Online Appendix to The Returns to Government R&D: Evidence from U.S. Appropriations Shocks

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ONLINE APPENDIX

Contents

A Data Sources and Definitions

Main data sources:

- F-TFP: FRB San Francisco Total Factor Productivity, see also Fernald (2012)
- BEA-NIPA: U.S. Bureau of Economic Analysis National Income and Product Accounts
- BEA-FA: U.S. Bureau of Economic Analysis Fixed Assets Accounts Tables
- NSCES: National Center for Science and Engineering Statistics,
  - National Patterns of R&D Resources

- Survey of Federal Funds for Research and Development, pre-1999 data from the NSCES/NSF archives

All additions and subtractions involving quantities in chained dollars are based on the Divisia index approximation to chained aggregates, see Whelan (2002). All real quantities are expressed in 2012 dollars using implicit deflators.

Capital stock variables: Quarterly real capital stocks are valued at real cost and constructed using the perpetual inventory method using quarterly NIPA data on real investment and initial capital stocks (year-end 1946) from the BEA-FA tables. Depreciation rates are quarterly interpolations of annual depreciation rates in the BEA-FA tables.

- **Government R&D Capital**: Chained sum of (i) federal nondefense R&D capital stock, (ii) federal defense R&D capital stock, and (iii) state & local R&D capital stock. R&D capital includes the BEA-NIPA categories 'research and development' and 'software development'. Investment series are lines 22, 30, and 38 in BEA-NIPA Table 3.9.3 (converted to 2012 dollars using Table 3.9.5). Depreciation rates are lines 35, 52, and 72 in BEA-FA Table 7.4 (converted to 2012 dollars using Table 7.3) divided by prior year capital stocks in the same lines of BEA-FA Table 7.2 (converted to 2012 dollars using Table 7.1). **Government Nondefense R&D Capital** and **Government Defense R&D Capital** are constructed analogously using the relevant subcategories.
- **Public Infrastructure Capital**: Chained sum of structures and equipment capital stocks for (i) federal nondefense and (ii) state & local governments. Investment series are lines 28, 29, 36, and 37 in BEA-NIPA Table 3.9.3 (converted to 2012 dollars using Table 3.9.5). Depreciation rates are lines 39, 40, 56, and 57 in BEA-FA Table 7.4 (converted to 2012 dollars using Table 7.3) divided by prior year capital stocks in the same lines of BEA-FA Table 7.2 (converted to 2012 dollars using Table 7.1).
- **Defense Capital**: Chained sum of defense structures and defense equipment capital stocks. Investment series are lines 20 and 21 in BEA-NIPA Table 3.9.3 (converted to 2012 dollars using Table 3.9.5). Depreciation rates are lines 23 and 30 in BEA-FA Table 7.4 (converted to 2012 dollars using Table 7.3) divided by prior year capital stocks in the same lines of BEA-FA Table 7.2 (converted to 2012 dollars using Table 7.1).
- **Business Sector R&D Capital**: Aggregate of BEA-NIPA categories 'research and development' and 'software development' for the business sector based on the weights and growth rates in F-TFP (`'wgt_r_and_d'`,`'dk_r_and_d'`,`'wgt_software'`, and `'dk_software'`), cumulated and converted to 2012 dollars using BEA-FA Table 7.1.
- **Total R&D Capital**: Chained sum of the components of government R&D capital and business-sector R&D capital.
- **Total Public Capital**: Chained sum of the components of government R&D capital, public infrastructure capital and defense capital.

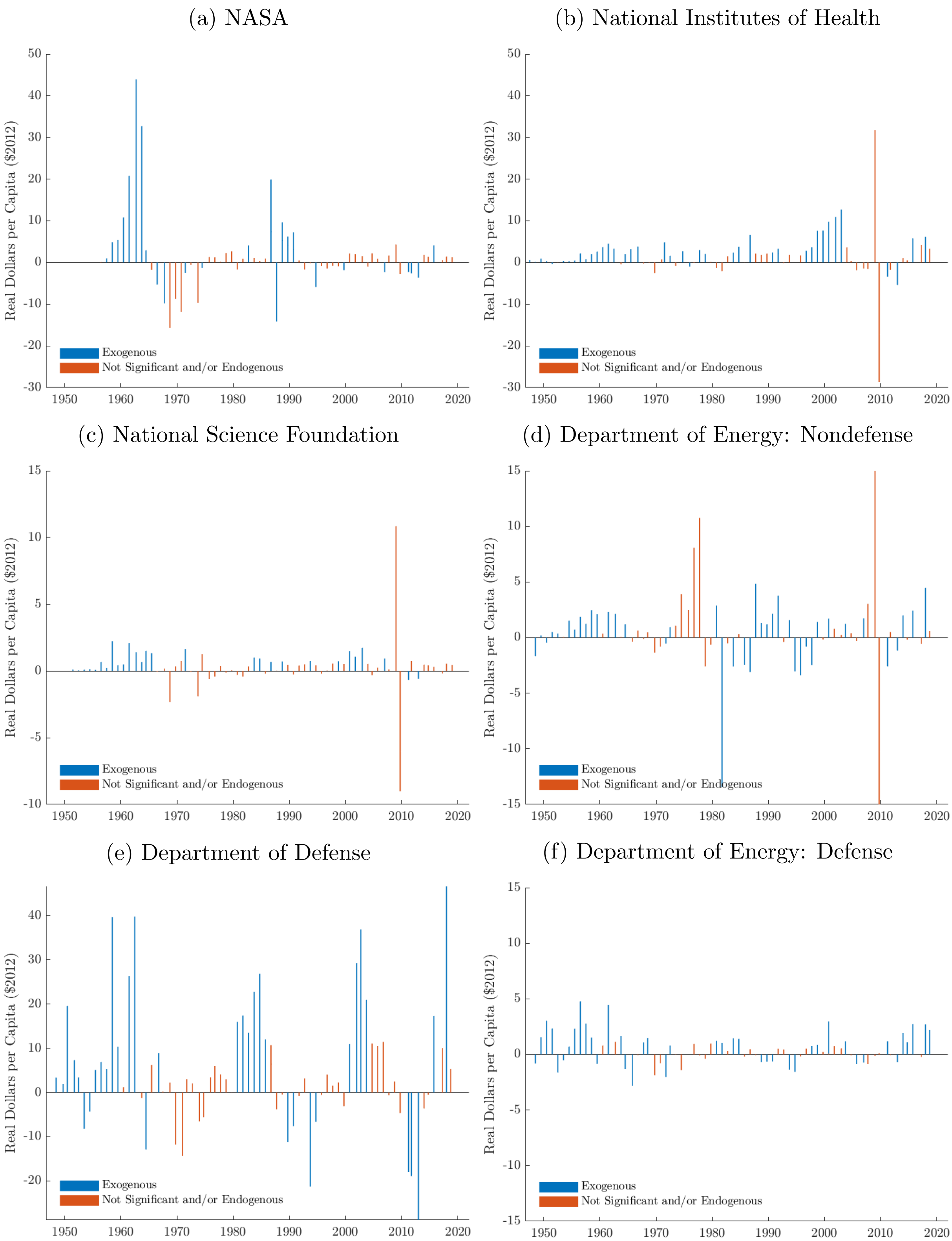
Other variables:

- Variables from F-TFP: **Business Sector TFP**: utilization-adjusted total factor productivity (F-TFP: `'dtfp_util'`); **Capacity utilization**: (F-TFP: `'dutil'`); **Labor Productivity**: (F-TFP: `'dLP'`); Log-level variables are obtained as cumulative sums of the annualized growth rates in the F-TFP dataset after dividing by 400.
- **Potential Output**: CBO estimate of potential real GDP. From 1949Q1 onward, `'GDPPOT'` from FRED. Observations before 1949Q1 are from the replication files of Ramey and Zubairy (2018).
- **Stock market returns**: Average of the cumulative sums of the equally weighted returns for manufacturing (`'R_EW_Manuf'`), high tech (`'R_EW_HiTec'`), and health industries (`'R_EW_Hlkth'`) from the Kenneth French Data Library (5 Industries Portfolios).
- **Military News**: `'news'` in replication files of Ramey and Zubairy (2018) converted to 2012 dollars by the implicit GDP deflator, divided by potential output.
- **Patent Innovation Index**: Quarterly version of the patent innovation index of Kogan et al. (2017), from the replication files of Cascaldi-Garcia and Vukotić (2022).
- **New PhDs in STEM**: Total number of doctoral recipients in science and engineering. Quarterly interpolation of annual data. Data for 1947-1957 is from the Historical Statistics of the U.S. (Colonial Times to 1970), series H766-787. Data from 1958 onward is from the NCSES Survey of Earned Doctorates.
- **Researchers**: Total researchers (full-time equivalents), from the OECD Main Science and Technology Indicators. Pre-2000 data is obtained from the replication files of Bloom et al. (2020). Quarterly interpolation of annual data.
- **Technology Books**: Books published in the field of technology, constructed Alexopoulos (2011) and obtained from the replication files of Kogan et al. (2017).

B Narrative Identification: Additional Background

Figure B.1 depicts the narrative R&D appropriations changes separately for each agency, before aggregation to nondefense versus defense R&D policy changes, as depicted in Figure 5 of the main text. The top four panels of Figure B.1 depict the R&D appropriations shocks for nondefense expenditures, with NASA in panel (a), NIH in panel (b), NSF in panel (c), and the nondefense functions of DoE in panel (d). The bottom two panels depict the R&D appropriations shocks for defense expenditures, with DoD in panel (e) and the nuclear security functions of DoE in panel (f). Appropriations shocks classified as exogenous are again depicted in blue and those classified as endogenous (or too small to classify) are depicted in red; and all R&D appropriations policy events are again measured in real dollars

FIGURE B.1: Changes in R&D Appropriations by Federal Agency



Notes: See Fieldhouse and Mertens (2023). Sample: 1947Q1–2019Q4.

per capita. The remainder of this section provides a brief overview of postwar federal R&D

policy in relation to our narrative R&D appropriations shocks depicted in Figure B.1.

Unlike defense R&D, the federal government was barely investing anything in nondefense research coming out of World War II, but that quickly changed during the Cold War. Vannevar Bush, the Director of the Office of Scientific Research and Development during the war, had urged President Roosevelt to build on the successes of wartime research and expand the federal government's role in supporting health and basic research for peaceful purposes, a case spelled out in his famous report "Science–The Endless Frontier" (Bush 1945). The effort to create a new government agency to promote research eventually led to the creation of the NSF in 1950, spurred on in part by the Soviet Union's first atomic test in 1949 and growing concerns over scientific and technological competition with the USSR; real appropriations for NSF-funded research surged in the late 1950s and early 1960s, as seen in panel (c). President Eisenhower was also determined to re-purpose wartime nuclear fusion breakthroughs to peaceful civilian uses—"Atoms for Peace" that could advance domestic energy production and serve as a tool for strengthening alliances and promoting democracy abroad; appropriations for nondefense energy research also jumped in the late 1950s and early 1960s, as seen in panel (d). But as seen in panel (a), the Sputnik crisis, ensuing creation of NASA, and JFK's moon mission ushered in a new era, and federal nondefense R&D spending per capita abruptly rose by an order of magnitude over FY1956-66.

This rapid growth in real appropriations for nondefense R&D activities quickly reversed course in the late 1960s and early 1970s. Congress lost interest in appropriating funds for NASA after the moon landing in 1969, as also seen in panel (a). And the increasingly inflationary environment of this era resulted in budgetary restraint—including for R&D activities—for most agencies, as seen in every panel of Figure B.1. But as is common, emergencies and policy priorities of the day led to exceptions to the rule. Cancer research was a major policy priority of President Nixon, who declared a "war on cancer" in 1971 and successfully pushed for increased NIH research funding, seen in panel (b). And the 1973-74 Organization of Petroleum Exporting Countries oil embargo led to the creation of the Energy Research and Development Administration (ERDA) in 1974 and then the DoE (which absorbed ERDA and several other agencies in 1977), accompanied by significant increases in renewable and alternative energy research funding, as seen in panel (d); the expansion in nondefense energy research was motivated by a mix of concerns about energy inflation and national security. But during the Reagan administration, priorities for R&D funding saw a pendulum swing away from civilian energy and other nondefense agencies and toward defense R&D activities, as exemplified by panels (d) and (e). That said, after initially being dismissive of the HIV/AIDS epidemic, President Reagan eventually prioritized HIV/AIDS research and related NIH funding during his second term, as seen in panel (b).

The "Peace dividend" from the end of the Cold War led to a trend increase in nondefense R&D spending during the presidencies of George H.W. Bush and Bill Clinton, with the one notable exception of budget austerity and deficit reduction early in the Clinton administration. For the first time in decades, NASA found a White House advocate in President George H.W. Bush, who announced an ambitious Space Exploration Initiative on the 20th anniversary of the Apollo 11 moon landing and viewed the International Space Station as a constructive, cooperative path forward with the Soviet Union as it careened toward dissolution; the corresponding increases in NASA appropriations in the late 1980s and early 1990s are clearly seen in panel (a). The Clinton administration championed the human genome project, both as a matter of science policy and realm of international competition, and again turbo-charged NIH research funding with the 21st Century Research Fund initiative, which had both an idealist and international competitiveness bent. Increased NIH funding maintained some momentum early in the presidency of George W. Bush, particularly following the Anthrax terrorist attacks of 2001, and panel (b) shows substantial increases in NIH appropriations throughout the late 1990s and early 2000s. The NSF also saw sustained increases in appropriations for research, similarly motivated, during this period.

But increased homeland security spending following the 9/11 attacks, the invasions of Afghanistan and Iraq, and multiple tax cuts led to budgetary pressures largely borne out by nondefense discretionary spending, including R&D appropriations. Funding cuts ensued for the NIH, and to a lesser extent NASA, later in the 2000s, as seen in panels (b) and (a). The 2007-08 oil price shock, however, fueled increased funding for nondefense energy research as the economy slid into the Great Recession, as seen in panel (d). Nondefense R&D spending saw a broader brief resurgence early in the Obama administration as ARRA increased funding for DoE, NIH, and NSF research as part of the fiscal stimulus response to the Great Recession, as seen in panels (b), (c), and (d). But before long, partisan backlash to swollen budget deficits and policy priorities of the Obama administration—epitomized by the debt ceiling crisis, Budget Control Act of 2011, and subsequent sequestration spending cuts—squeezed R&D appropriations in the early 2010s, as seen in all panels of Figure B.1.

Following a large increase in defense research during WWII, there have been three major waves of sustained increases in defense R&D appropriations during this postwar sample, as clearly seen in panel (e) and to a lesser extent in panel (f). Real funding per capita roughly quadrupled throughout the 1950s and 1960s, spurred on by the Korean War (1950-1953) and Sputnik's launch (1957). The Sputnik "crisis" and related fears of technological gaps with the Soviet Union—particularly an intercontinental ballistic "missile gap"—led to the creation of the Advanced Research Projects Agency (now DARPA) and NASA, both established in 1958. Defense R&D spending per capita roughly doubled in the 1980s, spurred on by the Soviet invasion of Afghanistan, President Reagan's election, and Reagan's subsequent military buildup and Strategic Defense Initiative—the predecessor to today's Missile Defense Agency (MDA). And defense R&D spending per capita increased roughly 50 percent during the George W. Bush administration, which revived fixation with developing and deploying missile defense systems; the administration withdrew the U.S. from the Anti-ballistic Missile (ABM) Treaty and turned the Ballistic Missile Defense Organization into the MDA in 2002, turbocharging its R&D budget. The 9/11 terrorist attacks and invasions of Afghanistan and Iraq also led to huge increases in appropriations for DoD, including R&D budgets, as the Global War on Terror and new realities of asymmetric warfare considerably changed R&D objectives (e.g., development of military drones). Lastly, there was a more minor, short-lived increase in federal defense R&D following the inauguration of President Trump, who promised a "great rebuilding of America's armed forces" and withdrew from the Intermediate-Range Nuclear Forces (INF) Treaty. Political preferences and election outcomes are partly responsible for this policy variation; these four waves of increased defense R&D conspicuously started during Republican administrations (Eisenhower, Reagan, G.W. Bush, and Trump).

Geopolitical shifts can also decrease the desirability or legality of defense R&D activities. Demobilization from the Korean War was accompanied with cutbacks in funding for defense R&D appropriations in the mid-1950s (before the Sputnik crisis), as seen in panel (e). And just as withdrawing from arms controls treaties opens the door to increase defense R&D, nonproliferation treaties have often been followed by modest reductions in (now disallowed) R&D activities for the development and testing of nuclear weapons. As panel (f) underscores, R&D appropriations for DoE's nuclear security functions fell shortly after the ratification of the Partial Test Ban Treaty in 1963, Nuclear Non-Proliferation Treaty in 1968, Strategic Arms Limitation Talks Agreement and ABM Treaty in 1972, INF Treaty in 1988, Strategic Arms Reduction Treaty (START I) in 1991, START II in 1996, and New START in 2010.[1] In addition to nonproliferation treaties of that era, the Soviet Union's exit from Afghanistan (1988-89) and collapse and dissolution of the Soviet Union (1988-91) contributed to a substantial decline in defense R&D and defense spending more broadly in the 1990s, as seen in panels (e) and (f). Defense R&D again fell substantially throughout the Obama administration, in part because of New START and pivot away from missile defense initiatives, but also because of budget cuts from the Budget Control Act of 2011 and the subsequent sequestration spending cuts, as seen in panel (e).

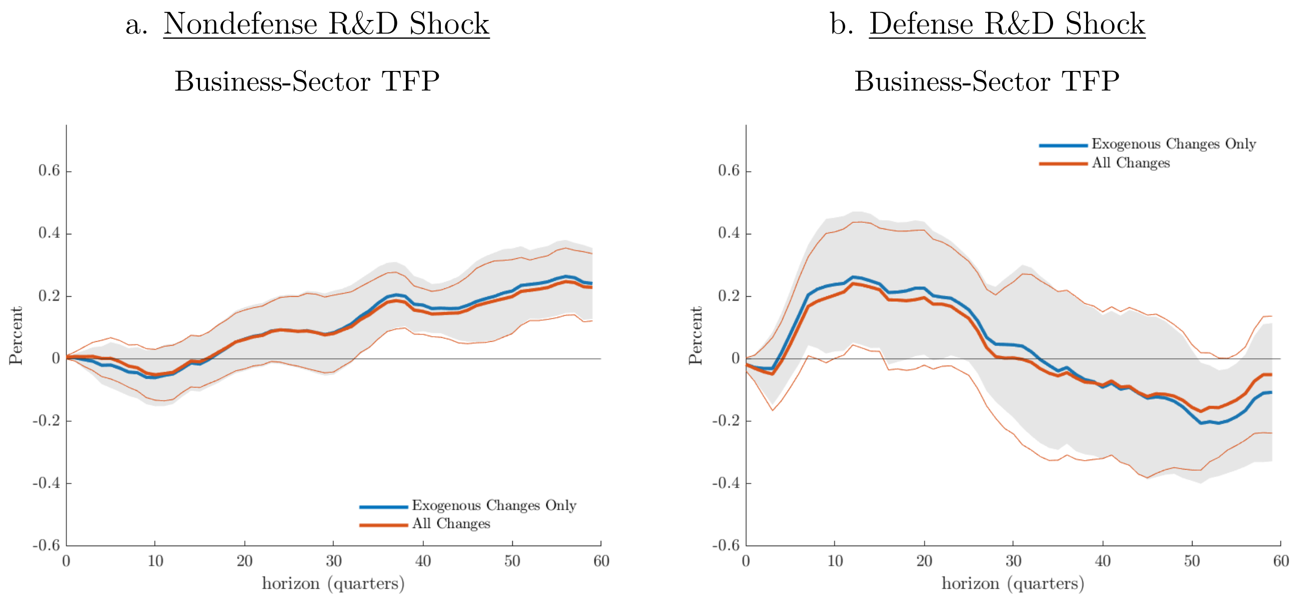
C Impulse Responses: Robustness and Additional Results

C.1 Robustness: Role of the Narrative Identification Step

This section discusses the role of the narrative classification of the changes in federal R&D appropriations as 'exogenous' or 'endogenous' for the impulse response estimates. Figure C.1 replicates the baseline impulse responses of TFP to nondefense and defense shocks from Figure 6 in the main text. The figure also shows estimates for the same specifications, but using all changes in R&D appropriations rather than just those identified as 'exogenous' in the narrative analysis. In this case, the z_t^i variables in (2) contain all changes in appropria-

[1] Defense research did increase following the ratification of the Strategic Offensive Reductions Treaty in 2003, presumably in part because the U.S. withdrew from the ABM Treaty.

Figure C.1: Role of Narrative Classification



Notes: Estimates based on (2) using the measures of changes in federal nondefense (left panel) and defense (right panel) R&D appropriations, see (1). 'Exogenous Changes Only' uses the orthogonalized narratively identified measures as in the baseline specification described in the main text. 'All Changes' uses orthogonalized measures based on all changes in appropriations. Lazarus et al. (2018) HAR bands are for 95 percent confidence levels. Impulses are scaled to imply a 1 percent peak increase in the total government R&D capital. Sample: 1948Q1–2021Q4.

tions shown in Figure 5, after orthogonalizing defense to nondefense appropriations and vice versa, as in (1). Both the point estimates and confidence intervals for the TFP responses to both the defense and nondefense R&D shocks are very similar when additionally using the endogenous and smaller, unclassified changes in appropriations in the regressions.

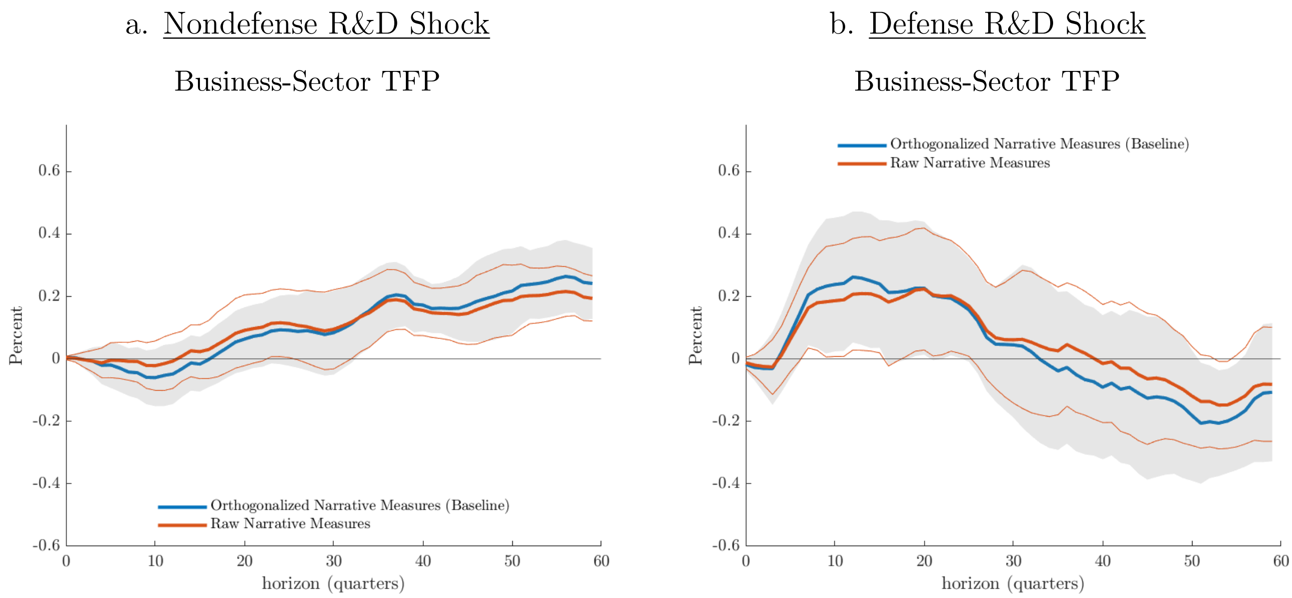
C.2 Robustness: Role of the Orthogonalization

This section discusses the role of mutually orthogonalizing the narrative measures of exogenous changes in defense and nondefense R&D appropriations for the impulse response estimates, as in equation (1) in the main text. Figure C.2 replicates the baseline impulse responses of TFP to nondefense and defense shocks from Figure 6 in the main text. The figure also shows estimates for the same specifications, but using all the raw changes in R&D appropriations $\Delta a_t^{exo,i}/K_{t-4}^i$, $i = D, ND$ as the z_t^i in the local projections in (2) rather the residuals in (1). As the figure shows, the point estimates and confidence intervals for the TFP responses to both the defense and nondefense R&D shocks are very similar.

C.3 Robustness: Additional Control Variables

Figure 6 in the main text shows that including lags of the baseline set of controls x_t reduces the variance of the impulse response estimates to a nondefense R&D shock, but has otherwise

Figure C.2: Role of Orthogonalization of the Narrative Measures



Notes: Estimates based on (2) using the measures of changes in federal nondefense (left panel) and defense (right panel) R&D appropriations. Lazarus et al. (2018) HAR bands are for 95 percent confidence levels. Impulses are scaled to imply a 1 percent peak increase in the total government R&D capital. Sample: 1948Q1–2021Q4.

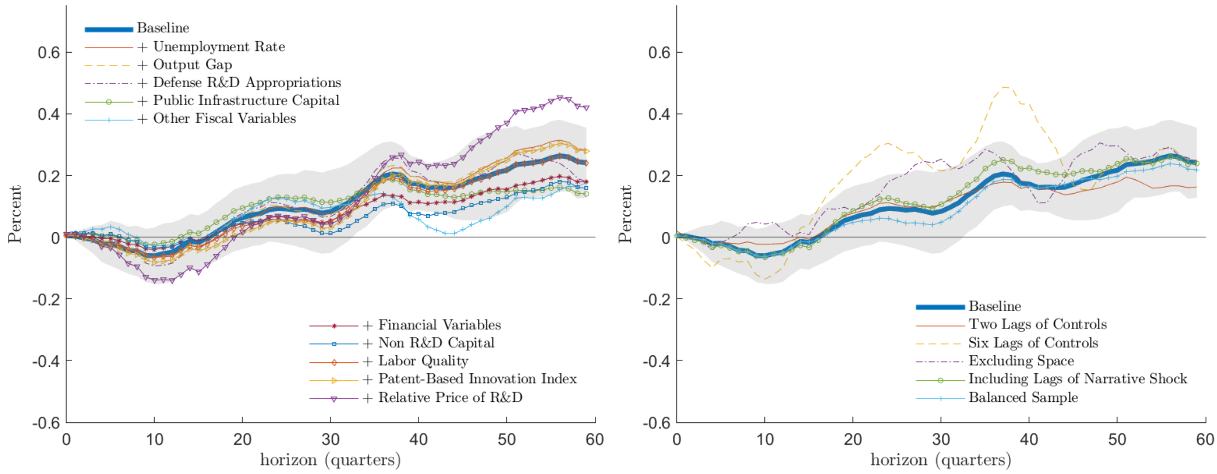
no major qualitative effects on the point estimates. This suggests that the controls do not capture any important simultaneous influences on both the narrative measures and future TFP that would threaten the causal interpretation of the estimates in the simpler specification. Here, we consider a number of additions to the baseline set of controls to gain further confidence in the causal interpretation of the positive TFP response to nondefense R&D shocks. Panel (a) of Figure C.3 plots the impulse responses of business-sector TFP to nondefense R&D shocks for these various additions. For reference, the figure repeats the baseline estimates and the associated 95 percent confidence bands from Figure 6 in the main text. Rows [2]-[11] in Table C.1 report the impulse response coefficients at horizons of 5, 10, and 15 years with HAR confidence bands in parentheses.

As mentioned in the main text, the baseline controls include capacity utilization to capture possible business cycle influences. The first two expanded control sets each add an alternative cyclical indicator: The headline unemployment rate or the output gap (the percentage difference between real GDP and CBO potential output). Neither one has much effect on the estimated TFP response to a nondefense R&D shock, and the TFP response remains highly statistically significant at longer horizons (see rows [2]-[3] in Table C.1). Replacing the utilization rate with either of these alternative cyclical indicators, or adding them both at the same time, similarly has no major effect on the estimates (these results are not reported).

It is possible is that R&D appropriations, despite accounting for only a small share of

Figure C.3: TFP Impact of Nondefense R&D Shock, Robustness

(a) Additional Control Variables (b) Model Specification



Notes: Estimates based on (2) using the narrative measure of federal nondefense R&D appropriations. Lazarus et al. (2018) 95 percent HAR confidence bands are for the baseline impulse responses. Impulses scaled to imply a 1 percent peak increase in government R&D capital. Sample: 1948Q1–2021Q4 (specification with patent-based innovation index, 1949Q1–2010Q4).

the federal budget, are predictable by other tax and spending policies that may have independent long-run effects on productivity. For instance, Antolin-Diaz and Surico (2022) find that government spending shocks raise long-run TFP, Cloyne et al. (2022) find that temporary tax cuts have long-run effects on TFP, and Croce et al. (2019) find that the public debt-to-GDP ratio significantly influences the cost of capital for R&D-intensive firms and productivity growth. The baseline controls include lags of cumulative nondefense appropriations, government R&D capital, and the Ramey and Zubairy (2018) military spending news variable. As these variables may not be sufficient to capture all relevant information about fiscal policy, the next three expanded control sets add information about fiscal policy. In turn, we add log cumulative appropriations for defense R&D, the log of the public infrastructure capital stock, and a set of broader fiscal policy indicators. The latter includes the log of total real government consumption expenditures, the ratio of government debt to GDP (based on the Market Value of U.S. Government Debt constructed by the Federal Reserve Bank of Dallas), and the measures of average federal personal and corporate income tax rates from Mertens and Ravn (2013). The addition of defense appropriations has no major impact on the estimates, and the TFP response remains highly statistically significant (row [4] in Table C.1). Adding public infrastructure capital induces a more front-loaded TFP response that is somewhat more muted at longer horizons. The TFP response remains highly statistically significantly at longer horizons (see row [5] in Table C.1). Controlling for lags of a broader set of fiscal policy indicators also leads to somewhat smaller TFP responses at longer horizons, but they nevertheless remain highly significant (see row [6] in Table C.1).

The baseline controls include cumulative real stock returns in R&D-intensive industries to capture any broad advance information about future technological developments. Next, we add a broader set of financial indicators. Financial conditions could matter for several reasons, for instance, by determining the relative attractiveness of long-horizon investments in R&D, by summarizing additional forward-looking economic information with an influence on both productivity and government R&D, or more generally by capturing additional types of disturbances with potential effects on long-run productivity. We add the 3-month and 10-year Treasury rates, the log real S&P500 index, and the spread between BAA- and AAA-rated corporate bonds to the controls (obtained from FRED and Shiller (2015)). As can be seen from panel (a) in Figure C.3, these additional financial controls attenuate the TFP response somewhat at horizons beyond eight years. The TFP response at longer horizons remains highly statistically significant (see row [7] in Table C.1).

The next four specifications each in turn rotate in a number of additional variables that conceivably could contain important independent information about future productivity: Non-R&D capital in the business-sector, the Fernald (2012) measure of labor quality, the patent-based innovation index of Cascaldi-Garcia and Vukotić (2022), and the relative price of R&D from the NIPA data. Including non-R&D capital leads to somewhat smaller estimates of the TFP response in the longer run, while including the relative price of R&D leads to estimates that are considerably larger. The addition of the indices for labor quality or innovation do not have any major impact on the estimates. As rows [8]-[11] in Table C.1 show, the estimates of the TFP response at longer horizons remain highly statistically significant in each case.

C.4 Robustness: Model Specification

This section reports impulse response estimates of TFP to a nondefense R&D shock under several additional alterations to the baseline specification in (2). Panel (b) in Figure C.3 plots the impulse responses along with the baseline estimates and their 95 percent confidence bands from Figure 6 in the main text. Rows [12]-[15] in Table C.1 report the coefficient estimates for the various alterations at horizons of 5, 10, and 15 years with HAR confidence bands in parentheses.

The baseline specification uses $p = 4$ lags of all control variables. The first two robustness checks consider shortening or lengthening the number of lags to $p = 2$ and $p = 6$, respectively. As Panel (b) in Figure C.3 shows, reducing lag length from four to two quarters leads to somewhat smaller TFP responses at horizon beyond 10 years; the long-run TFP responses remain statistically significant at the 5 or 10 percent levels (see row [12] of Table C.1). Increasing the lag length from four to six quarters makes the TFP response somewhat more volatile, but the response at the end of the forecast horizon is very similar to the baseline specification, and also remains highly significant (see row [13] of Table C.1).

Table C.1: TFP Impact of Nondefense R&D Shock, Robustness

		% Impact After		
		5 years	10 years	15 years
[1]	Baseline	0.05 (−0.05,0.15)	0.18*** (0.09,0.27)	0.24*** (0.13,0.35)
[2]	+ Unemployment Rate	0.04 (−0.06,0.13)	0.20*** (0.08,0.32)	0.28*** (0.13,0.44)
[3]	+ Output Gap	0.06 (−0.06,0.17)	0.20*** (0.09,0.30)	0.27*** (0.13,0.42)
[4]	+ Defense R&D Appropriations	0.06 (−0.12,0.25)	0.22*** (0.06,0.37)	0.18** (0.00,0.36)
[5]	+ Public Infrastructure Capital	0.09* (−0.01,0.18)	0.15*** (0.06,0.25)	0.14*** (0.06,0.22)
[6]	+ Other Fiscal Variables	0.06 (−0.08,0.20)	0.07 (−0.04,0.18)	0.18*** (0.06,0.30)
[7]	+ Financial Variables	0.04 (−0.05,0.13)	0.11** (0.02,0.20)	0.18*** (0.09,0.27)
[8]	+ Non R&D Capital	0.04 (−0.05,0.14)	0.08** (0.01,0.14)	0.16*** (0.07,0.24)
[9]	+ Labor Quality	0.03 (−0.07,0.13)	0.16*** (0.08,0.24)	0.24*** (0.12,0.37)
[10]	+ Patent-Based Innovation Index	0.01 (−0.11,0.12)	0.18*** (0.06,0.30)	0.28*** (0.14,0.42)
[11]	+ Relative Price of R&D	−0.00 (−0.14,0.14)	0.24*** (0.09,0.39)	0.42*** (0.16,0.68)
[12]	Two Lags of Controls	0.07** (0.00,0.14)	0.16** (0.03,0.28)	0.16* (−0.01,0.34)
[13]	Six Lags of Controls	0.19 (−0.06,0.45)	0.43*** (0.21,0.66)	0.25** (0.06,0.44)
[14]	Excluding Space	0.10 (−0.21,0.40)	0.19* (−0.02,0.39)	0.24** (0.02,0.47)
[15]	Including Lags of Narrative Shock	0.07 (−0.04,0.19)	0.22*** (0.12,0.32)	0.24*** (0.16,0.32)
[16]	Balanced Sample	0.04 (−0.07,0.15)	0.17*** (0.08,0.25)	0.22*** (0.12,0.32)

Notes: Estimates are based on (2) using the narrative measure of federal nondefense R&D appropriations. Numbers in parentheses are 95 percent HAR confidence bands based on Lazarus et al. (2018). Stars $*$, $**$ and $***$ denote statistical significance at 10, 5, and 1 percent significance levels, respectively. Impulses scaled to imply a 1 percent peak increase in government RD capital. Sample: 1948Q1–2021Q4 (specification with patent-based innovation index: 1949Q1–2010Q4).

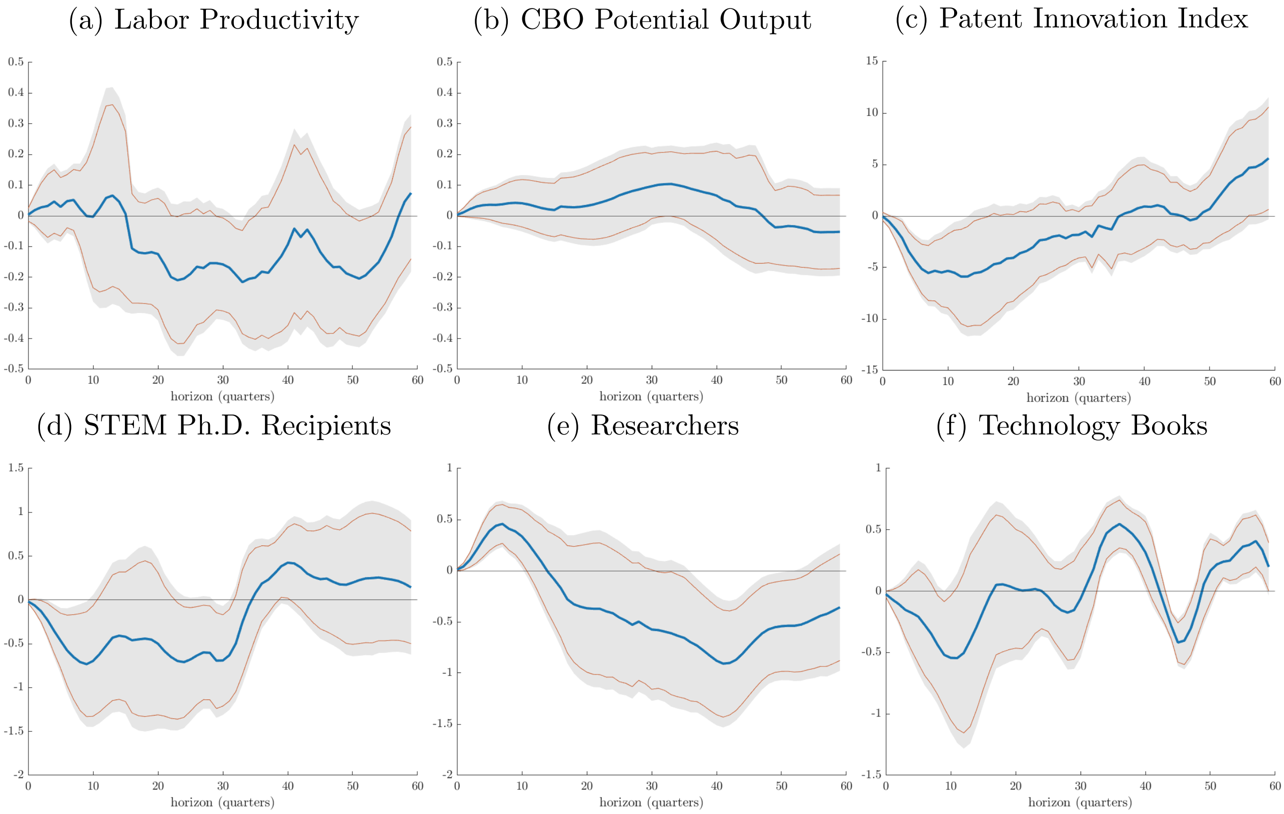
As discussed in the main text, the rapid expansion of government R&D expenditures during the early stages of the space race is important for the precision of the estimates of the production function elasticities and rates of return reported in Tables 1 and 2. Our next robustness check analogously verifies the role of the early NASA R&D appropriations for the estimated TFP response to a nondefense R&D shock. We remove the influence of the early expansion during the space race by orthogonalizing the narrative measure of exogenous nondefense R&D shocks not only to the defense R&D measure, but also to all appropriations for NASA over the 1958–1963 period. Figure C.3b shows that the gradual rise in TFP following a nondefense R&D shock is robust to excluding the space race episode. Row [14] of Table C.1 shows that the long-run TFP response also remains significant at conventional levels, even though the confidence become notably wider.

The baseline set of controls includes four lags of the (log) of cumulative nondefense R&D appropriations, but not lags of the (orthogonalized) narrative R&D measures themselves. Figure C.3b shows that additionally including these lags has very little effect on the estimated TFP response and the associated confidence bands (see row [15] in Table C.1).

Finally, the inference formulas for SP-IV developed in Lewis and Mertens (2023) require a balanced sample. The impulse response in Section 3 are instead estimated iteratively, i.e. using the largest possible estimation sample for each horizon h. Figure C.3b provides the estimated TFP response in the balanced sample, which leads to only relatively minor differences with the baseline estimates. As seen in row [16] of Table C.1, the estimates remain also highly statistically significant in the balanced sample.

C.5 Impact of a Defense R&D Shock on Other Productivity/Innovation Indicators

Figure C.4: Impact of a Defense R&D Shock on Other Productivity/Innovation Indicators



Notes: Estimates based on (2) using the orthogonalized narrative measure of changes in defense R&D appropriations, see (1). Lazarus et al. (2018) HAR bands are for 90 and 95 percent confidence levels. Impulses scaled to imply a 1 percent peak increase in government R&D capital. Sample: (a),(b),(d):1948Q1–2021Q4; (c):1949Q1–2010Q4; (e):1951Q1–2019Q4; (f):1956Q1–1997Q4. See Appendix A for variable definitions.

Figure 7 in the main text reports the impact of a nondefense R&D shock on various productivity measures and innovation indicators. Figure C.4 reports the impact of a defense R&D shock on the same variables. Whereas a positive nondefense R&D shock consistently leads to increases in all productivity and innovation indicators, the same is not the case for defense R&D shocks. Figure C.4 shows a hump-shaped transitory decline in labor productivity and no statistically or economically significant impact on potential output. There also are transitory declines in the patent innovation index and the number of Ph.D. recipients in STEM fields. The number of R&D researchers increases in the short run, but declines in the longer run. There is no meaningful change in the number of technology publications, except perhaps at longer horizons.

C.6 Responses of Private Labor and non-R&D Capital Inputs

Figure C.5 shows estimates of the responses of other private factor inputs following positive shocks to nondefense (panel a) and defense (panel b) R&D appropriations. The measures of private factor inputs are from Fernald (2012). The estimates are obtained from local projections as in (2) in the main text, with the same baseline controls and four lags of each outcome variable added as additional controls. As in Figures 6 and 7 in the main text, the impulse responses are scaled to imply a one percent peak increase in the total government R&D capital stock. The first row in Figure C.5 depicts responses of labor input adjusted for labor quality (cumulative sum of `'dhours'` + `'dLQ'` in F-TFP, see Appendix A). The second row shows the responses of the business-sector non-R&D capital stock, which consists of all types of capital excluding R&D and software (nonresidential equipment and structures, residential business structures, and non-R&D intellectual property).

The first row in Figure C.5 shows that a nondefense R&D shock leads to little change in (quality-adjusted) labor input in the business sector at most horizons. Towards the end of the 15-year forecast horizon, there is a decline in labor input that is marginally statistically significant at one or two horizons. The response of labor input to a defense R&D shock is somewhat volatile and imprecisely estimated, with none of estimates statistically significant from zero at the 5 percent level.

The second row in Figure C.5 shows that, with a long delay, a nondefense shock leads to a gradual and persistent increase in the business-sector non-R&D capital stock that is highly statistically significant at horizons between 6 to 14 years. The peak increase in non-R&D capital is roughly 0.2 percent and occurs after about 13 years. The response of non-R&D capital to a defense R&D shocks shows some evidence of a transitory decline in the short run, but is overall imprecisely estimated.

The final row in Figure C.5 shows the response of real GDP. A nondefense shock does not lead to any economically or statistically significant change in real GDP in the short run. In the longer run, real GDP increases by around 0.2 to 0.35 percent. The timing and magnitude of the GDP response is overall similar to that of business-sector labor productivity or potential output, see Figure 7 in the main text.

C.7 A Closer Look at the Public Infrastructure Response to a Nondefense Shock

Figure 9 in the main text shows that an increase in appropriations for nondefense R&D leads to a rise in public infrastructure, and specifically in nondefense structures. In this section, we present further decompositions similar to those in Figure 9 to better understand the nature of the rise in public infrastructure after a nondefense R&D shock.

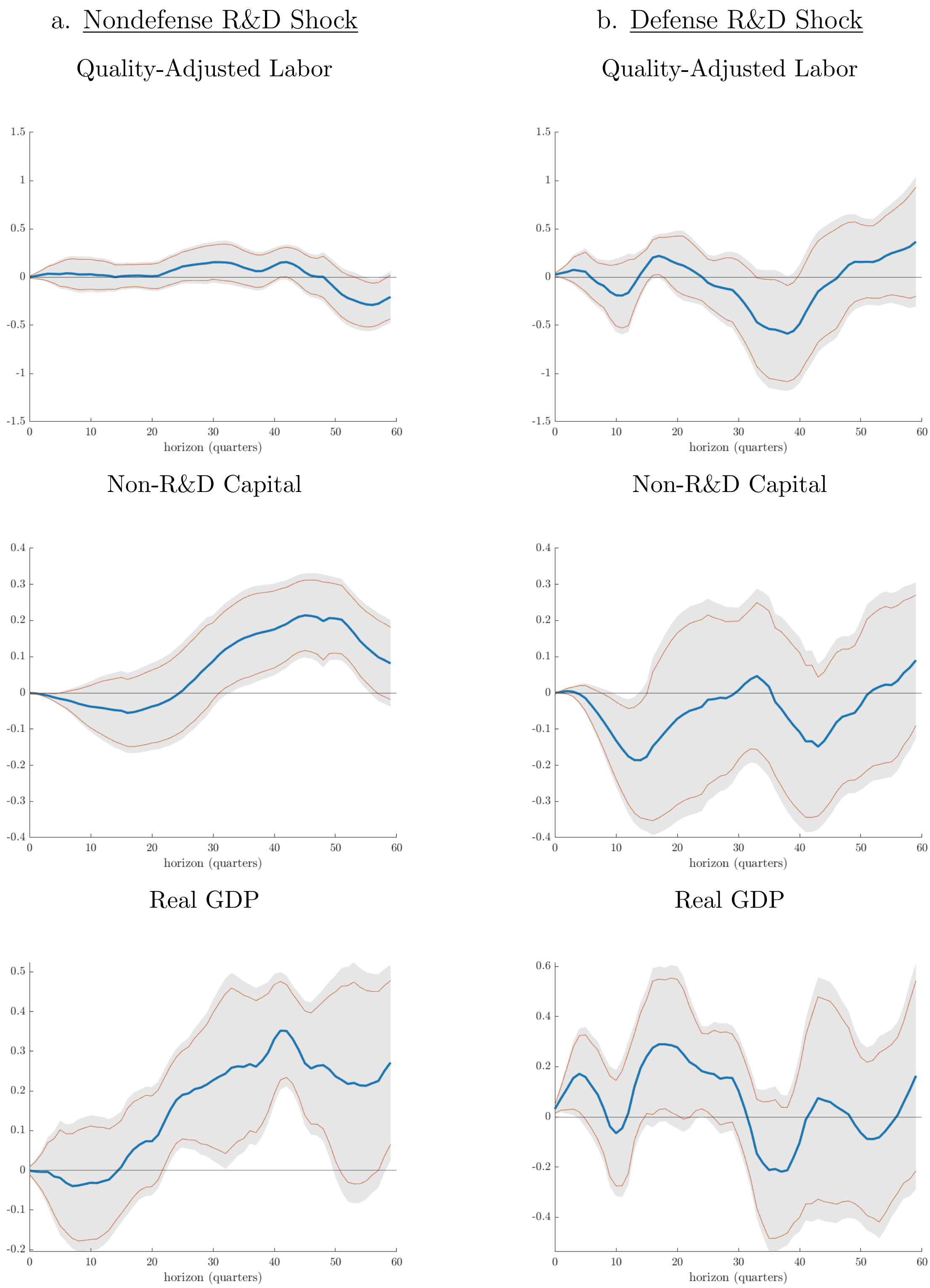
The first additional decomposition considers the response of various components of total nondefense public capital by type and level of government. Figure C.6 shows that the increase in public infrastructure after a nondefense shock is primarily driven by a rise in structures funded by state and local governments (up to 1.19 dollars), although there is also an increase in federal infrastructure spending on structures (up to 28 cents). Note that the total increase does not exactly add up to the 1.58 dollar increase in Figure 9 because of slight differences in the regression specifications (the lagged outcome variables y_{t-j} on the right hand side in (2) are different). The main text therefore reports the contribution of state and local government structures as a percentage $(1.19/(1.21 + 0.28) \approx 0.8)$.

Figure C.7 provides a further breakdown of the state and local government infrastructure response into various categories based on additional detail in the BEA Fixed Assets Accounts (Table 7.1), with quarterly values obtained by interpolation of the annual source data. The responses in this case are scaled to match the 1.21 peak increase in Figure C.6. As the figure shows, the largest increase occurs in educational structures. There are also meaningful increases in highways and streets as well as in power, water, and sewer systems. The change in all remaining types of state and local government infrastructure ('Other Infrastructure') are individually relatively small.

Figure C.8 provides a breakdown of the response of investment in structures by state and local (S&L) governments according to the means of financing: Debt, federal transfers or current surpluses (revenues less other spending). Note that, unlike in the previous figures, the decomposition pertains to the flow (real gross investment in structures) rather than the stock (the capitalized real cost value of structures). The decomposition is based on the budget constraint identity aggregated across state and local governments using data from the BEA (NIPA Table 3.3). The impulses are scaled to imply a unit peak increase in S&L gross investment in structures.

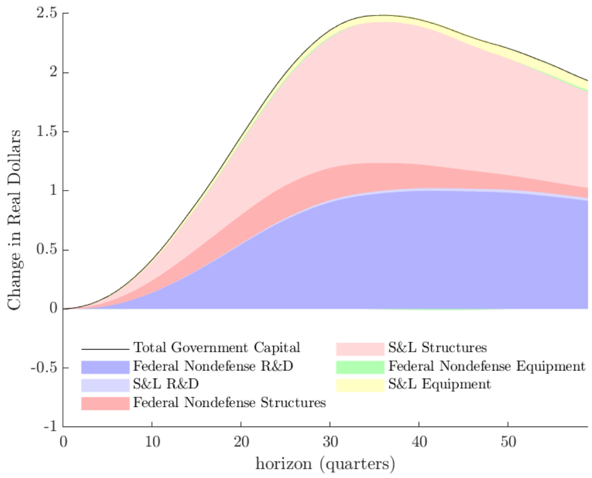
Figure C.8 shows that, consistent with the response of the corresponding capital stock, a nondefense R&D shock leads to a gradual rise in state and local investment in nondefense structures. Investment peaks after about seven years, subsequently returns to prior levels, and towards the end of the forecast horizons even dips slightly below the level predicted in the absence of the nondefense R&D shock. Figure C.8 also shows that the investment

Figure C.5: Labor and non-R&D Capital Following an Increase in R&D Appropriations



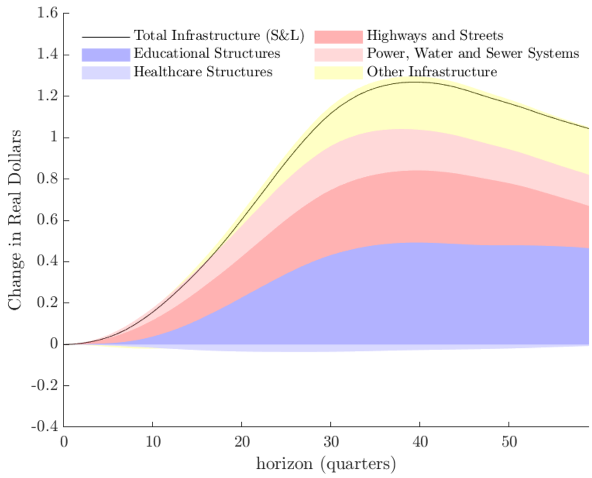
Notes: Estimates based on (2) using the orthogonalized narrative measure of changes in federal nondefense (left panel) and defense (right panel) R&D appropriations, see (1). 'Baseline' includes additional lagged controls described in the main text. Lazarus et al. (2018) HAR bands are for 95 percent confidence levels. Impulses scaled to imply a 1 percent peak increase in government R&D capital. Sample: 1948Q1–2021Q4.

FIGURE C.6: Nondefense Public Capital



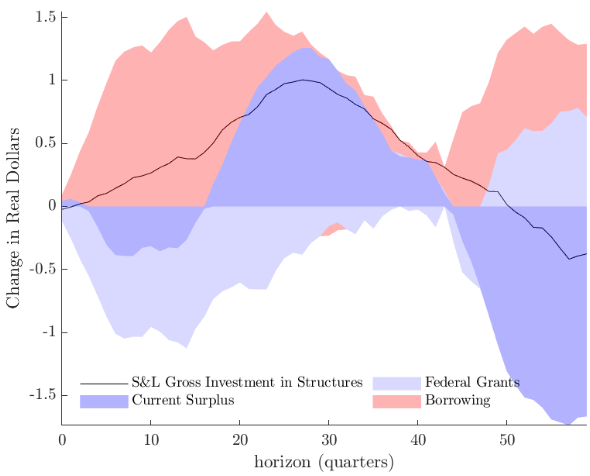
Notes: Estimates based on (2) using the orthogonalized narrative measure of changes in federal nondefense R&D appropriations, see (1). Impulses are scaled to imply a unit peak increase in federal nondefense R&D capital. Sample: 1949Q1–2021Q4.

FIGURE C.7: S&L Structures by Function



Notes: Estimates based on (2) using the orthogonalized narrative measure of changes in federal nondefense R&D appropriations, see (1). Impulses are scaled to imply a peak increase in in state and local structures of 1.21 dollars, to match Figure C.6. Sample: 1949Q1–2021Q4.

FIGURE C.8: Financing of S&L Investment in Structures



Notes: Estimates based on (2) using the orthogonalized narrative measure of changes in federal nondefense R&D appropriations, see (1). Impulses are scaled to imply a unit peak increase in S&L gross investment in structures. Sample: 1949Q1–2021Q4.

boom is not financed by an increase in federal transfers to state and local governments. The latter initially fall, and only revert to prior levels well after the peak in investment. For the first couple of years, the rise in investment is accounted for by an increase in borrowing by state and local governments. Between horizons of 4 to 10 years, the investment boom is implicitly financed by a surplus in revenues relative to other state and local spending. The main takeaway from Figure C.8 is that the rise in state and local investment in nondefense structures does not appear to be driven by increases in federal grants to state and local governments, for instance to increase spending on highways.

D Estimation of Production Function Elasticity: Additional Results

This section presents additional results for the estimation of the production function elasticity of government R&D capital ϕ in Section 4 in the main text.

D.1 SP-IV as a Regression in Impulse Response Space

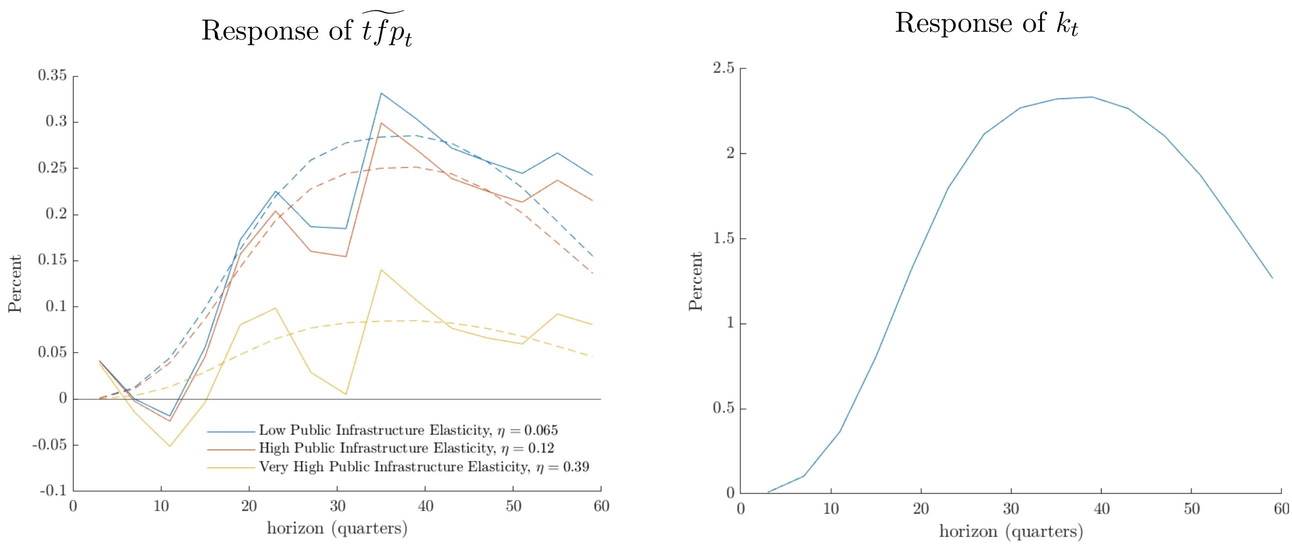
Figure D.1 provides the main intuition behind the SP-IV estimation of ϕ in (7) based on the response to the orthogonalized narrative measure of nondefense R&D appropriations, z_t^{ND}, using the specification in (2). The solid lines in the left panel show the response of $\widetilde{tfp}_t$ to a one standard deviation innovation in z_t^{ND} for three different values of η, and the right panel shows the estimated response of k_t, the government R&D capital stock. The figure shows the response for the endpoints of Ramey's (2021) plausible range, $\eta = 0.065$ and $\eta = 0.12$. To make the dependence on η visually clearer, the figure also shows the response for a much higher value $\eta = 0.39$, which is the estimate in Aschauer (1989). The SP-IV estimate of ϕ in each case is simply the OLS coefficient $\hat{\phi}$ in a regression (without intercept) of the impulse response coefficients of $\widetilde{tfp}_t$ in the left panel on those of k_t in the right panel. The dashed lines in the left panel show the resulting fitted values—$\hat{\phi}$ times the impulse response of k_t—that minimize the sum of squared residuals for each value of η. The SP-IV regression framework thus estimates the structural parameter as the value of ϕ that best fits the relationship between $\widetilde{tfp}_t$ and k_t along the impulse response trajectories. The functional form in (7) imposes very specific assumptions on the lags between R&D spending and the TFP effects. As Figure D.1 shows, the dynamics of the fitted TFP responses align well with those of the actual TFP responses, such that the timing assumptions implied by the structural equation appear to align well with the responses estimated in the local projections.

SP-IV can make use of more than one set of impulse response coefficients for identification, e.g. to both defense and nondefense shocks, in which case the different impulse responses are weighted by the inverse covariance matrix of the identifying innovations. The SP-IV estimator also applies to structural equations with multiple endogenous regressors, as in specification (9) in the main text, in which case it reduces to multiple regression in the impulse response space.

D.2 Simultaneous Confidence Sets

For the specifications with two endogenous regressors, such as (9) or (11) in the main text, the confidence intervals reported in Tables 1 and 2 are subvector confidence sets obtained

FIGURE D.1: Illustration of the SP-IV Estimator



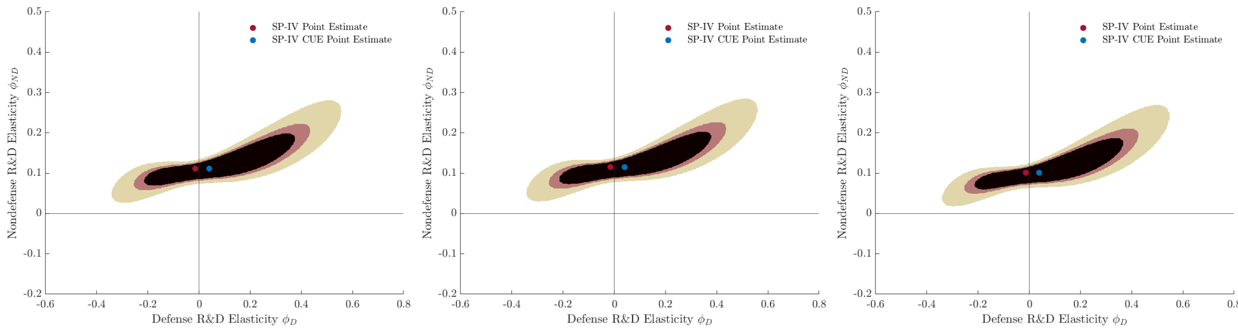
Notes: Solid lines show impulse response estimates (at one-year intervals) to a one standard deviation innovation in the orthogonalized narrative measure of changes in nondefense R&D appropriations using the baseline specification in (2) in a balanced sample. The SP-IV estimator $\hat{\phi}$ results from regressing the impulse response coefficients of $\widetilde{tfp}_t$ in the left panel on the impulse response coefficients of k_t in the right panel without intercept, see Lewis and Mertens (2023). The dashed lines in the left panel show the fitted responses obtained by multiplying $\hat{\phi}$ by the response of k_t in the right panel.

using the projection method, see for example Andrews et al. (2019). As an illustration, the panels in Figure D.2 show the 68, 90, and 95 percent weak-instrument-robust confidence sets for the full parameter vector $[\phi_{ND}, \phi_D]$ associated with the estimates reported in row [6] of Table 1. The confidence intervals reported in Table 1 for $\hat{\phi}_{ND}$ ($\hat{\phi}_D$) are the largest and smallest values of $\hat{\phi}_{ND}$ ($\hat{\phi}_{ND}$) across all values of ϕ_D ($\hat{\phi}_{ND}$) that belong to the 95 percent simultaneous confidence set. The simultaneous confidence sets are based on inverting the KLM statistic of Kleibergen (2005). The latter is based on the score of the continuously updated Anderson-Rubin statistic (or equivalently, the S-statistic of Stock and Wright (2000) for GMM) as a function of ϕ_{ND} and ϕ_D, see Lewis and Mertens (2023). The minimum of the Anderson-Rubin objective does not correspond to the SP-IV point estimate, such that the latter does not generally lie at the 'center' (or is even within) of the confidence sets. An alternative estimator of (ϕ_{ND}, ϕ_D) is the minimand of the continuously-updated Anderson-Rubin objective function, which by construction lies at the 'center' of the confidence sets. This continuously-updated estimator (CUE) is marked by the blue dots in Figure D.2. As can be seen from the figure, the CUE estimators of ϕ_{ND} are all very close to the SP-IV estimates, whereas those for ϕ_D are marginally larger.

Figure D.3 shows the simultaneous confidence sets for the three remaining specifications in Table 1 that include nondefense and defense capital separately (rows [7]-[9]). For brevity, the figure reports only the confidence sets for the specifications that assume the interme-

Figure D.2: Simultaneous Weak-Instrument Robust Confidence Sets

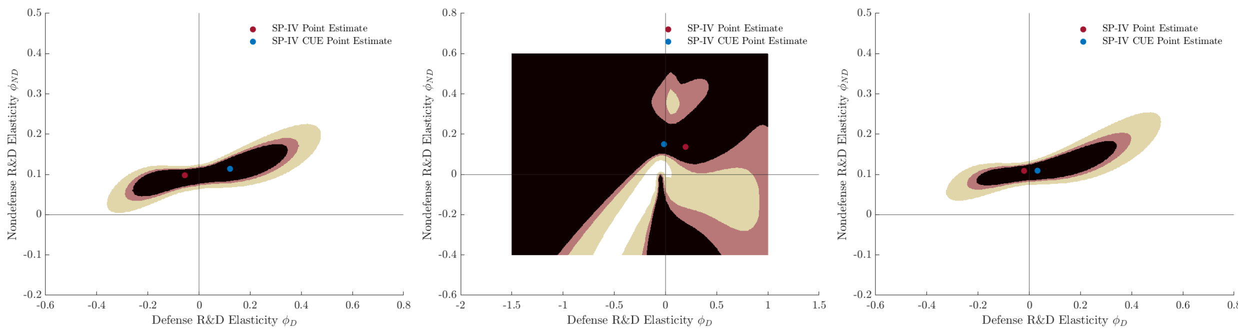
(a) Intermediate $\eta = 0.08$ (b) Low $\eta = 0.065$ (c) High $\eta = 0.12$



Notes: Confidence sets based on inverting the KLM statistic of Kleibergen (2005) for the specification in row [6] of Table 1.

Figure D.3: Simultaneous Weak-Instrument Robust Confidence Sets

(a) Using Both Shocks (b) Excluding Space (c) All Appropriations



Notes: Confidence sets based on inverting the KLM statistic of Kleibergen (2005) for the specification in rows [7]-[9] of Table 1 for $\eta = 0.08$.

diate value of the infrastructure elasticity, $\eta = 0.08$. As can be seen from the figures, the CUE estimate is usually close to the SP-IV estimate, and always nearly identical for the nondefense elasticity. The simultaneous confidence sets are also all very similar across the specifications. The exception is the specification with the narrative measure that excludes the large appropriations for the space race, see panel (b) in Figure D.3. For that specification, the confidence sets have highly irregular shapes, and most values of either parameter cannot be ruled at conventional levels of confidence.

D.3 Wald Inference

In the main text, inference for the SP-IV estimates is based on the weak-instrument robust methods for GMM described in Kleibergen (2005). Lewis and Mertens (2023) show that the SP-IV estimator is equivalent to a restricted 2SLS estimator in a system of equations,

Table D.1: SP-IV Elasticity Estimates with Wald Inference

	Public R&D Measure	Instruments	Intermediate η		Low η	High η
			ϕ_{ND}	ϕ/ϕ_D	ϕ/ϕ_{ND}	ϕ/ϕ_{ND}
[1]	Total	Exo ND	0.12*** (0.08,0.16)		0.12*** (0.08,0.17)	0.11*** (0.07,0.15)
[2]	Total	Exo ND, No Space	0.14*** (0.05,0.23)		0.14*** (0.05,0.24)	0.13*** (0.04,0.22)
[3]	Total	All ND	0.11*** (0.07,0.16)		0.12*** (0.08,0.16)	0.10*** (0.06,0.14)
[4]	Total	Exo D		−0.30 (−0.86,0.25)		
[5]	Total	All D		−0.29 (−0.83,0.26)		
[6]	ND/D	Exo ND	0.11*** (0.07,0.16)	−0.01 (−0.33,0.30)	0.12*** (0.07,0.16)	0.10*** (0.06,0.15)
[7]	ND/D	Exo ND/D	0.10*** (0.06,0.14)	−0.06 (−0.34,0.23)	0.10*** (0.06,0.14)	0.09*** (0.05,0.13)
[8]	ND/D	Exo ND, No Space	0.14** (0.03,0.24)	0.20 (−0.71,1.10)	0.14** (0.04,0.25)	0.13** (0.02,0.23)
[9]	ND/D	All ND	0.11*** (0.07,0.15)	−0.02 (−0.33,0.29)	0.11*** (0.07,0.15)	0.10*** (0.06,0.14)

Notes: See notes to Table 1 in the main text. The only difference is that the confidence intervals are based on the Wald formulas derived under the assumption of strong identification, see Lewis and Mertens (2023).

where the number of equations is equal to the number of impulse response horizons used for identification. Under strong identification and otherwise standard assumptions, this formulation of the SP-IV estimator leads to conventional Wald inference formulas. It is well known that—when identification is weak—Wald inference can suffer from large size distortions in small samples, and the simulations in Lewis and Mertens (2023) show that this is also the case for the SP-IV estimator. Table D.1 shows the same point estimates as Table 1 in the main text, but reports confidence intervals based on the conventional Wald formulas. Qualitatively, the only specification for which there are large differences in the inference results is the one in row [8], i.e. the specification with the narrative measure that excludes the large appropriations for the space race. The Wald-based inference points to estimates that are highly statistically significant, whereas the weak-instrument-robust inference result leads to the conclusion that the instrument is uninformative.

D.4 Specification with Constant Elasticities

In specification (9) in the main text, the production function elasticities of defense and nondefense R&D capital scale with their nominal shares in total government R&D capital. The following specification instead imposes constant elasticities:

$$\text{(D.1)} \qquad \Delta\widetilde{tfp}_t = \phi_{ND}\left(\bar{s}_{ND}\Delta k_t^{ND}\right) + \phi_D(1-\bar{s}_{ND})\Delta k_t^D + \Delta w_t$$

Table D.2: Government R&D Production Function Elasticities
Alternative Specification

	Public R&D Measure	Instruments	Intermediate $\eta = 0.08$ $\hat{\phi}/\hat{\phi}_{ND}$	Intermediate $\eta = 0.08$ $\hat{\phi}/\hat{\phi}_{D}$	Low $\eta = 0.065$ $\hat{\phi}/\hat{\phi}_{ND}$	High $\eta = 0.12$ $\hat{\phi}/\hat{\phi}_{ND}$
[1]	ND/D	Exo ND	0.07^{**} (0.02,0.13)	0.16 (-0.43,0.47)	0.07^{**} (0.02,0.13)	0.06^{**} (0.01,0.12)
[2]	ND/D	Exo ND/D	0.08^{**} (0.01,0.13)	-0.04 (-0.33,0.37)	0.09^{**} (0.01,0.13)	0.08^{**} (0.00,0.12)
[3]	ND/D	Exo ND, No Space	0.16 ($-2.00^{\dagger}$,0.11)	-0.23 (-0.98,$2.00^{\dagger}$)	0.16 ($-2.00^{\dagger}$,0.11)	0.15 ($-2.00^{\dagger}$,0.10)
[4]	ND/D	All ND	0.07^{***} (0.02,0.13)	0.13 (-0.41,0.43)	0.07^{***} (0.02,0.13)	0.06^{**} (0.01,0.12)

Notes: Rows [1]-[4] show SP-IV estimates of ϕ_{ND} (nondefense) and ϕ_D (defense) in (D.1). All specifications include the baseline set of lagged controls described in Section 3. Numbers in parentheses are weak-instrument robust confidence intervals at the 5 percent significance level based on inverting the KLM statistic of Kleibergen (2005). Test inversion is limited to a grid with endpoints -2 and 2, † denotes intervals constrained at these endpoints. Subvector inference is based on the projection method. $*$, $**$ and $***$ denote statistical significance at 10, 5 and 1 percent levels respectively. 'Exo ND/D' denotes the orthogonalized narrative measure of exogenous changes in nondefense/defense R&D appropriations. 'All ND/D' denotes the orthogonalized series of all changes in nondefense/defense R&D appropriations, ignoring our narrative classification. 'No Space' indicates that the instrument is also orthogonalized to all changes in space appropriations between 1958 and 1963.

We multiply the regressors by the average shares, $\bar{s}_{ND}$ and $1 - \bar{s}_{ND}$, over the estimation sample, such that the estimates are on a comparable scale to those reported in Table 1 in the main text. The estimation results based on (D.1) are reported in Table D.2. The estimates can be multiplied by $\bar{s}_{ND} \approx 0.5$ to obtain the elasticities with respect to Δk_t^{ND} and Δk_t^{D}.

The main difference with the results in the main text is that the point estimates for ϕ_{ND} are smaller. The only exception is in row [3], but this is also the specification for which the estimates are very imprecise. Ignoring the results in row [3], the point estimates of ϕ_{ND} are around 0.07, as compared to 0.12 under the specification discussed in the main text. The estimates of ϕ_{ND} are relatively precisely estimated (except in row [8]), and they are highly statistically significant. Just as in the main text, the estimates of ϕ_D vary considerably across the specifications. They are always imprecise and never statistically distinguishable from zero.

The difference in the estimates of ϕ_{ND} between the specification in equation (9) and the one in (D.1) is not too surprising, given that the share of nondefense R&D varies considerably over the estimation sample. Given that the stock of nondefense R&D capital is small in the beginning of the sample, the log differences Δk_t^{ND} are very large early on, which leads to lower overall estimates of ϕ_{ND}. Weighting by the shares as in the baseline specification (9) in the main text attenuates the influence of these early observations, and should therefore lead to more accurate estimates for the whole sample.

Even if one would prefer the lower estimates in Table D.2, they do not change the overall conclusion that the rate of return on nondefense government R&D is very high. Dividing the estimates in rows [1],[2] and [4] of Table D.2 by 0.06 (the average ratio of government R&D capital to GDP), the implied rates of returns range from 100 to 150 percent.

Finally, note that the point estimates of ϕ_{ND} in row [3] of Table D.2 lie outside of the reported weak-instrument-robust confidence intervals. As explained in Appendix D.2, this is possible with the inference methods based on Kleibergen (2005).

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