^*$ from the empirical R&D impulse response, we solve for λ numerically by finding the root of

$$F(\lambda) \equiv \phi \frac{d\hat{A}_t}{dt}\bigg|_{t=\hat{t}^*} + \psi_j \frac{d\hat{S}_{j,t}}{dt}\bigg|_{t=\hat{t}^*} = 0 \tag{C13}$$

where both $\hat{A}_t$ and $\hat{S}_{j,t}$ are computed from the closed-form solutions in equations (C3) and (C8).[41]

Table C3 reports the implied diffusion rates for each agency under this calibration. Agencies with later peak responses have lower implied diffusion rates, reflecting slower absorption of public knowledge by private researchers. DOD exhibits the fastest diffusion ($\lambda = 17\%$ annual), consistent with applied defense research being quickly absorbed by contractors. DOE and NSF show the slowest diffusion ($\lambda \approx 7$–8% annual), consistent with basic research taking longer to diffuse.

[41] Note that ψ_j cancels from the peak condition since both terms are proportional to it.

Table C3: Agency-Specific Diffusion Rates

	DOD	DOE	NIH	NASA	NSF
Peak $\hat{t}^*$ (quarters)	18	36	26	22	34
λ (annual)	17%	7%	11%	13%	8%

Note. The diffusion rate λ is inferred from the timing of the peak R&D response using equation (C13) with $\delta_G = 5\%$ and $g = 2\%$ annual.

C3.3 Estimating ψ_j

The agency-specific spillover elasticities ψ_j determine how strongly public research from each agency complements private R&D. We estimate ψ_j by matching the theoretical R&D impulse response to the empirical agency-specific R&D responses. From equation (C4), both terms contributing to $\hat{R}_t$ are linear in ψ_j, so we can write

$$\hat{R}_t = \psi_j \cdot r(t; \lambda, \delta_G, \delta_A, g, \phi) \tag{C14}$$

where the shape function $r(t) = \phi \cdot h(t) + f(t)$, with $f(t)$ from equation (C3) and $h(t)$ from Equation (C8).

Given calibrated values for $\{\delta_G, \delta_A, g, \phi\}$, and estimated λ_j, we estimate ψ_j by OLS regression of the empirical R&D impulse response on the theoretical shape function:

$$\hat{\psi}_j = \frac{\sum_t \hat{R}_t^{\text{data}} \cdot r(t)}{\sum_t r(t)^2} \tag{C15}$$

To discipline the degree of overall spillovers, we estimate Ψ by fitting the theoretical R&D impulse response to the empirical response following an aggregate government-private patent shock. This yields $\Psi = 1.29$. To arrive at our final estimates of ψ_j, we rescale estimates of C15 to impose $\Psi = \sum_j \psi_j$. Table C4 reports the resulting ψ_j estimates.

Table C4: Estimates of Agency-Specific Spillover Elasticities ψ_j

	DOD	DOE	NIH	NASA	NSF	Total
ψ_j	0.12	0.30	0.26	0.17	0.43	1.29

Note. Spillover elasticities estimated in two steps: (1) estimate aggregate $\Psi = 1.29$ from overall public patent shocks, (2) estimate relative shares from agency-specific IRFs using λ_j from Table C3, then scale by Ψ. Other parameters: $\delta_G = 5\%$, $\delta_A = 15\%$, $g = 2\%$ annual, $\phi = -2$.

C3.4 Returns to Public R&D

We now combine the parameter estimates to compute the social return to public R&D for each agency. We follow the approach in Fieldhouse and Mertens (2023b), but incorporate agency-specific spillover elasticities and the decreasing-returns-to-ideas parameter, ϕ.

On the balanced growth path, the knowledge accumulation equation $\dot{A} = R - \delta_A A$ implies $R/A = g + \delta_A$. Substituting the R&D function $R = \chi L_R A^{\phi} \prod_j S_j^{\psi_j}$ and rearranging yields $A^{1-\phi} = \chi L_R (g+\delta_A)^{-1} \prod_j S_j^{\psi_j}$. Taking logs and differentiating with respect to $\ln S_j$ gives the elasticity of output with respect to the knowledge stock S_j:

$$\varepsilon_j \equiv \frac{\partial \ln Y}{\partial \ln S_j} = \frac{\sigma \psi_j}{1-\phi} \tag{C16}$$

where we have used the production function $Y = A^{\sigma} L_Y$. The static gross social return (dollars of GDP per dollar of public R&D) is then

$$\rho_j^{\text{gross}} = \varepsilon_j \cdot \frac{Y}{S_j} = \frac{\sigma \psi_j}{1-\phi} \cdot \frac{Y}{S_j} \tag{C17}$$

Given the uncertainty in estimating agency-level knowledge stocks, we use the calibration in Fieldhouse and Mertens (2023b) of $S/Y = 0.06$ and apportion knowledge stocks equally across agencies ($S_j/Y = 0.012$). Table C5 reports the social return to public R&D by agency.

Table C5: Returns to Public R&D by Agency

Agency	ψ_j	ε_j	ρ_j
DOD	0.12	0.011	0.89
DOE	0.30	0.026	2.15
NIH	0.26	0.023	1.89
NASA	0.17	0.015	1.26
NSF	0.43	0.037	3.09
Average			1.86

Note. The output elasticity is $\varepsilon_j = \sigma\psi_j/(1-\phi)$ with $\sigma = 0.26$ and $\phi = -2$. The social return is $\rho_j = \varepsilon_j \times (Y/S_j)$ with $S_j/Y = 0.012$.

Agency-specific returns are proportional to spillover elasticities: NSF and DOD have the highest and lowest returns. Our average agency-level return is 186%, which falls within the 140–210% range estimated by Fieldhouse and Mertens (2023b).

These estimates suggest scope for welfare gains from reallocating public R&D to high-ψ_j agencies—particularly NSF, DOE, and NIH. Of course, such calculations abstract from adjustment costs, political economy constraints, and the possibility that marginal spillovers differ from average spillovers as agency budgets change.

D The Anatomy of Public Innovation

This Appendix provides further details on government-funded innovations. We report the top government-private and private-private assignees in our dataset, provide details on government-funded historically important patents, and offer insights from key studies.

D1 Top assignees in public-private partnerships and examples of important public-interest patents

Table D1 reports entities that own most patents in the government-private and private-private categories. The University of California, MIT, and General Electric are the top three assignees in the first category. IBM, Samsung and Canon are the top three in the privately funded patents.

Table D2 reports government-funded patents in the historically important group identified by Kelly et al. (2021).[42] As the list ended in 2002, we have extended it till 2015 by employing *Chat-GPT Deep Research* and manually verifying all information.

[42] The list was based on a list of 250 historically important patents formerly available from the USPTO.

Table D1: Top Assignees by Public and Private Interest

Public-Private		*Private-Private*	
Name	**Count**	**Name**	**Count**
University of California	6537	IBM Corporation	113608
Massachusetts Institute of Technology	3301	Samsung Electronics	87658
General Electric Company	2547	Canon	65872
California Institute of Technology	2266	Fujitsu	48771
Wisconsin Alumni Research Foundation	2158	Sony Group	41398
Stanford University	1523	General Electric Company	40694
University of Texas System	1425	Toshiba	39858
Johns Hopkins University	1256	Hitachi	37172
University of Michigan	1157	Intel Corporation	34992
Harvard University	1079	Mitsubishi Electric	32575
Columbia University	1013	Sumitomo Electric Industries	30523
Boeing Company	1000	NEC Corporation	28600
UT-Battelle, LLC	1000	Siemens AG	27206
Northwestern University	966	Microsoft Corporation	26115
Raytheon Company	885	Micron Technology	24477
Honeywell International Inc.	869	LG Electronics	23918
University of Pennsylvania	841	Seiko Epson	22734

Table D2: Historically important patents with public interest

Patent	Year	Inventor	Invention	Govt. Interest	Private actor	Agency
1980972	1934	Small Lyndon Frederick	Morphine	pub–pub		-
2206634	1940	Enrico Fermi et al	Radioactive Isotopes	pub–pub		DOE
2329074	1943	Paul Muller	DDT – Insecticide	pub–priv	Novartis	DOD
2404334	1946	Frank Whittle	Jet Engine	pub–priv	Power Jets Limited	DOD
2682050	1954	Andrew Alford	Radio Navigation System	pub–priv	Andrew Alford	DOD
2708656	1955	Enrico Fermi et al	Neutronic reactor	pub–pub		DOE
2708722	1955	An Wang	Magnetic Core Memory	pub–priv	An Wang	DOD
2816721	1957	R. J. Taylor	Rocket Engine	pub–pub		DOD
2835548	1958	Robert C. Baumann	Satellite	pub–pub		DOD
2879439	1959	Charles H. Townes	Maser	pub–priv	Charles H. Townes	DOD
3093346	1963	M. A. Faget et al	First Manned Space Capsule	pub–pub		NASA
3156523	1964	G. T. Seaborg	Americium (Element 95)	pub–pub		DOE
3478216	1969	G. Carruthers	Far-Ultraviolet Camera	pub–pub		DOD
4237224	1980	Boyer & Cohen	Molecular chimeras	pub–priv		NSF
4363877	1982	H. M. Goodman et al	Human Growth Hormone	pub–priv	UCSD	NIH
4399216	1983	Richard Axel et al	Genetic transformation	pub–priv	Columbia University	NIH
4468464	1984	Boyer & Cohen	Molecular chimeras	pub–priv	Stanford	NSF
4634665	1987	Richard Axel et al	Genetic transformation	pub–priv	Columbia University	NIH
4838644	1989	Ellen Ochoa et al	Recognizing Method	pub–pub		DOE
5149636	1992	Richard Axel	Genetic transformation	pub–priv	Columbia University	NIH
6285999	2001	Larry Page	Google PageRank	pub–priv	Stanford	NSF
6677082	2001	Michael Thackeray et al	Lithium ion batteries	pub–priv	UChicago Argonne	DoE
6413802	2002	Chenming Hu et al	3D-transistor geometry	pub–priv	UCSD	DoD
6506559	2003	Andrew Fire et al	RNA interference (dsRNA)	pub–priv	Carnegie Institution, UMass Boston	NIH
6794534	2004	Robert H. Grubbs	Olefin-metathesis Ru catalyst	pub–priv	Caltech	NIH
8278036	2009	Katalin Kariko and Drew Weissman	mRNA	pub–priv	U Penn	NIH
7797367	2010	David Gelvin et al	Wireless Integrated Network Sensors	pub–priv	Sensoria Corporation	DoD
8367991	2011	Timothy Bradley	Modulation device for a mobile tracking device	pub–pub		DoD
8183038	2012	James A. Thomson	Induced-pluripotent stem cells	pub–priv	U of Wisconsin	NIH
8185551	2012	Bradley Kuzmaul et al	Disk-resident streaming dictionary	pub–priv	Rutgers University et al	NSF
8399645	2013	Dario Campana et al	CAR-T cell therapy (cancer treatment)	pub–priv	St Jude Childrens Research Hospital	NIH
8697359	2014	Feng Zhang	CRISPR–Cas9 genome editing	pub–priv	MIT, Broad Institute	NIH

Note. The table reports public-interest patents within the list of historically important patents defined by Kelly et al. (2021), extended to 2015 using ChatGPT Deep Research.

D2 Case Studies

In this Appendix, we present eight case studies – six success stories and two notable failures – of patents that exemplify the main categories of interest in this paper: patents funded by the government but developed and owned by the private sector; patents funded and owned by the public sector; patents funded by the government and developed by private startups.

I) Public-private patents funded by the National Institutes of Health (NIH). There are many notable examples of successful patents funded by the government but owned by the non-federal entities that have laid the foundation for profound technological acceleration across various fields. Among others, breakthroughs in medical research conducted together with the private sector improved disease treatment planning and enabled earlier and more accurate diagnosis. One of them is the groundbreaking research on RNA interference (RNAi) using double-stranded RNA, published by Andrew Fire and Craig Mello in 1998. A patent on that discovery was filed by the two researchers under US Patent No. 6,506,559, granted in 2003. This discovery, funded in part by the NIH, revolutionized molecular biology by providing a powerful tool to selectively inhibit genes, enabling advances in drug development and therapeutic interventions. RNAi technology has had vast implications in biotechnology and medicine, leading to new treatments for diseases such as viral infections and cancers and spurring a thriving industry centered on gene-silencing technologies. For such achievement, Andrew Fire and Craig Mello received the Nobel Prize in Physiology or Medicine in 2006.

II) Public-private patents funded by the National Science Foundation (NSF). Other examples pertain to the role of the National Science Foundation in developing foundational research across manufacturing, networking, and computer technologies. In the field of computer science, the development of the PageRank algorithm at Stanford University under NSF's Digital Library Initiative formed the backbone of Google's search engine. Before PageRank, most search engines ranked web pages based mainly on counting how often search terms appeared in a page's text, often leading to low-quality or spammy pages ranking high. PageRank, by contrast, introduced a network-based ranking system in which pages gained importance not just by their content but also by how many other pages linked to them and by the importance of those linking pages. In other words, a link from a highly ranked page (like a respected academic site) counted much more than a link from a random blog. This foundational algorithm that considers the quality of links and capture the 'collective intelligence' of the Web revolutionized the search of the Internet, transformed the access of information and catalyzed the growth of the digital economy. The assignee of the patent was Stanford University, as Larry Page was a Ph.D. student there when, together with Sergey Brin, he developed the algorithm. The patent was filed in January 1998 (U.S. Patent No. 6,285,999) and preceded by a few months the foundation of Google.

III) Public-private patents involving a startup. Publicly funded research has been particularly effective when collaborating with private startups, which have greatly benefited from such partnerships. A prime example is U.S. Patent No. 7,148,040, filed in 2002 and titled "Method of Rapid Production of Hybridomas Expressing Monoclonal Antibodies on the Cell Surface," which was developed shortly after the founding of a pioneering biotech startup, Abeome Corporation. This patent, which includes a government interest statement acknowledging direct public-sector involvement in its development, describes innovative methods for rapidly generating hybridoma cells that display monoclonal antibodies on their surfaces, greatly accelerating antibody discovery and production. The underlying research was firmly rooted in publicly funded work in cellular biology and immunology, supported by the National Institutes of Health (NIH). The startup utilized this foundational knowledge to create practical, scalable technologies that streamlined monoclonal antibody development for therapeutic and diagnostic applications. Patents like this have advanced biotechnology by enabling faster drug discovery and personalized medicine, reinforcing the vital role of translating government-sponsored research into impactful commercial innovations.

IV) Highly-disruptive public patents funded by the Department of Defense. Some patents with public interest and public ownership have also been extraordinarily disruptive. One of the most consequential examples is U.S. Patent No. 3,789,409, titled "Navigation System Using Satellites and Passive Ranging Techniques," issued in 1974 and attributed to Roger L. Easton, a key figure in the development of the Global Positioning System (GPS).

This patent laid the groundwork for satellite-based positioning by describing a system that used precise timing signals from orbiting satellites to determine the location of a receiver on Earth. Crucially, the invention introduced concepts such as passive ranging, time synchronization via atomic clocks, and orbital tracking—all of which became central to modern GPS systems. Developed at the Naval Research Laboratory (NRL) and fully funded by the U.S. Department of Defense, the invention was assigned to the U.S. government, exemplifying a case of direct public ownership of high-impact intellectual property. Initially intended for military navigation and targeting, the technology was eventually declassified and released for civilian use, catalyzing a transformation in global navigation, logistics, agriculture, and everyday consumer behavior. The patent's core principles have since been embedded in virtually every GPS-enabled device—from smartphones and car navigation systems to precision-guided farming equipment and autonomous vehicles—demonstrating the enormous long-term value of publicly funded innovation.

V) Highly disruptive public patents funded by the Department of Energy and the Department of Defense. Other examples of important patents developed through federal agency initiatives come from the energy sector. One of the most consequential is U.S. Patent No. 2,708,656, titled "Neutronic Reactor," filed on December 19, 1944, by Enrico Fermi and Leo Szilard, and granted on May 17, 1955. This patent describes a nuclear reactor design using graphite as a moderator and natural uranium arranged in a geometric lattice to sustain a controlled nuclear chain reaction. The innovation solved critical challenges in reactor stability and safety, laying the foundation for nearly all modern nuclear reactor designs. The research was conducted under the Manhattan Project, a top-secret World War II initiative managed by the Department of War (a precursor to today's Department of Defense), and later transferred to the Department of Energy, which now oversees many of the resulting technologies and intellectual property. The University of Chicago, through its Metallurgical Laboratory (Met Lab), was a central site of this work and where Fermi's team achieved the world's first controlled nuclear chain reaction in 1942. The patent's long-term impact has been profound: it enabled the development of both civilian nuclear power plants—now a major source of carbon-free energy—and numerous advances in nuclear safety, reactor design, and scientific instrumentation. The reactor principles outlined in this patent continue to influence nuclear innovation across energy, medicine, and defense.

VI) The role of the public in developing GPS technologies. Some patents with public interest and public ownership have also been extraordinarily disruptive. A prime example is U.S. Patent No. 3,126,545, titled "Satellite Hyperbolic Navigation System," issued on March 24, 1964, to I. D. Smith Jr. and assigned to the United States government. This patent encapsulated the core principles of the Transit navigation system, the world's first operational satellite-based navigation network. Developed in the late 1950s and early 1960s by Johns Hopkins University's Applied Physics Laboratory (APL) in close collaboration with and under the sponsorship of the U.S. Navy, the project was fully funded by the Department of Defense (DoD). Transit eliminated the need for fixed ground-based infrastructure and delivered global positioning capabilities long before the advent of GPS. Operational from 1964 through the 1990s, the system introduced precursor technologies to the architecture of the Global Positioning System (GPS).

NASA subsequently played a critical role in extending these capabilities into space-based applications. One such contribution is captured in U.S. Patent No. 7,548,199, titled "Radiation Hardened Fast Acquisition Weak Signal Tracking System and Method," issued in 2009 and assigned to NASA. This invention enabled GPS receivers to rapidly acquire and track weak positioning signals in the challenging environment of Low Earth Orbit, allowing for precise autonomous navigation of satellites and spacecraft. By hardening GPS technology for use in space, NASA extended the utility of satellite navigation beyond Earth, reinforcing the broad and enduring impact of federally funded innovation.

VII) Public failure (a). A notable example of government-funded research that is regarded as a failure is U.S. Patent No. 2,992,981, titled "Neutronic reactor core", granted on July 08, 1961, and assigned to the U.S. Atomic Energy Commission (AEC), a predecessor to the Department of Energy. This patent outlined a design for a nuclear reactor that could be used to power a jet aircraft, promising virtually unlimited flight endurance. Funded by the AEC and the Department of Defense through the Aircraft Nuclear Propulsion (ANP) program in the 1950s, the initiative included the NB-36H "Crusader" testbed and plans for the Convair X-6 nuclear bomber. Despite over $1 billion of funding and years of high-profile research, reactor flights never moved beyond shielding tests, and no aircraft ever flew using nuclear power. The entire program was canceled in 1961, with the X-6 never built. Though the scientific work informed later nuclear and shielding technologies, the core promise—an operational nuclear-powered airplane—was never realized.

VIII) Public failure (b). Another example is that of U.S. Patent No. 7,394,016, titled "Bifacial Elongated Solar Cell Devices with Internal Reflectors," granted on July 15, 2008, to Benyamin Buller et al. and assigned to Solyndra LLC. The patent outlines the company's signature cylindrical CIGS (copper indium gallium selenide) solar cell design, arranged in tubular casings with internal reflectors, intended to enhance efficiency. The technology was backed by a large federal commitment—a $535 million loan guarantee from the U.S. Department of Energy (DOE) under the 2009 stimulus program, making Solyndra a high-profile centerpiece of clean-energy investment. Yet, despite its patented innovation, Solyndra could not compete with rapidly declining costs of silicon-based panels from overseas, and by August 2011, the company filed for bankruptcy, leaving taxpayers with a substantial loss.

These cases stand as cautionary examples: even with robust federal funding, dramatic technological breakthroughs are not guaranteed.

E Construction of the Narrative Instrument

In this section, we describe the construction of the narrative instrument used in one of our fourteen alternative time-series identification strategies. The goal is to isolate variation in patent *filings* that is plausibly orthogonal to short-run macroeconomic conditions. To do so, we focus on discrete institutional and policy events that generated sharp changes in patenting incentives or ownership rules, including doctrinal shifts in patent law, reforms to government patent and technology-transfer policies, geopolitical or security-driven shocks (e.g., the Space Race), international harmonization and treaty deadlines (TRIPS/URAA), and major antitrust remedies affecting appropriability. These episodes are attractive for narrative identification because their timing is typically predetermined by legislation, court calendars, or administrative implementation schedules, and their primary motivations are legal, institutional, or national-security related rather than cyclical stabilization.

Table E1 lists the events retained in the baseline narrative instrument and maps each episode to the patent category affected. The table provides a brief characterization of the events and the dates on which they affected patent filings.

Table E1: Events used in the construction of narrative IV

Date	**Patents**	**Event**	**Description**
1950-Q1	Pub-pub	Gov't title policy (E.O. 10096)	Administrative harmonization
1950-Q2	Pub-priv	NSF Act	Long-run basic research architecture
1952-Q4	Priv-priv	Patent Act of 1952	Technical legal codification of patent standards
1954-Q3	Pub-pub	Atomic Energy Act (1954 revision)	Cold War / Atoms for Peace governance; security driven
1956-Q1	Priv-priv	Bell Labs antitrust consent decree	Antitrust remedy
1958-Q1	Pub-pub	NASA Act (Sputnik response)	National security shock
1958-Q3	Pub-priv	National Defense Education Act (NDEA)	Sputnik-driven human-capital policy (security)
1958-Q4	Pub-pub	NASA Act (continued build-up)	Continued space/security expansion
1959-Q3	Pub-pub	NASA Act (continued build-up)	Continued space/security expansion
1963-Q3	Pub-pub	Kennedy Patent Memorandum (decision)	Admin harmonization of federal patent policy
1966-Q1	Priv-priv	*Graham v. John Deere*	Supreme Court doctrine on non-obviousness
1969-Q4	Pub-pub	Mansfield Amendment	Vietnam-era oversight of DoD R&D
1969-Q4	Pub-priv	HEW IPA reinstatement (Q4)	Bureaucratic commercialization fix
1970-Q1	Pub-priv	HEW IPA reinstatement (Q1)	Bureaucratic commercialization fix
1974-Q2	Pub-pub	Energy Reorganization Act / ERDA (Q2)	OPEC / nuclear safety governance; structural reorg
1974-Q4	Pub-pub	Energy Reorganization Act / ERDA (Q4)	OPEC / nuclear safety governance; structural reorg
1975-Q3	Priv-priv	Xerox antitrust decree	Antitrust remedy
1980-Q2	Priv-priv	*Diamond v. Chakrabarty*	Patentable subject matter doctrine (biotech)
1982-Q3	Priv-priv	CAFC creation	Judicial reform/unification of patent appeals
1995-Q2	Pub-priv	NIH rescinds "reasonable pricing" clause	Contracting friction correction; collaboration-driven
1995-Q2	All	URAA/TRIPS pre-deadline	Treaty deadline; mechanical disclosure/filing incentive
2006-Q2	Priv-priv	*eBay v. MercExchange*	Injunction standard; doctrinal shift
2007-Q2	Priv-priv	*KSR v. Teleflex*	Obviousness doctrine; doctrinal shift

Date	Patents	Event	Description
2013-Q2	Priv-priv	*Myriad*	Patent eligibility doctrine (genes)
2014-Q2	Priv-priv	*Alice*	Patent eligibility doctrine (software)

We next provide brief institutional background for each event listed in Table E1, emphasizing the channel through which it plausibly moves patent filings while being largely unrelated to cyclical conditions.

Executive Order 10096 (1950). Issued in the postwar reorganization of federal R&D, E.O. 10096 standardized presumptive government ownership for inventions made by federal employees within the scope of employment, while clarifying exceptions and an appeals process. By reducing uncertainty over title allocation inside the federal government, it rationalized patenting and reporting practices for government-owned inventions.

NSF Act (1950). The creation of the National Science Foundation established a durable institutional framework for funding basic research through grants and peer review. It shaped the architecture of publicly funded research with private-sector and university participation.

Patent Act (1952). The 1952 Act codified core patentability standards and procedures (including statutory non-obviousness in §103), improving legal clarity for applicants. This kind of technical codification can shift filing incentives by reducing doctrinal uncertainty and standardizing prosecution.

Atomic Energy Act revision (1954). The 1954 revisions relaxed the strict postwar regime that limited private rights in atomic energy technology, permitting private patenting for civilian applications under safeguards. The reform was driven by Cold War strategy and the "Atoms for Peace" agenda, and it altered the governance of inventions in a security-sensitive sectors.

Bell Labs antitrust consent decree (1956). The AT&T/Bell Labs consent decree imposed licensing and conduct remedies intended to curb market power and broaden technology diffusion. By changing appropriability and licensing constraints in a major innovation hub, the decree could generate discrete changes in private patenting behavior.

NASA Act (1958) and subsequent build-up (1958–1959). The National Aeronautics and Space Act created NASA in response to Sputnik and reorganized federal space R&D. Beyond institutional creation, the rapid expansion of mission-oriented programs and procurement can generate clustered movements in patenting over several quarters.

National Defense Education Act (1958). The NDEA was a security-motivated human-capital response to Sputnik, expanding federal support for science and engineering education. By increasing the supply of STEM training and research capacity, it strengthened the longer-run innovation pipeline associated with publicly funded research and contractor activity.

Kennedy Patent Memorandum (1963). President Kennedy's memorandum sought to harmonize federal patent policy by moving away from a one-size-fits-all rule and instructing agencies to weigh public access against commercialization prospects. In practice, the memo encouraged agencies to adopt clearer guidance on title and licensing, which could shift the composition of government-related patenting.

***Graham v. John Deere* (1966).** The Supreme Court articulated a structured approach to non-obviousness, emphasizing prior art and objective indicia. By tightening or clarifying the patentability threshold, the decision plausibly changed the expected returns to filing and the screening of applications.

Mansfield Amendment (1969). The Mansfield Amendment increased Congressional oversight by requiring the Department of Defense to focus R&D expenditures on projects with direct military relevance. This is a governance change—not a cyclical policy intervention—that negatively affected innovation related to defense research.

HEW Institutional Patent Agreement (IPA) reinstatement (1969–1970). HEW's revival of the IPA program granted selected universities and nonprofits a clearer route to elect title to inventions from federally funded biomedical research, reducing contracting frictions and encouraging commercialization. By clarifying ownership and expected licensing rights, the reinstatement can raise filings where public funding is paired with private (non-federal) ownership.

Energy Reorganization Act and ERDA (1974). The Energy Reorganization Act reorganized federal energy governance, including nuclear oversight, and created ERDA in the context of post-OPEC energy security and safety concerns. This structural reorganization plausibly changes the management and incentives around federally funded energy-related inventions.

Xerox antitrust decree (1975). The Xerox settlement imposed licensing and other remedies intended to reduce barriers to entry and technology access. Such antitrust actions can shift the private incentives to patent (and to license) by changing the strategic value of intellectual property portfolios.

***Diamond v. Chakrabarty* (1980).** The Supreme Court's decision expanded patent-eligible subject matter to include certain biotechnology inventions, providing a major doctrinal signal to innovators and investors. This broadened appropriability in a high-growth sector.

Creation of the Court of Appeals for the Federal Circuit (1982). The establishment of the CAFC centralized patent appeals and increased doctrinal consistency across circuits. The resulting shift in perceived enforcement strength and predictability can affect expected patent value and filing incentives.

NIH rescinds the "reasonable pricing" clause (1995). NIH removed the clause from CRADAs after concerns that it discouraged private participation and complicated negotiations. Eliminating this contractual friction plausibly increased the attractiveness of collaboration and downstream commercialization in NIH-related research.

URAA/TRIPS pre-deadline (1995). International harmonization under TRIPS (Uruguay Round) and associated U.S. implementation created a sharp timing incentive: applicants rushed filings to exploit grandfathering provisions and the pre-deadline regime, producing a mechanical spike across categories. This is a deadline-driven legal transition rather than a response to short-run economic conditions, and it can generate broad-based filing swings; see, e.g., the discussion in Bertolotti (2022).

***eBay v. MercExchange* (2006).** The Court limited the automatic granting of injunctions after findings of infringement, altering the leverage of patent holders and the expected payoff from litigation. By affecting enforcement remedies, the decision can change filing incentives and strategic patenting.

***KSR v. Teleflex* (2007).** *KSR* modified the obviousness analysis by rejecting rigid tests and endorsing a more flexible approach. This doctrinal shift can tighten effective patentability standards in some areas and affect the propensity to file.

***Association for Molecular Pathology v. Myriad* (2013).** The Court restricted patent eligibility for naturally occurring DNA, reshaping the boundaries of protection in genetics. The resulting change in expected enforceability can lead to discrete adjustments in private filing behavior in affected technologies.

***Alice v. CLS Bank* (2014).** *Alice* tightened patent eligibility for abstract ideas, with substantial implications for software and business-method patents, increasing uncertainty and lowering the expected grant/enforcement probability in these domains.

F Historical Decomposition and Counterfactuals

In this Appendix, we outline how we compute historical decompositions across multiple forecast horizons and construct counterfactual scenarios using our baseline LP model.

F1 Historical Decomposition

Given the set of observables $\mathbf{y_t}$ that constitute our information set (or set of controls), consider pat_t as the patent group of interest from which we want to extract an innovation shock. In this discussion, we consider total factor productivity (TFP) as the variable of interest (but the same holds for any other variables, e.g., GDP). Let h^* denote the forecast horizon.

Following Gorodnichenko and Lee (2020), we extract our innovation shock ε_t by regressing pat_t on the information set at $t-1$:

$$\text{pat}_t = \sum_{j=1}^{4} \boldsymbol{\phi_j}\, \mathbf{y}_{t-j} + \varepsilon_t \tag{F18}$$

Then, define the h^* cumulated growth rate of TFP_t that isolates low-frequency movements as $h^* = 32$ ($h^* = 6$ for a cross check reported in Figure F1):

$$\Delta_{h^*}\text{TFP}_t := \text{TFP}_{t+h^*} - \text{TFP}_{t-1} \tag{F19}$$

Regress $\Delta_{h^*}\text{TFP}_t$ on lagged $\mathbf{y_t^*} = [\mathbf{y_t}\, \varepsilon_t]$ that contains the observables and the shock themselves to construct the forecast error of the baseline model:

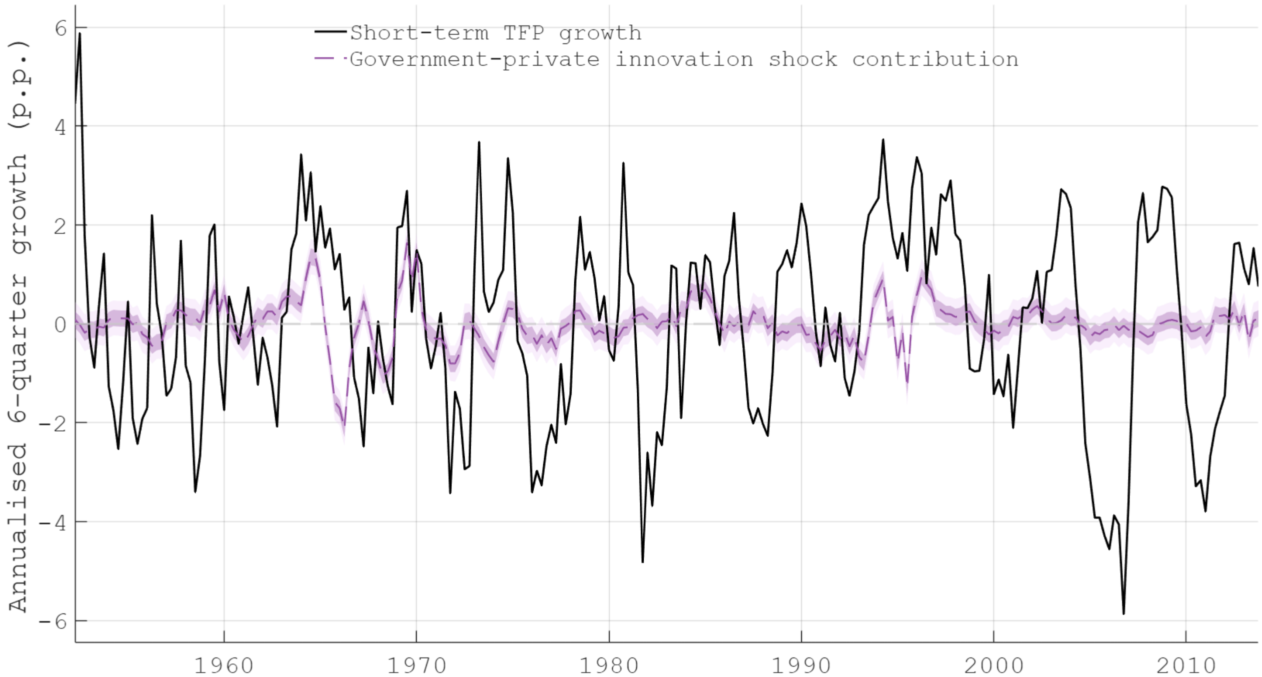
$$\Delta_{h^*}\text{TFP}_t = \alpha + \sum_{j=1}^{4} \boldsymbol{\phi_j^*} \mathbf{y}^*{}_{t-j} + e_{t+h^*} \tag{F20}$$

Then we regress the forecast error on the shocks realized between t and the forecast horizon h^*:

$$e_{t+h^*} = \sum_{k=0}^{h^*} \theta_{h^*,k}\, \varepsilon_{t+k} + u_{t+h^*} \tag{F21}$$

Equation F21 is estimated separately for each forecast horizon $h = 0, \ldots, H$ by setting $h^* = h$. The R^2 of this regression for each forecast horizon represents the variance contribution (i.e. the average over the sample). For the historical decomposition, we fix $h^* \in \{6, 32\}$ and the fitted values from (F21) deliver the historical contribution of the shock of interest. Inference is based on a VAR-based bootstrap as in Gorodnichenko and Lee (2020).

Figure F1: Historical Decomposition of the Short-Term Component of TFP Growth



Note. The figure displays the historical contribution of public-private innovation shocks to the forecast errors of the 6-quarter TFP growth rate. The estimation by local projections is based on the method in Gorodnichenko and Lee (2020). The solid black line represents the stochastic component of TFP at the 6-quarter horizon, while the purple line (bands) represents the point estimate (68% and 90%) contribution of the public-private innovation shocks. Inference is based on 2000 bootstrap replication with small-sample adjustment. Sample: quarterly data 1950:Q1-2015:Q4.

F2 Counterfactual Scenario

We consider a counterfactual scenario for the 2000s to quantify the implications of the decline in the government-private innovation shock contribution after its peak. The exercise aims to answer the question: what would have the level of medium-term TFP been if the shock's contribution had remained at its 1996 peak level? We use the bias-corrected median historical series for the 32-quarter annualized TFP forecast error growth (g_t) and the corresponding median contribution of the innovation shock (s_t).

First, we identify the peak median shock contribution that occurred in 1996, which we denote s^*. We then construct a counterfactual series for the TFP medium-term growth, $\tilde{g}_t$, starting from 1996 and extending to 2007. For all data points after the 1996 peak, the counterfactual is defined as:

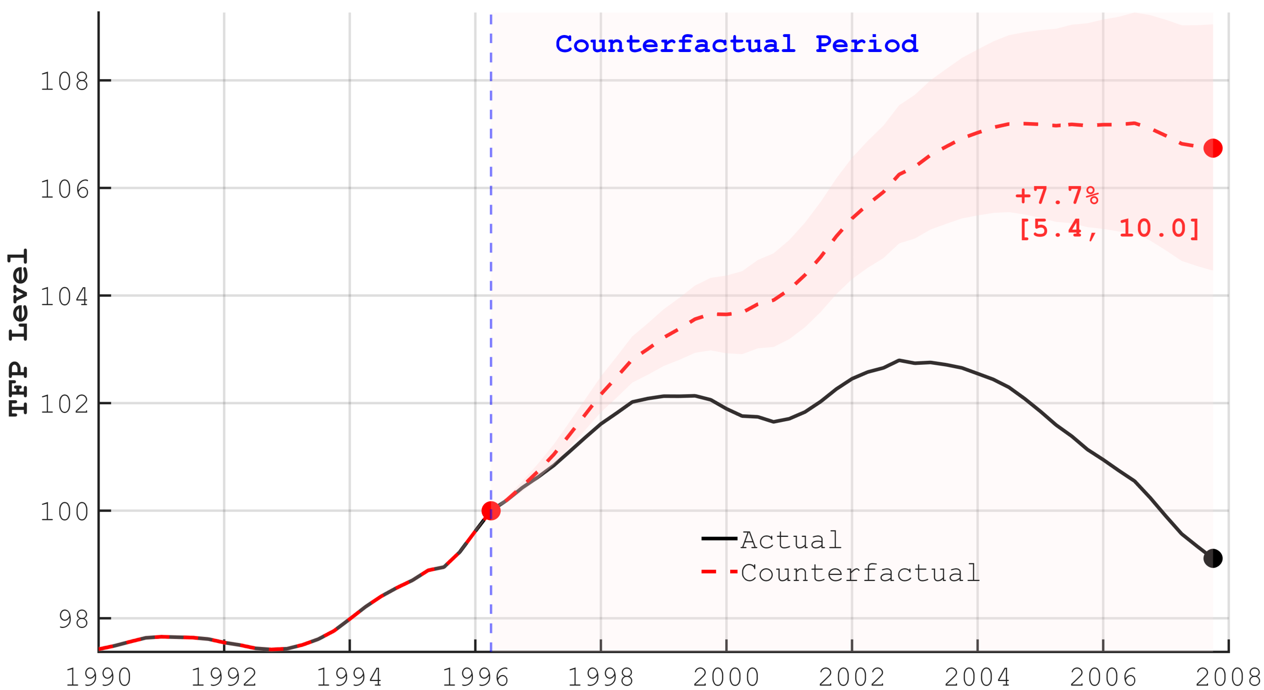
$$\tilde{g}_t = g_t - s_t + s^*$$

This procedure effectively replaces the actual shock contribution from the peak onwards with the constant peak value, while leaving the baseline growth and the contributions of all other shocks unchanged.

Both the actual series (g_t) and the counterfactual series ($\tilde{g}_t$) are given in annualized percentage points. We convert these to equivalent quarter-on-quarter growth rates (g_t^q and $\tilde{g}_t^q$) using the standard compounding formula: $g_t^q = (1 + g_t/100)^{1/4} - 1$.

We then construct the level of TFP by setting it to a normalized value of 100 at the quarter of the 1996 peak. The time path of the TFP level is computed by compounding these quarterly rates. To construct a 90% confidence interval for our counterfactual estimate, we repeat the entire exercise using the 5th and 95th percentile levels of the shock contribution at the 1996 peak.

Figure F2: Counterfactual Scenario



Note. The figure displays the level of realized medium-term TFP (black solid line) and a counterfactual scenario (red dashed line; bands denote 90% confidence bands) where we hold the government-private innovation shock contribution at the 1996 peak level till 2007. The numbers displayed in red denote the difference (with confidence interval in square brackets) between the counterfactual TFP level at the end of the sample and the realized value.

G Alternative Measures of Basicness

In this Appendix, we show that our main findings of: (i) a larger average association between GDP/TFP and innovations funded by the government and owned by the private sector; (ii) a leading role for fully public patents among the most fundamental, basic and scientific innovations, are robust to several variants of the measures of basicness developed by Kelly et al. (2021); Kogan et al. (2017); Marx and Fuegi (2020) respectively.

G1 Importance

We consider an alternative definition of the *importance* measure from Kelly et al. (2021). In the paper, we use the 5-year version and construct dummies for percentiles that are computed within each group of patents (i.e., government-private, private-private, and government-government).

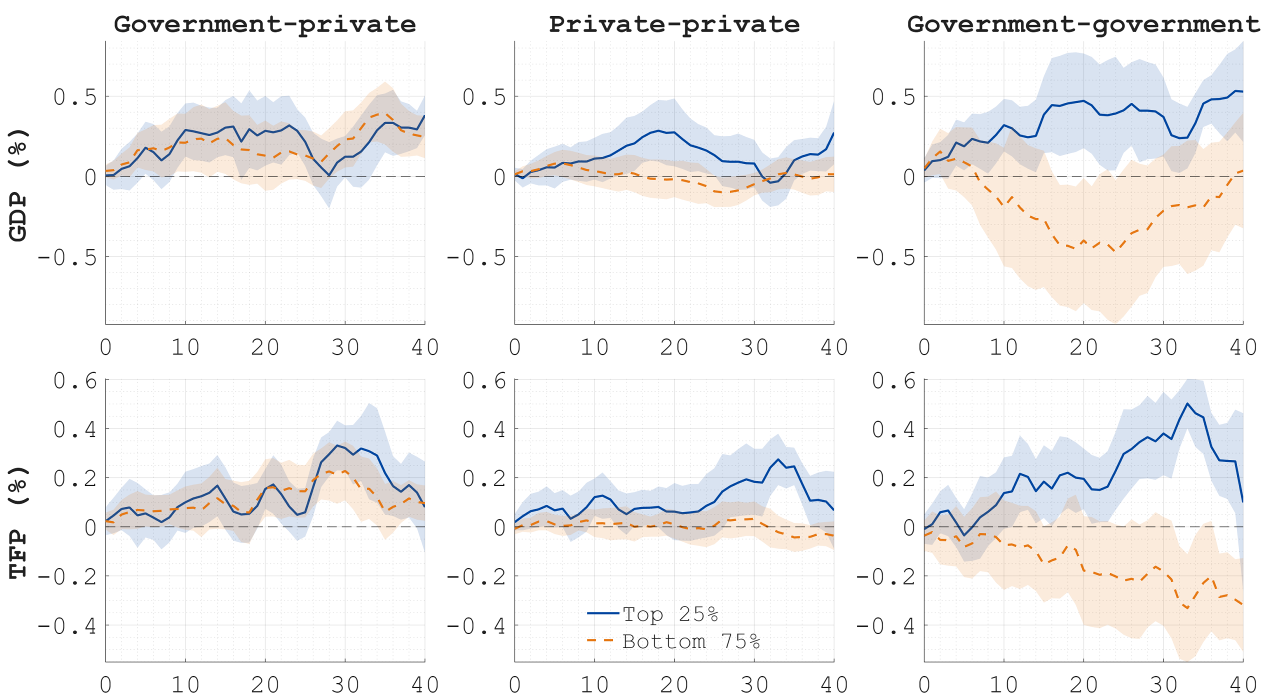
Figure G1 reports the corresponding results obtained by using the 10-year version of the importance measure. This measure provides a longer-term perspective, but due to the truncation of the 10-year forward similarity, it ends in 2010. The picture is very similar to our baseline.

We also construct alternative dummies for above versus below the median (Figure G2) and across the entire distribution of patents (Figure G3). In both cases results are consistent with our baseline.

G2 Reliance on Science

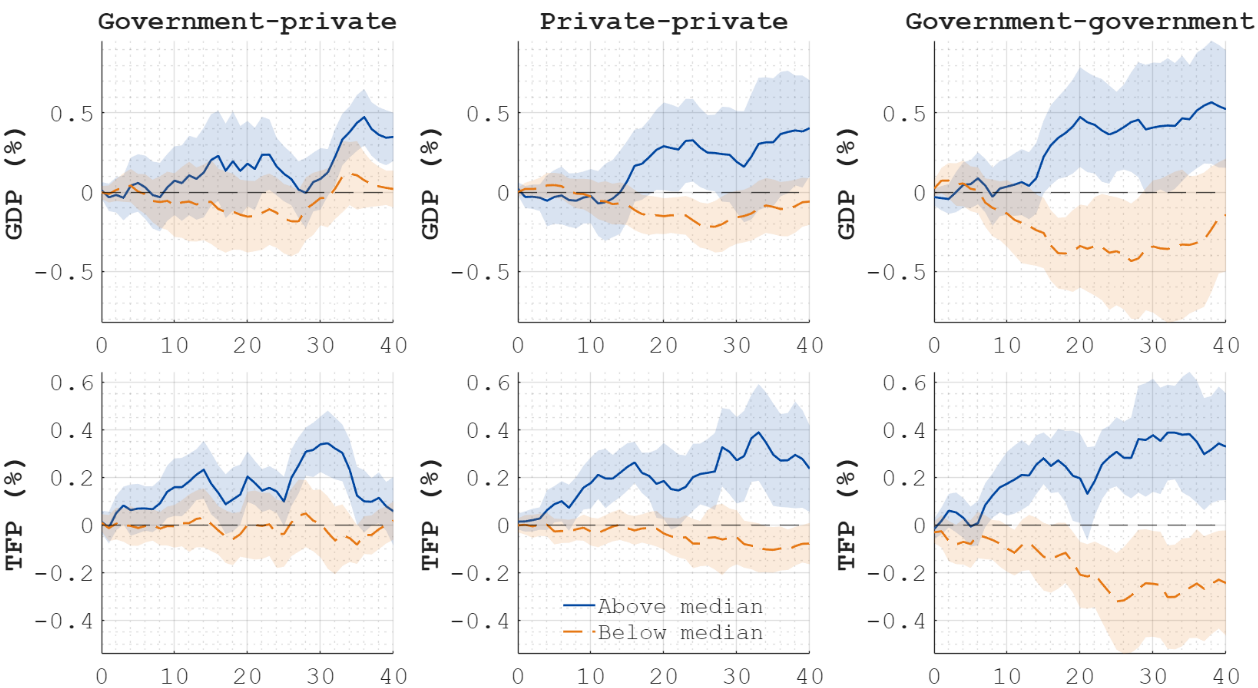
We also consider an alternative definition of top/bottom reliant on science patents based on the top 25% percentile (Figure G4) and another one that exploits exclusively the extensive margin of papers' citations (Figure G5). These two exercises yield overall consistent results with our baseline, although in this case, only government-government patents display marked statistical significance, possibly reflecting a more even distribution of this measure within each group. The exercise based on the extensive margin is important because it indicates that the trend in citations within the sample does not influence our conclusions about the role of science-based patents.

Figure G1: Importance - 10 year measure



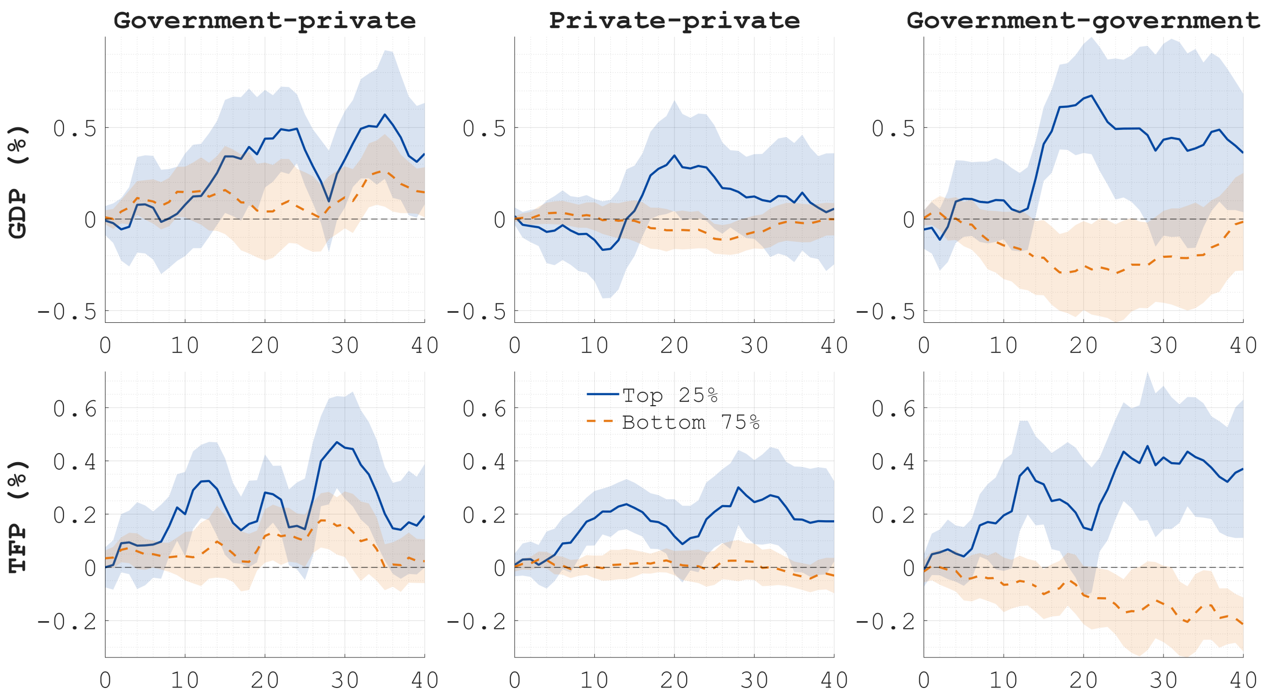
Note. *The figure replicates the analysis in Figure 6, comparing the dynamic effects of innovation shocks from the top quartile versus the bottom three quartiles of patents ranked by importance. As a robustness check, this figure uses the 10-year patent similarity measure from Kelly et al. (2021) instead of the 5-year measure used in the main text. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The solid blue (dashed orange) line represents the point estimate for top 25% (bottom 75%) important patents, while the corresponding shaded areas report 90% confidence intervals. Sample: 1950:Q1-2010:Q4 (due to the 10-year window).*

Figure G2: Importance - above/below median



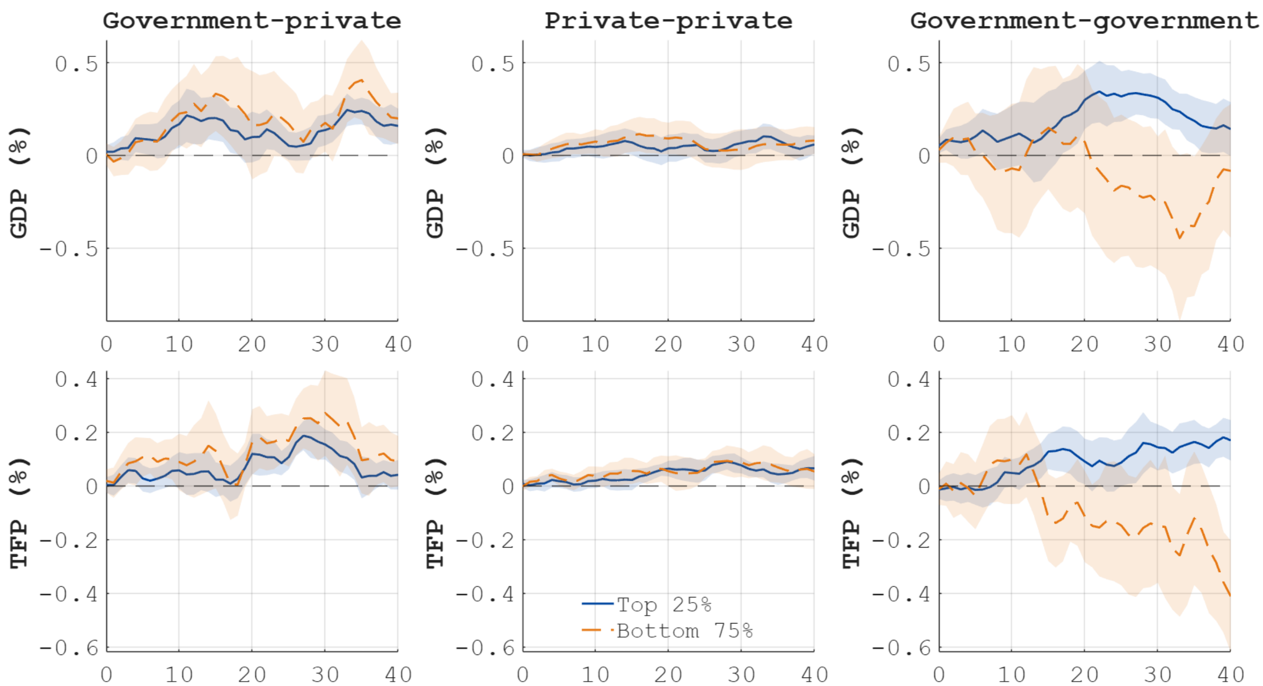
Note. The figure replicates the analysis in Figure 6, but splits patents at the median of the importance distribution (top 50% vs. bottom 50%) instead of the top quartile. The 5-year patent similarity measure from Kelly et al. (2021) is used. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The solid blue (dashed orange) line represents the point estimate for top 50% (bottom 50%) important patents, while the corresponding shaded areas report 90% confidence intervals. Sample: quarterly data 1950:Q1-2015:Q4.

Figure G3: Importance - percentiles for each category



Note. The figure replicates the analysis in Figure 6, but the importance ranking is done across all patents rather than within each patent category (public-private, private-private, and public-public). This tests whether the top quartile of patents in each funding category is more impactful than the bottom three quartiles of the same category. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The solid blue (dashed orange) line represents the point estimate for top 25% (bottom 75%) important patents within each category, while the corresponding shaded areas report 90% confidence intervals. Sample: quarterly data 1950:Q1-2015:Q4.

Figure G4: Reliance on Science - Alternative percentiles



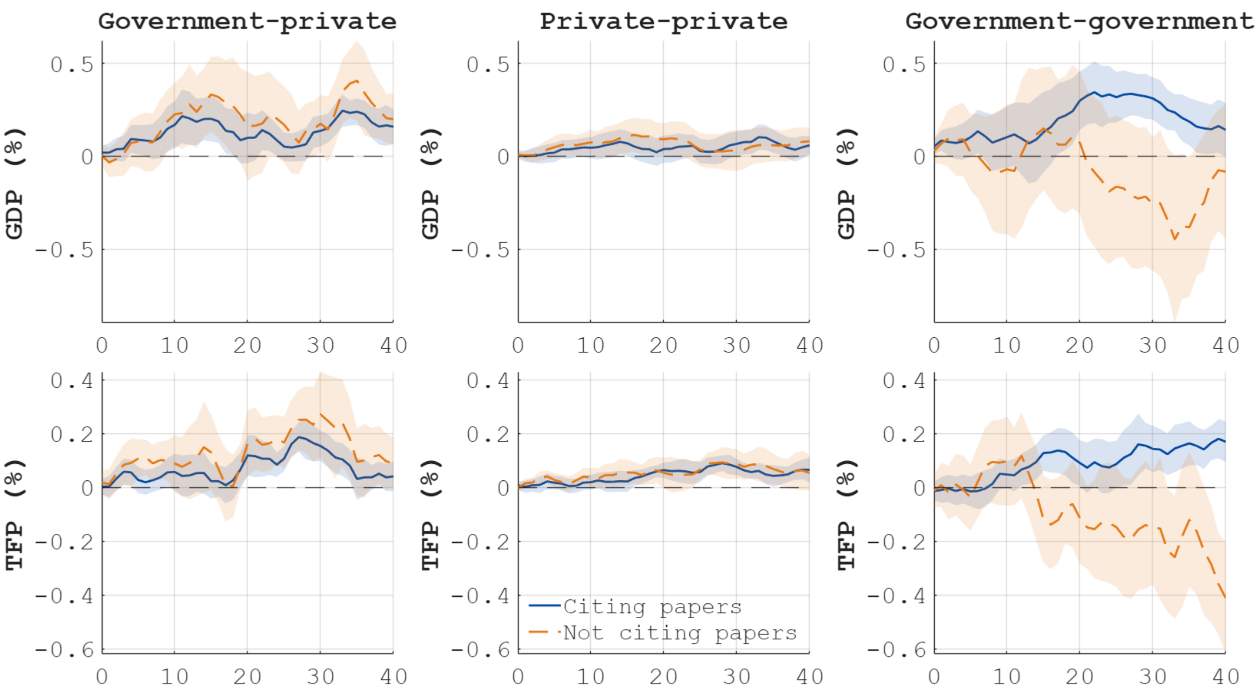
Note. The figure replicates the analysis in Figure 6b, but compare top 25% with bottom 75% percentiles. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The solid blue (orange dashed) line represents the point estimate for top 25% (bottom 75%) most reliant on science patents within each category, while the corresponding shaded areas report 90% confidence intervals. Sample: quarterly data 1950:Q1-2015:Q4.

G3 Results Based on an Extended Kogan et al. (2017) Measure

As a further robustness exercise, we construct an alternative measure of patent importance based on the approach of Kline et al. (2019) to extend the Kogan et al. (2017) patent value measure to the universe of patents. The objective is to impute a value proxy for patents that lack observed market-based valuations, using only information available at the time of filing.

We estimate a predictive model of the Kogan et al. (2017) value measure. The explanatory variables include (following Kline et al. (2019)) patent family size and the number of claims, which we extend to pre-1976 patents using text analysis of the Google Patents public corpus. We also include four measures of patent technological relevance, constructed by Martinez and Moen-Vorum (2025), who demonstrate that these indicators are strong predictors of the Kogan et al. (2017) patent values, as well as CPC 3-digit technology classes and filing-year fixed effects. Since our objective is to cover the patent universe, we cannot include firm-level characteristics such as revenue and employment as predictors, which Kline et al. (2019) show have high explanatory power for patent values.

Figure G5: Reliance on Science - Extensive Margin

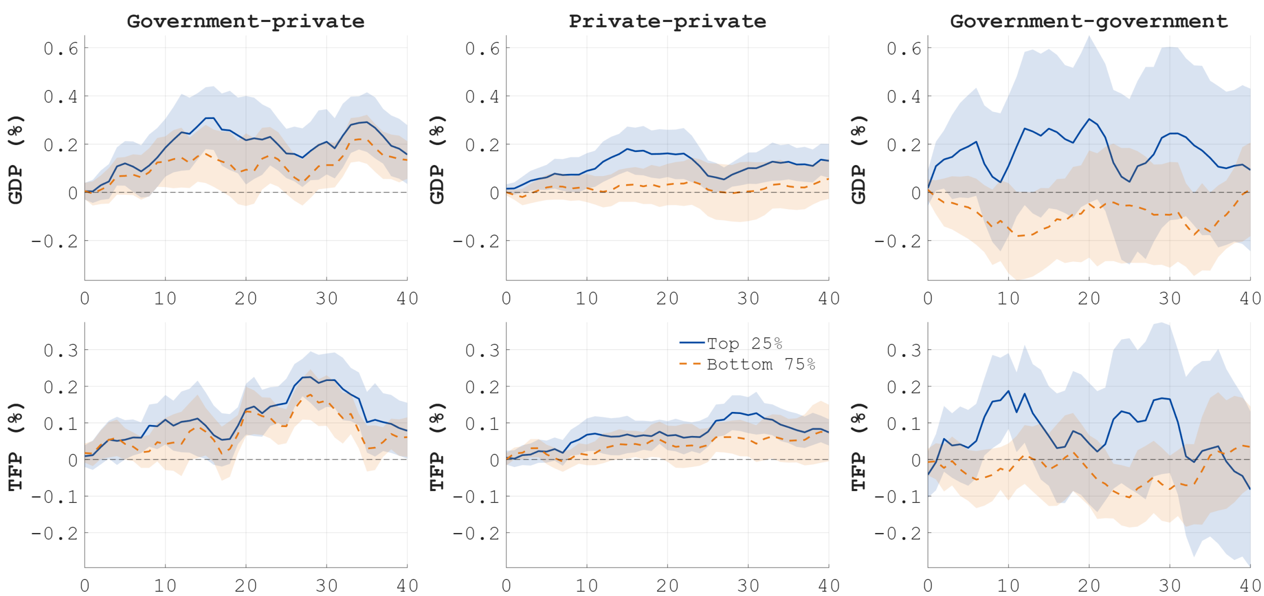


Note. The figure replicates the analysis in Figure 6b, but the reliance on science groups are based on citing at least one paper versus not citing any paper. The estimation by local projections follows eq.(1). The size of the shock is normalized to increase total patents by 1% on impact. The solid blue (dashed orange) line represents the point estimate for patents citing at least one paper (not citing any papers) within each category, while the corresponding shaded areas report 90% confidence intervals. Sample: quarterly data 1950:Q1-2015:Q4.

The fitted coefficients from this regression are then used to predict patent values for all observations, including those without market-based valuations.

We employ this measure as a robustness check alongside the Kelly et al. (2021) importance metric used in the main analysis. Following the approach described in Section 5, in Figure G6 we divide each patent category into two groups—top 25 percent (blue solid lines) and bottom 75 percent (orange dashed lines)—using the extrapolated Kogan et al. (2017) value measure. Two main results emerge. First, the top 25 percent of patents are associated with larger effects on GDP and TFP across all categories. Second, the bottom 75 percent of patents by value exhibit mostly insignificant effects for private-private and government-government patents. Overall, these results confirm that the heterogeneity observed in the main analysis is closely linked to underlying differences in patent value: patents with higher predicted values account for a disproportionate share of the macroeconomic impact of innovation.

Figure G6: The Dynamic Effects of the Most Valuable Innovations



Note. This figure represents the dynamic effects of innovation shocks to the top quartile of patents ranked by the extended Kogan et al. (2017) patent value measure (described in the text) versus other patents in each category of patents (public-private, private-private, public-public; by column) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row). The estimation by local projections follows eq.(1). The size of the shock is normalized such as to increase total patents by 1% on impact. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for top 25% (bottom 75%) patents by value, while the corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

H Definitions of industry and research field patent groups

This Appendix provides detailed information on the construction of industry and research fields by specifying the exact CPC codes that enter each category. We also show the composition of patents within agencies, universities, research institutes, and private-private by all research fields and the four research fields we focus on in the paper.

H1 Industry groups

A patent is assigned to a sector if its primary CPC code in the USPTO Cooperative Patent Classification (CPC) Master Classification Files for US patent grants matches any of the criteria listed below.

Table H1: Sector names and associated CPC codes

Sector Name	**CPC Codes**
Energy	B01D, C01B, C10L, C25B, F03B, F03D, G21, H01M, H02J, H02K, H02S, Y02C, Y02E, Y02P, Y02T
Aerospace	B64, F02K, F03H, F42B, F42E, F42F, G05D 1/xx
Health	A61B, A61F, A61J, A61K, A61L, A61M, A61N, A61P, A61Q, B01L, C07H, C07K, C12M, C12N, C12P, C12Q, G01N, G16H
Manufacturing	B08, B21-B30, B29C, B29D, B32B, B33B, B33Y, B65, B66, C21-C25, G05B 19/xx, H05K, Y02P
Education	*Based on assignee name keywords, not CPC codes*

Patents from the education sector. Unlike the technological sectors, this category is not based on CPC codes. A patent is flagged as being university-assigned if its disambiguated assignee organization name, converted to lowercase, contains specific keywords. This is determined using regular expression matching. The keywords include general terms such as "university", "college", and "institute of technology", as well as the names and common abbreviations of major research universities. The full list reads:

`caltech`, `carnegie mellon`, `cmu`, `college`, `columbia`, `cornell`, `cornell research foundation`, `drexel`, `georgia inst tech`, `georgia tech`, `harvard`, `institute` of technology, jhu, johns hopkins, massachusetts inst tech, mit, new york univ, nyu, ohio state, penn state, pennsylvania state, princeton, regents of the university of california, rutgers, suny, tamu, texas a&m, texas a&m university, u-m, uc berkeley, uc davis, uc irvine, uc los angeles, uc merced, uc riverside, uc san diego, uc santa barbara, uc santa cruz, uiuc, umich, university, usc, yale.

H2 Research fields

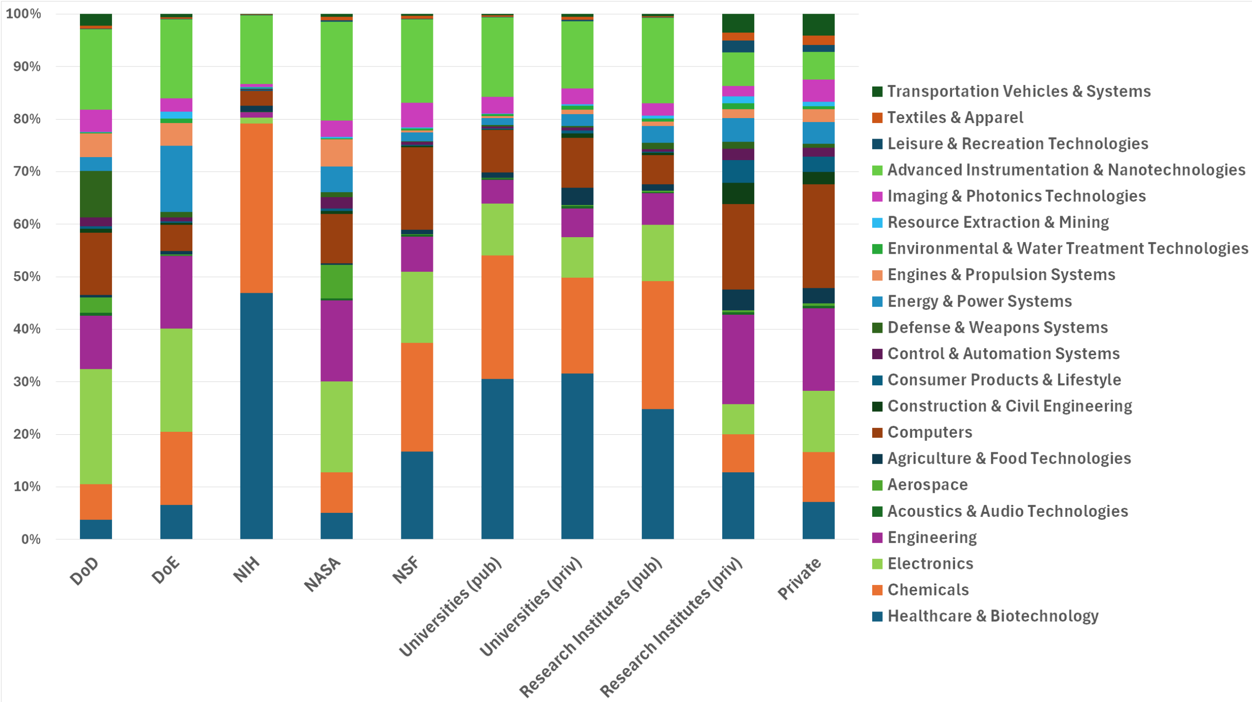
In Figures H1 and H2, we report the innovation composition of federal agencies and institutional players, such as research institutes and universities, by research field. In Table H2, we show how individual CPC codes map into the major research fields that we focus upon.

Research field name	**CPC codes**
Chemicals	B01, C01, C07, C08, C09B, C09D, C09J, C09K
Electronics	H01, H03, H05, H10
Engineering	B03, B04, B05, B06, B07, B21, B22, B23, B24, B25, B26, B29, B30, B31, B32, B33, B41, B65, B66, B67, C03, C04, C21, C22, C23, C25, D21, F04, F15, F16, F26, F27
Healthcare & Biotechnology	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61K, A61L, A61M, A61N, A61P, C12M, C12N, C12P, C12Q

Table H2: Research field names and associated CPC codes

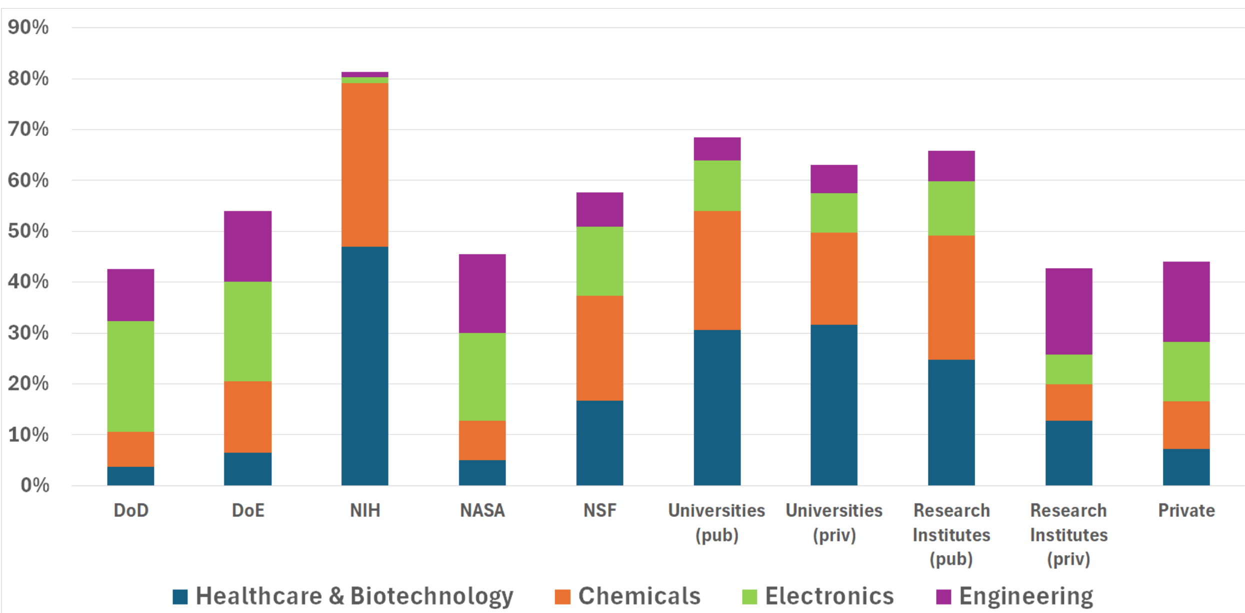
Note. This chart shows the proportions of patents in the four research fields studied in the paper. A patent is assigned to a research field if its primary CPC code in the USPTO Cooperative Patent Classification (CPC) Master Classification Files for US patent grants matches any of the criteria listed below.

Figure H1: Share of patents by all research fields in each agency and player



Note. This chart illustrates the proportions of patents in research fields for different groups. The first five bars (DoD, DoE, NIH, NASA, NSF) show the composition of patents for the five agencies we study, followed by public interest patents involving research institutes and universities. The final bar shows the proportions for all private-private patents. Sample: quarterly data 1950:Q1-2015:Q4.

Figure H2: Share of patents by main research fields in each agency and player



Note. This chart illustrates the proportions of patents in the four research fields studied in the paper, and detailed in Table H2. The first five bars (DoD, DoE, NIH, NASA, NSF) show the composition of patents for the five agencies we study, followed by public interest patents involving research institutes and universities. The final bar shows the proportions for all private-private patents. Figure H1 below shows the total composition of patents by research field. Sample: quarterly data 1950:Q1-2015:Q4.

I Innovation Network Centrality

In this Appendix, we look at spillovers through the lens of the innovation network. We first ask whether the effects documented in the main text are stronger for innovations that are more central in the innovation network. Then, we describe the sectoral composition along the innovation networks.

Following Liu and Ma (2024), network centrality is defined as the dominant left eigenvector of the patent citation network studied by Acemoglu et al. (2016). Those authors define the patent citation network as the rate at which patents in category j' receive citations from patents in category j, scaled by the number of patents in category j', where categories are USPC patent classes. In defining the network, we cumulate their annual measures over ten years and exclude self-citations (citations within USPC categories). Our centrality measure is therefore the dominant left eigenvector of the citation flow network, with the leading diagonal set to zero. Finally, we crosswalk the centrality measure from USPC to CPC codes using the statistical mapping provided by the USPTO.

I1 Innovation Network Effects

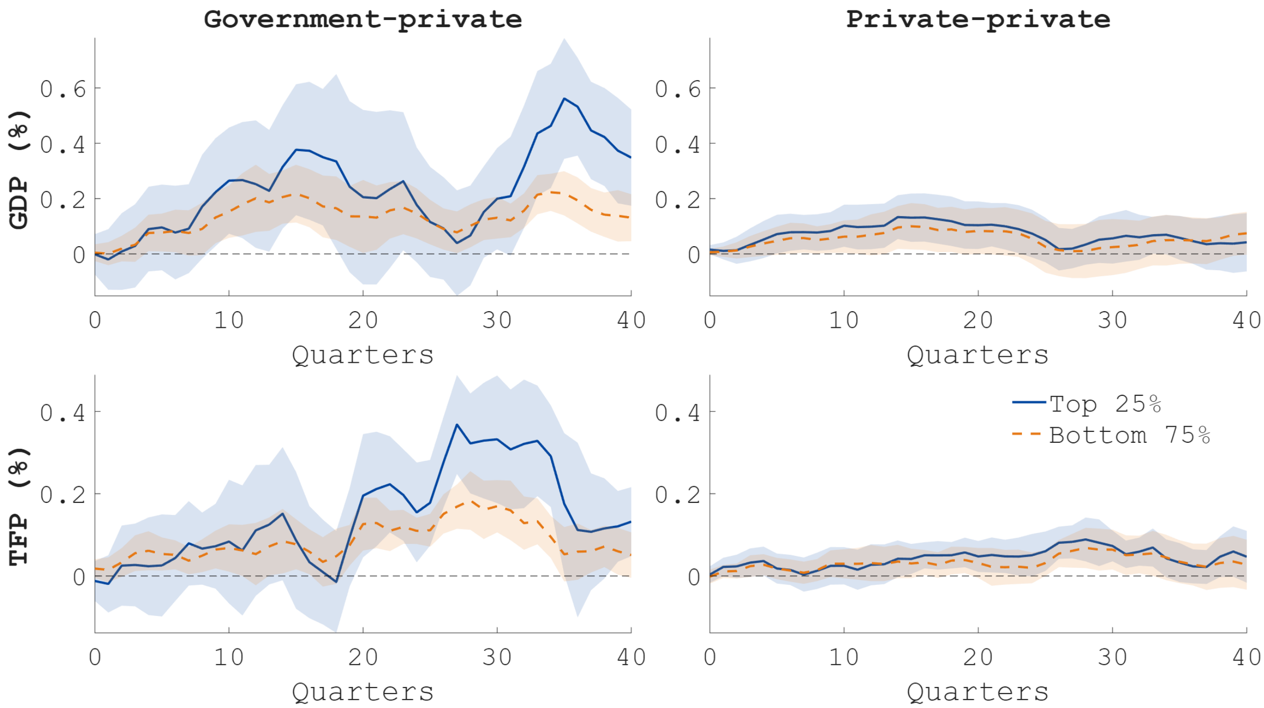
In this section, we expand on the spillover result in Section 6.3 by looking at innovation network centrality. To the extent that spillovers are an important part of knowledge diffusion, patents that are more central in the innovation network could yield a stronger cascade effect and a larger economic impact.

To evaluate this hypothesis, we split public-private patents and private-private patents into two further groups: top 25% and bottom 75% of the innovation network centrality distribution.[43] Following Liu and Ma (2024), network centrality is defined as the dominant left eigenvector of the patent citation network studied by Acemoglu et al. (2016). Those authors define the patent citation network as the rate at which patents in category j' receive citations from patents in category j, scaled by the number of patents in category j', where categories are USPC patent classes. We cumulate their annual measures and construct the network using the citation intensity of any granted patent over ten years, excluding citations

[43]Given the very small number of public-public patents in the top quartile, we exclude this group from this analysis.

within the same USPC patent class.

Figure I1: The Effects of Innovation by Innovation Network Centrality



Note. The figure compares the dynamic effects of innovation shocks to the top quartile of patents ranked by innovation network centrality versus innovation shocks to other patents in each category (public-private, private-private; by column) on (log) real per-capita GDP and (log) utilization-adjusted TFP (by row). Innovation network centrality is the dominant left eigenvector of the USPC-level patent citation network, as reported in Acemoglu et al. (2016) (see the text for further details). The estimation by local projections follows eq.(1). The size of the shock is normalized such that total patents increase by 1% on impact. The set of controls includes 4 lags of the patent group shocked and real per-capita GDP, TFP, real per-capita investment, real stock prices, the T-bill, real per-capita R&D expenditure, and the number of patents in other groups. All variables except the T-bill are in logs. The solid blue (dashed orange) line represents the point estimate for the top 25% (bottom 75%) patents by centrality, while the corresponding shaded areas report 90% confidence intervals computed from Newey and West (1987) standard errors. Sample: quarterly data 1950:Q1-2015:Q4.

The findings of this exercise are summarized in Figure I1. Following the previous charts, the top (bottom) row stands for GDP (TFP) while the first (second) column refers to innovations from public-private collaborations (only private sector). Blue solid lines and blue shaded areas display the results for the top 25% most central patents in each category, while the orange solid broken lines and orange shaded areas depict their bottom 75% counterpart. The main inference one can draw from Figure I1 is that the top 25% most central innovations produced by public-private collaborations exert a larger medium-term impact on GDP and TFP, with peaks towards the end of the forecast horizon that are roughly twice as large as the maximum effect of public-private patents in the bottom 75% of the innovation network centrality distribution. In contrast, we find little economic or statistical difference between the effects of these two sub-groups among patents that are fully funded and developed by the private sector.

To appreciate the connection between network centrality and macroeconomic impact, we examine the distribution of high-centrality patents within research fields, agencies, and (anticipating the following section) assignee types. Figure I2 shows the fraction of patents within each group that are in the top percentiles of the innovation network centrality distribution; Figure I3 illustrates the relative concentration of each group at the top of the same distribution. Among research fields, 'chemicals' and 'healthcare & biotechnology' have the largest share of high-centrality patent categories. These are also the fields for which we estimate the largest GDP and TFP responses for government-private and (for 'healthcare & biotechnology') government-government patents (see Figure 7b). Among agencies, the NIH has the highest share of patents at the top of the innovation network centrality distribution, followed by NSF and DoE, consistent with the results in Figure 7. Finally, universities and research institutes are the assignees with the highest share of high-centrality patents; in the next section, we will show that these two players produce the most impactful innovations.

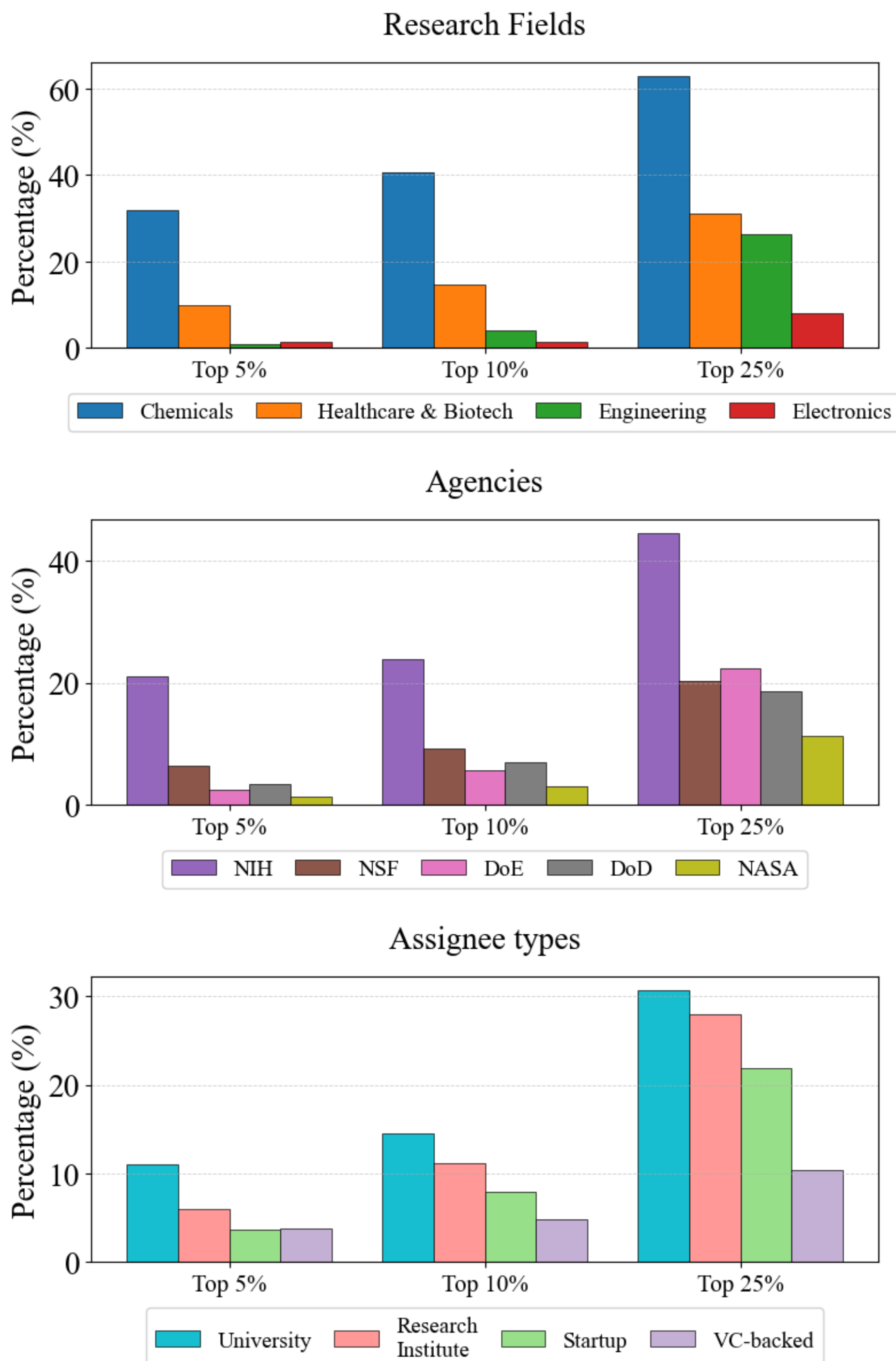
I2 Innovation Network Composition

In this Section, we illustrate the composition of patent categories at the top of the innovation network centrality distribution by research field, agency, and assignee type.

In Figure I2, we report the share of patents within each research field, agency, and assignee type that are in the top 5%, 10%, and 25% of the innovation network centrality distribution. Among research fields, 'chemicals' and 'healthcare & biotechnology' have the largest share of high-centrality patent categories. These are also the fields for which we estimate the largest GDP and TFP responses for government-private and (for 'healthcare & biotechnology') government-government patents (see Figure 7b). Among agencies, the NIH has the highest share of patents at the top of the innovation network centrality distribution, followed by NSF and DoE, consistent with the results shown in Figure 7. Finally, universities and research institutes are the assignees with the highest share of high-centrality patents, consistent with the results presented in Section 7.

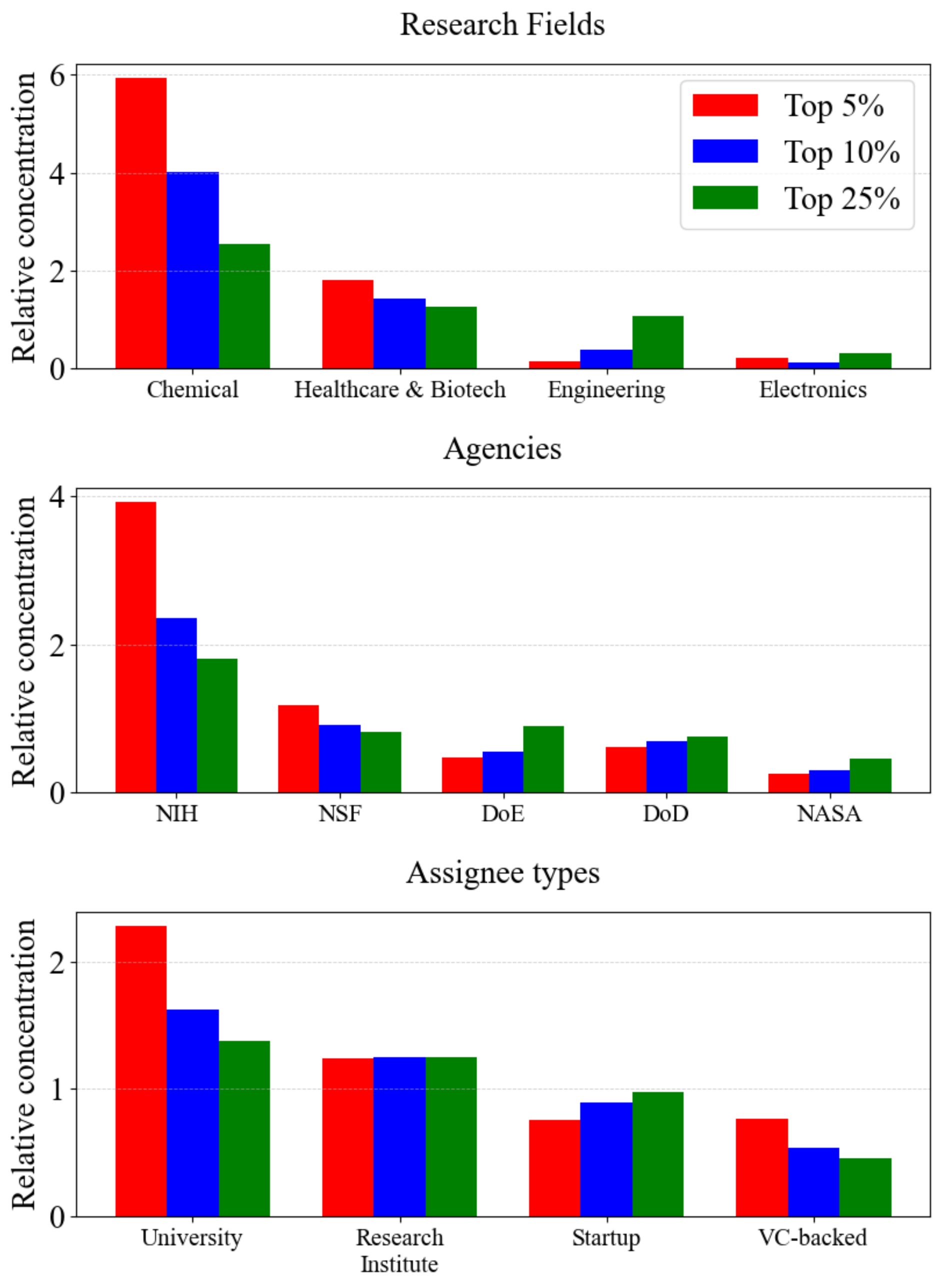
In Figure I3, we illustrate the relative concentration of each research field, agency, and assignee within each top centrality group. Relative concentration is defined as a research field, agency, or assignee's share of patents above a given centrality percentile, divided by that research field, agency, or assignee's share of total patents. For example, 'Chemicals' patents comprise 9.5% of all patents, and 56.5% of patents in the top 5% of patents by innovation network centrality, so the relative concentration of chemicals in the top 5% is $56.5/9 = 5.9$. Consistent with the results illustrated in Figure I2, 'chemicals' and 'healthcare & biotech.' (among research fields), NIH and NSF (among agencies) and universities and research institutes (among assignee types) have the highest relative concentration in top innovation centrality groups.

Figure I2: Share of patents in top centrality percentiles by research field, agency, and assignee type



This figure shows the percentage of patents within research fields (top panel), agencies (middle panel) and assignee types (bottom panel) that are in each of the top percentiles of the innovation network centrality distribution, from left to right in each panel and category top 5% (red), 10% (blue), and 25% (green). The innovation network is defined using patent citations across technology classes (USPC codes), following Acemoglu et al. (2016); see Section I for further details.

Figure I3: Relative concentration in top innovation centrality groups by research field, agency, and assignee type



This figure shows the relative concentration of research fields (top panel), agencies (middle panel), and assignee types (bottom panel) in the composition of three top percentile groups of the innovation network centrality distribution, from left to right in each panel and category, the top 5% (red), top 10% (blue), and top 25% (green). Relative concentration is defined as each categories' share in the total number of patents within a innovation centrality group, relative to that categories' share in the total number of patents. For example, Chemicals patents comprise 9.5% of all patents, and 56.5% of patents in the top 5% of patents by innovation network centrality, so the relative concentration of chemicals in the top 5% is 56.5/9.5 = 5.95. *The innovation network is defined using patent citations across technology classes (USPC codes), following Acemoglu et al. (2016); see Section I for further details.*

J The Composition of Basic R&D in the United States

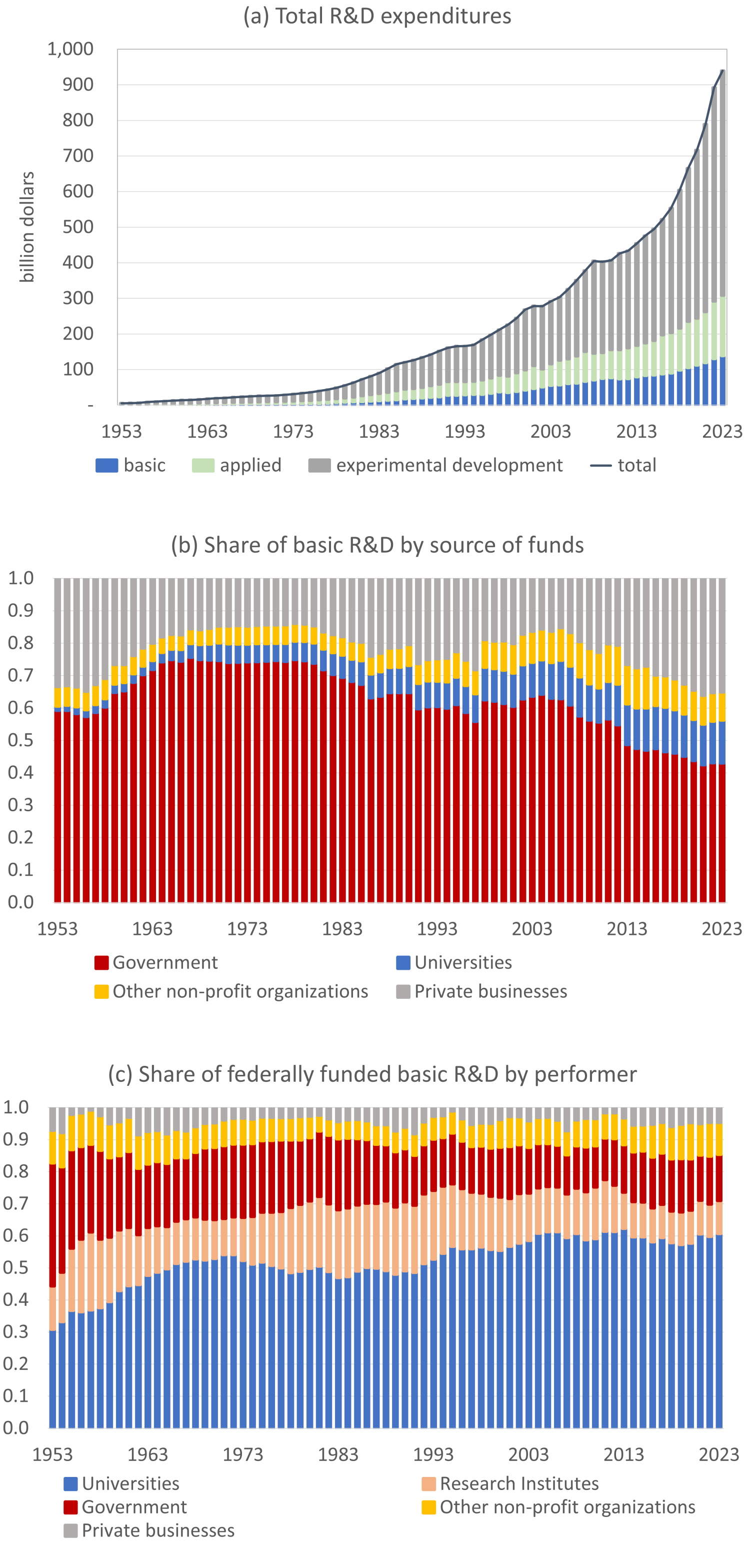
National statistics on R&D funding and performance in the US are provided by the National Center for Science and Engineering Statistics of the NSF. The Center compiles the *National Patterns of R&D resources*, an annual statistical report that provides an integrated overview of the U.S. research and development landscape. Data contained in the National Patterns are based on the following annual surveys: *Business Enterprise Research and Development Survey*, *Annual Business Survey*, *Higher Education Research and Development Survey*, *Survey of Federal Funds for Research and Development*, *FFRDCs Research and Development Survey*, and *Survey of State Government Research and Development*.

R&D is typically divided into three categories: (i) basic research, aimed at acquiring new knowledge on the foundations of observable facts and phenomena without a specific application as outlet; (ii) applied research, directed primarily towards a specific solution or objective; (iii) experimental development, translating research findings into new or improved products, processes, or services, and implying prototyping, testing, and iterative improvements. Panel (a) of Figure J1 reports the breakdown of annual R&D expenditures since 1953 by these three categories.

R&D expenditures have four main funders: the US government (on average 95% federal and 5% state/local) through its departments and agencies; higher education institutions (universities and colleges, here called "universities" for brevity); "private businesses" (98% per year by US businesses and 2% by foreign companies); "Other non-profit organizations" including private foundations, research institutes not affiliated with government or higher education, charitable and philanthropic organizations that conduct or fund research. Panel (b) of Figure J1 reports the breakdown of annual R&D expenditures since 1953 by source of funds, focusing on basic research only. The federal government has historically been the primary source of funding for this type of R&D, although its share has gradually declined over time as private sector contributions have increased.

The R&D actors discussed above not only fund but also conduct research activities using either their own resources or external funding. Panel (c) of Figure J1 focuses specifically on federally funded basic research, showing how these funds are distributed across different types of performers. Historically, universities have been the dominant performers of federally funded basic research, with their share increasing steadily over time. Another major group of performers is that of Federally Funded Research and Development Centers (FFRDCs), referred to here as ”research institutes,” which are typically operated by universities, non-profit organizations, or industrial firms under contract with federal agencies. Collectively, universities and research institutes account for approximately 70% of total federal spending on basic research, on average.

Figure J1: R&D expenditures in the United States



Source: National Patterns of R&D Resources *2022-2023, NSF. In Figure (b) and (c), Government includes both federal government and state and local governments, when the former accounts on average for 95% of the provided funds (b) and almost 100% of the expenditures (c). The share of basic research performed by the federal government is done with its departments and agencies.*

K Further Details on Some Key Institutional Players

In this Appendix, we provide more information on some key institutional players, among non-profit organizations such as research institutes and universities as well as among for-profit companies such as start-ups. In Table K1, we describe major research institutes and national lab operators. In Table K2, we group innovations by universities and research institutes by federal agencies. In Table K3, we show the shares of non-profit assignees (left column) and startup assignees (right column) among public-private patents by funding agency. In Table K4 , we provide some descriptions of the top start-up companies among innovators who leverage government funds.

Table K1: Top U.S. Research Institutes and National-Lab Operators

Institute / Entity	**Count**	**Description**	**FFRDC Status**
Battelle Memorial Institute	829	Major United States nonprofit science and technology research institute; manages or co-manages several national laboratories for the United States Department of Energy (DOE) and the Department of Homeland Security (DHS); deep ties to government and academia.	Yes
The General Hospital Corporation	795	Legal entity for Massachusetts General Hospital, the oldest and largest teaching hospital of Harvard Medical School; a world leader in biomedical research and clinical care.	No
The Scripps Research Institute	642	Leading nonprofit American medical research facility focusing on biomedical research; headquartered in La Jolla, California, and Jupiter, Florida; historically affiliated with universities and hospitals.	No
Los Alamos National Security, LLC	453	Consortium including the University of California, Bechtel National, BWXT Government Group, and URS Energy and Construction that managed Los Alamos National Laboratory for the United States Department of Energy; the laboratory is a premier United States nuclear research facility.	Yes
UChicago Argonne, LLC	442	Limited liability company formed by the University of Chicago to manage Argonne National Laboratory for the United States Department of Energy; closely tied to University of Chicago and federal research.	Yes
The Brigham and Women's Hospital	411	Major teaching hospital of Harvard Medical School in Boston, Massachusetts; recognized for biomedical research and clinical care.	No
Dana-Farber Cancer Institute, Inc.	347	Major cancer treatment and research center in Boston, Massachusetts; principal teaching affiliate of Harvard Medical School; member of the Dana-Farber/Harvard Cancer Center consortium.	No
Salk Institute for Biological Studies	319	Nonprofit scientific research institute in La Jolla, California, founded by Jonas Salk; world-renowned for biomedical research, especially in neuroscience and genetics; independent but collaborates with universities such as the University of California, San Diego and with the National Institutes of Health.	No
Sloan-Kettering Institute for Cancer Research	276	Biomedical research division of Memorial Sloan Kettering Cancer Center in New York City; world leader in cancer research and treatment; affiliated with multiple universities including Cornell University, Rockefeller University, and Weill Cornell Medical College.	No
Brookhaven Science Associates, LLC	275	Limited liability company formed by Battelle Memorial Institute and Stony Brook University to manage Brookhaven National Laboratory for the United States Department of Energy; strong ties to the federal government and academia, including collaborations with other universities and private sector partners.	Yes

Table K2: Breakdown of non-profit public-private patents

	Universities		Research Institutes	
Agency	Frequency	Percent	Frequency	Percent
DOD	6,749	14.2%	996	9.1%
DOE	5,012	10.6%	3,623	33.0%
NIH	21,978	46.3%	5,231	47.6%
NASA	1,579	3.3%	163	1.5%
NSF	9,936	20.9%	422	3.8%

Notes: This table reports the share of university and research institute public–private patents by funding agency.

Table K3: Non-profit and startup firm shares in public–private patents by agency

Agency	Non-profit share	Startup share
DoD	38.9%	3.2%
NASA	54.0%	4.2%
DoE	53.2%	3.6%
NIH	78.2%	5.9%
NSF	84.8%	6.8%

Notes: The first column shows the share of public–private patents involving non-profit organizations (universities and research institutes) by funding agency. The second column reports the share of startups among for-profit participants in public–private patents.

Table K4: Top startup innovators in public-private patenting

Company	**Patents**	**Description**
Nanosphere, Inc.	21	Biotechnology company specializing in nanoparticle-based molecular diagnostics; developed the Verigene platform for multiplex genetic and infectious disease testing; acquired by Luminex in 2016.
Superior MicroPowders LLC	18	Advanced materials company based in Albuquerque, New Mexico; developed fine powders and inks (e.g., for fuel cells, batteries, and catalysts) via spray-based processes; acquired by Cabot Corporation in 2003.
Pacific Biosciences of California, Inc.	16	Developer of single-molecule, real-time (SMRT) DNA sequencing systems enabling long-read genomics applications in human, plant, and microbial biology.
ARCH Development Corporation	15	University of Chicago–affiliated technology commercialization and incubation arm established in 1986; incubated and managed startups to commercialize research from the university and Argonne National Laboratory.
Molecular Optoelectronics Corp. (MOEC)	10	Research and development firm founded in 1993 in Watervliet, New York; worked on optoelectronic materials and thin-film devices for display, sensing, and photonic applications.