

THE PUBLIC ORIGINS OF AMERICAN INNOVATION*

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Abstract

We document new empirical patterns linking the institutional design of American innovation to postwar productivity and growth of the U.S. economy. Using recently digitized patent data that distinguish funding sources and ownership structures, we find that government-funded but privately-owned patents —though only 2% of the total— account for roughly 20% of medium-term fluctuations in TFP and GDP growth. These patents are also associated with higher business-sector investment in R&D. Privately funded patents display significant but smaller aggregate comovements, whereas publicly owned patents have muted average effects yet are more prevalent among disruptive innovations in health and biotechnology. Patents funded by the NIH and NSF exhibit the strongest links to subsequent productivity gains and R&D spillovers, while research institutes and universities outperform for-profit firms in transforming public funds into high-impact innovation. Taken together, our findings highlight the central role of government support in sustaining U.S. technological leadership and economic growth.

JEL: E32, E61, O38, O43

Keywords: government funds, TFP, R&D spillovers, NIH, NSF, research institutes, universities.

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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

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 (WWII), 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 in wartime, and ensure that scientific progress would benefit public health, economic growth, and national security in peacetime.

Bush’s reply laid the foundation for post-WWII American innovation. His vision was based on three pillars exemplifying the role of three players: (i) the government to fund areas of public interest; (ii) universities and research institutes to nurture the intellectual freedom necessary for significant discoveries; (iii) the private sector to turn new knowledge into new products. [Bush \(1945a\)](#)’s recommendations led directly to the creation of influential institutions such as the National Science Foundation (NSF), the substantial expansion of the National Institutes of Health (NIH), and established the framework for the contemporary American innovation ecosystem, characterized by close collaboration between government, universities, and industries.

In this paper, we assess the macroeconomic impact of the postwar American innovation model through the lens of [Bush \(1945a\)](#)’s architecture. More specifically, we lever on the detailed categorization in [Gross and Sampat \(2025a\)](#) of the universe of patents granted in the U.S. since 1950 to construct novel time-series of innovation activity that distinguish: (i) patents that are funded by the government but owned by a private entity; (ii) patents that

are funded, developed and owned by a private entity; (iii) patents that are funded and owned by the public sector.

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 previously identified fiscal and monetary policy shocks. By controlling for a rich set of business-cycle indicators, we ensure that the remaining variation captures fluctuations specific to innovation rather than macroeconomic conditions. The dynamic correlations we uncover have the hallmark of technological disruption, moving quantities and prices in opposite directions ([Miranda-Agrippino et al., 2025](#)).

Our analysis uncovers new empirical regularities. Publicly funded but privately owned patents display the greatest link to medium-term GDP and TFP: though only 2% of the total, they are associated with roughly 20% of aggregate fluctuations, with significant spillovers to private investment, R&D spending, real wages, and consumption. Privately funded patents exhibit weaker comovements, while government-funded and government-owned patents show, on average, insignificant correlations. However, this average effect masks an important nuance: patents funded and owned by the public sector include a relatively large share of highly disruptive innovations, whose estimates exceed those of all other categories. Our evidence suggests that the returns to government-funded patents may be more than twice those of fully private innovations.

Turning to federal agencies, industries and research fields, a clear ranking emerges. Among patents funded by the government but owned by the private sector, NIH and NSF support the most successful innovations in terms of their medium-term correlations with TFP and GDP growth as well as with 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 -owned patents, health-related patents — those funded by NIH, and those in the fields of healthcare & biotechnology — have associations with medium-term GDP and TFP that dwarf those of their private sector counterparts. Moreover, public patents with higher innovation network centrality are associated with larger increases in productivity and output, providing further evidence of significant spillovers to the broader economy.

Regarding the primary actors, research conducted by non-profit organizations shows larger correlations to aggregate outcomes than innovations produced by for-profit entities, with universities and research institutes performing best on a per-patent basis. Among for-profit businesses, start-ups —and to a lesser extent venture capital-backed firms— are more strongly linked to subsequent TFP and GDP growth than established private-sector companies, but only when backed by public funding: without government support, their productivity advantage vanishes.

Concrete examples highlight the disproportionate impact of government funded but privately owned patents. NIH support enabled Fire and Mello’s RNA interference discovery (2003), transforming molecular biology and therapeutic design. NSF funding at Stanford produced PageRank (1998), the foundation of Google’s search technology. DARPA- and NSF-backed advances in signal processing led to Qualcomm’s CDMA patent (1992), central to modern mobile communications. More recently, federal funding has seeded breakthroughs such as induced pluripotent stem cells, CAR-T therapies and CRISPR–Cas9 genome editing, showing how public support paired with private ownership can lead to innovations with large social returns.

[Bush \(1945a\)](#)’s report offers a natural interpretation of our findings. Research institutes and universities are associated with the largest productivity gains because they engage in fundamental research unconstrained by short-term commercial goals. Private firms, in contrast, pursue profit-driven innovations with smaller aggregate effects. The public sector is distinctive in bearing the risks of transformative research: while fully public innovations leave little macroeconomic trace on average, the most fundamental are linked to substantial productivity gains. These patterns chime with [Nelson \(1959\)](#) and [Arrow \(1962\)](#), who emphasized the role of government and non-profits in fostering knowledge creation where competitive markets underprovide.

Of independent interest, our work illustrates how the richness and granularity of patent data can be exploited to construct aggregate time series across a wide range of heterogeneities. Here, we focus on the macroeconomic impact of patents by funding source and ownership. However, our bottom-up approach can be easily extended to many other dimensions emphasized in the innovation literature —for instance, to estimate the *aggregate effects* of patents

by inventors’ and firms’ characteristics such as demographics (Bell et al., 2019), ancestry (Terry et al., 2025), capital structure and organizational design (Jaravel et al., 2018).

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, 2025b), 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 empirical macro —spanning Blanchard and Quah (1989), Galí (1999), Christiano et al. (2003, 2004), Francis and Ramey (2005, 2006), Fisher (2006), Basu et al. (2006), Fernald (2012), and more recently Miranda-Agrippino et al. (2025), Aghion et al. (2025)— examines the effects of technology shocks on long-run GDP growth using time series drawn solely from national accounts. While we also focus on aggregate fluctuations and comovements, 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 technological progress and aggregate productivity.

A growing literature explores how fiscal policy can foster productivity. Several studies—including Cozzi and Impullitti (2010), Janeway (2012), Mazzucato (2013), Liu and Ma (2021), Kantor and Whalley (2025), Antolin-Diaz and Surico (2025), Fieldhouse and Mertens (2023), Dyèvre (2024), Gomez-Cram et al. (2025), 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 consequences of government-funded innovation, linking different federal agencies, industries, research fields, and institutional actors —such as universities, research institutes, start-ups, VC-backed firms, and incumbents— to aggregate productivity.

Structure of the Paper. In Section 2, we describe the patent data and the empirical framework to isolate independent movements in innovation activity. The main results across the three patent groups are reported in Section 3, where we also provide back-of-the-envelope estimates of the returns to public and private innovations as well as a sensitivity analysis to alternative time-series strategies, including a narrative identification. In Section 4, we study the relative disruptiveness of publicly vs. privately funded innovation. Next, we focus on federal agencies, industries, research fields, and innovation spillovers, which we use to shed light on the mechanisms driving our results. In Section 6, we explore the role played by research institutes, universities and companies in the business sector, paying particular attention to start-ups and venture capital funding. Conclusions are in Section 7. The appendices contain further details on the data, case studies, and an extensive set of robustness checks.

2 Data and Empirical Framework

This section outlines the data used in the empirical analysis as well as the econometric framework that allows us to elicit its most salient correlations. After describing the primary data sources, we summarize the main statistics of the three categories of innovations we focus on, which combine information on public interest with the ultimate patent ownership. Then, the section examines the role played by the different federal agencies in supporting public-interest innovation. Finally, we discuss the time series approach and estimation strategies that we use to associate government funds with macroeconomic outcomes.

2.1 Patents Classification by Government Interest

Our analysis draws on the *Government Patent Register* (GPR) database compiled by [Gross and Sampat \(2025a\)](#), which combines information on government interest and the assignee for each patent granted in the U.S. since 1890. The GPR defines three categories of patents based on government involvement: i) patents that are funded by the government but developed and assigned to a private entity, which we label *public-private* (“license” in GPR);¹ ii) patents that are both financed and owned by a private entity, which we deem *private-private*; iii)

¹More specifically, by ‘private’ entity we mean a ‘non-federal’ organization.

patents that are funded and owned by the government, which we refer to as *public-public* (“title” in GPR)². The GPR also provides information on whether a federal agency funded and possibly owned a patent. By combining information from multiple databases (Table 1 in Gross and Sampat, 2025a), the GPR reduces measurement errors arising from potential non-compliance with government interest reporting requirements.³ In Section 5, we explore heterogeneity by funding agency.

Our analysis spans the period 1950-2015, due to data limitations. For instance, before 1950 only a small number of patents is available in the *public-private* category. Additionally, some key macroeconomic aggregates that we use as controls start only in 1950 at the quarterly frequency. Finally, patent registration delays mean that we cannot reliably extend the sample beyond 2015.⁴ Throughout the paper, we consider the filing date as the relevant timing for the patents as in Miranda-Agrippino et al. (2025). The filing date is the earliest available indication of a patent’s existence and, hence, its use ameliorates concerns about anticipation.

Other Data Sources. We complement the GPR patent dataset with additional information from several sources. We employ *PatentsView* to identify patent assignees’ characteristics and draw on the measures of *importance* and of *reliance on science*, constructed by Kelly et al. (2021) and Marx and Fuegi (2020, 2022) respectively, by patent category. These will be exploited in Section 4 to evaluate any heterogeneity in the aggregate effects of highly disruptive innovations. We complement these indicators with the measure of market evaluation provided by Kogan et al. (2017) and extended to non-listed firms using the procedure in Kline et al. (2019).

The USPTO Cooperative Patent Classification (CPC) Master Classification Files for U.S. patent grants are used in the sectoral analysis. Information about startups and firms backed by venture capital (VC) is available from Ewens and Marx (2024). For aggregate variables, we rely on the data collected by Antolin-Diaz and Surico (2025). In Appendix A, we report

²“Title” or public-public patents are those that name a government agency as an assignee, meaning the agency owns a share of the patent, often alongside other (private) entities

³The 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. To categorize patents in this residual group, 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*. In Appendix A, we provide further details on the procedure we follow to impute the unclassified cases, along with a more detailed description of the GPR database. Our main results are unaffected if we exclude these ambiguous cases from the analysis.

⁴Although the GPR database covers years up to 2020, the number of patents after 2015 drops due to registration delays.

detailed information on data sources and variables construction.

2.2 Descriptive Statistics

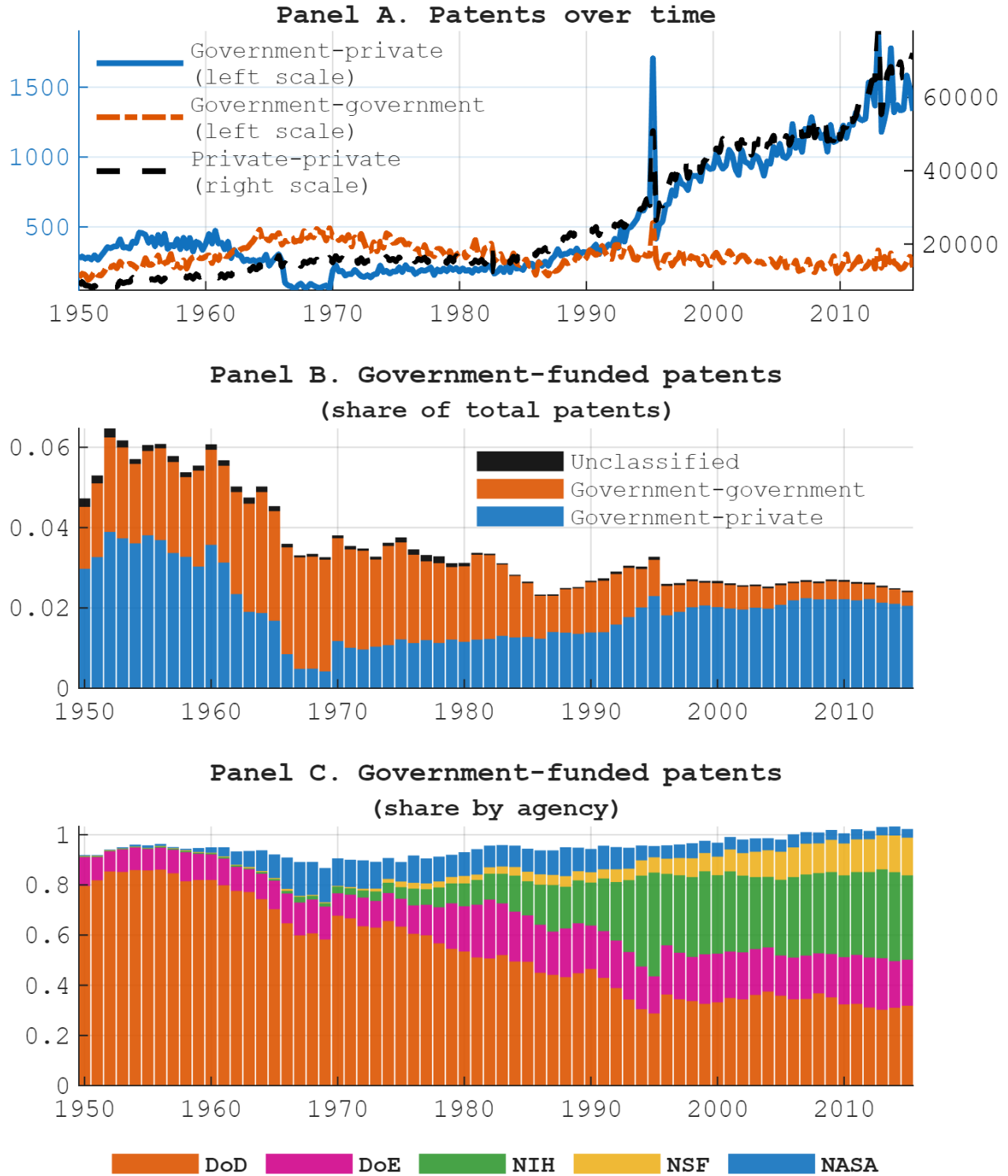
The GPR database covers more than 7 million granted patents in our sample. The vast majority belongs to the *private-private* category (Table 1, Panel A). Patents with no public interest account for about 97% of total patents. Among the rest, 2% have been funded by a federal agency but are owned by the private sector (i.e. *public-private*), while the government funds and owns the remaining 1%. The dynamics of each group over time highlight that the number of *public-public* patents has remained relatively stable throughout our sample (Figure 1, Panel A).

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. Our main findings are not qualitatively affected if we obviate the changes introduced by the Act and pool all publicly-funded patents into a single specification (see Appendix B). Moreover, our analysis of non-profit private sector innovation (Section 6) begins in 1976, meaning that our sample consists predominantly of post-Act observations. Moving to shares, we observe that the incidence of solely public patents has been progressively falling over time (Figure 1, 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 a major legislative change: the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS).⁵

The *importance* measure proposed in Kelly et al. (2021) weights positively (negatively) the forward (backward) similarity of a patent. The intuition is that a patent is more disruptive and groundbreaking whenever it differs more from previous patents but influences more

⁵In Appendix B, we show that our results are unaffected when we control for this and other major institutional patent events.

Figure 1: 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 \(2025a\)](#)). 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.

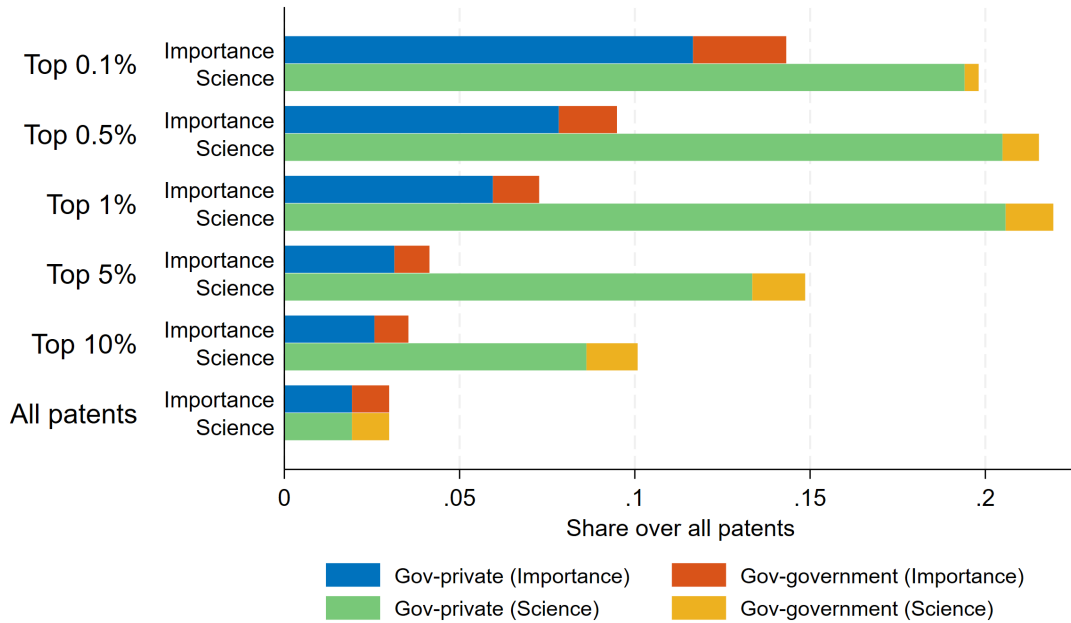
Table 1: Descriptive Summary of Patent Types and Importance

<i>Panel A: Publication Type Breakdown</i>			
	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%
<i>Panel B: Importance by Public Interest Type</i>			
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
<i>Panel C: Reliance on Science</i>			
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
<i>Panel D: Agency Breakdown</i>			
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%
<i>Panel E: Government Interest by Assignee Type</i>			
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 \(2025a\)](#). 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 \(2025a\)](#) 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 \(2024\)](#).

future patents. In Panel B of Table 1, 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, which Marx and Fuegi (2020, 2022) propose as a measure of *reliance on science*. Publicly funded innovations emerge as the most exposed to academic publications along the whole distribution, especially at the top end. 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.

Figure 2: Patents *Importance* and *Reliance on Science*



Note. The barchart displays the share of public interest patents across different levels of importance from Kelly et al. (2021) and across different levels 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: 1950:Q1-2015:Q4.

In Figure 2, we examine the composition of disruptive innovations. Publicly funded patents—whether owned by the public sector (orange and yellow) or the business sector (blue and green)—represent only about 3% of all patents, but their share rises sharply among the most disruptive ones. Government-funded patents account for over 4% (14%) and 7% (20%) of the top 5% and top 1% most disruptive patents, respectively, based on Kelly et al. (2021)’s

importance indicator (Marx and Fuegi, 2020, 2022, ’s reliance on science).⁶ Among the top 0.1% of the disruptiveness distribution, the share approaches 15%–20%, largely driven by public–private patents. In Section 4, we show that more disruptive patents are associated with larger subsequent increases in GDP and TFP, especially among innovations funded and owned by the government.

Focusing on public interest patents in Panel D of Table 1, we report the breakdown by five key federal agencies. In the first column, we note that the Department of Defense (DoD) has played the leading role in terms of absolute number of public-interest patents, followed by the National Institutes of Health (NIH, within the Health and Human Services Department), the Department of Energy (DoE), the National Science Foundation (NSF), and the National Aeronautics and Space Administration (NASA). These agencies, however, display marked heterogeneity in their patenting composition. 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 1, the share of public patents that are funded by DoD fell from nearly 100% in 1950 to 20% in 2015. Conversely, the NSF and especially the NIH (HHS) have played an increasingly central role since the 1970s, followed by the DoE. Furthermore, patents funded by NASA have 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. In Appendix C, we provide more statistics on public patents and present examples of government-funded but privately developed innovations.

Finally, in Panel E of Table 1, we describe the data employed in Section 6. 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

⁶This share rises to nearly 10% among the patents that Kelly et al. (2021) narratively identify as historically important—a threefold increase relative to their share in the full sample.

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.

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 :

$$\Delta_h y_{t+h} = \alpha_h + \beta_h x_t + \gamma_h \mathbf{w}_t + v_{h,t}, \quad h = 0, 1, \dots, H \quad (1)$$

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 (Jorda 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 , as well as GDP, TFP, investment, stock prices, the T-bill, R&D spending, and the number of patents filed 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 information set spanned by the lags of our rich set of controls helps us to isolate unanticipated changes in x_t .

In Table 2, we test for any possible remaining endogeneity in our implicit shock $\varepsilon_t = x_t \perp \mathbf{w}_t$.⁷ First, we reject the null that our set of controls do not predict x_t , thereby validating our choices of variables. 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

⁷In 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.”

(Ramey and Zubairy, 2018), taxes (Romer and Romer, 2010; Mertens and Ravn, 2013) and monetary policy (Romer and Romer, 2004).⁸ In Panel A, we report the results of these tests;⁹ in Panel B, we repeat the same exercise by agency. 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.¹⁰

Table 2: The Sufficient Information Test of Forni and Gambetti (2014).

Panel A: <i>p</i> -values from <i>F</i> -test of joint significance — by patent type					
Variable	<i>Test for controls' explanatory power</i>		<i>Test for implied patent shocks' orthogonality</i>		
	(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: <i>p</i> -values from <i>F</i> -test of joint significance — by agency					
Variable	<i>Test for controls' explanatory power</i>		<i>Test for implied patent shocks' orthogonality</i>		
	(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. “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).

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 presents the baseline results; in Section 3.2, we show that these remain virtually unchanged when we employ leading approaches from the applied macro-literature, including the narrative identification of Romer and Romer (1989, 2010) and Ramey and Shapiro (1998), the max-

⁸We employ an extension of the monetary policy series until 2007 from Coibion et al. (2017).

⁹We cannot reject the orthogonality of ε_t also to factors extracted from the FRED-QD database.

¹⁰We 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, the extrapolation of VAR of 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 3.2 we will verify that our baseline estimates are not overturned using a VAR. Inference is based on Newey and West (1987) standard errors.

share variance of Uhlig (2003), and the long-lag BVAR in Antolin-Diaz and Surico (2025).

3 Main Results

Bush (1945a) envisioned a research architecture built on three pillars: (i) fostering public-private collaboration, (ii) using government funding to spearhead fundamental research, and (iii) leveraging universities and research institutes to deliver major innovation breakthroughs. In this section, we examine the macroeconomic consequences of the first two pillars on output and productivity, and quantify their contributions to aggregate fluctuations and TFP growth. We return to the third pillar in Section 6, where we analyze the role of different innovation actors, including universities, research institutes, start-ups, and VC-backed firms. Section 3.1 presents our baseline conditional correlations, controlling for possibly confounding macroeconomic factors, while Section 3.2 shows that the results remain robust across a range of state-of-the-art time-series identification strategies, including a narrative approach that isolates legislative changes in patenting unrelated to economic conditions.

3.1 Baseline Conditional Correlations

In this section, we estimate the dynamic association between an increase in innovation activity and major macroeconomic variables, such as GDP, TFP, and R&D expenditure. Furthermore, we are interested in finding out whether patenting correlates with capital investment in the business-sector, the stock market and standards of living, as measured for instance by wages and consumption.

To investigate the macroeconomic role of patents that are funded by the government but owned by private organizations and compare it with innovation driven only by the private or the public sector, we use the categorization in Section 2. The first column of Figure 3 records the responses of GDP, TFP (top two rows) and innovation activity (bottom two rows) over a 10 year horizon to an 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. Given the sheer difference in group sizes, we normalize the shocks across specifications so that each corresponds to a 1% rise in total patents on impact.

Four main results emerge from Figure 3. First, public-private patents (first column) are characterized by the largest medium-term impact on both output (first row) and productivity (second row). The effects are delayed, consistent with the slow pace that is typically associated with the process of knowledge diffusion, and highly significant, with peaks around 0.2% after 8 to 9 years. Second, while private sector innovations (second column) also have a statistically significant influence, their effects on GDP and TFP tend to be smaller and do not exceed 0.1%.¹¹

In addition, the third column of Figure 3 reveals that, on average, patents funded and owned by the public sector fail to have any significantly positive impact. In the next section, however, we will show that this average effect masks pervasive heterogeneity: the most disruptive patents in the government-government group are associated with the largest effects on GDP and TFP. Fourth, government-private innovations are associated with the most significant increase in private R&D (third row) and total patents (last row), with a peak around 0.5%.¹²

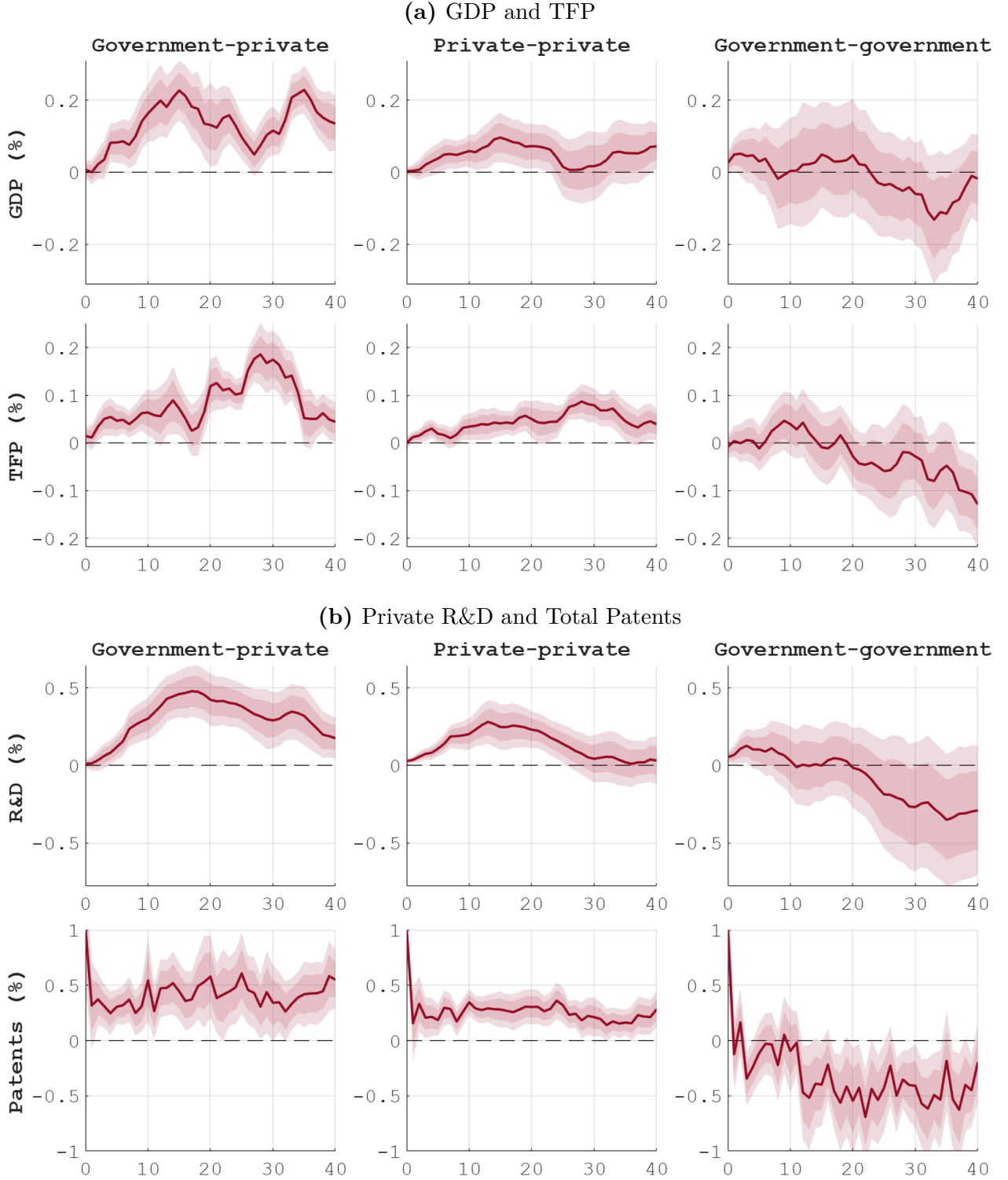
In Figure 4, we explore the relation of innovation with the broader economy. Interestingly, the ‘ranking’ of patent categories from Figure 3 is confirmed when we look at macro outcomes for firms (Panel A) or households (Panel B) in Figure 4. Panel A shows that a temporary increase in total patents driven by private ownership with public funding is linked to a subsequent expansion of private investment (first row) and a significant stock market appreciation (second row). In contrast, we find small and insignificant spillovers to investment from private-sector innovations in the second column, despite a sizable aggregate response of stock prices.

As for living standards in Panel B, it is also the case that only public-private partnership are associated with large, persistent and highly significant correlations with real wages (third row) and real consumption (fourth row). This contrasts with the smaller and less persistent trace of solely private innovation (second column) and the insignificant average association with patents funded and owned by the public sector (third column).

¹¹Two statistical tests (Sup-Wald and Cramér-von Mises, both based on bootstrap) reject the null of equal estimated effects of government-private versus private-private innovations on GDP and TFP. In Appendix B2, we explicitly report the difference of IRFs across the two patent groups, which is economically sizable and highly statistically significant for both GDP and TFP.

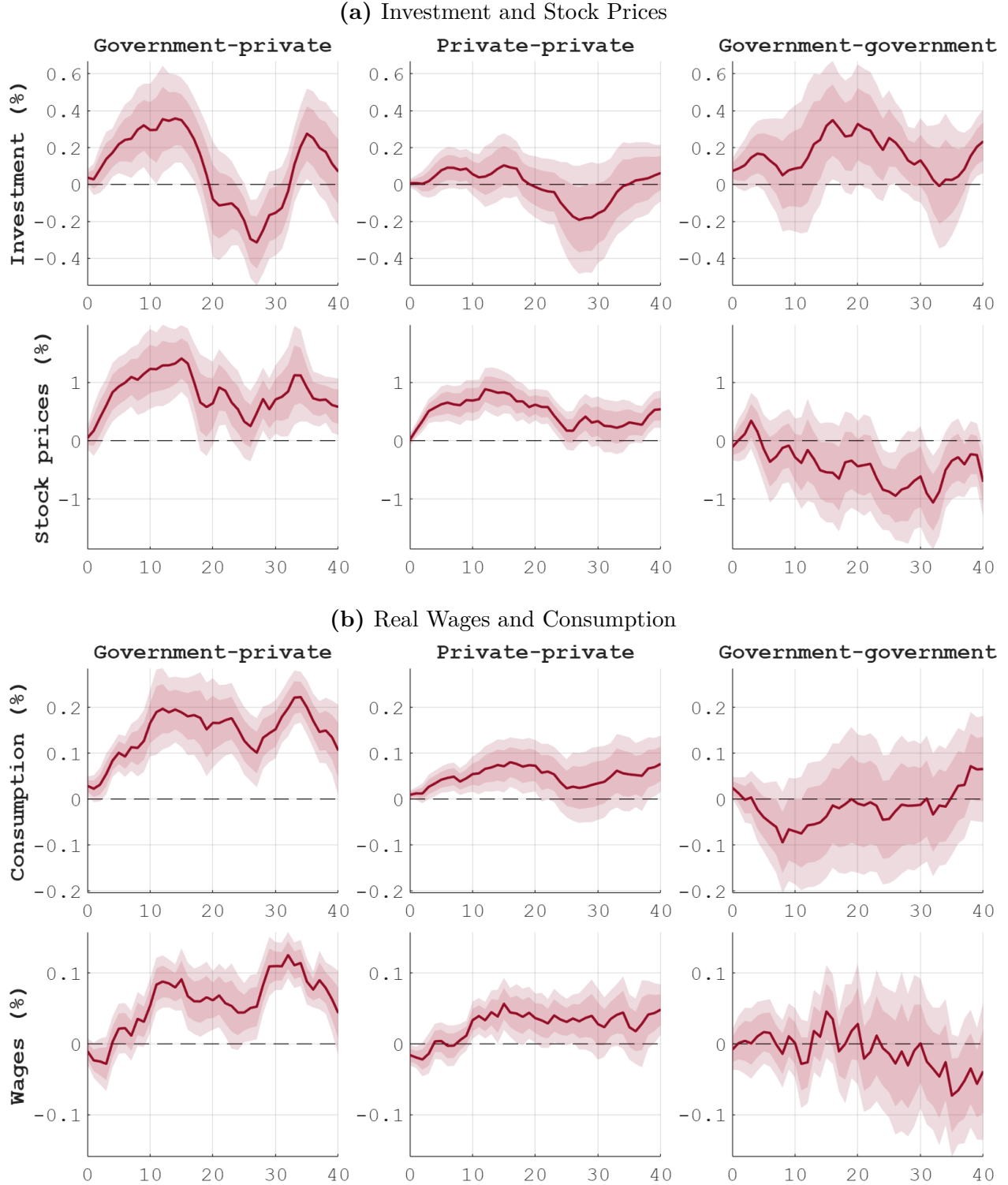
¹²We obtain very similar results for total patents when, in each specification, we exclude patenting activity in the other two categories. Moreover, we find that government-funded but privately owned innovations are associated with the largest increase in total patents over a ten-year horizon, even when weighting by the importance measure of Kelly et al. (2021): so, the interaction between public funding and private ownership is linked to gains in both the quantity and quality of subsequent innovation.

Figure 3: The Dynamic Effects of Innovation



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 (panel a) and (log) real per-capita private R&D and (log) patents (panel b; 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 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: 1950:Q1-2015:Q4.

Figure 4: The Dynamic Effects of Innovation on Firms and Households



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 investment and (log) real stock prices (panel a) and (log) real wages and (log) real per-capita consumption (panel b; 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 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: 1950:Q1-2015:Q4.

3.2 Alternative Time-series Approaches

In the previous section, we estimated the dynamic correlations between different categories of innovation activity and macroeconomic indicators using local projections and OLS. To mitigate concerns about confounding factors and reverse causality, we dated innovations by the time of application (rather than grant) and augmented the specification with a rich set of aggregate controls, including lags of GDP, TFP, investment, stock prices, short-term interest rates, and R&D spending. While this approach ensures transparency, the time-series literature offers several alternative methods to isolate the unanticipated component of the driving variable. In this section, we implement ten such approaches, beginning with one of the most widely used in applied macroeconomics: the narrative identification.

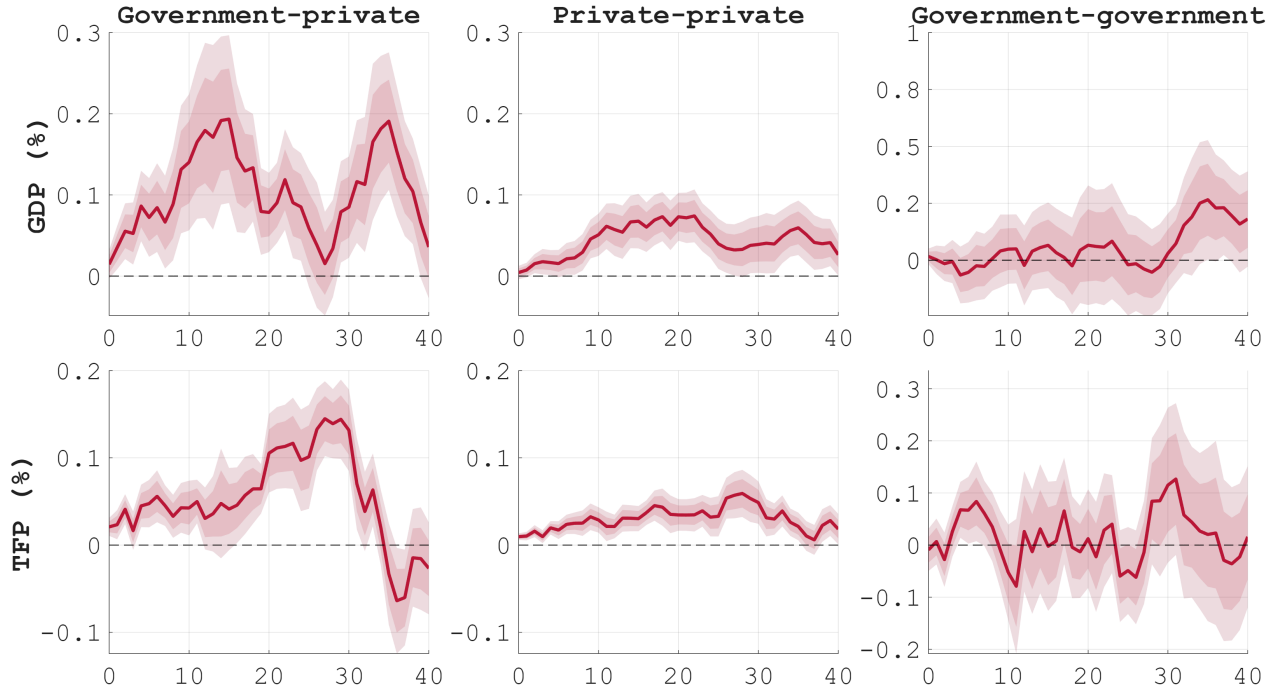
Narrative Identification. A long-standing tradition in macroeconomics—originating with [Friedman and Schwartz \(1963\)](#) and revived by [Hamilton \(1985\)](#), [Romer and Romer \(1989\)](#), [Romer and Romer \(2010\)](#), and [Ramey and Shapiro \(1998\)](#)—relies on examining policymakers’ stated motivations around major pieces of federal legislation and treating as “exogenous” those changes not driven by current or anticipated economic conditions. Following this approach, we identify large swings in patent filings around key legislative events and, based on a systematic reading of their underlying motivations, construct an instrument capturing quarterly percentage changes in patent applications induced by institutional events unrelated to the economy.

In [Figure 5a](#), we use the narrative instruments described above to compute LP-IV estimates as described in [Stock and Watson \(2018\)](#).¹³ Further details on the construction of the instruments and the classification of major legislative events are provided in [Appendix D](#). The results show that government-funded but privately owned patents generate the largest increases in GDP and TFP, with peaks at about 0.2% and 0.15%, respectively. Fully private innovations also raise aggregate productivity and output, though to a lesser extent, while fully public patents exhibit insignificant and imprecise responses. Overall, the magnitude and significance of the LP-IV estimates closely mirror the OLS results in [Figure 3](#), consistent with [Appendix B1](#) showing that patent applications are virtually a-cyclical.

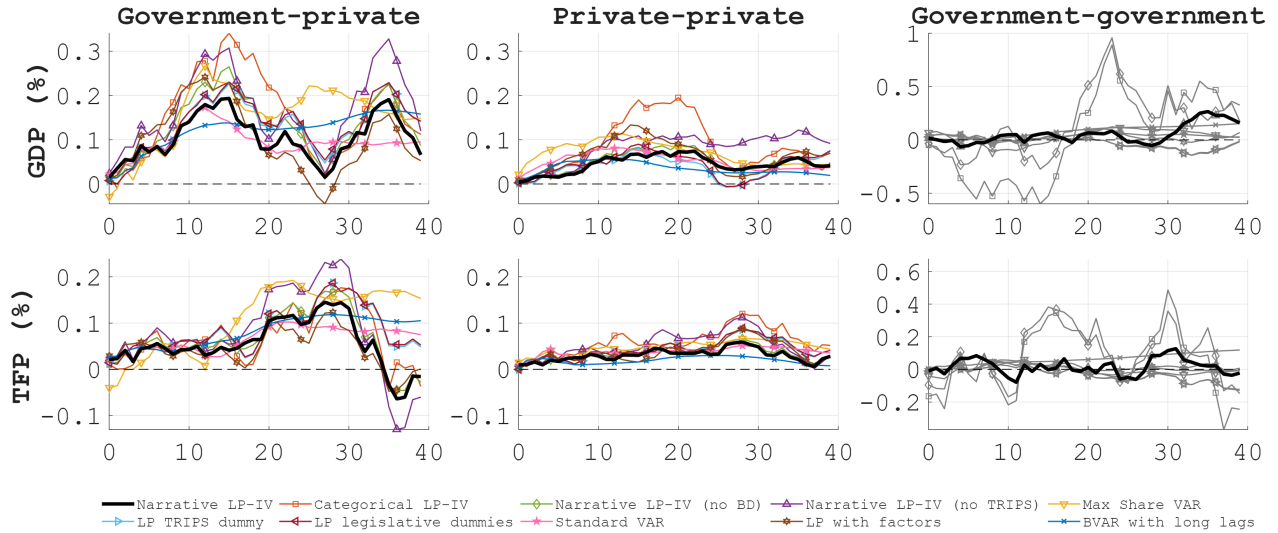
¹³The robust first-stage F -statistics are 786 for government-private, 510.5 for private-private, and 28.4 for government-government patents, thereby exceeding conventional thresholds for weak instruments.

Figure 5: Sensitivity Analysis

(a) Narrative LP-IV



(b) Alternative Time-series Strategies



Note. Panel (a) displays the dynamic effects of innovation shocks identified through a narrative LP-IV approach in each category of patents (government-private, private-private, government-government; by column) 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 ten 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: 1950:Q1-2015:Q4. Grey lines indicate impulse responses that are statistically insignificant at conventional level for the vast majority of forecast horizons.

Alternative Strategies. We next assess the robustness of our results across a range of alternative time-series approaches. Figure 5b reports point estimates from ten specifications: (i) Narrative LP-IV (baseline, as in Figure 5a); (ii) Categorical LP-IV, which uses the same events but only the sign of changes, as in Ramey and Shapiro (1998); (iii) Narrative LP-IV (no Bayh–Dole) and (iv) Narrative LP-IV (no TRIPS), which exclude the Bayh–Dole Act and TRIPS, respectively; (v) Max-share VAR, identifying the innovation shock that explains the largest share of forecast error variance in patenting over a two-year horizon using a VAR(12), following Uhlig (2003);¹⁴ (vi) LP with TRIPS dummy; (vii) LP with legislative dummies, which include dummies for four major legislative events; (viii) Standard VAR (12 lags), with a Cholesky factorization; (ix) LP with factors, adding the first two principal components from the FRED-QD database as controls; and (x) BVAR with long lags, a 40-lag Bayesian VAR with priors specified as in Antolin-Diaz and Surico (2025).

Across all ten specifications, the results consistently point to a strong and persistent medium-term association between aggregate productivity and innovation funded by the government but owned by the private sector, with smaller macroeconomic effects for fully private patents.

3.3 Contribution to Aggregate Fluctuations and Economic Growth

In the previous sections, we have shown that public–private patents generate innovations most strongly associated with medium-term movements in macro variables. We now quantify the contribution of unanticipated surges in government-funded but privately owned patenting to aggregate fluctuations and economic growth. To this end, we conduct two decomposition exercises. Using the R^2 approach for local projections proposed by Gorodnichenko and Lee (2020), we assess how much these shocks contribute to the h -period-ahead forecast errors of output and productivity growth. First, we compute the forecast error variance decomposition, which measures the share of forecast variance explained by each shock at each horizon. Second, within the same framework, we perform a historical decomposition of TFP growth at an eight-year horizon ($h = 32$), capturing the contribution of these shocks to the medium-term component of productivity growth. Eight-years is standard for filtering beyond business-

¹⁴This approach generalizes the Cholesky decomposition that is implicitly behind our baseline LP specification (Ramey, 2016). The Cholesky factorization restricts the shock to explain the entire conditional variance on impact; the max-share relaxes this.

cycle frequencies.¹⁵

In Figure 6, we record the share of the forecast error variance for GDP (top row) and TFP (bottom row) explained by each innovation shock. Solid lines stand for point estimates, while shaded areas refer to 68% (darker) and 90% (lighter) confidence intervals. Three conclusions can be drawn from this decomposition exercise. First, public-private innovation shocks in the left column account for about 20% of the medium-term variance of GDP and TFP growth, but explain little of their short-term fluctuations. Second, private patents in the middle column tend to make a smaller contribution, which peaks at business-cycle frequencies. Third, the share of variation explained by fully public patents in the right column seems negligible at all forecast horizons.

In Figure 6 Panel B, we identify a prominent role over the medium-term for innovation shocks to patents that are publicly funded and privately owned. We investigate the extent to which these shocks explain low-frequency movements in the TFP growth rate presenting a historical decomposition for $h = 32$.¹⁶ The main take away is that innovations funded by the government and developed by the private sector move together with some of the major swings in the medium-term component of productivity growth during the post-WWII period. In particular, our estimates suggest that the ‘prosperous’ 1950s, the ‘roaring’ 1990s and the diminished business dynamics of the 2000s may have originated, at least partially, in the rise and fall of innovations coming from public-private collaborations. In Appendix E2, we calculate that if the medium-term contribution of government-private innovations during the 2000s had counterfactually continued at the same pace of their 1990s peak, then the level of TFP in 2007 would have been between 5.4% and 10% higher than it actually was.¹⁷

3.4 Returns to Innovation: a Back-of-the-Envelope Calculation

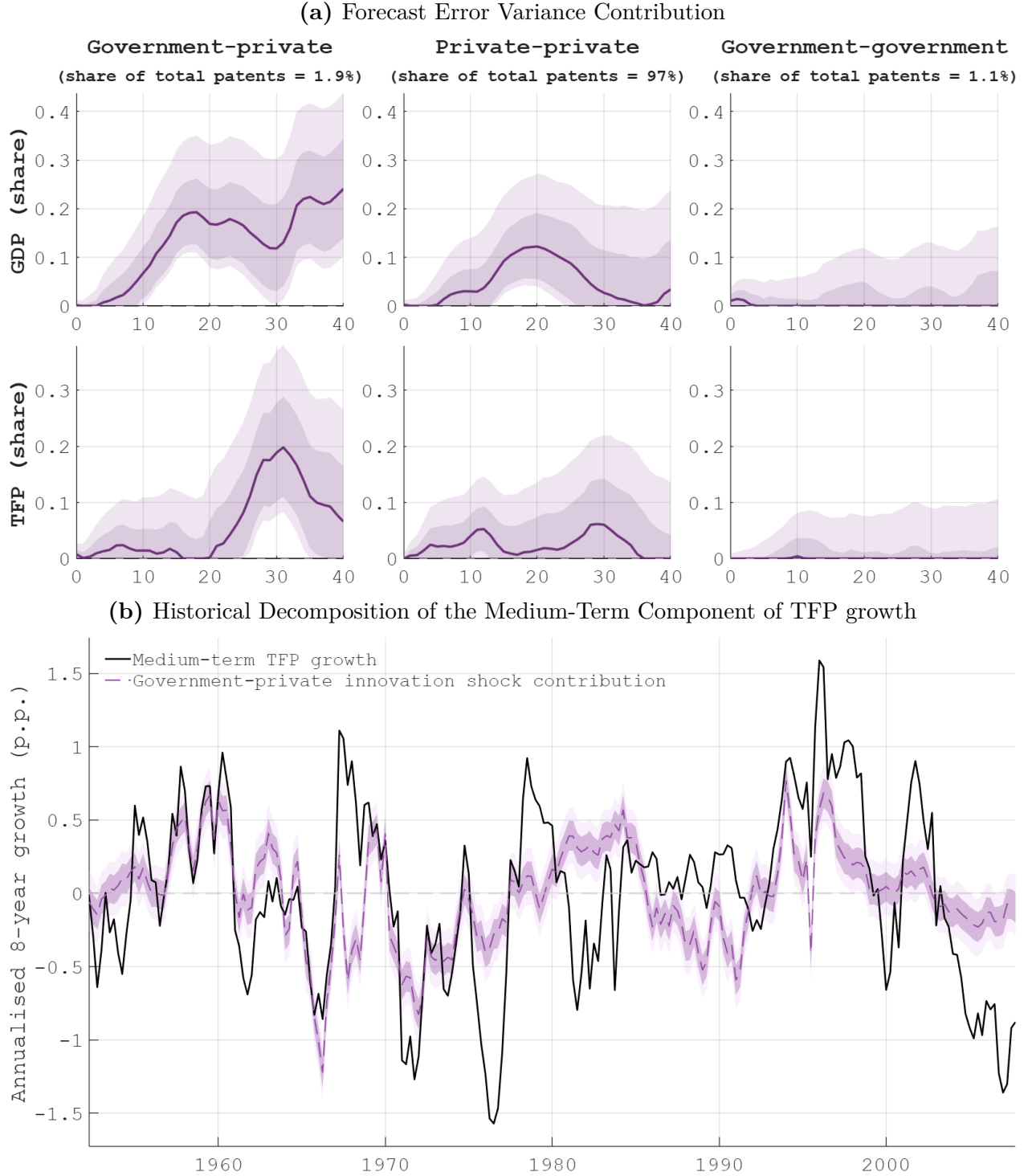
So far, we have shown that publicly funded and privately owned innovation produces significantly larger effects than patents funded and developed privately. Our estimates, however,

¹⁵Appendix E provides details on the procedure. To our knowledge, this is the first application of LP methods to estimate and generalize historical decompositions across horizons. Appendix Figure E1 repeats the analysis for $h = 6$, showing that public-private innovation shocks contribute modestly to short-term TFP growth.

¹⁶The historical decomposition combines the shocks implied by our local projection model with the estimated dynamic impulse response effects to compute the contribution of the shock to movements in the endogenous variables. We follow the approach by Gorodnichenko and Lee (2020), which was originally designed for the estimation of the forecast error variance in local projections, and adapt it to compute the historical decomposition.

¹⁷Our findings therefore complement existing explanations for the 2000s diminished business dynamism and the post-2005 productivity slowdown such as the rise in intangible inputs put forward by De Ridder (2024).

Figure 6: Forecast Error Variance Contribution and Historical Decomposition



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: 1950:Q1-2015:Q4.

do not yet provide a readily available measure of the *returns* to public and private innovation, as the shocks are not scaled in monetary units and we do not directly observe the costs of producing innovation.

To deliver a back-of-the-envelope estimate of the returns to innovation, we proceed in three steps. First, we calculate a measure of the average real dollar cost of privately and publicly funded patents, respectively. We do so by taking the ratio between the cumulative real R&D expenditure and the count of patents in each sector over the full sample. Since the available data do not allow us to separately attribute government R&D expenditures to different categories of publicly-funded patents, for this exercise, we group together all government-funded patents, independently from ownership. Using national accounts measures of private and government R&D expenditure, deflated by the GDP deflator, we find that the historical average real cost of a publicly funded patent is \$25.1 million of USD versus \$0.82 million for the private sector.

Second, we rescale the estimated IRFs to express the real-dollar responses of GDP and R&D to a shock that generates one additional patent in each category.¹⁸ We then compute back-of-the-envelope multipliers by dividing the discounted responses of GDP and private R&D—averaged over forty quarters—by the estimated per-patent cost. Because patent shocks are dated at the time of application, we apply an additional time discount to account for the lag between R&D spending and patenting. Empirical estimates suggest a lag of 5 to 20 years (Hausman et al., 1984; Li et al., 2017; Wang and Hagedoorn, 2014; Dyèvre, 2024), which we use below.

In Table 3, we present our back-of-the-envelope calculations. The rows refer to privately-funded and government-funded innovation, respectively. The first column reports the average cost per patent. The following four columns summarize the GDP returns, assuming a lag between R&D spending and patent filing varying from 5 to 20 years. The last four columns measure the spillovers of private innovation and government-funded innovation onto business-sector R&D. Below each point estimate, we report 68% confidence bands.

Three main results emerge from Table 3. First, on average, government-funded patents are characterized by far larger cost. Second, for every dollar of taxpayers' money invested in

¹⁸In Appendix Figure B4, we obtain very similar results when we pull all government-funded patents into a single group.

Table 3: Returns to Innovation: a Back-of-the-Envelope Calculation

funding source	cost per patent	GDP RETURN				PRIVATE R&D RETURN			
		<i>R&D—patenting lag</i>				<i>R&D—patenting lag</i>			
		5y	10y	15y	20y	5y	10y	15y	20y
<i>private</i>	0.82M\$	6.92 [1.5, 12]	5.69 [1.3, 10]	4.68 [1.0, 8.3]	3.84 [0.9, 6.8]	0.43 [.22, .64]	0.35 [.18, .52]	0.29 [.15, .43]	0.24 [.12, .35]
<i>government</i>	25.1M\$	14.4 [8.1, 21]	11.9 [6.6, 17]	9.74 [5.4, 14]	8.01 [4.5, 12]	1.03 [.67, 1.4]	0.84 [.55, 1.2]	0.69 [.45, .94]	0.57 [.37, .77]

Note: returns to private innovation and to public innovation are measured as the average real dollar increases in GDP or Private R&D (evaluated at the end of the sample period) between 1 and 40 quarter horizons per dollar of R&D expenditures, calculated by dividing the cumulative discounted response by the unit cost of patents. The R&D patent lag is the delay in years between R&D investment and patent filing. Each entry in the table is computed as $\frac{1}{40} \sum_{h=1}^{40} \Delta X_h^{disc} / \text{Cost per patent}$, where X_h^{disc} is the discounted IRF at horizon h of either GDP or Private R&D, $\Delta X_h^{disc} = \Delta X_h (1+r)^{-(L+h/4)}$, and $L \in \{5, 10, 15, 20\}$ is the R&D-patent lag. All values are discounted at an annual real rate of 4%. Numbers in brackets show 68% confidence intervals.

innovation, the U.S. economy expands between 8 and 14 dollars (second row). In contrast, the returns from private patents (first row), while still sizable, are smaller than their public counterparts, between 3.8 and 6.9 dollars. Third, government-funded patents generate significantly larger spillovers than private innovation, with R&D returns between 57 and 103 cents for every dollar of government funds. Interestingly, the R&D returns in Table 3 are consistent with the firm-level evidence reported by Bloom et al. (2013) and Dyèvre (2024) for the U.S., by Bergeaud et al. (2025) for France, and by Leicester et al. (2024) for the U.K., using different methods.

In summary, although government-funded patents cost an order of magnitude more than private-sector patents, our back-of-the-envelope estimates seem to suggest that, per dollar spent, they generate over twice the spillovers to business R&D and more than double the impact on GDP relative to fully private innovations.

4 The Macroeconomic Impact 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 5, we will zoom on federal agencies such as NIH and NSF, while in Section 6, 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.

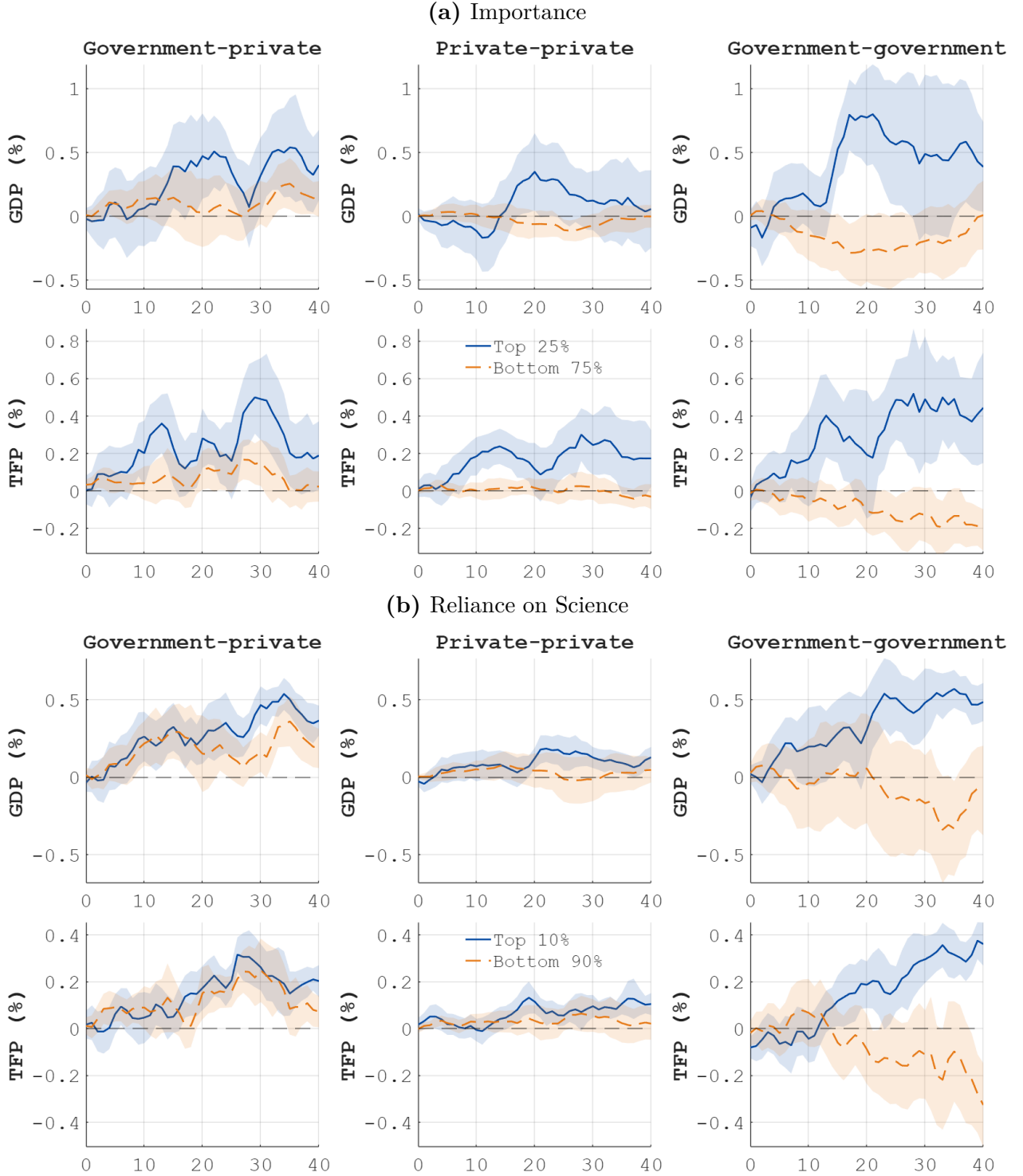
As discussed in Section 2, the measure of importance or fundamentalness in [Kelly et al. \(2021\)](#) is a function of both forward and backward patent similarity, with the former (latter) receiving a positive (negative) weight in the importance measure. Accordingly, a patent with high textual similarity 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).¹⁹

Given this background, in Panel A of Figure 7, 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. \(2021\)](#).²⁰ 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

¹⁹A 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 6, 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 F3, 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. \(2019\)](#).

²⁰We 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. The ranking is computed in every year and across all categories.

Figure 7: The Dynamic Effects of the Most *Important* and *Reliant on Science* Innovations



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 [Marz 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: 1950:Q1-2015:Q4.

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 C2, 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 7 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 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 F4, 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 1). In Appendix Figure F5, 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.

5 On the Mechanism

In the previous sections, we have documented a prominent role for publicly-funded/private-owned innovations in driving productivity and prosperity in the post-WWII U.S. economy, with a significant crowding-in of 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, innovation spillovers, and networks. In the next section, we quantify the contributions of the different players, including research institutes and universities, start-ups, and VC-backed companies.

5.1 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.²¹ 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 1– account for 98% of government-funded patents.²² 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 G).

In the top and bottom rows of Figure 8, 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

²¹In 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.*”

²²The 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’.

the findings for industries that most closely match the main industry in which each federal agency or department mainly operates.²³ 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 8a and 8b, 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 (2023).

Three main results emerge from Figure 8a. First, NSF and NIH innovations lead to the largest medium-term gains in TFP and GDP among the public-private patents of the first column, with peaks around 0.3% and 0.5%, respectively, 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 economically and statistically substantial. Second, fully-private innovations in the second column display muted heterogeneity, especially in terms of TFP responses. Third, in 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 4). Within those, NIH and DoD stand out as the most and least impactful agency/department, respectively. In the next section, we will come back to this result by looking at the healthcare research field, showing that government-funded patents systematically outperform private-funded innovations in terms of GDP and TFP impact.

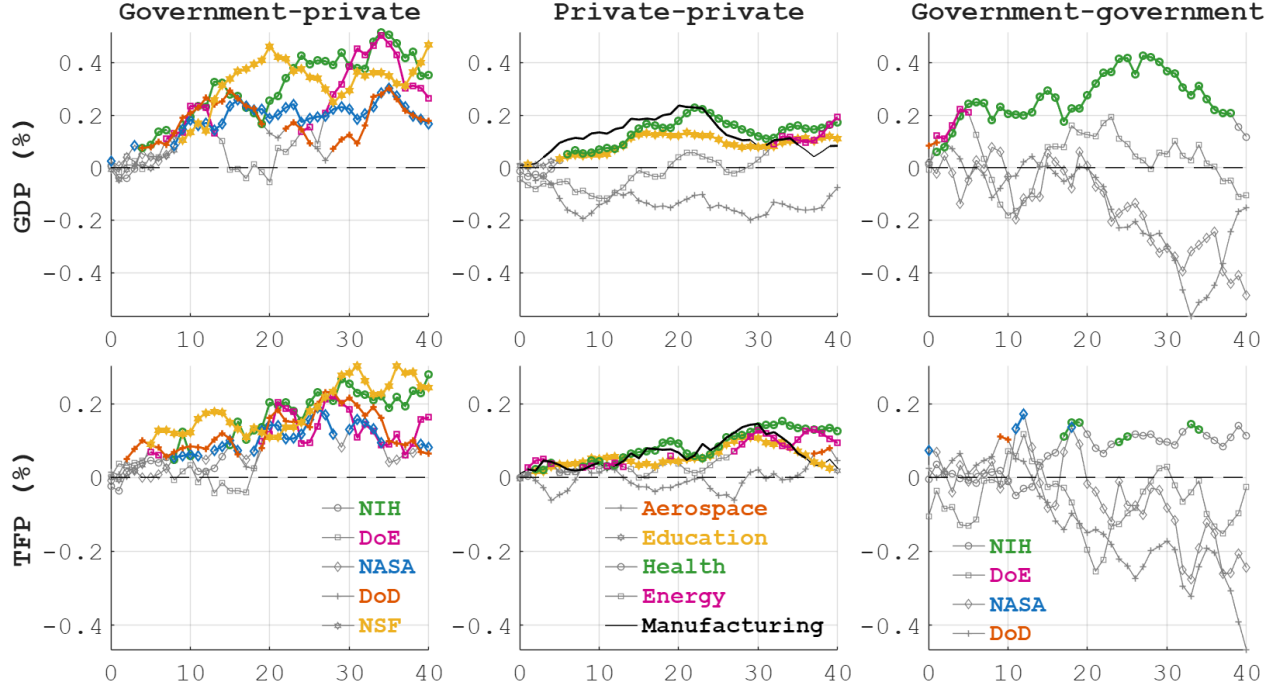
5.2 Research Fields

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 G1 and G2, we report the share of all pooled patents by research field for the players under investigation, namely the main federal

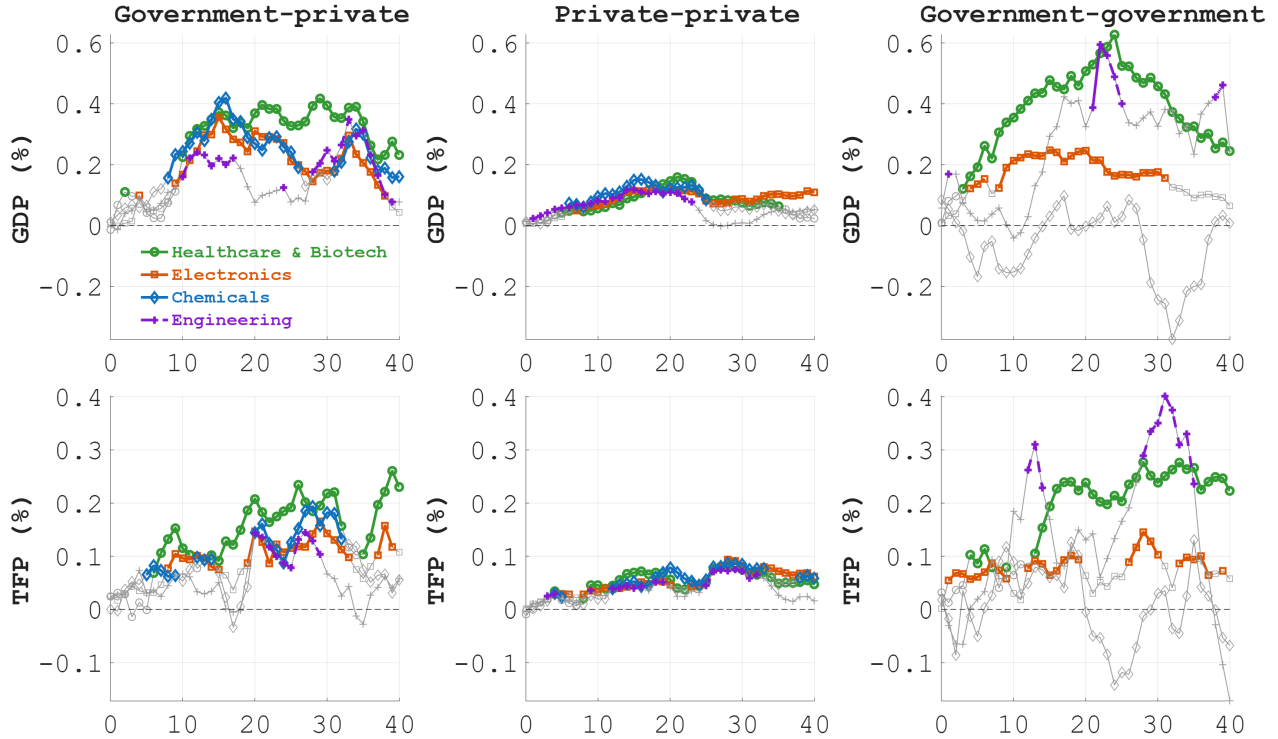
²³In Appendix G, we bridge federal agencies, research fields, and industries using CPC codes. Due to data limitations in PatentsView, the sample for the ‘Education’ sector in the second column of Figure 8 begins in 1976.

Figure 8: 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 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 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: 1950:Q1-2015:Q4 (except for 'University' in the second column, 1975q1-2015:Q4).

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.²⁴

In Figure 8b, we replicate the setting and format of Figure 8a. 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).²⁵ Second, a substantial share of private R&D 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).

²⁴Appendix Table G2 shows the mapping between CPC codes and fields of knowledge.

²⁵More 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.

5.3 Innovation Spillovers

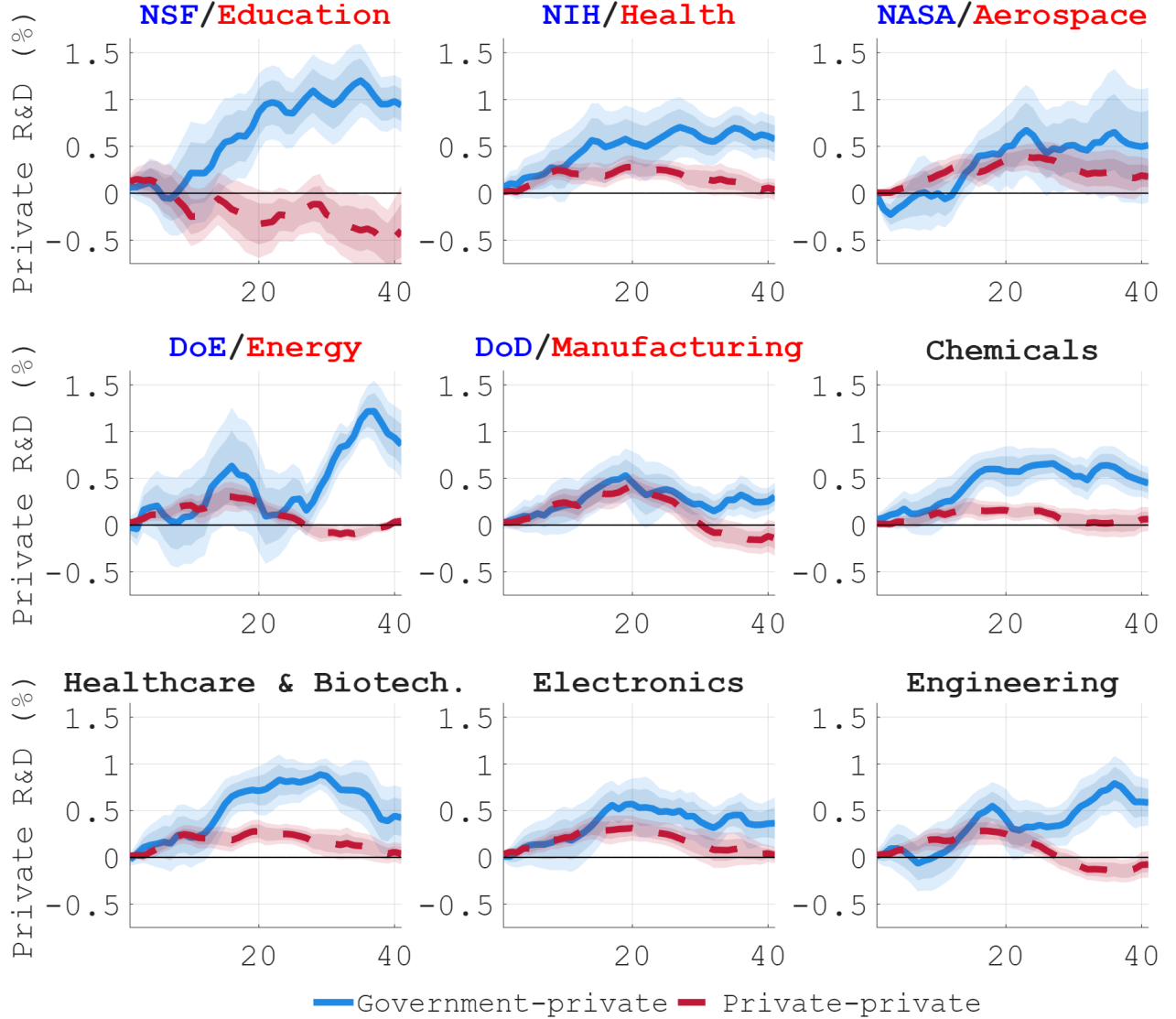
In Section 3.1, we have shown that publicly-funded/privately-owned patents generate substantial spillovers to the rest of the economy by stimulating a significantly larger response of capital and R&D expenditure in the business sector than the other two patent categories. In this section, we aim to explore this finding further and examine the contributions of different federal agencies, industries, and research fields to driving innovation spillovers compared to their private-sector counterparts. We do so in the spirit of Williams (2017), who provide a comprehensive survey of the various channels through which patents affect research investment in the economy.

In Figure 9, we report the response of R&D expenditure by the business sector to a set of innovation shocks that suddenly increase patenting activities by only one federal agency, an industry or a research field at the time. The blue lines and bands refer to public-private innovation, while the red broken lines and shaded areas stand for private-private patents. The first row summarizes the results for NSF, NIH and NASA, which we match in the private sector with university, ‘healthcare and biotechnology’ and aerospace, respectively. The first (second) panel of the second row depicts the Department of Energy among public-private patents and the energy sector for only private enterprises (Department of Defense and manufacturing). These groups correspond to those displayed in Figure 8a. The remaining panel in the second row and the third row contrast the spillover generated by public-private collaborations vis-a-vis those by fully private initiatives in the research fields of ‘Chemicals’, ‘Healthcare and Biotechnology’, ‘Electronics’, and ‘Engineering’ (which correspond to the groups in Figure 8b).

A few findings emerge from Figure 9. 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.²⁶ In particular,

²⁶Interestingly, 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. Our results of significant private R&D spillovers from patents funded by the Department of Energy aligns well with the evidence provided by Myers and Lanahan (2022) based on public R&D expenditure data.

Figure 9: 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 (top row and two leftmost panels of the second row) 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: 1950:Q1-2015:Q4.

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 \(2023\)](#), respectively.²⁷

5.4 Innovation Networks

In this section, we expand on the spillover result above 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.

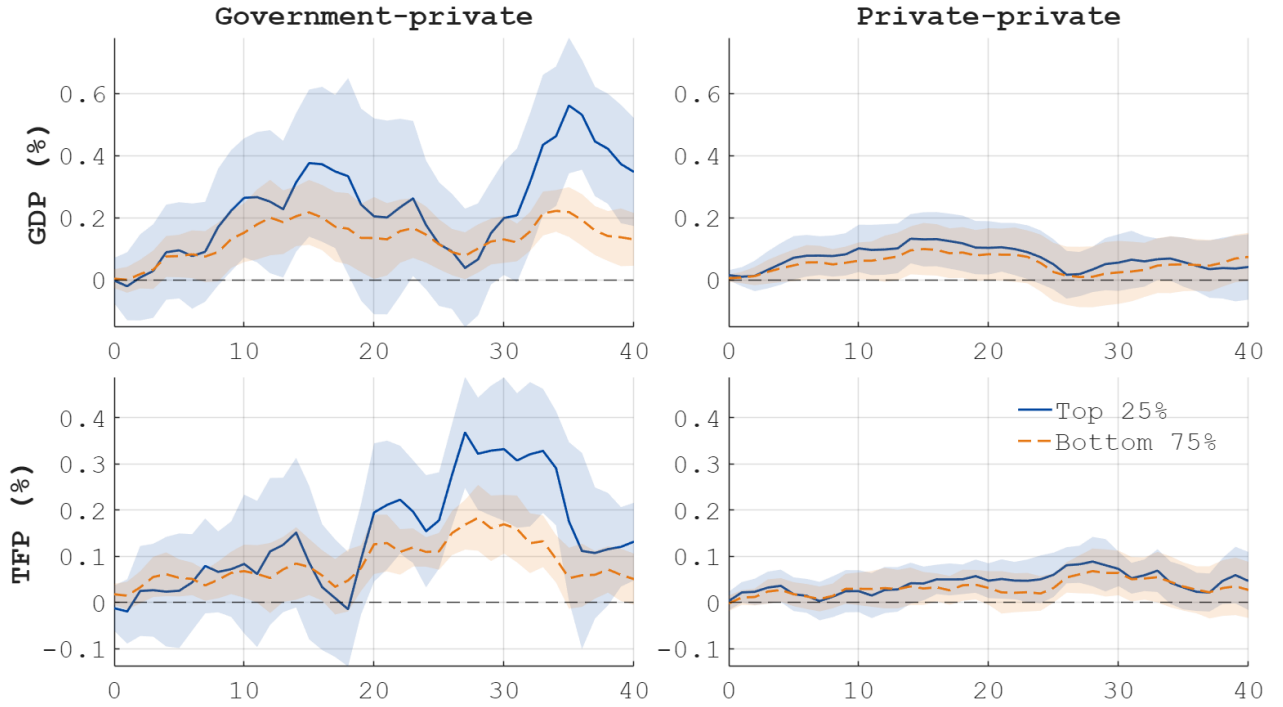
To evaluate this hypothesis, we split public-private patents and private-private patents into two further groups: top 25% and bottom 75% of the innovation network centrality distribution.²⁸ Following [Liu and Ma \(2024\)](#), network centrality is defined as the dominant left eigenvector of the patent 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 within the same USPC patent class.

The findings of this exercise are summarized in Figure 10. 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 10 is that the top 25% most central innovations

²⁷The significant spillovers to private R&D in Figure 9 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.

²⁸Given the very small number of public-public patents in the top quartile, we exclude this group from this analysis.

Figure 10: 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: 1950:Q1-2015:Q4.

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 H1 shows the fraction of patents within each group that are in the top percentiles of the innovation network centrality distribution; Figure H2 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 8b). 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 8. 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.

6 Who are the Main Innovators?

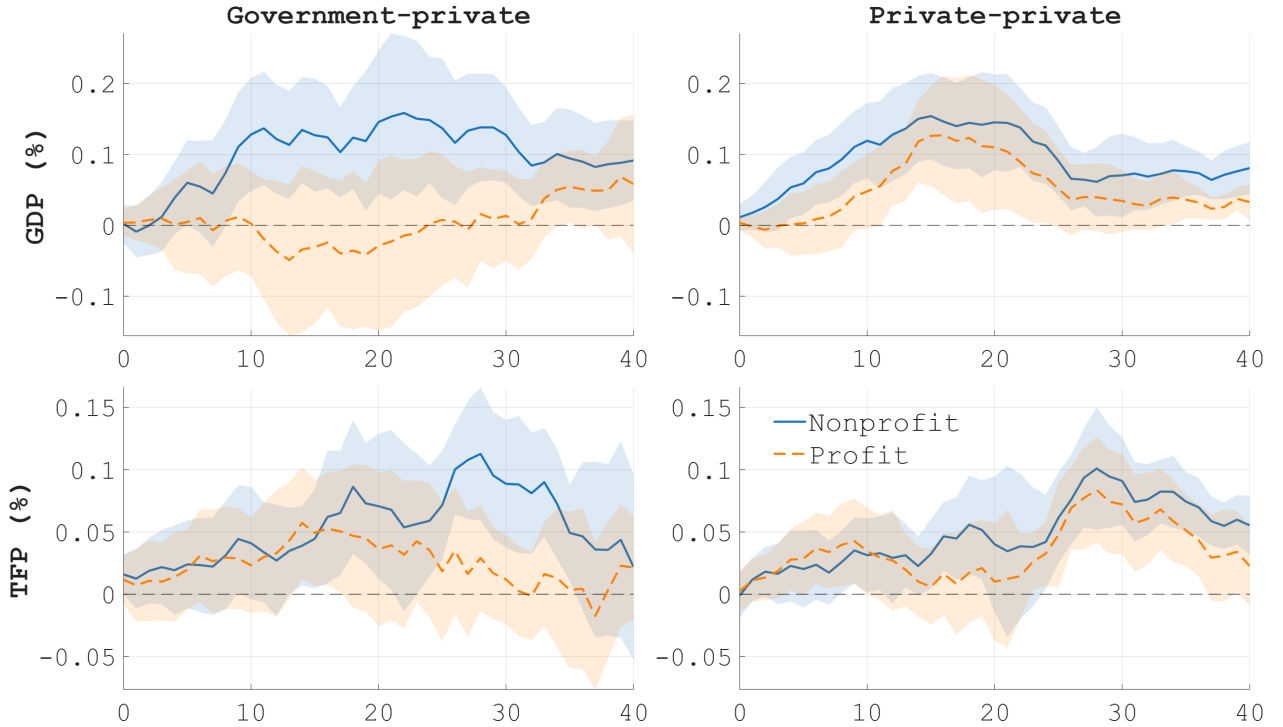
In the previous section, we identified NSF and NIH as the agencies that develop innovations with the largest medium-term impact on TFP and GDP. Furthermore, we have contrasted the higher performance of public-public patents in ‘healthcare & biotechnology’ relative to the far smaller productivity gains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

6.1 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 summarized in Figure 11, 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.

Figure 11: 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.

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 6.2, we will focus on research institutes and universities within the non-profit sector, while in Section 6.3, we will consider start-ups and VC-backed for-profit companies.

6.2 Research Institutes and Universities

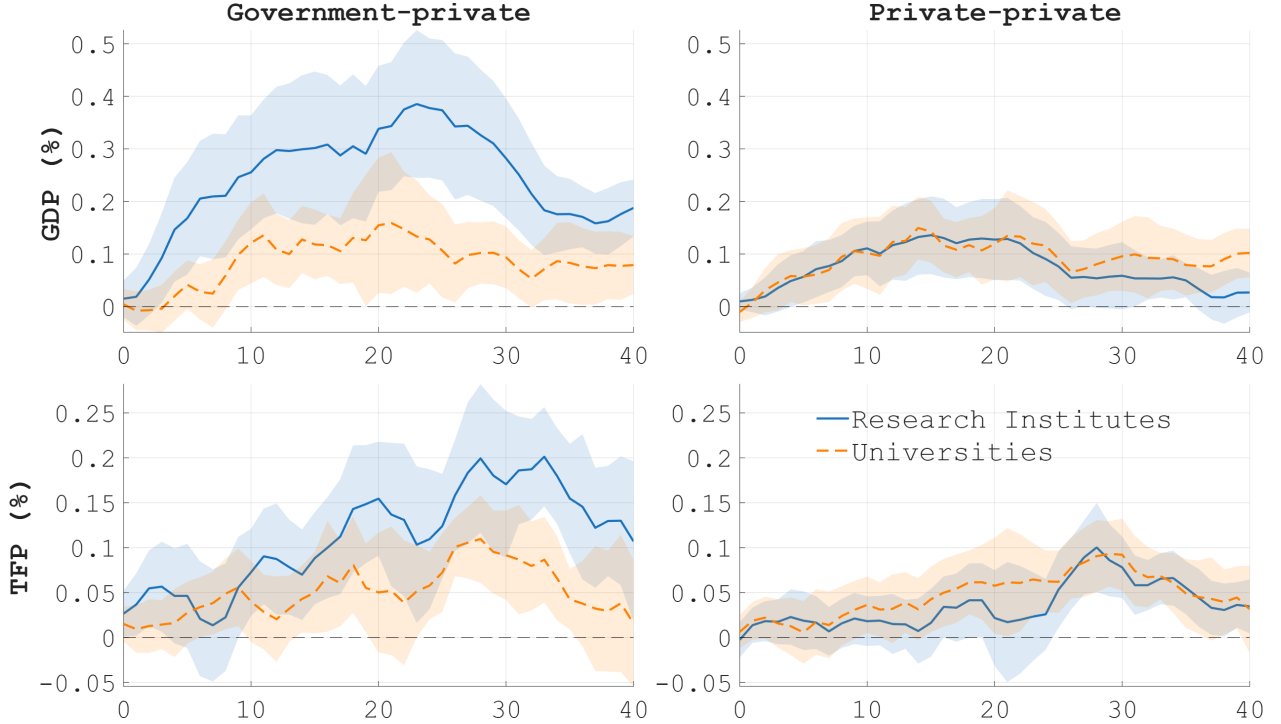
In his report, [Bush \(1945a\)](#) envisioned a central role for ‘basic’ research, defined as “*research performed without thought of practical ends*” and for the “*general knowledge and understanding of nature and its laws*”. In the letter to President Truman presenting the report, [Bush \(1945b\)](#) 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*”.²⁹ Bush’s vision has been reflected in the sustained commitment of higher education institutions and research laboratories to basic research.

In Appendix Figure I1 Panel A, we show that most of the post-WWII R&D spending in the American economy 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 Appendix Figure I1 Panel B, we show that the U.S. (federal) government accounts for the lion’s share of funding sources, financing an average of 60% of annual basic R&D expenditures 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 R&D, Appendix Figure I1 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

²⁹In [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.*”

universities as primary drivers of ‘basic’ research.³⁰ These two groups span the vast majority of the non-profit world.

Figure 12: The Effects of Innovation by Research Institutes and Universities



Note. The figure compares the dynamic effects of innovation shocks in each category of patents (public-private, private-private; by column) across research institutes and universities 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 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 12, we report the effects of innovation by universities (orange broken lines) and research institutes (blue solid lines) on GDP and TFP. The left (right) column refers to public-private (solely private sector) patents. It is worth noting that [Gross and Sampat \(2025a\)](#) categorise all research institutes and universities as ‘private’ entities. Accordingly, any difference between the columns in Figure 12 is only due to whether funds are made available by the government or the private sector. In the words of [Bush \(1945a\)](#), only the estimates in the left column can be interpreted as “basic” research (i.e. government-funded and carried out by research institutes and universities). Furthermore, as the estimates in the

³⁰Looking at research institutes and universities to proxy for ‘basic’ research compares favorably with alternative metrics based on citations (Section 4) 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.

right column refer to the same institutions but privately funded, any difference between the two columns can be interpreted as the marginal contribution of government support towards ‘basic’ research.

The estimates in Figure 12 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 4 and 5.1, we conclude that ‘basic’ research in universities and research institutes funded by NIH and NSF is a fundamental driver of post-WWII American innovation.

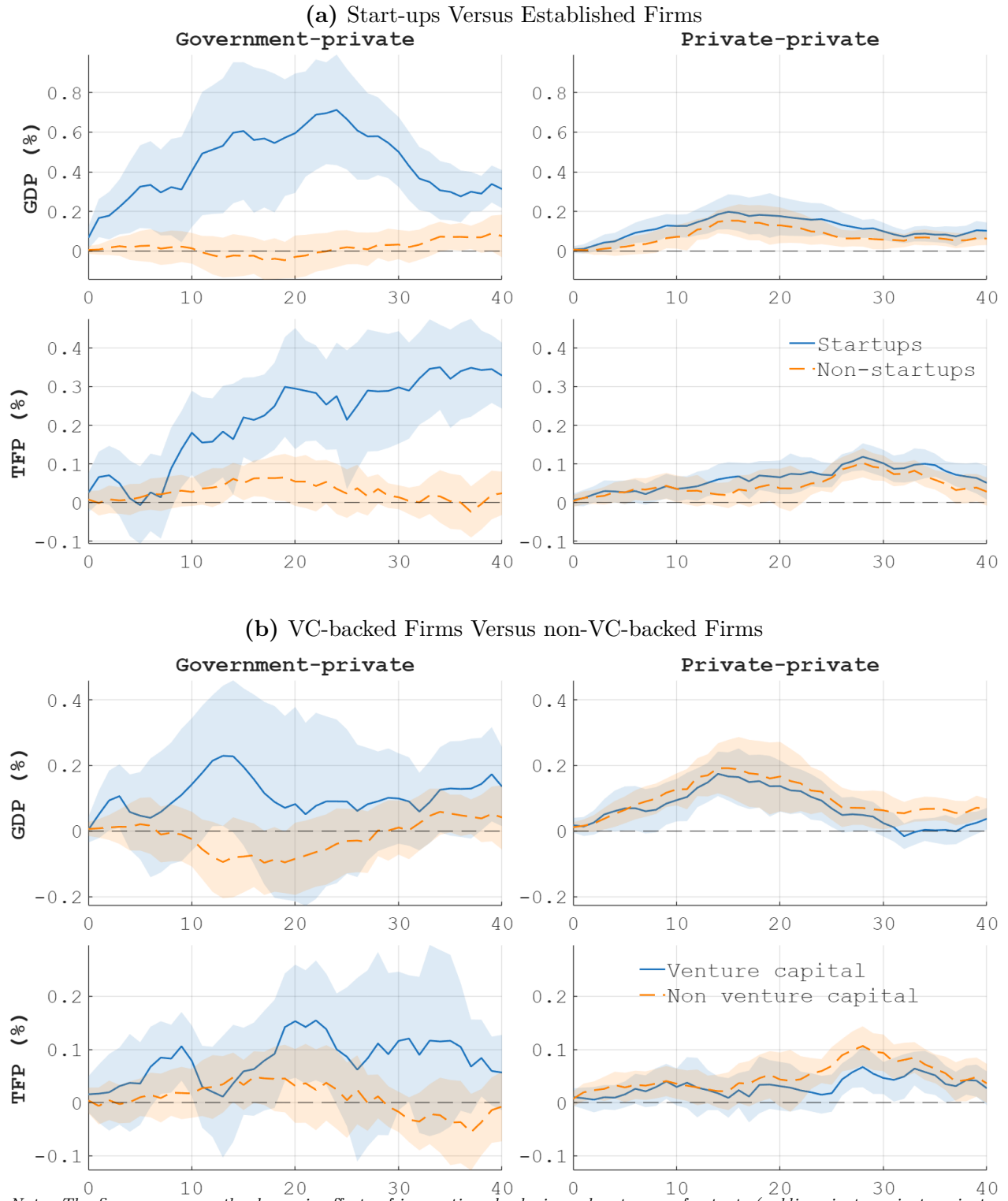
6.3 Are start-ups and venture capital-backed firms special?

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 13. In Panel A (B), start-ups (VC-backed firms) show as blue solid lines and 90% confidence bands while other firms show as orange broken lines and shaded areas.

When government-funded (left column), the difference between start-ups and other firms 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 13), the gap between the effects generated by the two groups of firms is negligible. In other words, start-ups are far more innovative than established 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

Figure 13: The Effects of Innovation by Firms' Characteristics



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.

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.

7 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 under-

provide 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. Beyond patents, future work can examine the macroeconomic role of grants, clinical trials, and other channels of knowledge creation. 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 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 living standards in the long-run.

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Online Appendix

A Data Sources and Definitions

This Appendix reports further details on data sources and the transformation of the key variables employed in the empirical analysis of the paper.

A1 Government Patent Registry Database

Gross and Sampat (2025a) 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 usá", "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.

A2 Additional Patent Data Sources

Importance. We employ the measure of patents’ importance from [Kelly et al. \(2021\)](#), which is the ratio of forward over backward similarity, where similarity is computed using natural language processing techniques. We use the variable `lqsim05` (importance based on a 5-year window) in our baseline analysis and `lqsim010` (10-year window) in the robustness analysis. In the baseline, we define dummy groups based on percentiles computed within each category. In Appendix [F](#), 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 title and in the text body of

the patent. We rely on the measure that aggregate papers’ citations in both title and text. In Appendix F 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 statistical mapping provided by the USPTO. See H 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 \(2024\)](#).³¹ 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.

A3 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 CNP160V (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 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.

³¹The dataset used in [Ewens and Marx \(2024\)](#) is shared through [foundingpatents.com](#)

B Additional Results

This Appendix presents additional results on the cyclicalities 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 Cyclicalities and Effects of Total Patents

In this Section, we show that, unlike R&D expenditure, patent filings do not exhibit business-cycle cyclicalities. 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. Government-private patents are negatively correlated with GDP, driven by the 1970 recession. 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 Are the effects of government-private and private-private patents different?

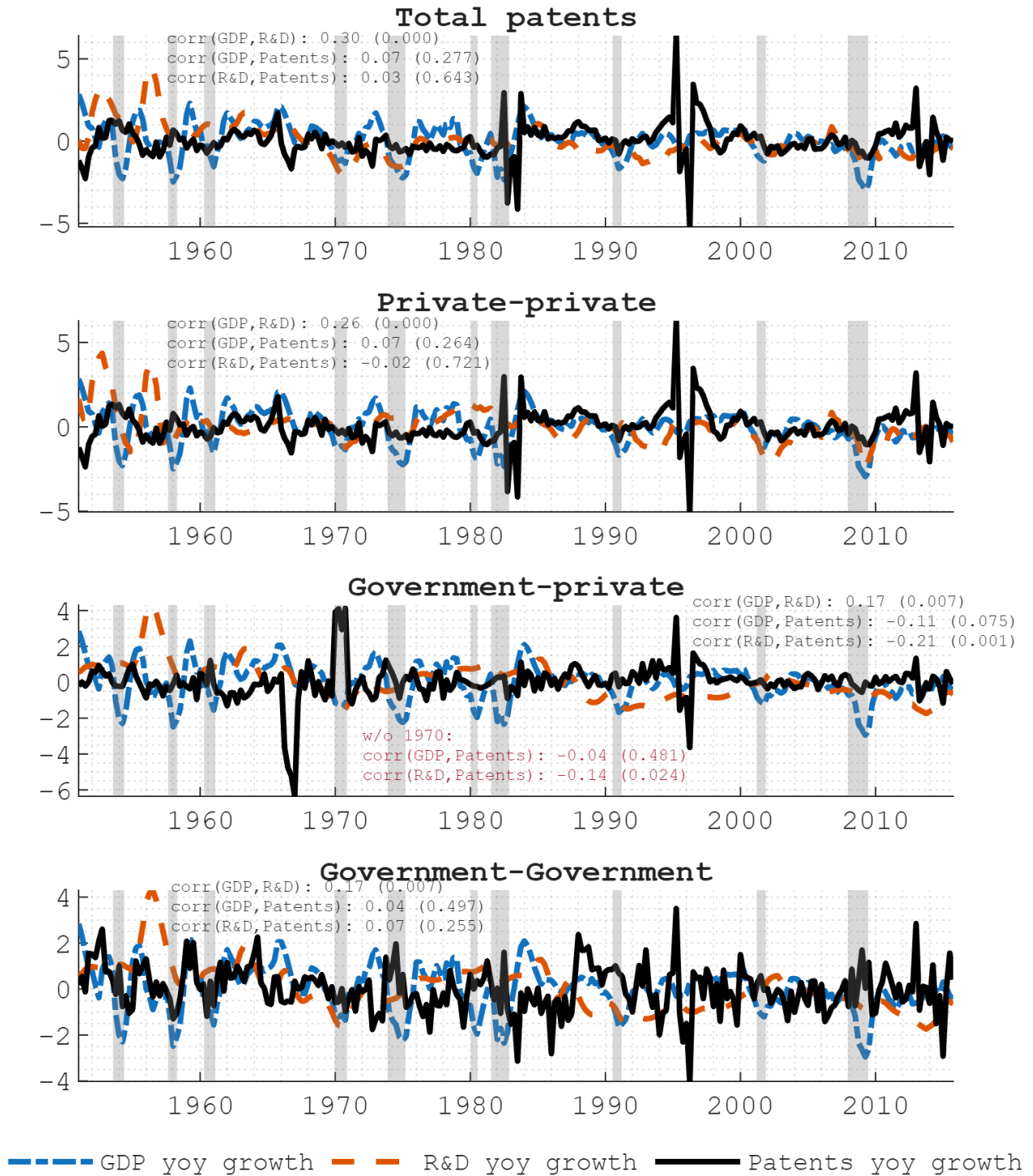
To explicitly assess the statistical difference between the effects of patenting in government-private and private-private groups, we rely on wild bootstrap with the same multiplier across the three local projection equations. Both the Sup-Wald test and the Cramér-von Mises test reject the equality of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

B3 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.

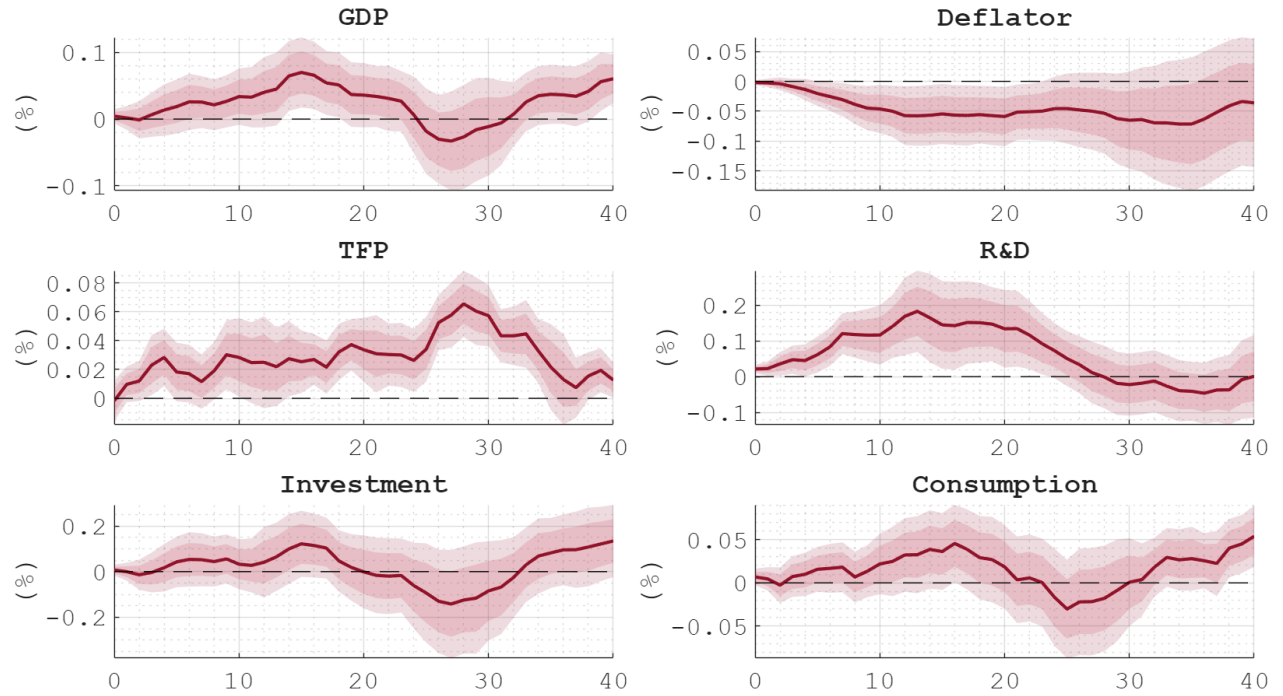
Additionally, the Act also led to the reclassification of the ownership of government-funded patents from the government to contractors (universities, firms, etc.). To assess whether classification affects our results, we consolidate the two types of government-funded patents into a single category. Figure B4 - which corresponds to Figure 3) - 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

Figure B1: Patent filing cyclicality



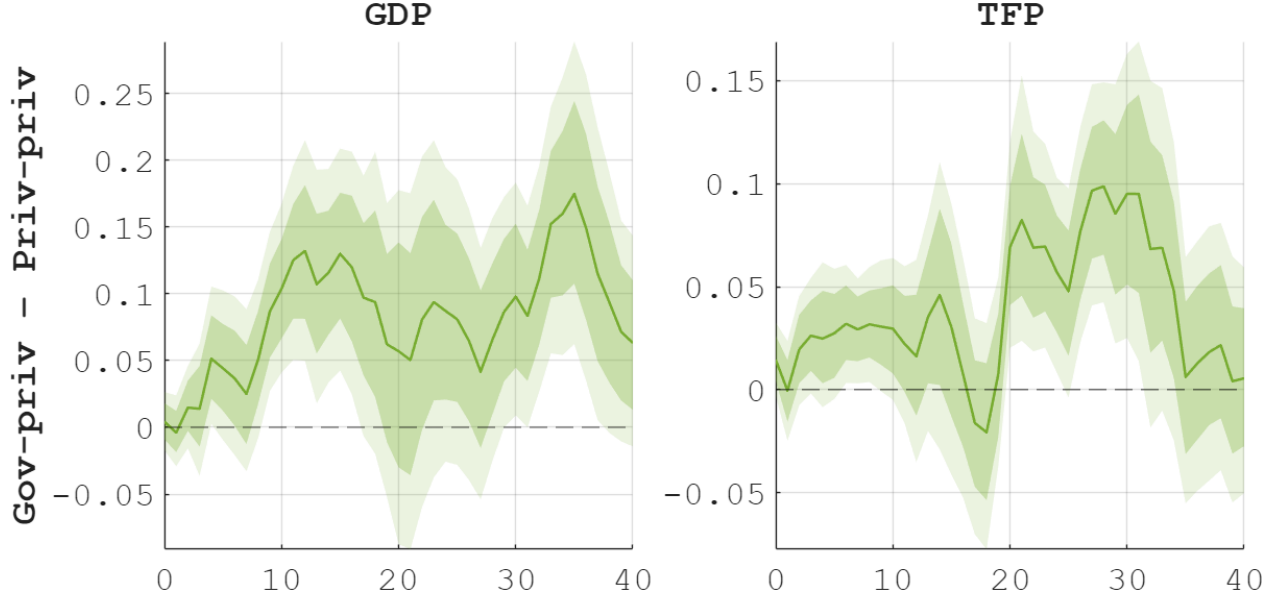
Note. The figure displays the growth rates of real per-capita GDP, RD expenditure, and the number of patents filed in each category (total, public-private, private-private, and public-public), along with their contemporaneous correlations (p-values in parentheses). The figure shows that, unlike R&D expenditure,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

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: 1950:Q1-2015:Q4

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: 1950:Q1-2015:Q4

B5 - which corresponds to Figure 8a) - 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.

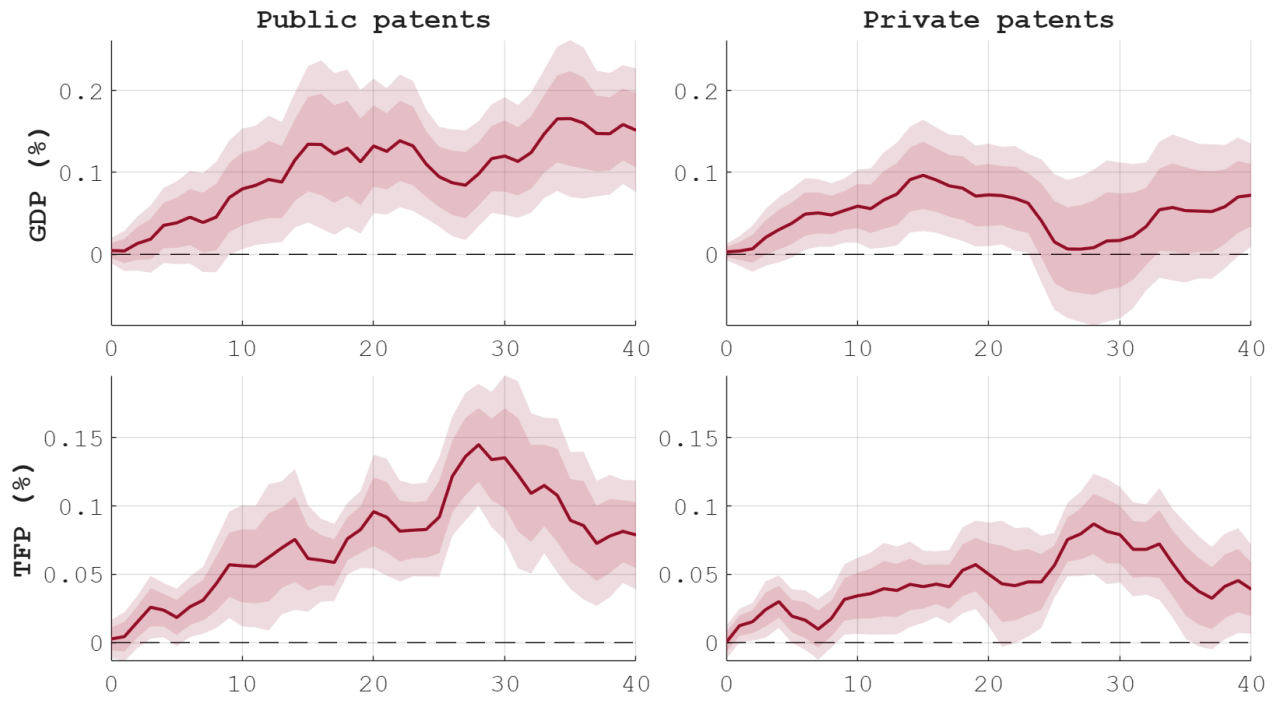
B4 Controlling for Major Institutional Events

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

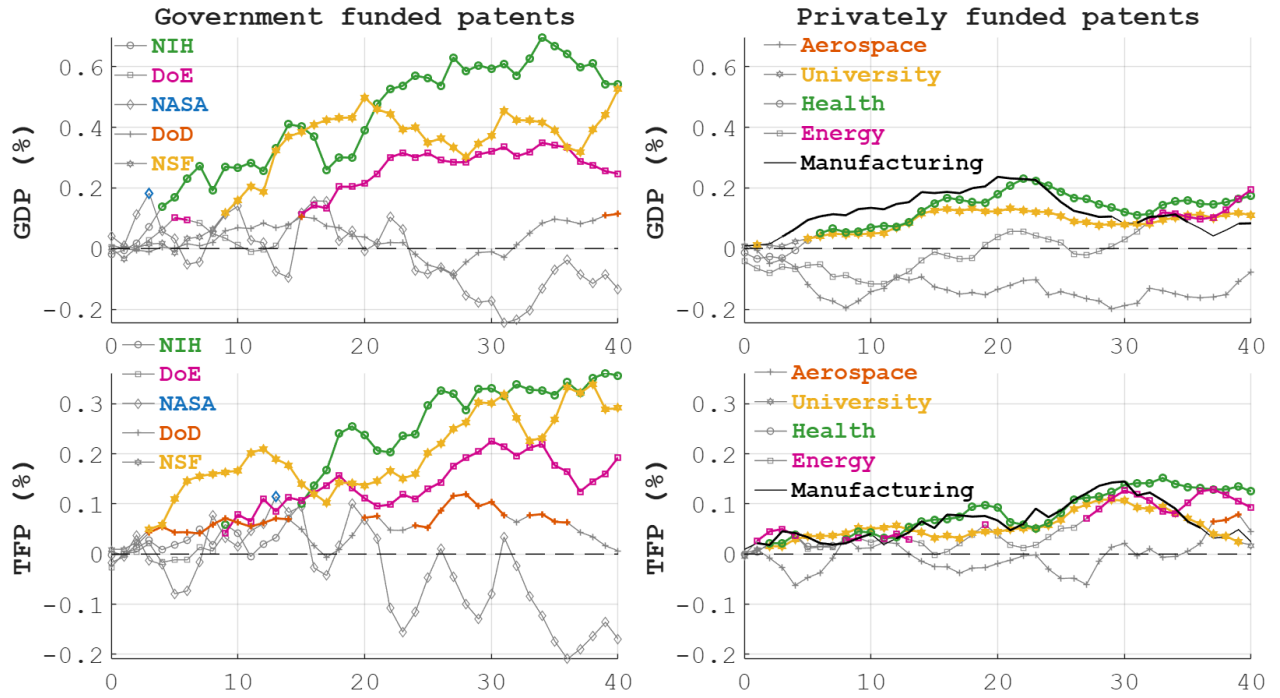
Implementation of the TRIPS Agreement (1995). The introduction of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) in 1995 standardized international patent regulations (following the GATT Uruguay Round agreements), significantly enhancing transparency and discouraging strategic patenting behaviors. By aligning

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 3. 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: 1950:Q1-2015:Q4.

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: 1950:Q1-2015:Q4 (except for 'University' in the second column, 1975q1-2015:Q4).

U.S. patent rules with global norms, the agreement notably diminished practices such as "submarine patents" and modified the duration of patent protection, resulting in an immediate increase in patent filings.

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 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.

C1 Top assignees in public-private partnerships and examples of important public-interest patents

Table C1 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 C2 reports government-funded patents in the historically important group identified by Kelly et al. (2021).³² As the list ended in 2002, we have extended it till 2015 by employing *Chat-GPT Deep Research* and manually verifying all information.

³²The list was based on a list of 250 historically important patents formerly available from the USPTO.

Table C1: Top Assignees by Public and Private Interest

<i>Public-Private</i>		<i>Private-Private</i>	
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 C2: 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 o3-pro with deep research.

C2 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. The same year, a patent on that discovery was filed by the two researchers with US Patent No. 6,506,559, then 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 has spurred a thriving industry centered around 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 where pages gained importance not just by their content but 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 outlines the design of a nuclear reactor 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 under the stewardship of 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.

D Construction of the Instrument for the LP-IV Model

In this section we provide further details on the construction of the narrative IV.

We identify swings in patent filings as those quarters in which q-o-q growth rates are above one standard deviation for each category of patents. We then run a narrative search on regulatory/legislative events associated with those dates. We rely on Chat-GPT o3-pro deep search, which we then cross-validate with Gemini, and verify the consistency of the sign of the swing with the direction of the institutional event. Finally, we manually audit all cases. Table D1 reports the related information, including an assessment of the directness of the connection between the event and the patent swing. This assessment, in particular, reflects the potential delay between the institutional event and the swing in patents. Results are robust if we retain only the "direct" events.

Table D1: Swings in patents filings and associated institutional events

Date	Patents	Event	Type
Q4-1950	Pub-pub	Gov't title to employee inventions	Direct
Q4-1952	Pub-pub	no event	NA
Q1-1953	Pub-pub	no event	NA
Q2-1954	Pub-pub	Atomic Energy Act of 1954	Direct
Q3-1954	Pub-pub	no event	NA
Q1-1958	Pub-pub	National Aeronautics and Space Act	Direct
Q4-1958	Pub-pub	National Aeronautics and Space Act	Direct
Q3-1959	Pub-pub	National Aeronautics and Space Act	Direct
Q4-1959	Pub-priv	NASA patent stance + EO 10930 (contractor adjustment effects)	Indirect
Q1-1960	Pub-priv	NASA patent stance + EO 10930 (contractor adjustment effects)	Indirect
Q4-1960	Pub-pub	no event	NA
Q1-1961	Pub-pub	National Aeronautics and Space Act	Direct
Q2-1961	Pub-pub	National Aeronautics and Space Act	Direct
Q1-1962	Pub-priv	NASA patent stance + EO 10930 (contractor adjustment effects)	Indirect
Q3-1963	Pub-pub	1963 Presidential Memorandum (flexible gov't patent policy)	Direct
Q3-1964	Pub-pub	1963 Presidential Memorandum (flexible gov't patent policy)	Direct
Q1-1966	Priv-priv	Graham v. John Deere (non-obviousness)	Indirect
Q1-1966	Pub-pub	1963 Presidential Memorandum (flexible gov't patent policy)	Direct
Q2-1966	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q3-1966	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q1-1967	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q2-1967	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q3-1967	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q4-1967	Pub-priv	Implementation of 1963 policy across agencies	Indirect
Q3-1969	Pub-priv	HEW reinstates Institutional Patent Agreement (IPA) program	Direct
Q4-1969	Pub-priv	HEW reinstates Institutional Patent Agreement (IPA) program	Direct
Q1-1970	Pub-priv	HEW reinstates Institutional Patent Agreement (IPA) program	Direct
Q1-1972	Priv-priv	no event	NA
Q2-1972	Pub-priv	Nixon 1971 patent policy + momentum toward IPA expansion	Direct

Date	Patents	Event	Type
Q4-1972	Pub-pub	no event	NA
Q4-1973	Pub-pub	no event	NA
Q4-1973	Pub-priv	NSF adopts IPA model (1973)	Direct
Q2-1974	Pub-pub	Nixon 1971 policy reaffirmation (shift to contractor ownership)	Direct
Q4-1974	Pub-pub	Nixon 1971 policy reaffirmation (shift to contractor ownership)	Direct
Q2-1976	Pub-pub	Nixon 1971 policy reaffirmation (shift to contractor ownership)	Direct
Q1-1977	Pub-pub	no event	NA
Q1-1977	Pub-priv	Legislative push/Carter DPR on innovation (anticipation)	Indirect
Q1-1978	Pub-priv	Legislative push toward uniform policy (anticipation)	Indirect
Q3-1978	Pub-pub	no event	NA
Q1-1982	Pub-pub	Bayh-Dole implementation period (ownership to universities/small biz)	Direct
Q2-1982	Pub-pub	Bayh-Dole implementation (OMB A-124 issued Feb 1982)	Indirect
Q3-1982	Priv-priv	Federal Courts Improvement Act (CAFC created)	Indirect
Q3-1982	Pub-pub	Bayh-Dole implementation (large drop in gov't-owned patents)	Direct
Q4-1982	Priv-priv	no event	NA
Q4-1982	Pub-pub	Bayh-Dole implementation (large drop in gov't-owned patents)	Direct
Q4-1982	Pub-priv	Bayh-Dole + implementing regs (universities/small biz retain title)	Direct
Q1-1983	Priv-priv	no event	NA
Q1-1983	Pub-priv	Bayh-Dole (continuing surge of non-federal ownership)	Direct
Q4-1983	Pub-priv	Reagan 1983 memo (extends Bayh-Dole rights to all contractors)	Direct
Q1-1986	Pub-pub	Federal Technology Transfer Act (1986)	Direct
Q2-1986	Pub-pub	no event	NA
Q4-1986	Pub-pub	no event	NA
Q1-1987	Pub-pub	Federal Technology Transfer Act (1986)	Direct
Q1-1988	Pub-pub	Federal Technology Transfer Act (1986)	Direct
Q2-1992	Pub-pub	no event	NA
Q4-1992	Pub-pub	no event	NA
Q4-1992	Pub-priv	American Technology Preeminence Act (Feb 1992) + STTR Act (Oct 1992)	Direct
Q1-1993	Pub-pub	no event	NA
Q1-1993	Pub-priv	American Technology Preeminence Act + STTR Act	Direct
Q2-1993	Pub-pub	no event	NA
Q4-1994	Pub-pub	no event	NA
Q2-1995	Priv-priv	URAA patent-term change (pre-6/8/1995)	Direct
Q2-1995	Pub-pub	no event	NA
Q2-1995	Pub-priv	NIH rescinds "reasonable pricing" clause (Apr 1995)	Direct
Q3-1995	Priv-priv	URAA (post-deadline)	Direct
Q3-1995	Pub-pub	no event	NA
Q3-1995	Pub-priv	NIH rescinds "reasonable pricing" clause (aftermath)	Direct
Q4-1995	Priv-priv	URAA (aftermath)	Direct
Q4-1995	Pub-priv	NIH rescinds "reasonable pricing" clause (aftermath)	Direct
Q3-1996	Priv-priv	URAA (long-term adjustment)	Direct
Q4-1996	Pub-priv	National Technology Transfer and Advancement Act (1995/96)	Direct
Q3-1997	Pub-pub	no event	NA
Q1-1998	Pub-pub	no event	NA
Q4-1998	Pub-pub	no event	NA
Q1-1999	Pub-pub	no event	NA
Q1-2000	Pub-pub	no event	NA
Q4-2003	Pub-pub	no event	NA
Q1-2004	Pub-pub	no event	NA
Q1-2005	Pub-pub	no event	NA
Q2-2005	Pub-pub	no event	NA
Q1-2008	Pub-pub	no event	NA
Q2-2008	Pub-pub	no event	NA
Q3-2008	Pub-pub	no event	NA
Q4-2008	Pub-pub	no event	NA
Q4-2009	Pub-pub	no event	NA
Q2-2010	Pub-pub	no event	NA
Q1-2012	Pub-pub	AIA* (anticipatory/admin changes ahead of 2012-2013 roll-out)	Direct
Q1-2013	Priv-priv	AIA (pre-3/16/2013 first-to-file)	Direct
Q1-2013	Pub-pub	no event	NA
Q1-2013	Pub-priv	AIA (pre-3/16/2013 first-to-file)	Direct

Date	Patents	Event	Type
Q2-2013	Priv-priv	AIA (post-deadline dip)	Direct
Q2-2013	Pub-pub	no event	NA
Q2-2013	Pub-priv	AIA (post-deadline dip)	Direct
Q3-2013	Priv-priv	AIA (aftermath/normalization)	Direct
Q3-2013	Pub-pub	no event	NA
Q1-2014	Pub-pub	no event	NA
Q1-2014	Pub-priv	AIA (adjustment period)	Direct
Q2-2014	Pub-pub	no event	NA
Q2-2014	Pub-priv	AIA (adjustment period)	Direct
Q3-2014	Pub-pub	no event	NA
Q4-2014	Pub-pub	no event	NA
Q1-2015	Pub-pub	no event	NA
Q2-2015	Pub-pub	no event	NA
Q2-2015	Pub-priv	AIA (adjustment period)	Direct

Note. This table lists quarters in which patent filings exhibit a “swing,” defined as a quarter-over-quarter growth rate exceeding one standard deviation within each patent category. Dates are labeled by calendar quarter. Patents indicates the category: **Pub-pub** = government-funded and government-owned; **Pub-priv** = government-funded and privately owned; **Priv-priv** = privately funded and privately owned. Event summarizes statutes, executive orders/memoranda, agency rules/guidance, or major court decisions plausibly linked to the swing. Type classifies the linkage: **Direct** = a specific, timeable policy/judicial change with clear relevance to the category and expected near-term impact; **Indirect** = broader policy climate or anticipatory/implementation effects; **NA** = no salient event identified. We enforce sign consistency between the swing and the event’s expected direction.

We then turn to a more detailed description of institutional events associated with patent swings:

Executive Order 10096 (1950). Issued by President Truman in response to the growing size of federally financed research during World War II, this order established presumptive government ownership of inventions created by federal employees within the scope of their duties, with limited exceptions and an appeals process.

Atomic Energy Act Amendments (1954). Congress reversed the 1946 ban on private ownership of nuclear inventions, permitting private patents for civilian nuclear power technology with safeguards and licensing provisions. The change sprang from Eisenhower’s “Atoms for Peace” Cold War strategy.

National Aeronautics and Space Act (1958). Section 305 granted NASA default ownership of contract inventions but allowed the agency to waive those rights whenever private control was expected to yield faster progress. The waiver clause was intended to mobilize industrial potential in the wake of the Sputnik crisis. Within three years, waivers were routinely granted on NASA discoveries, and “pub-priv” aerospace filings spiked, signaling that flexible patent ownership could accelerate mission technology.

NASA Waiver Practice and Executive Order 10930 (1959–1961). As NASA’s Inventions and Contributions Board processed hundreds of waiver petitions, Kennedy abolished the older Government Patents Board and reassigned its functions. These refinements were administrative lessons from the Space Race. Faster decisions reassured contractors, resulting in a noticeable increase in privately owned space-related patents between 1961 and 1963.

Presidential Memorandum on Government Patent Policy (1963). President Kennedy instructed agencies to strike a balance between public access and commercial promise, abandoning any single rule of ownership. The memo drew on NASA’s success. Agencies that embraced the guidance saw contractor assignments rise sharply. In other areas the government encouraged direct government ownership, leading to surge in pub-pub patent filings.

Graham v. John Deere (1966). The Supreme Court clarified “non-obviousness,” requiring courts to compare prior art and secondary factors before granting patents. This legal tightening reflected a shift in the legal doctrine on patenting.

Agency Roll-Out of Flexible Policy (1966–1967). Departments translated the 1963 guidance into waiver rules and contract clauses, thereby reducing administrative ambiguity and supporting the wider use of contractor titles where commercialization prospects warranted. The clearer playbook halved processing times and contributed to boosting the share of government-funded inventions patented by non-federal entities.

HEW Institutional Patent Agreement Revival (1968). To spur drug development, HEW (later NIH) reinstated the Institutional Patent Agreement (IPA), giving trusted universities the first option on patent title, in an effort to enhance public health. Medical schools increased their patent filings.

Nixon Patent Memorandum and Early IPA Expansion (1971–1972). The administration reinforced agency flexibility and, crucially, authorized exclusive licenses on government patents. Exclusive rights were seen as a lever to boost the interconnections between private entities and the government-interest research. Exclusive-license clauses boosted filings tied to government research.

NSF Adoption of the IPA Model (1973). The NSF extended automatic university ownership to its grants following the NIH and the Nixon memo. NSF-funded patents climbed steeply.

Reaffirmations of Contractor Ownership (1974–1976). The Federal Council for Science and Technology documented and encouraged agency use of contractor title and exclusive licensing when commercialization prospects warranted. They helped sustain high public-private filing rates, signaling a stable and favorable policy climate towards public-private interactions.

Carter Domestic Policy Review and Legislative Push (1977–1978). The Carter administration branded inconsistent and fragmented patent policy a drag on productivity and called for statutory uniformity. The anticipation of a later legislative overhaul alone prompted universities to formalize their technology-transfer offices and nudged filings upward, particularly in engineering labs.

Bayh–Dole Act Goes Live (1981–1983). Effective July 1981, the Bayh–Dole Act allowed universities, nonprofits, and small firms to elect patent title on federally funded inventions; OMB Circular A-124 standardized contract language in 1982. The law addressed inconsistent and fragmented patent policy related to federally funded research. University patenting and licensing accelerated through the 1980s as Bayh–Dole was implemented.

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 cases. This judicial shift increased the incentives for patent filings, resulting in a significant increase in applications.

Reagan Memorandum Extending Bayh–Dole Rights (1983). President Reagan directed agencies to grant Bayh–Dole privileges also to large contractors whenever statutes allowed. The order aligned with a broader supply-side agenda. Large corporations integrated the new clauses, and patents on joint R&D projects climbed between 1983 and 1986.

Federal Technology Transfer Act (1986). This statute empowered federal laboratories to sign CRADAs and share royalty streams with staff scientists, aiming at improving competitiveness. Lab-industry collaborations had multiplied tenfold by 1991, and a new category of lab-origin patents licensed to private firms emerged.

American Technology Preeminence Act and STTR Program (1992). Congress improved tech-transfer rules and launched STTR grants by pairing small businesses with research institutions. Within five years, STTR partnerships had accounted for hundreds of joint patents, many of which were in advanced composites and medical devices.

URAA-TRIPS (1995). The introduction of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) in 1995 standardized international patent regulations (following GATT Uruguay Round agreements), significantly enhancing transparency and discouraging strategic patenting behaviors. By aligning U.S. patent rules with global norms, the agreement notably diminished practices such as “submarine patents” and modified the duration of patent protection. This resulted in an immediate increase in patent filings in an effort to exploit the old regime ([Bertolotti, 2022](#)).

NIH Drops the “Reasonable Pricing” Clause (1995). After concluding that price controls discouraged industry collaboration, NIH rescinded the clause from CRADAs, leading to a subsequent increase in collaboration with non-federal entities.

National Technology Transfer and Advancement Act (1996). By requiring agencies to rely on private consensus standards and clarifying licensing rights in CRADAs, Congress sought to align federal procurement with global standards and reduce transaction costs. Standardized interfaces gave lab innovations a quicker commercial edge, and exclusive licenses issued by federal labs more than doubled between 1996 and 2000.

America Invents Act—Preparatory Measures (2012). Ahead of the first-to-file switch, USPTO overhauled fees, opened satellite offices, and issued examiner guidance. These administrative steps reflected modernization goals. Practitioners rushed to clear backlogs; the total number of applications increased by roughly eight percent in fiscal 2012.

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.

AIA Aftermath and Normalisation (2013–2015). New post-grant reviews, micro-entity discounts, and clarified prior-art rules have been in place for over two years, lowering prosecution costs and screening out weak continuations. Small-entity filings rose steadily.

E Historical Decomposition and Counterfactuals

In this Appendix, we lay out how we compute historical decompositions at multiple forecast horizons and construct counterfactual scenarios on our baseline LP model.

E1 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 $t - 1$:

$$pat_t = \sum_{j=1}^4 \phi_j \mathbf{y}_{t-j} + \varepsilon_t \quad (\text{E1})$$

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 E1](#)):

$$\Delta_{h^*} TFP_t := TFP_{t+h^*} - TFP_{t-1} \quad (\text{E2})$$

Regress $\Delta_{h^*} TFP_t$ 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:

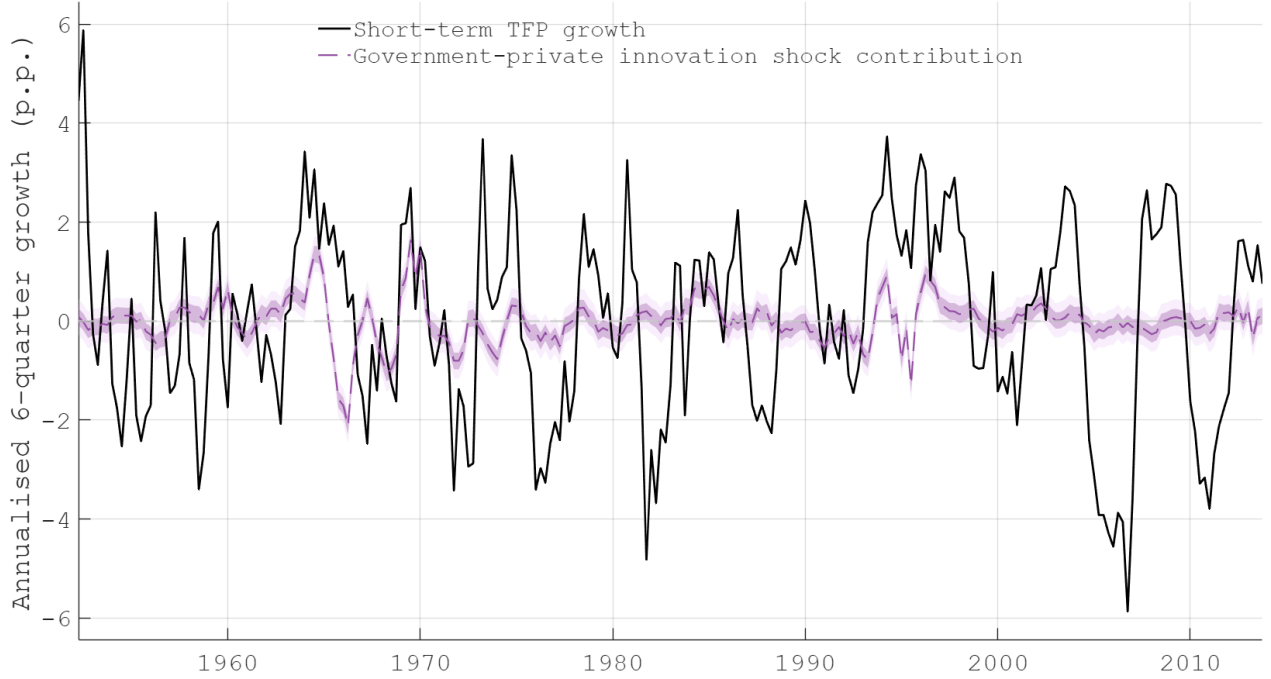
$$\Delta_{h^*} TFP_t = \alpha + \sum_{j=1}^4 \phi_{t-j}^* \mathbf{y}_{t-j}^* + e_{t+h^*} \quad (\text{E3})$$

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

$$e_{t+h^*} = \sum_{h=0}^{h^*} \theta_h \varepsilon_{t+h} + u_{t+h^*} \quad (\text{E4})$$

The R^2 of this regression for each forecast horizon h is the variance contribution (i.e. the average over the sample). Conversely, the fitted values eq.(E4) contain the historical contribution of the shock of interest. Inference is based on a VAR-based bootstrap as in [Gorodnichenko and Lee \(2020\)](#).

Figure E1: 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: 1950:Q1-2015:Q4.

E2 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 the end of the sample. For all data points after the 1996

peak, the counterfactual is defined as:

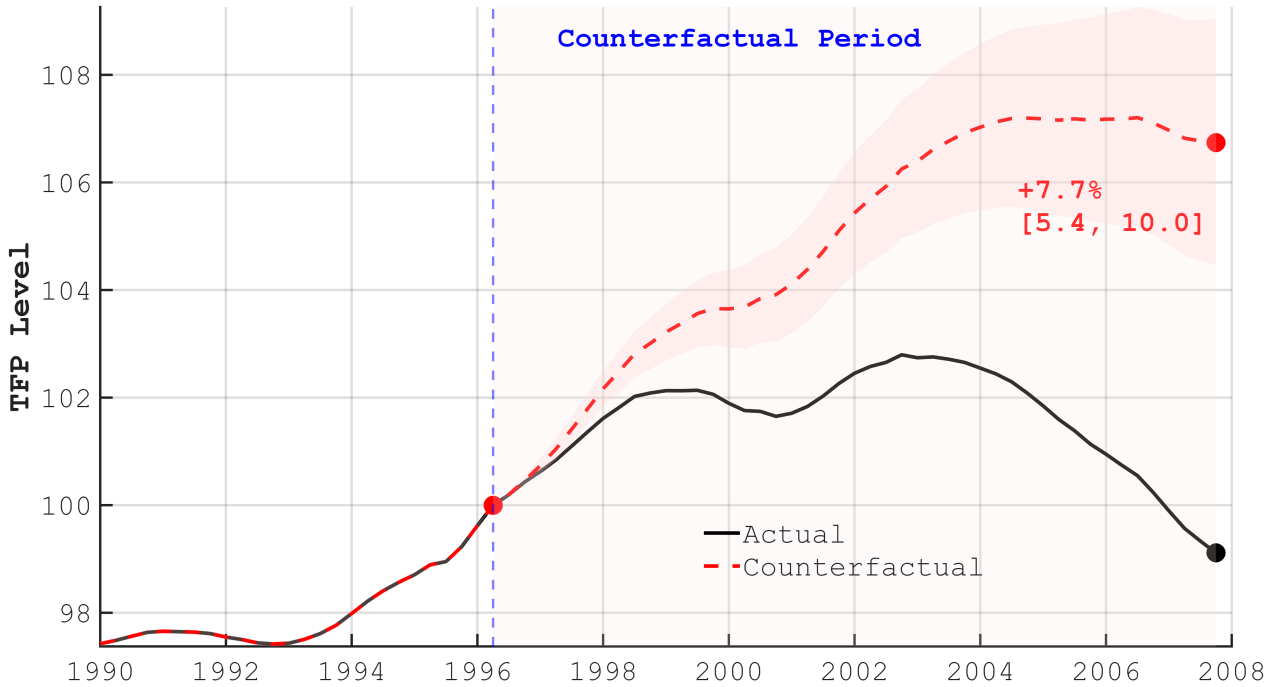
$$\tilde{g}_t = g_t - s_t + s^*$$

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 E2: 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.

F 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.

F1 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 F1 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 F2) and across the entire distribution of patents (Figure F3). In both cases results are consistent with our baseline.

F2 Reliance on Science

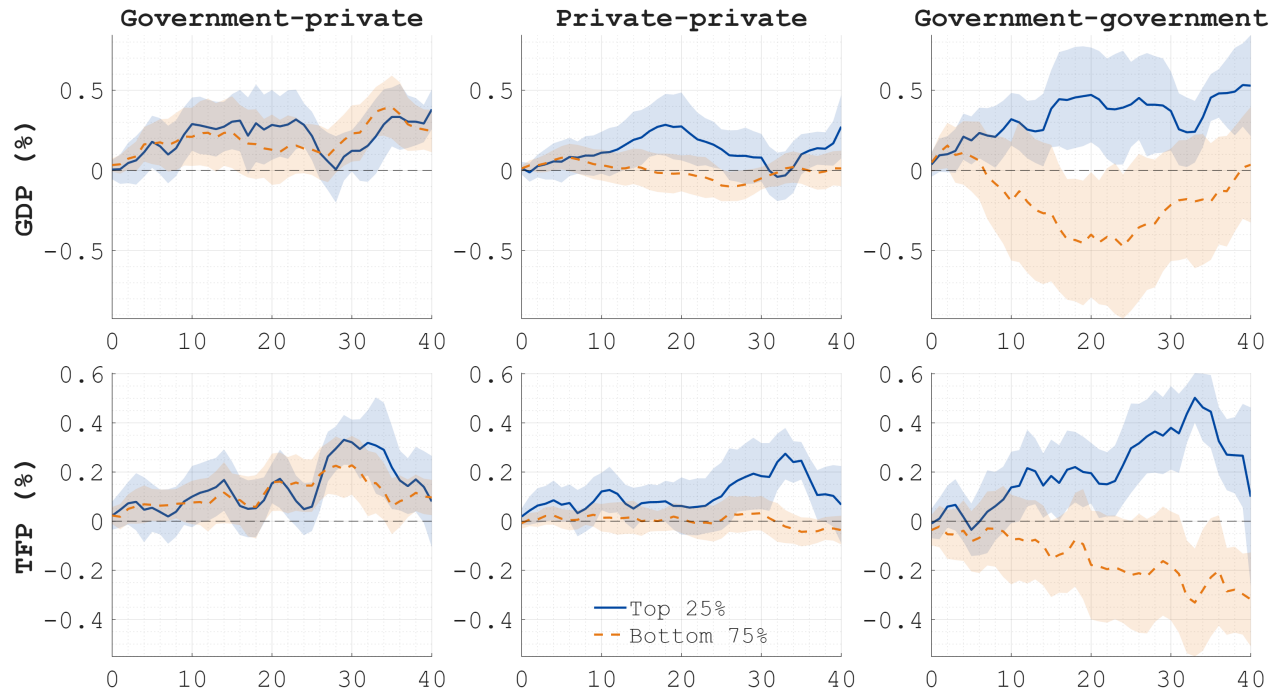
We also consider an alternative definition of top/bottom reliant on science patents based on the top 25% percentile (Figure F4) and another one that exploits exclusively the extensive margin of papers' citations (Figure F5). These two exercises yield overall consistent results with our baseline, although 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.

F3 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.

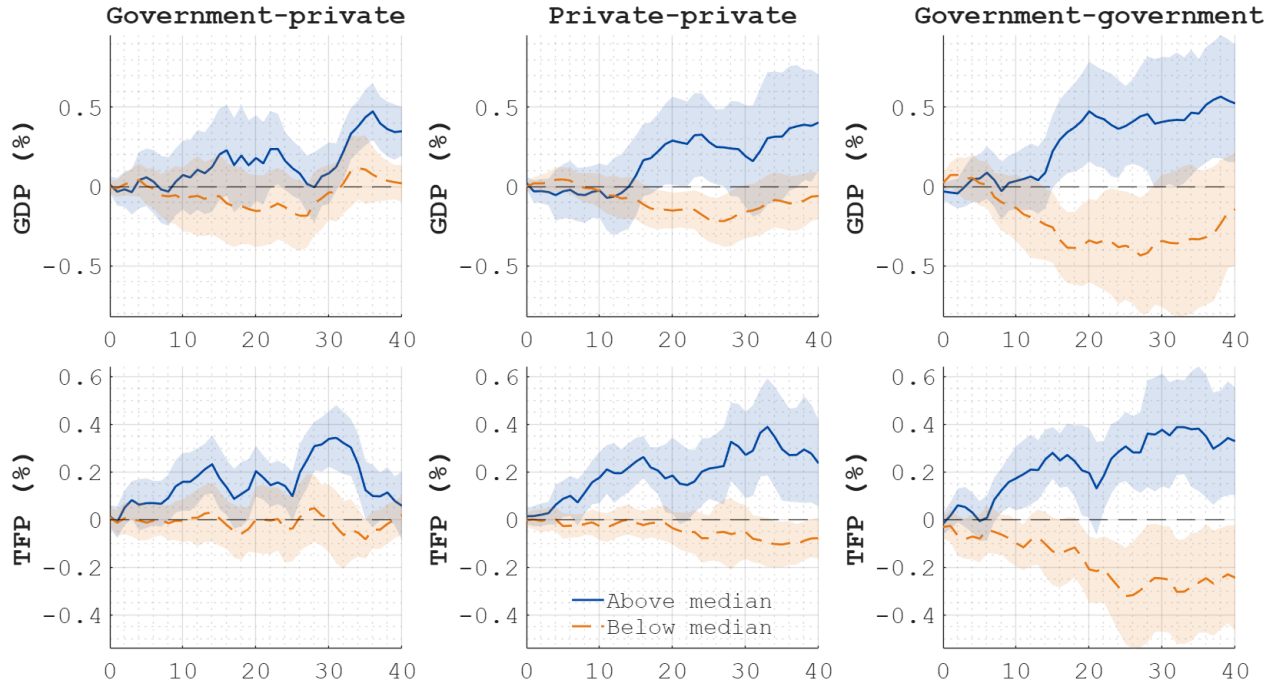
We estimate a predictive model of the [Kogan et al. \(2017\)](#) value measure. The explanatory variables include (following [Kline et al. \(2019\)](#)) patent family size and the number of claims, which we extend to pre-1976 patents using text analysis of the Google Patents public corpus. We also include 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 F1: Importance - 10 year measure



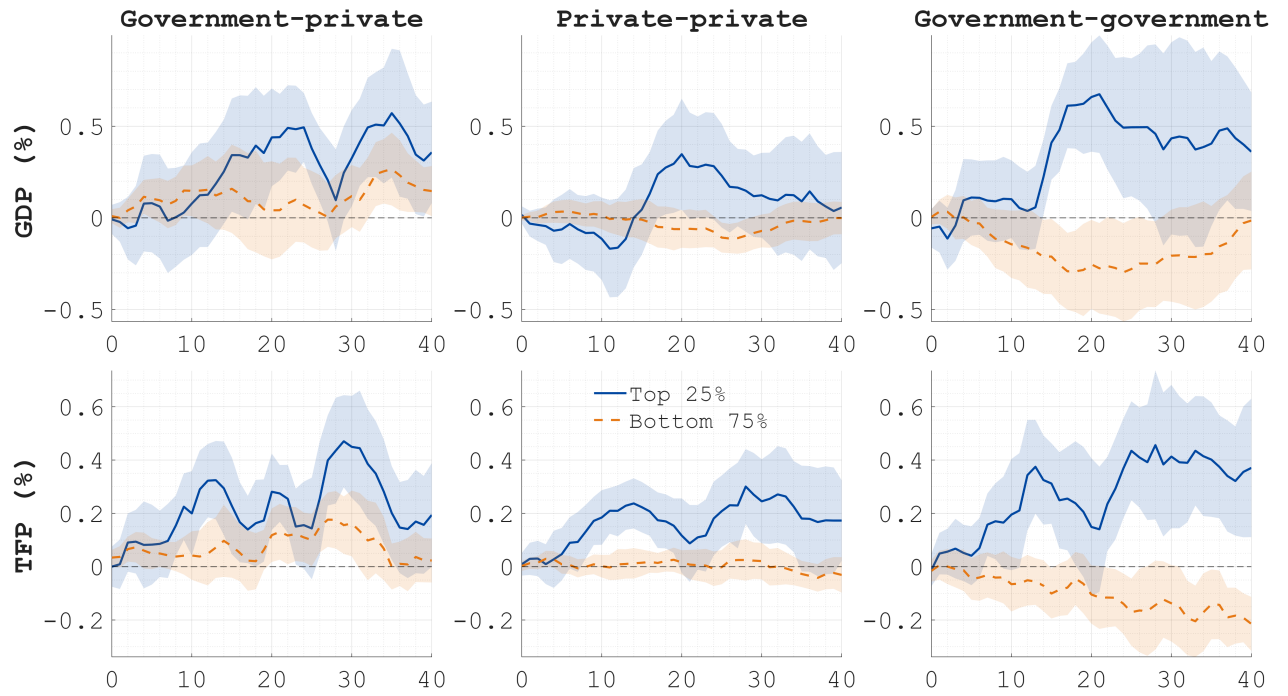
Note. The figure replicates the analysis in Figure 7, comparing the dynamic effects of innovation shocks from the top quartile versus the bottom three quartiles of patents ranked by importance. As a robustness check, this figure uses the 10-year patent similarity measure from Kelly et al. (2021) instead 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 F2: Importance - above/below median



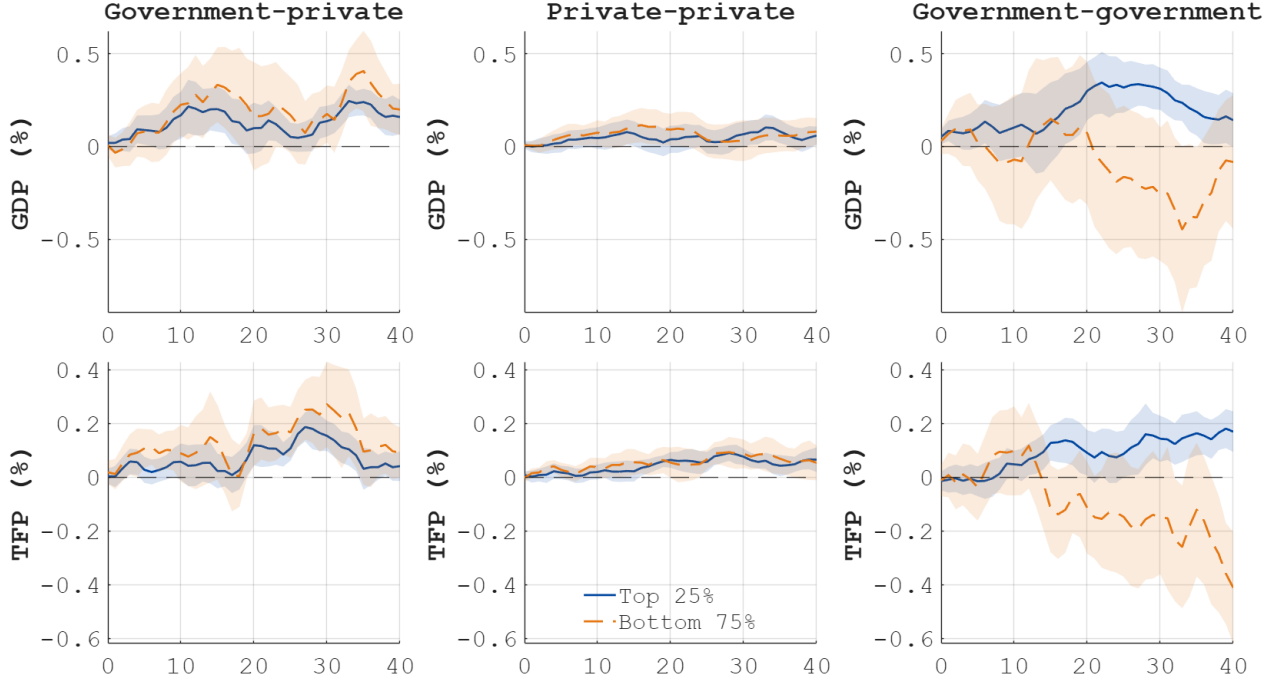
Note. The figure replicates the analysis in Figure 7, but splits patents at the median of the importance distribution (top 50% vs. bottom 50%) instead of the top quartile. The 5-year patent similarity measure from Kelly et al. (2021) is used. The estimation by local projections follows eq.(1). The size 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: 1950:Q1-2015:Q4.

Figure F3: Importance - percentiles for each category



Note. The figure replicates the analysis in Figure 7, but the importance ranking is done within each patent category (public-private, private-private, and public-public) rather than across all patents. 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: 1950:Q1-2015:Q4.

Figure F4: Reliance on Science - Alternative percentiles



Note. The figure replicates the analysis in Figure 7b, 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: 1950:Q1-2015:Q4.

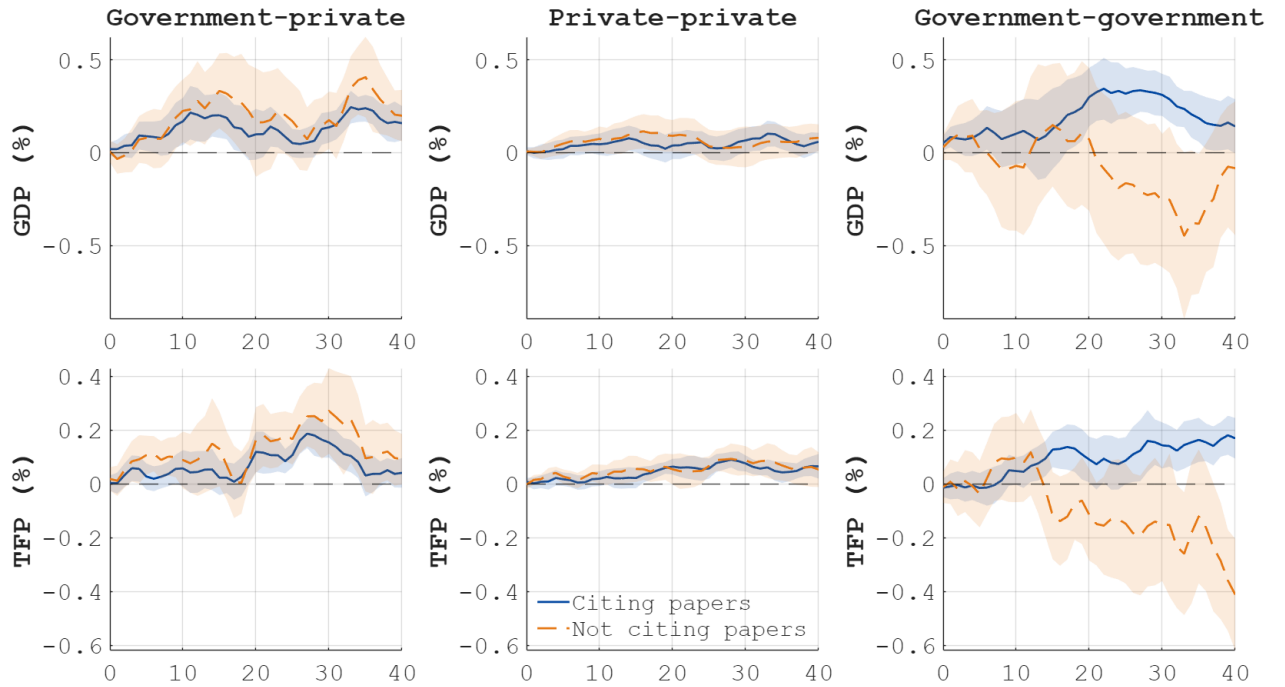
The fitted coefficients from this regression are then used to predict patent values for all observations, including those without market-based valuations.

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 4, in Figure F6 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.

G Definitions of industry and research field patent groups

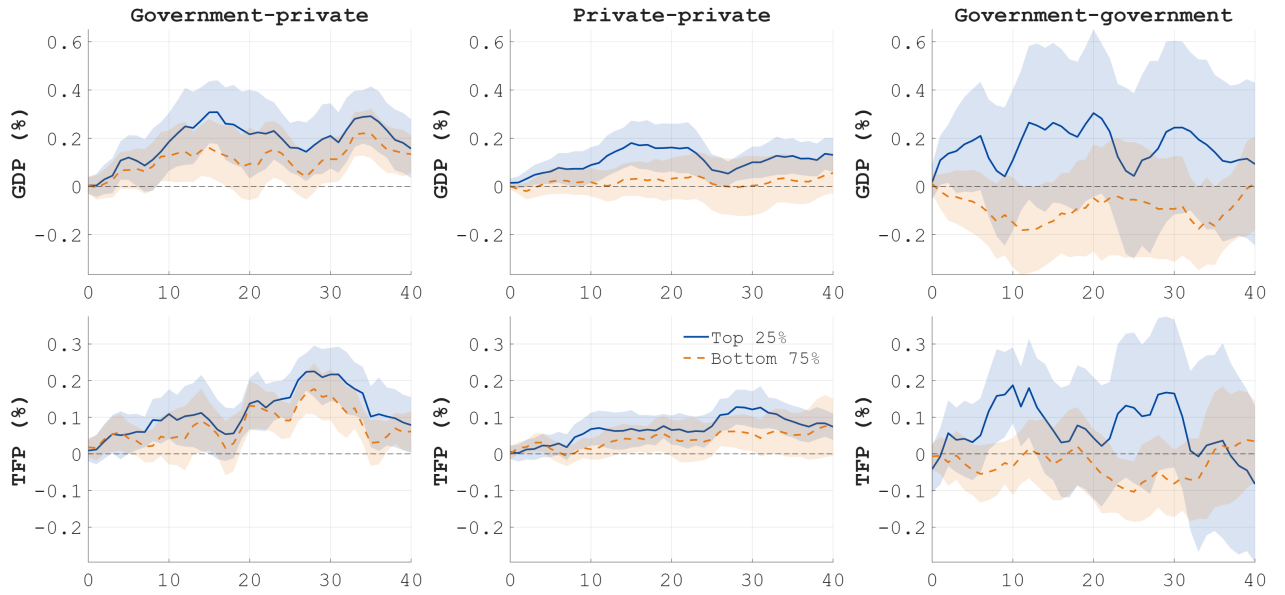
This Appendix provides detailed information on the construction of industry and research fields by specifying the exact CPC codes that enter each category. We also show the composition of patents within agencies, universities, research institutes, and private-private by all research fields and the four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

Figure F5: Reliance on Science - Extensive Margin



Note. The figure replicates the analysis in Figure 7b, 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: 1950:Q1-2015:Q4.

Figure F6: 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: 1950:Q1-2015:Q4.

G1 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 G1: 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	<i>Based on assignee name keywords, not CPC codes</i>

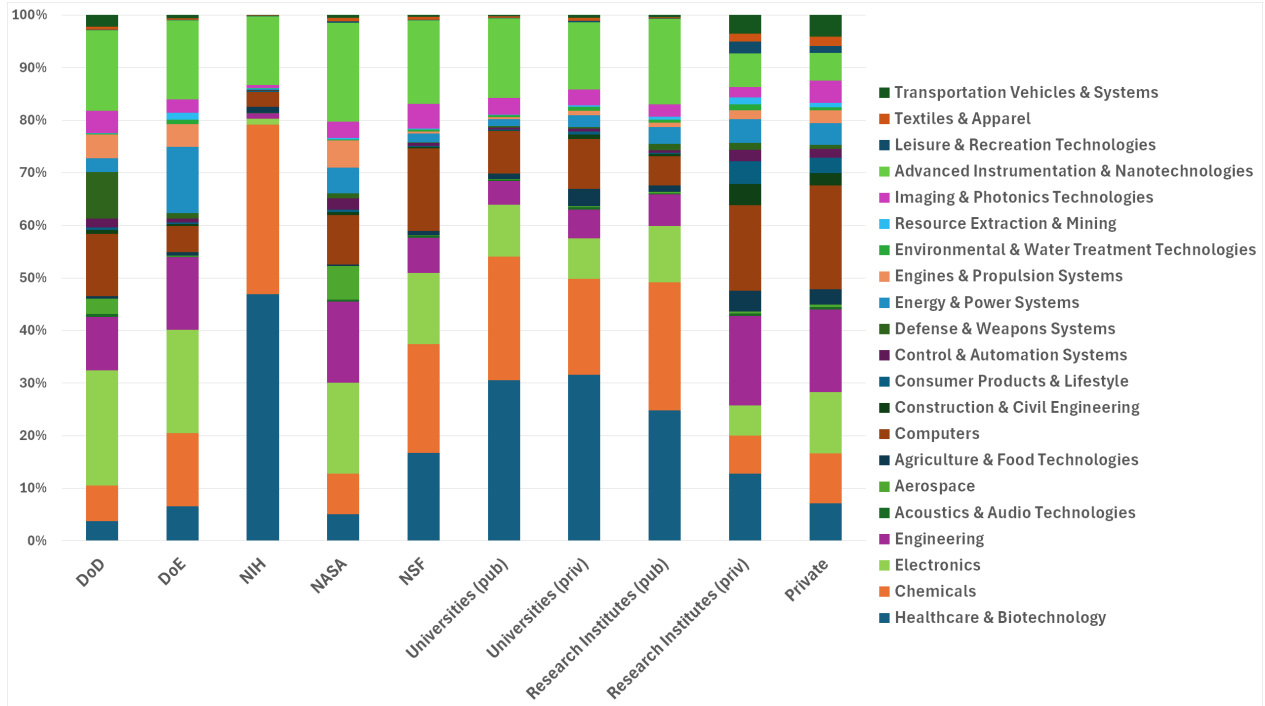
Patents from the education sector. Unlike the technological sectors, this category is not based on CPC codes. A patent is flagged as being university-assigned if its disambiguated assignee organization name, converted to lowercase, contains specific keywords. This is determined using regular expression 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.

G2 Research fields

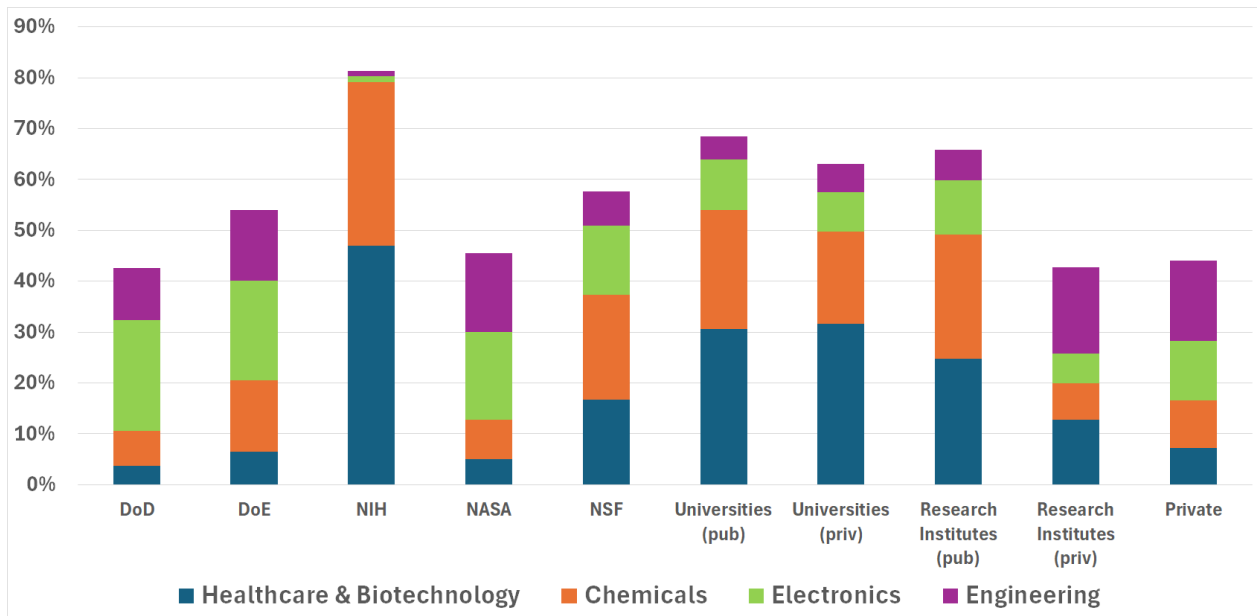
In Figures [G1](#) and [G2](#), we report the innovation composition of federal agencies and institutional players, such as research institutes and universities, by research field. In Table [G2](#), we show how individual CPC codes map into the major research fields that we focus upon.

Figure G1: 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: 1950:Q1-2015:Q4.

Figure G2: 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 G2. 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 G1 below shows the total composition of patents by research field. Sample: 1950:Q1-2015:Q4.

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 G2: 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.

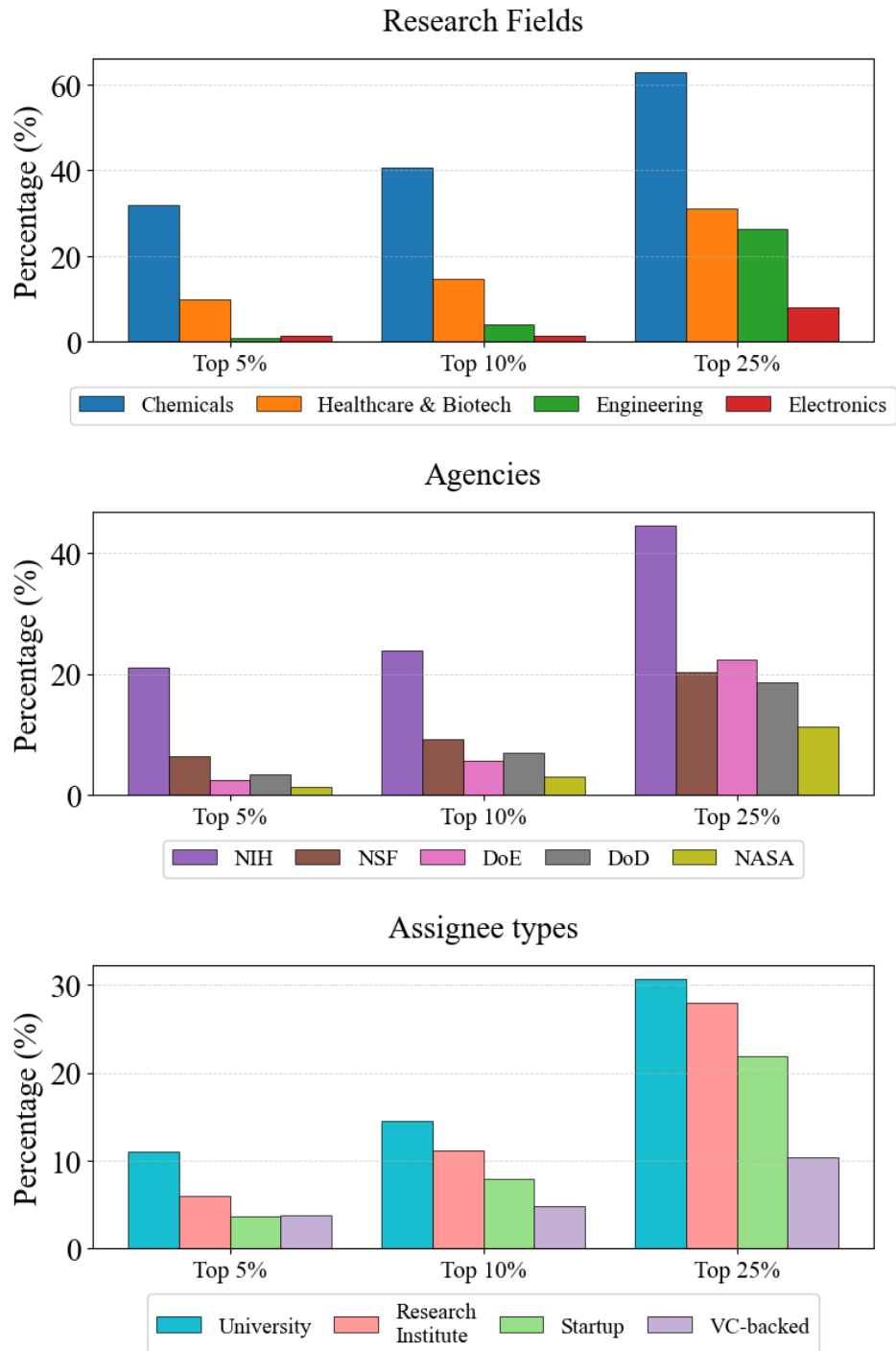
H Innovation network centrality

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. 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.

In [Figure H1](#), 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 8b](#)). 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 8](#). Finally, universities and research institutes are the assignees with the highest share of high-centrality patents, consistent with the results presented in [Section 6](#).

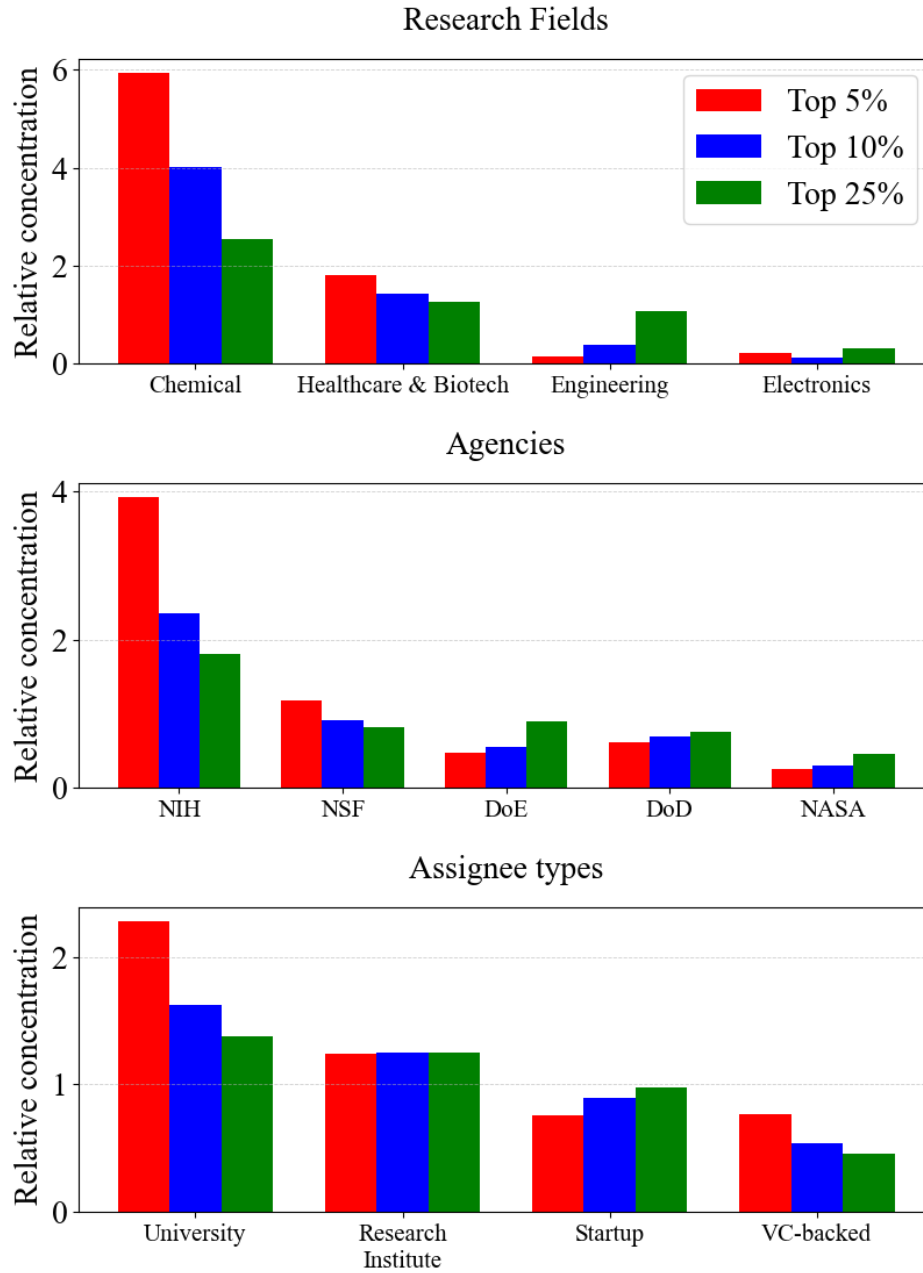
In [Figure H2](#), we illustrate the relative concentration of each research field, agency, and assignee within each top centrality group. Relative concentration is defined as a research field, agency, or assignee’s share of patents above a given centrality percentile, divided by that research field, 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 H1](#), ‘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 H1: 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 5.4](#) for further details.

Figure H2: 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 5.4 for further details.

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

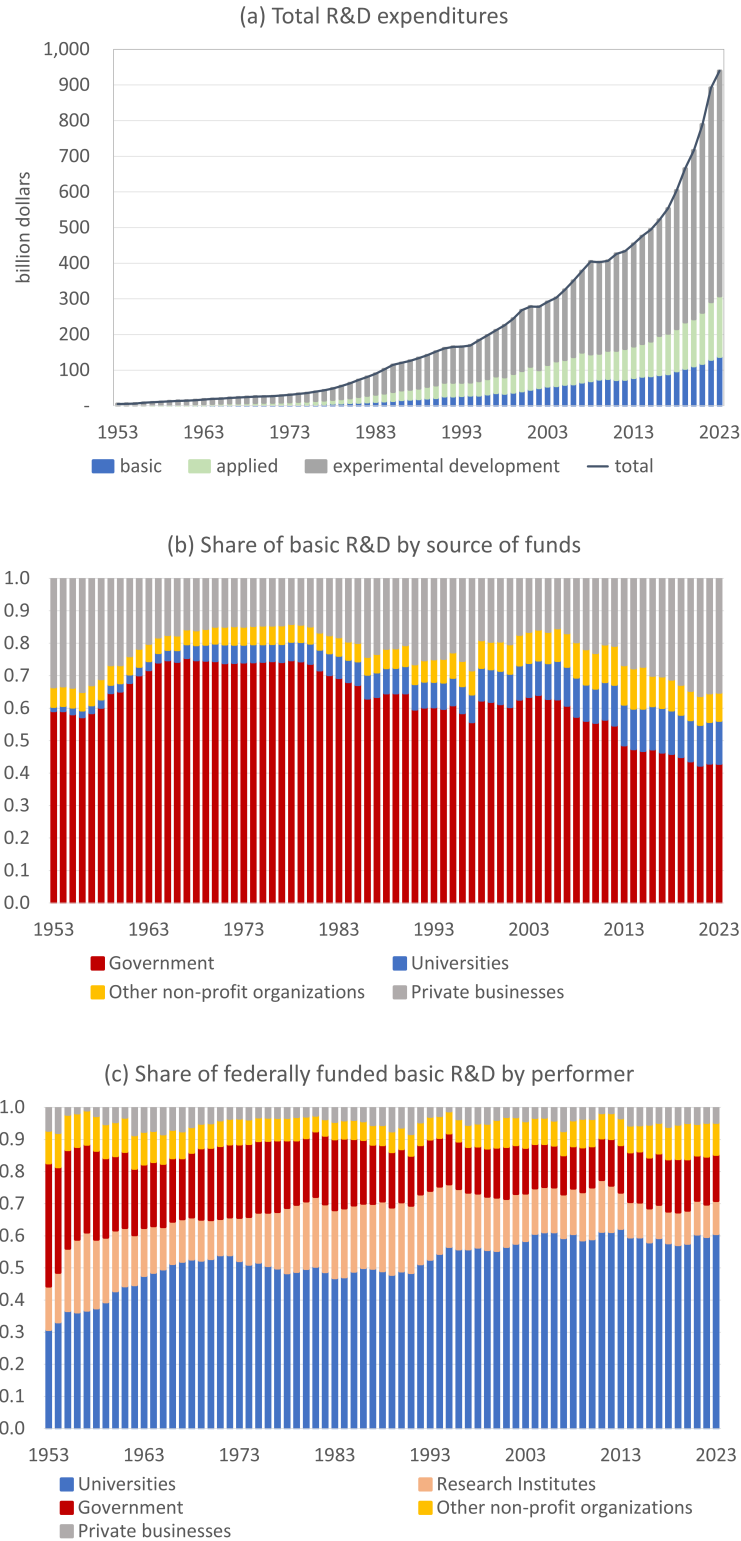
National statistics on R&D funding and performance in the US are provided by the National Center for Science and Engineering Statistics of the NSF. The Center compiles the *National Patterns of R&D resources*, an annual statistical report that provides an integrated overview of the U.S. research and 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 I1 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 I1 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 I1 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 I1: 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.

J 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 [J1](#), we describe major research institutes and national lab operators. In Table [J2](#), we group innovations by universities and research institutes by federal agencies. In Table [J3](#), we provide some descriptions of the top start-up companies among innovators who leverage government funds.

Table J1: 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 J2: Breakdown of non-profit public-private patents

Agency	Universities		Research Institutes	
	Frequency	Percent	Frequency	Percent
DOD	6,749	14.22%	996	9.07%
DOE	5,012	10.56%	3,623	32.99%
NIH	21,978	46.30%	5,231	47.63%
NASA	1,579	3.33%	163	1.48%
NSF	9,936	20.93%	422	3.84%

Table J3: 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 Water-vliet, New York; worked on optoelectronic materials and thin-film devices for display, sensing, and photonic applications.