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
- NCSES: 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 NCSES/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 2.1.

- **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 Industry Portfolios).

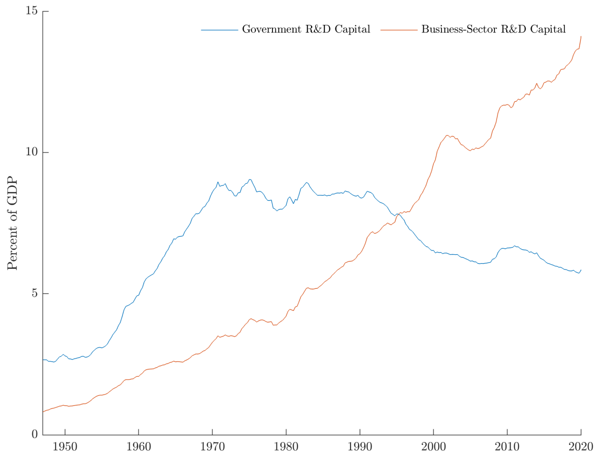
- **Military News**: `'news'` in replication files of Ramey and Zubairy (2018) converted to 2012 dollars by the implicit GDP deflator, divided by potential output.

- **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. 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. Quarterly interpolation of annual data.

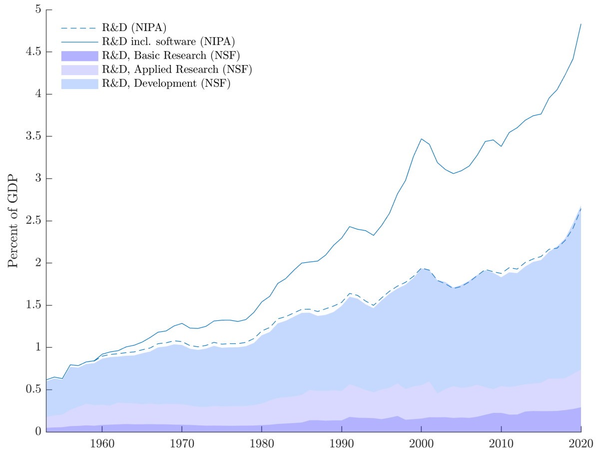
- **Researchers**: Total researchers (full-time equivalents), from the OECD Main Science and Technology Indicators. Pre-2000 data is obtained from the replication files of Bloom et al. (2020). Quarterly interpolation of annual data.

FIGURE B.1: R&D Capital Stocks



Notes: R&D capital includes software. See Appendix A for variable definitions. *Source*: BEA, Fernald (2012).

FIGURE B.2: Private R&D Expenditures



Notes: Fiscal year NCSES data are converted to calendar years and exclude R&D plant. *Sources*: BEA; NCSES, National Patterns of R&D Resources (Tables 7, 8, and 9).

- **Technology Books**: Books published in the field of technology, constructed by Alexopoulos (2011) and obtained from the replication files of Kogan et al. (2017). Quarterly interpolation of annual data.

B Government and Private R&D: Additional Facts

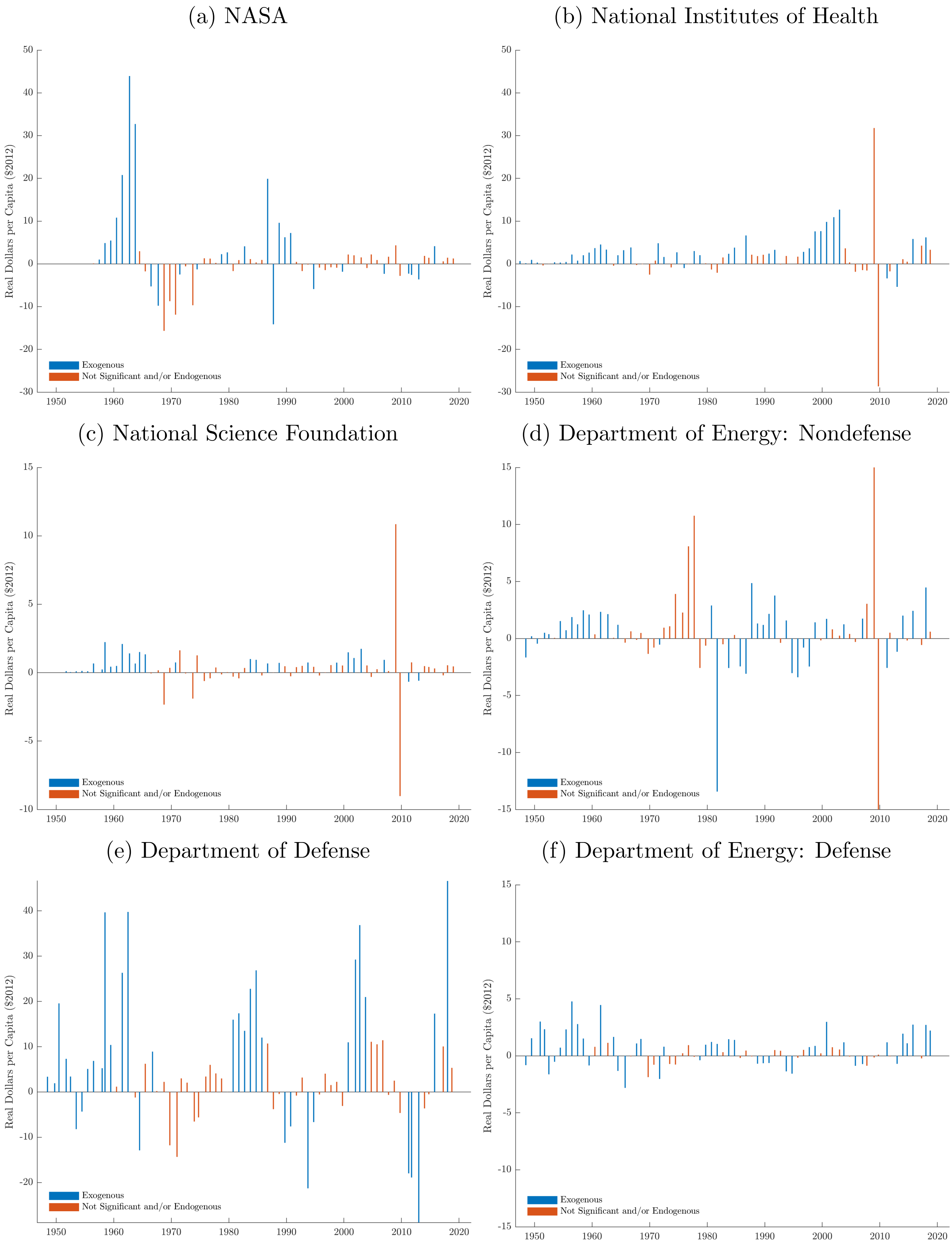
Figure B.1 plots the government and business-sector R&D capital stocks as a ratio of GDP. Over the postwar sample, government R&D capital (blue line) averages 6.6 percent of GDP (3.9 percent nondefense and 2.7 percent defense). The business-sector R&D capital stock (red line) averages 6.3 percent, rising from around 1 percent immediately after WWII to almost 15 percent in recent years.

Figure B.2 plots the NCSES measures of private R&D spending by type as a ratio of GDP, along with the NIPA totals for comparison. As the figure shows, the NIPA measure of private R&D spending (excluding software development) aligns closely with the NCSES total. Over the postwar period, average private R&D expenditures are 0.14 percent of GDP on basic research, 0.30 percent of GDP on applied research, 0.97 percent on experimental development (excluding software), and 0.77 percent on software.

C Narrative Appropriations Shocks by Agency

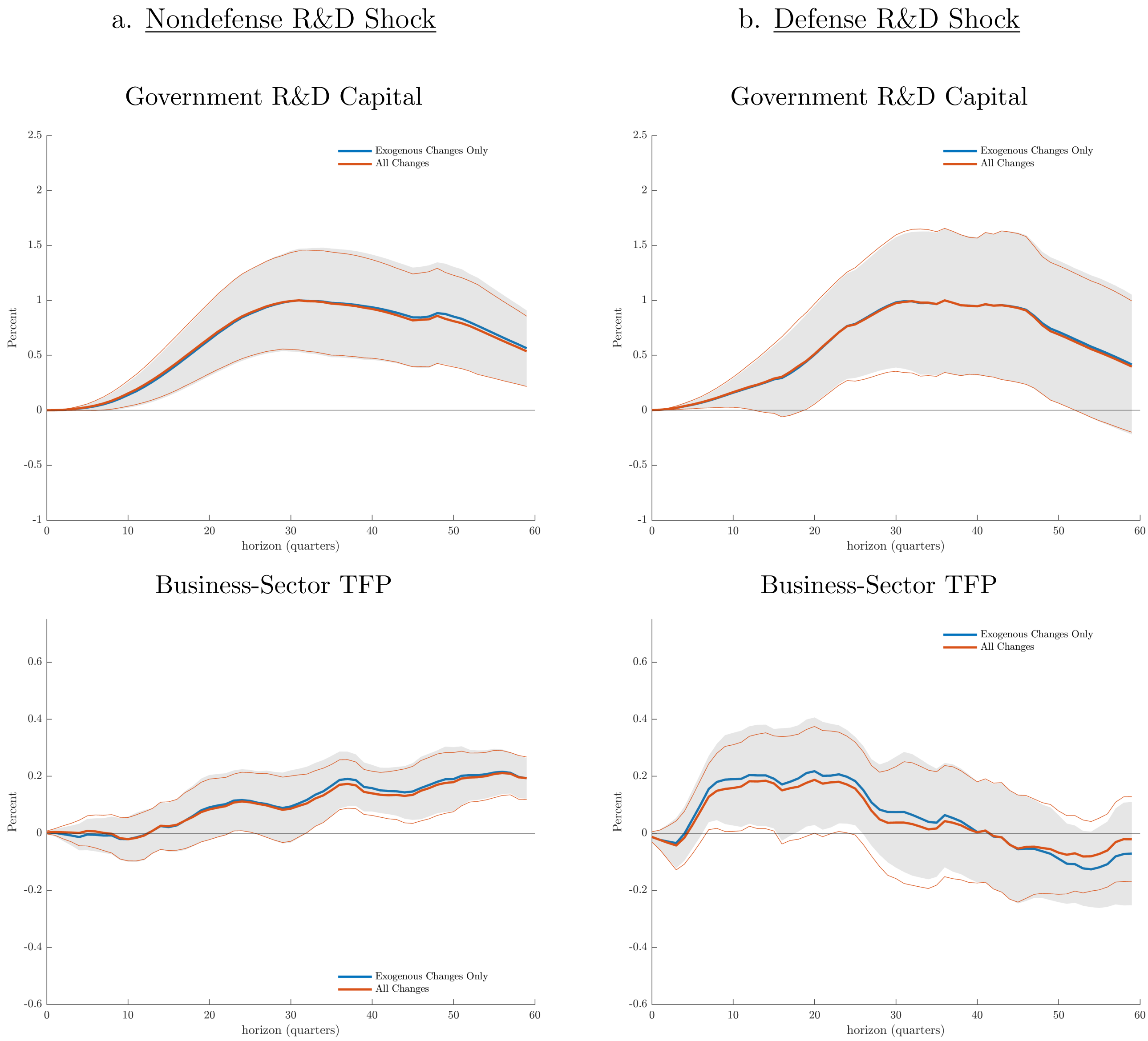
Figure C.1 depicts the narrative R&D appropriations changes separately for each agency, before aggregation to nondefense versus defense R&D policy changes, as depicted in Figure 5 of the main text. The top four panels of Figure C.1 depict the R&D appropriations shocks for nondefense expenditures, with 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 depicted in blue, and those classified as endogenous

Figure C.1: Changes in R&D Appropriations by Federal Agency



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

Figure D.1: Role of Narrative Classification



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

(or too small to classify) are in red; all R&D appropriations shown are measured in real dollars per capita.

D Impulse Responses: Robustness and Additional Results

D.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 D.1 replicates the baseline impulse responses to nondefense and defense shocks from Figure 6 in the main text (blue lines and gray bands). The figure also shows estimates for the same specifications but using all changes in R&D appropriations rather than just those identified as 'exogenous' (red lines). In this case, the z_t^i variables in (1) are redefined to contain all changes in appropriations shown in Figure 5 instead of only those that are classified exogenous by the narrative analysis. As the figure show, 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.

D.2 Robustness: Mutually Orthogonalized Narrative Measures

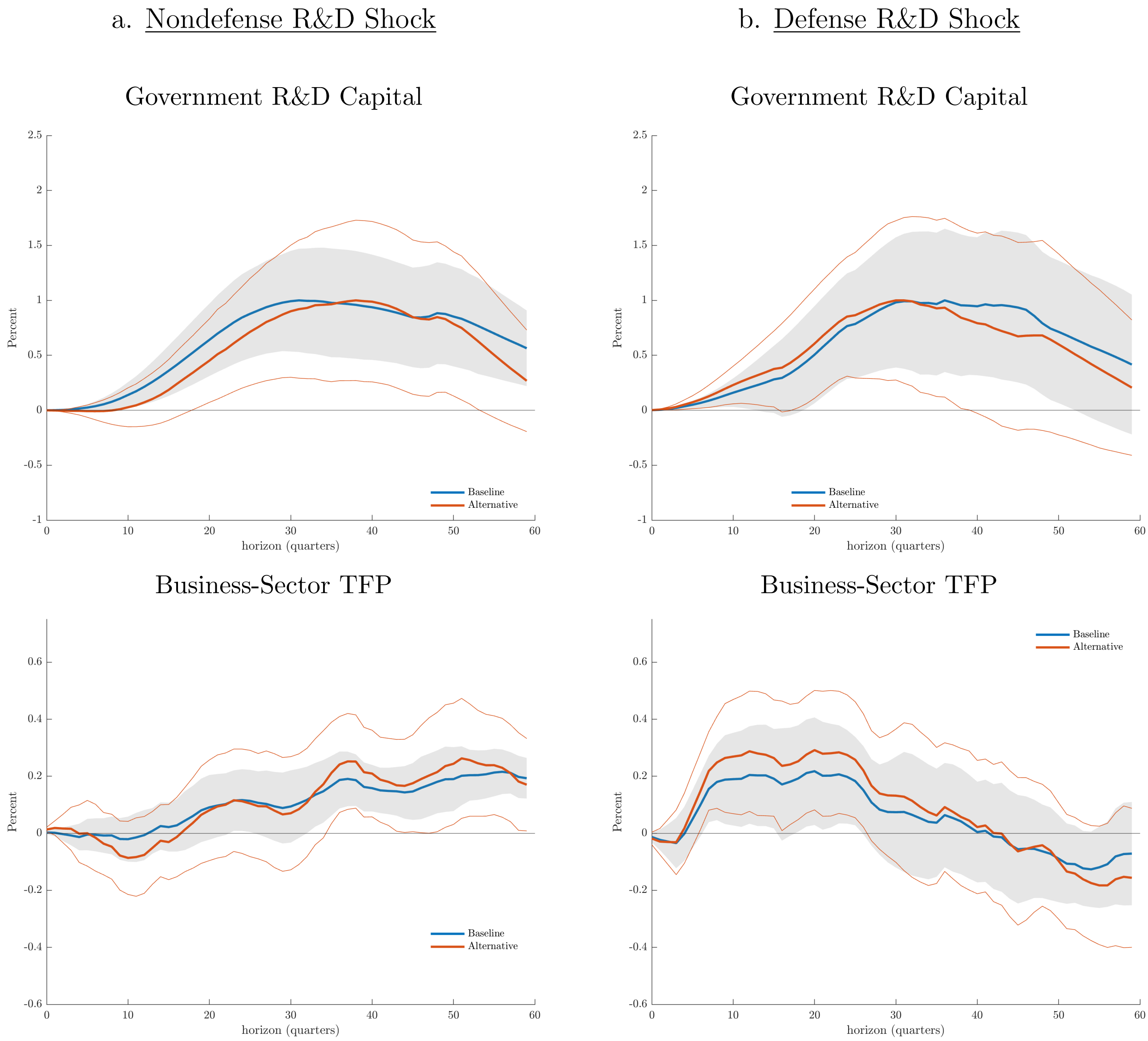
As mentioned in the main text, the correlation between both narrative measures is 0.31, which indicates that changes in one category of government R&D tend to go hand in hand with changes in the other. This section discusses an alternative local projections specification that simultaneously includes both narrative measures. The alternative specification estimates impulse responses to an innovation in the nondefense (defense) measures after controlling for the contemporaneous value of the defense (nondefense) measure. Specifically, we estimate the impulse response coefficients to both shocks using

$$\text{(D.1)} \qquad \sum_{j=0}^{3}\left(\frac{1}{4}\times y_{t+h-j}\right) = c_h + \gamma_h^{ND} z_t^{ND} + \gamma_h^{D} z_t^{D} + \sum_{j=1}^{p}\beta_h^j \ln(a_{t-j}^{ND}) + \sum_{j=1}^{p}\beta_h^j \ln(a_{t-j}^{D}) + \sum_{j=1}^{p}\delta_h^j y_{t-j} + \sum_{j=1}^{p}\zeta_h^{j\prime} x_{t-j} + v_{t,h}$$

where $\{\gamma_h^{ND}\}_{h=0}^{H-1}$ and $\{\gamma_h^{D}\}_{h=0}^{H-1}$ are the impulse response coefficients to a nondefense and defense shock, respectively. By conditioning on the appropriations in the other category, the alternative specification estimates causal effects of more idiosyncratic movements in nondefense (defense) appropriations by imposing that the contemporaneous response of the narrative measure for the defense (nondefense) category is zero. The impulse responses have the interpretation as the impact of a change in R&D funding targeting one category while leaving appropriations for the other category unchanged on impact (but not necessarily in future quarters).

Figure D.2 replicates the baseline impulse responses to nondefense and defense shocks from Figure 6 in the main text (blue lines and gray bands), and also plots the impulse responses from the alternative specification in (D.1) (red lines). As the figure shows, the impulse responses to both the defense and nondefense R&D shocks under the alternative specification remain very similar to the baseline.

FIGURE D.2: Role of Orthogonalization of the Narrative Measures

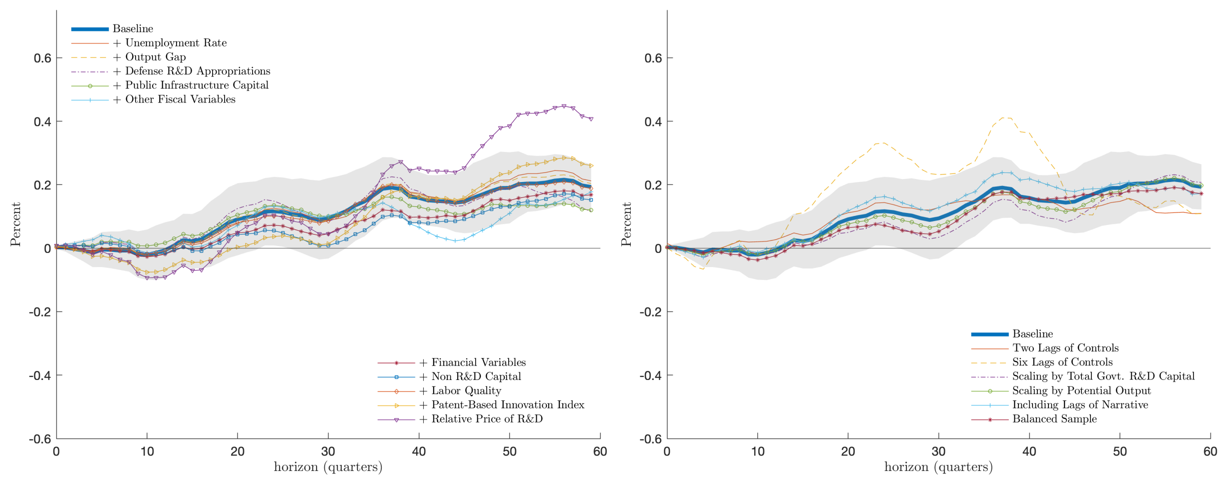


Notes: Baseline estimates are based on (1) and use the narrative measures of changes in federal nondefense (left panel) and defense (right panel) R&D appropriations. The estimates for the alternative specification are based on (D.1) and the same narrative measures. Confidence bands are 95 percent HAR based on Lazarus et al. (2018). Impulses are scaled to imply a 1 percent peak increase in government R&D capital. Sample: 1948Q1–2021Q4.

The timing of the responses to a nondefense shock changes slightly, with effects on government R&D capital and TFP that are somewhat more delayed relative to the baseline but otherwise very similar in magnitude. The impact of a defense shock on government R&D capital, on the other hand, is slightly more frontloaded, while both the short-run increase and longer-run decrease in TFP are a little more pronounced. The positive long-run effect on TFP of a shock to nondefense appropriations remains statistically significant at horizons beyond 8 years. In general, the inclusion of the additional regressors in the alternative specification leads to estimates that are less precise than our baseline specification.

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

(a) Additional Control Variables (b) Model Specification



Notes: Estimates based on (1) using the narrative measure of federal nondefense R&D appropriations. Lazarus et al. (2018) 95 percent HAR confidence bands shown 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).

D.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 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 D.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 (a) in the main text. Rows [2]-[11] in Table D.1 report the impulse response coefficients at horizons of 5, 10, and 15 years with 95 percent 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 D.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 that R&D appropriations, despite accounting for only a small share of 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 (2025) find that government spending shocks raise long-run TFP, Cloyne et al. (2025) 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 results in a slightly faster TFP response that is larger at medium horizons and somewhat smaller after 15 years. The TFP response remains statistically significant (row [4] in Table D.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 significant at longer horizons (see row [5] in Table D.1). Controlling for lags of a broader set of fiscal policy indicators results in a more delayed response of TFP, but at longer horizons, the magnitude is roughly the same, and the estimates remain highly significant (see row [6] in Table D.1).

The baseline controls include cumulative real stock returns in R&D-intensive industries to capture any broad, advanced 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 D.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 D.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 either the relative price of R&D or the innovation index leads to estimates that are considerably larger. The addition of the labor quality index does not have any major impact on the estimates. As rows [8]-[11] in Table D.1 show, the estimates of the TFP response at longer horizons remain highly statistically

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

		% Impact After		
		5 years	10 years	15 years
[1]	Baseline	0.08 (−0.03,0.19)	0.16*** (0.08,0.25)	0.19*** (0.12,0.26)
[2]	+ Unemployment Rate	0.07 (−0.05,0.18)	0.18*** (0.07,0.28)	0.21*** (0.12,0.31)
[3]	+ Output Gap	0.08 (−0.03,0.19)	0.17*** (0.08,0.26)	0.20*** (0.12,0.28)
[4]	+ Defense R&D Appropriations	0.11 (−0.08,0.30)	0.19*** (0.07,0.30)	0.12* (−0.01,0.24)
[5]	+ Public Infrastructure Capital	0.09* (−0.01,0.20)	0.13*** (0.06,0.21)	0.12*** (0.06,0.18)
[6]	+ Other Fiscal Variables	0.06 (−0.07,0.19)	0.08 (−0.03,0.19)	0.18*** (0.07,0.29)
[7]	+ Financial Variables	0.04 (−0.04,0.12)	0.10** (0.01,0.18)	0.17*** (0.09,0.25)
[8]	+ Non R&D Capital	0.04 (−0.05,0.12)	0.08** (0.01,0.15)	0.15*** (0.09,0.22)
[9]	+ Labor Quality	0.07 (−0.04,0.18)	0.17*** (0.09,0.25)	0.19*** (0.11,0.27)
[10]	+ Patent-Based Innovation Index	−0.00 (−0.10,0.09)	0.16*** (0.05,0.27)	0.26*** (0.14,0.38)
[11]	+ Relative Price of R&D	0.02 (−0.14,0.19)	0.25*** (0.09,0.40)	0.41*** (0.18,0.64)
[12]	Two Lags of Controls	0.10** (0.01,0.20)	0.15*** (0.04,0.27)	0.11** (0.00,0.21)
[13]	Six Lags of Controls	0.23* (−0.02,0.48)	0.37*** (0.18,0.55)	0.11 (−0.07,0.29)
[14]	Scaling by Total Govt. R&D Capital	0.05 (−0.07,0.16)	0.12*** (0.03,0.21)	0.21*** (0.14,0.27)
[15]	Scaling by Potential Output	0.07 (−0.04,0.18)	0.15*** (0.07,0.22)	0.20*** (0.13,0.27)
[16]	Including Lags of Narrative	0.10 (−0.02,0.23)	0.21*** (0.12,0.31)	0.17*** (0.11,0.23)
[17]	Balanced Sample	0.06 (−0.06,0.18)	0.16*** (0.08,0.24)	0.17*** (0.11,0.24)

Notes: Estimates are based on (1) 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 R&D capital. Sample: 1948Q1–2021Q4 (specification with patent-based innovation index: 1949Q1–2010Q4).

significant in each case.

D.4 Robustness: LP 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 (1). Panel (b) in Figure D.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]-[17] in Table D.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 D.3 shows, reducing lag length from four to two quarters leads to somewhat smaller TFP responses at horizons beyond 10 years; the long-run TFP responses remain highly statistically significant (see row [12] of Table D.1). Increasing the lag length from four to six quarters makes the TFP response somewhat more volatile, with a much larger and highly significant response at 5 or 10 years but a somewhat smaller response that ceases to be statistically significant at longer horizons (see row [13] of Table D.1).

In the baseline specification, the narrative nondefense and defense measures, z_t^{ND} and z_t^{D}, are constructed by scaling the real appropriations by the nondefense and defense R&D capital stocks, respectively. The next robustness checks consider two alternative scalings for constructing the narrative measures. The first is based on scaling the appropriations by the total government R&D capital stock (defense and nondefense) for both categories. The second is based on scaling the appropriations by potential GDP for both categories. As in the baseline specification we scale in each case by the observations lagged by one year to avoid introducing endogeneity problems. As panel (b) in Figure D.3 shows, the alternative scalings have only modest effects on the impulse responses of TFP. Rows [14] and [15] in Table D.1 show that the point estimates remain similar to those of the baseline specification.

The baseline set of controls includes four lags of the (log) of cumulative nondefense R&D appropriations but not lags of the narrative measures themselves. Panel (b) in Figure D.3 shows that including these lags has very little effect on the estimated TFP response and the associated confidence bands (see row [16] in Table D.1).

Finally, the inference formulas for SP-IV developed in Lewis and Mertens (2024) require a balanced sample. The impulse responses in Section 3 are instead estimated iteratively, i.e., using the largest possible estimation sample for each horizon h. Panel (b) in Figure D.3 provides the estimated TFP response in the balanced sample, which shows only relatively minor differences with the baseline estimates. As seen in row [17] of Table D.1, the estimates also remain highly statistically significant in the balanced sample.

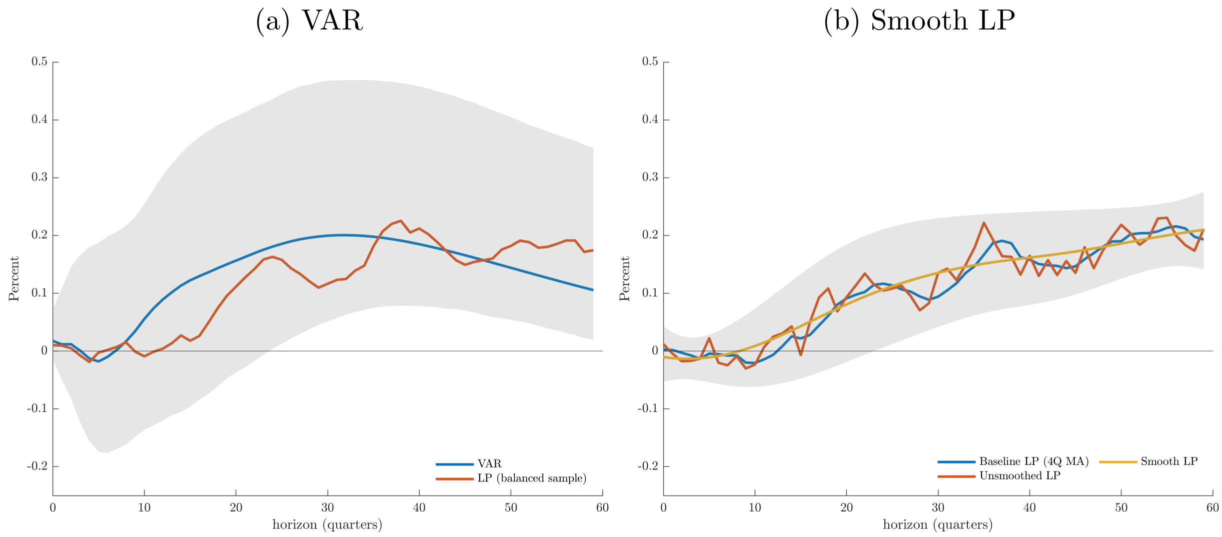
D.5 Robustness: Alternative Impulse Response Estimators

The impulse responses in the main text are estimated using Jordà (2005) local projections. This section instead reports results for two less densely-parameterized impulse response estimators: Vector Autoregressive Models (VARs) and Smooth Local Projections (SLP).

Asymptotically, VARs estimate approximately the same impulse response as local projections up to the lag length of the VAR model, see Plagborg-Møller and Wolf (2021). An advantage of LPs is that they avoid misspecification in finite-order VAR-based impulse response estimators at horizons beyond the lag length. In small samples, however, this advantage generally comes at the cost of greater variance, as shown, for instance, in the simulations of Li et al. (2024). In practice, VAR and LP impulse response estimates can differ meaningfully in small samples, raising questions about robustness.

Panel (a) in Figure D.4 presents estimates of the TFP response to a nondefense R&D shock based on

Figure D.4: TFP Impact of Nondefense R&D Shock, VAR and Smooth LP Estimates



Notes: Left panel: Estimates from an eight-variable VAR(4) model that includes all the variables from the baseline specification: the nondefense narrative measure, cumulative appropriations, (log) utilization-adjusted TFP, and the additional baseline controls described in the main text). VAR impulses are to an innovation in the narrative measure, scaled to imply a 1 percent peak increase in government R&D capital. The 95 percent confidence bands for the VAR impulse are percentile intervals based on the wild bootstrap described in Section 5 of Montiel Olea and Plagborg-Møller (2021). Right panel: Point estimates and 95 percent confidence bands using smooth LP as in Barnichon and Brownlees (2019), along with estimates from the baseline LP model both for quarterly TFP and 4Q-moving average TFP. Sample: 1948Q1-2021Q4.

a VAR model, together with 95 percent confidence bands obtained using the wild bootstrap procedure described in Montiel Olea and Plagborg-Møller (2021). The estimates are obtained from an 'internal instrument' VAR with four lags in eight variables: the nondefense narrative measure, (log) utilization-adjusted TFP, (log) cumulative sum of past changes in real nondefense R&D appropriations, and the additional controls of the baseline specification described in the main text. For comparison, the figure also shows the point estimates from the corresponding LP model obtained in the same balanced sample that is used to estimate the VAR model.

As panel (a) in Figure D.4 shows, the VAR-based impulse response confirms our key finding: after a substantial delay, a positive shock to nondefense R&D appropriations leads to a gradual increase in business-sector TFP that becomes statistically significant in the long run. Overall, the magnitude of the VAR response is also similar to the LP response. The restrictions on the dynamics implied by the VAR do lead to some qualitative differences with the LP-based estimates. Specifically, the increase in TFP starts somewhat earlier and is hump-shaped. Despite these differences, we conclude that the positive long-run TFP response is robust to the choice of a VAR or LP-based impulse response estimator.

Panel (b) in Figure D.4 compares the baseline LP response of TFP to a shock to nondefense R&D appropriations to those obtained from the SLP estimator proposed by Barnichon and Brownlees (2019). The baseline specification estimates the response of a backward 4-quarter moving average of the quarterly TFP series, which is shown in blue in the figure. For comparison, the red line shows the estimated response of the original quarterly TFP series before taking the 4-quarter moving average. Unsurprisingly, the 4-quarter averaging smooths out some of the quarterly noise in the estimates that is evident in the response of the original TFP series. An alternative approach is that of Barnichon and Brownlees (2019), who propose a 'smooth' LP estimator that approximates the IRF by a linear combination of basis functions while using a shrinkage estimator to penalize deviations from a polynomial function of choice. The resulting SLP estimator balances the flexibility of LP with the variability in the IRF estimates depending on the degree of shrinkage. The yellow line shows the TFP response estimated by SLP with shrinkage towards a second-order polynomial and the degree of shrinkage determined by the cross-validation procedure recommended in Barnichon and Brownlees (2019), while the gray region depicts the associated 95 percent confidence band. As the figure shows, the SLP estimates deliver a smoothed version of the underlying IRF of quarterly TFP obtained with standard LP. The SLP response of TFP is statistically significant at longer horizons, and the width of confidence bands is generally comparable to those of the baseline estimates in panel (a) of Figure 6. We find similar results (available on request) for the other outcome variables, with SLP usually leading to similar or tighter confidence bands than LP.

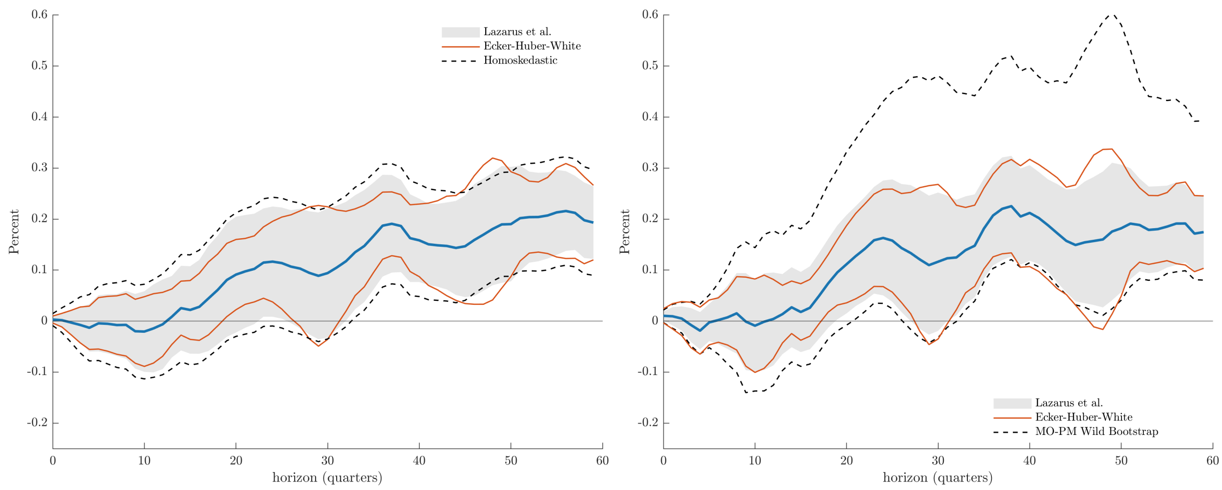
D.6 Robustness: Alternative LP Inference Procedures

The confidence intervals for the impulse responses are based on the equal-weighted cosine (EWC) test recommended by Lazarus et al. (2018). Herbst and Johanssen (2024) show in simulations that EWC delivers better empirical coverage than heteroskedasticity-and-autocorrelation robust (HAR) inference based on Newey and West (1987) or heteroskedastic-robust inference based on Eicker-Huber-White. Montiel Olea and Plagborg-Møller (2021) show that accounting for autocorrelation is redundant in lag-augmented LPs and that it suffices to use Eicker-Huber-White standard errors. The same authors also describe a wild bootstrap procedure that—in simulations of AR(1) models—delivers better coverage in small samples, especially at longer horizons and when the data is highly persistent.

Figure D.5 compares various inference procedures for the impulse response of utilization-adjusted TFP based on the narrative measure for nondefense R&D appropriations. The left panel shows Eicker-Huber-White intervals and the simple intervals assuming homoskedasticity, along with the Lazarus et al. (2018) intervals, for the baseline specification with additional controls (same as in the bottom left panel of Figure 6). To capture a longer history of appropriations for R&D, the baseline specification includes lags of cumulative appropriations as controls rather than lags of the narrative measures. The right panel shows point estimates and confidence intervals based on specifications that additionally include four lags of the narrative measure, i.e., the explicit lag-augmented specification considered in Montiel Olea and Plagborg-Møller (2021). Apart from the Lazarus et al. (2018) intervals, the right panel again shows the Eicker-Huber-White intervals as well as the intervals based on the Montiel Olea and Plagborg-Møller (2021) wild bootstrap procedure.

The main conclusion from Figure D.5 is that the choice of inference procedures is relatively unimportant. The homoscedastic and Eicker-Huber-White bands are similar to the Lazarus et al. (2018)

Figure D.5: TFP Impact of Nondefense R&D Shock, Alternative Inference Procedures



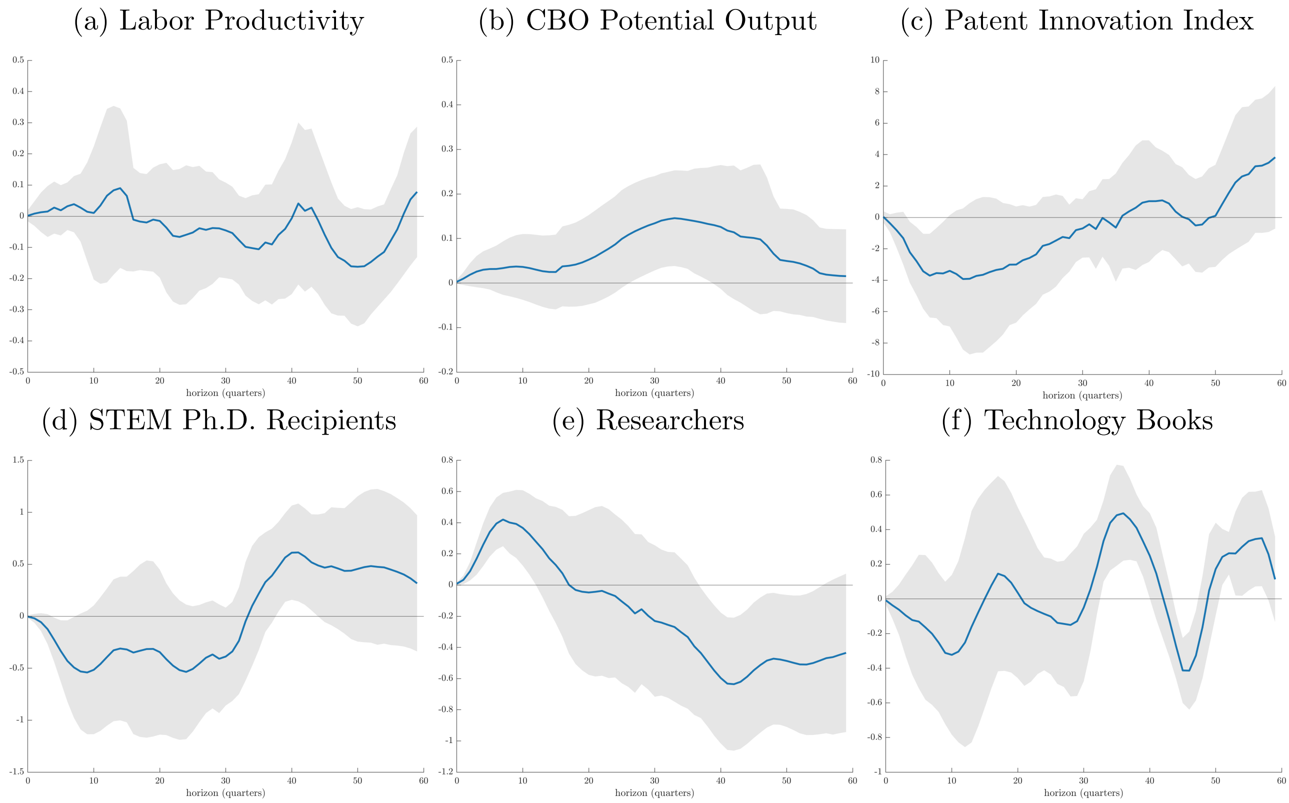
Notes: All confidence intervals are for the 95 percent level. *Left Panel*: Point estimates and shaded confidence intervals (Lazarus et al. (2018) HAR) are identical to those in the bottom left panel of Figure 6 (baseline specification). *Right Panel*: Point estimates and shaded confidence intervals (Lazarus et al. (2018) HAR) are based on the baseline specification with four lags of the nondefense narrative measure added to the controls. The figure also shows bootstrap intervals as described in Section 5 of Montiel Olea and Plagborg-Møller (2021), based on 10,000 samples. Impulses are scaled to imply a 1 percent peak increase in government R&D capital. Sample: 1948Q1-2021Q4.

EWC bands. The wild bootstrap bands are meaningfully wider, but the increase in coverage lies mostly to the north of the Lazarus et al. (2018) region. Especially at longer horizons, the lower bootstrap band is relatively close to the Lazarus et al. (2018) band. Importantly, the finding that a shock to nondefense R&D appropriations leads to a statistically significant long-run increase in business-sector TFP is not affected by the choice of inference procedures. We caution the reader that inference at long horizons in finite samples is generally challenging, and meaningful undercoverage remains a possibility for all procedures discussed.

D.7 Impact of a Defense R&D Shock on Other Productivity/Innovation Indicators

Figure 7 in the main text reports the impact of a nondefense R&D shock on various productivity measures and innovation indicators. Figure D.6 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 a positive defense R&D shock. Figure D.6 shows no evidence of any increase in labor productivity. Potential output rises gradually up to 0.10 percent, and the response becomes statistically significant between 8 to 10 years. The response reverts back to zero towards the end of the forecast horizon and is neither economically or statistically significant in the long run. There are also 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.

Figure D.6: Impact of a Defense R&D Shock on Other Productivity/Innovation Indicators



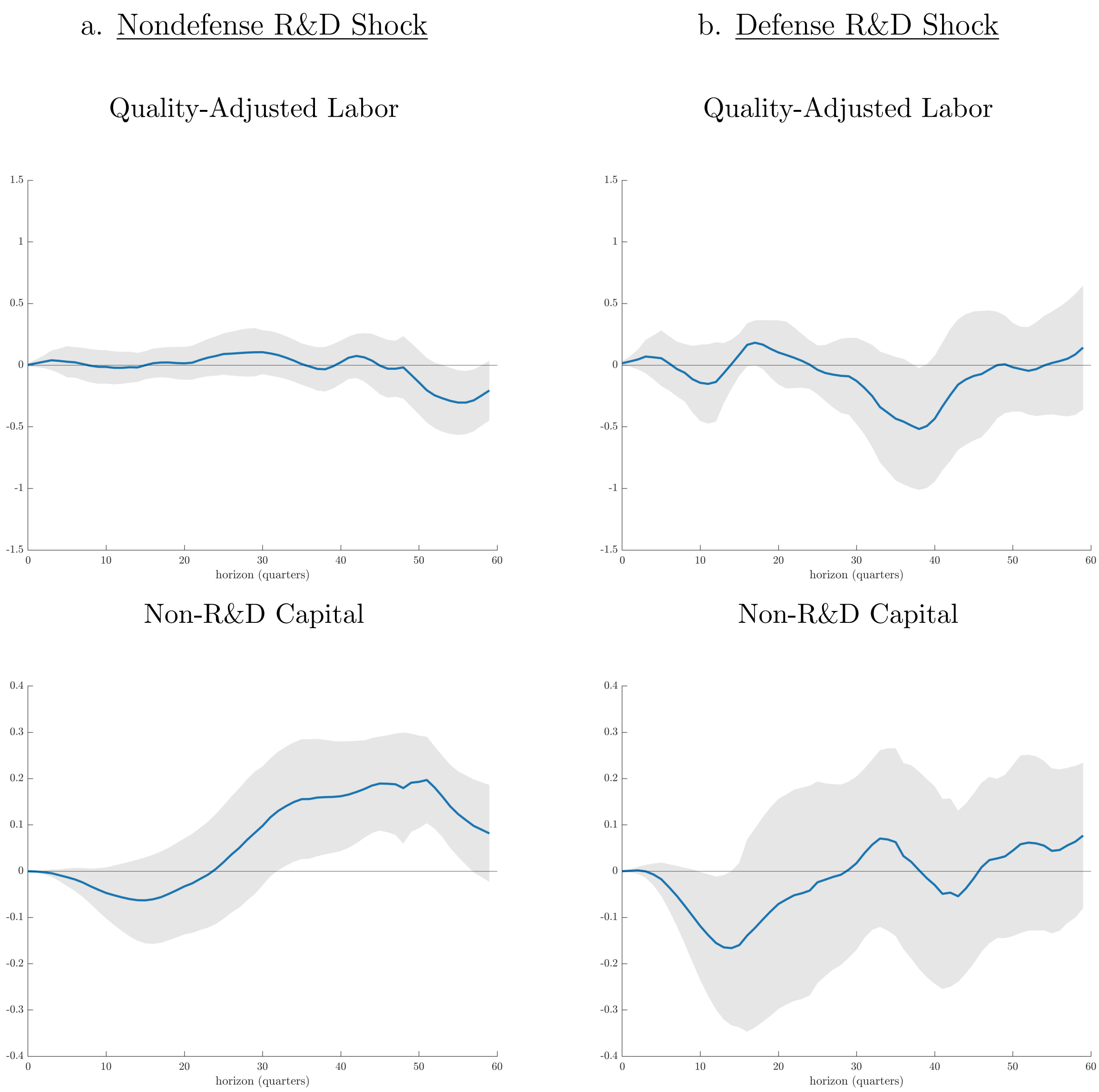
Notes: Estimates based on (1). Confidence bands are 95 percent HAR based on Lazarus et al. (2018). Impulses scaled to imply a 1 percent peak increase in government R&D capital. Sample: (a),(b),(d): 1948Q1–2021Q4; (c): 1949Q1–2010Q4; (e): 1951Q1–2019Q4; (f): 1956Q1–1997Q4. See Appendix A for variable definitions.

D.8 Responses of Private Labor and non-R&D Capital Inputs

Figure D.7 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 (1) 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 D.7 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 intellectual property excluding R&D and software).

The first row in Figure D.7 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 a few horizons. The response of labor input to a defense R&D shock is somewhat volatile and imprecisely estimated,

Figure D.7: Labor and non-R&D Capital Following an Increase in R&D Appropriations

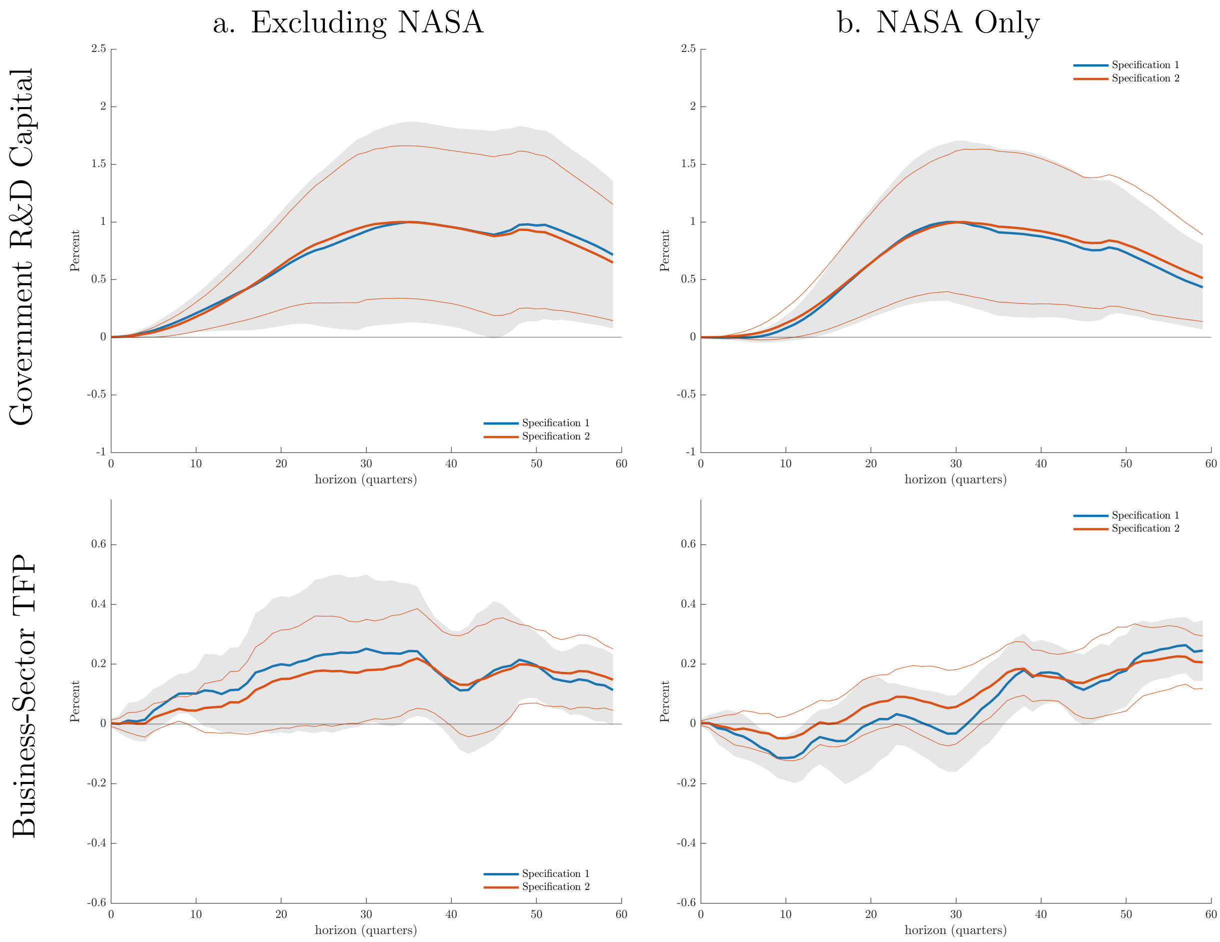


Notes: Estimates based on (1) using the measures of changes in federal nondefense (left panel) and defense (right panel) R&D appropriations. 'Baseline' includes additional lagged controls described in the main text. Confidence bands are 95 percent HAR based on Lazarus et al. (2018). Impulses scaled to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

with estimates that are mostly not statistically significantly different from zero at the 5 percent level.

The second row in Figure D.7 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 9 to 12 years, with a peak increase in non-R&D capital of roughly 0.2 percent. 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.

FIGURE D.8: Government R&D Capital and TFP Following a Nondefense Shock



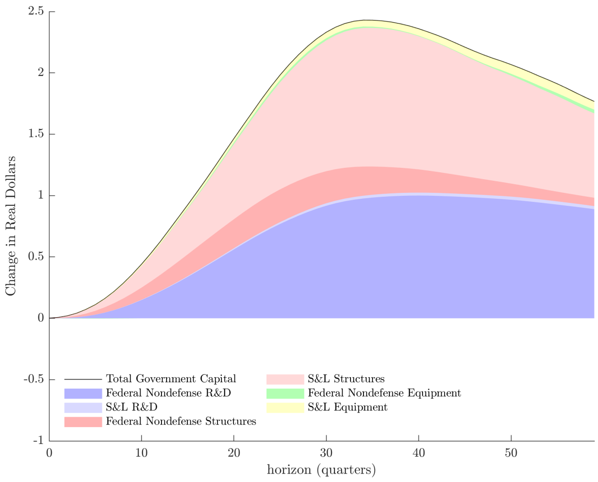
Notes: All confidence intervals are for the 95 percent level. Estimates based on (1) using the nondefense measure after excluding all NASA appropriations (*Left Panel*), or including only NASA appropriations (*Right Panel*). 'Specification 1' adds the NASA-only (non-NASA) nondefense narrative measures as an additional contemporaneous control to the baseline specification. 'Specification 2' is simply the baseline specification with the alternative narrative measures. Impulses are scaled to imply a 1 percent peak increase in government R&D capital. Sample: 1948Q1-2021Q4.

D.9 Robustness: The Role of NASA

As discussed in the main text, the rapid expansion of government R&D expenditures during the early stages of the space race is a particularly large source of changes in nondefense appropriations. Figure D.8 looks deeper into the role of NASA R&D appropriations for the impulse response estimates to a nondefense R&D shock. The left column shows impulse responses of government R&D capital (top) and TFP (bottom) identified with a version of the nondefense narrative measure that excludes all NASA appropriations. The right column shows the responses with a version of a measure that includes only the appropriations for NASA.

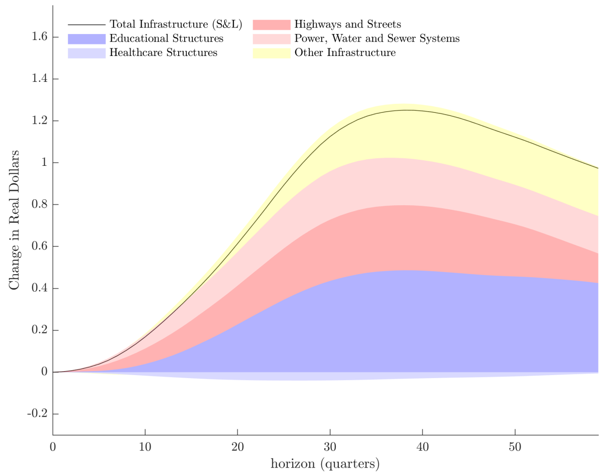
Similar to the defense/nondefense split of the R&D appropriations, one issue is that NASA-only and non-NASA nondefense appropriations are positively correlated. 'Specification 1' therefore additionally includes the NASA-only (left) and non-NASA (right) nondefense narrative measures as contempora-

Figure D.9: Nondefense Public Capital



Notes: Estimates based on (1) using the narrative measure of changes in federal nondefense R&D appropriations. Impulses are scaled to imply a unit peak increase in federal nondefense R&D capital. Sample: 1948Q2–2021Q4.

Figure D.10: S&L Structures by Function



Notes: Estimates based on (1) using the narrative measure of changes in federal nondefense R&D appropriations. Impulses are scaled to imply a peak increase in state and local structures of $1.13 to match Figure D.9. Sample: 1948Q2–2021Q4.

neous controls, which imposes that appropriations in the other category do not change on impact (as in the mutual orthogonalization of defense and nondefense shocks in Appendix D.2). 'Specification 2' ignores the issue, and simply uses the baseline specification with the non-NASA or NASA-only nondefense narrative measures, respectively. Note that in rows [2] and [8] in 1 and rows [2] and [6] in Table 2, the estimates are based on the impulse responses using 'Specification 1'.

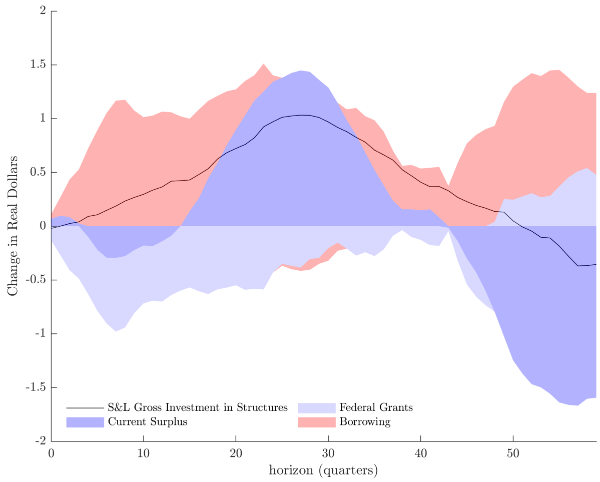
As Figure D.8 shows, government R&D capital rises similarly after both shocks and in both specifications. TFP also rises in all cases, with peak responses that are similar in magnitude to our baseline results (approximately 0.2). The TFP responses remain significant at longer horizons, although the 95 percent bands are wider, especially when excluding NASA appropriations. There is also a meaningful difference in timing: the effects of non-NASA shocks occur sooner, whereas the effects of a NASA-only shock are more delayed, especially in 'Specification 1'.

D.10 A Closer Look at Public Infrastructure After 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 capital, 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, i.e., federal versus state and local (S&L) government. Figure D.9 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 1.13 dollars), although there is also an increase in federal infrastructure spending on structures (up to 27 cents). Note that the total increase in public structures does not exactly add up to the increase seen in Figure 9 because of slight

Figure D.11: Financing of S&L Investment in Structures



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

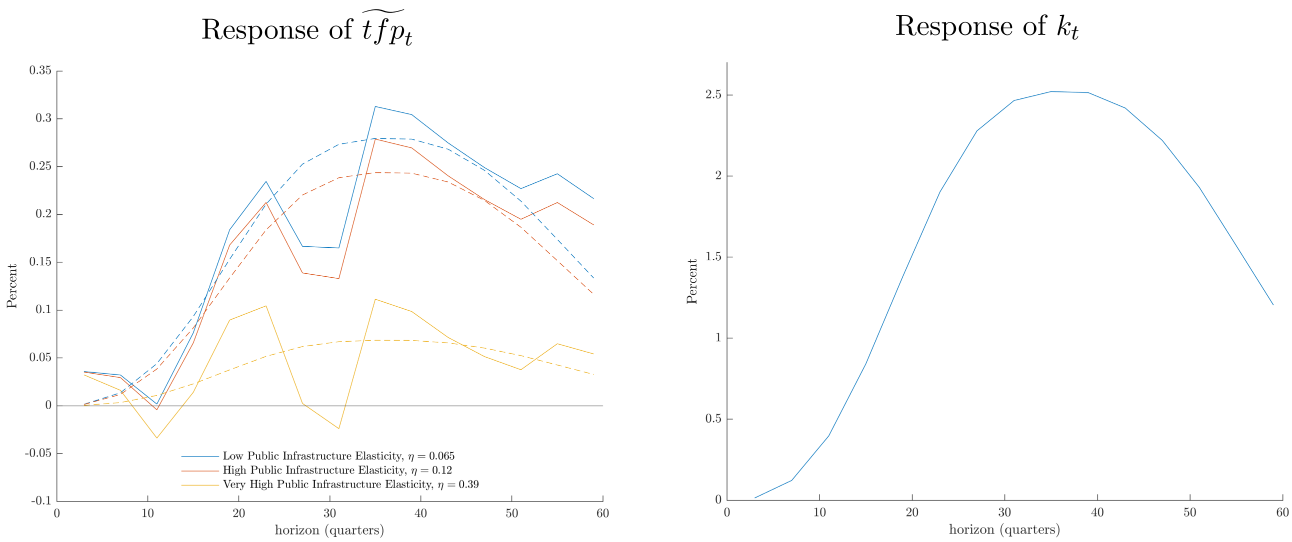
differences in the regression specifications (the lagged outcome variables y_{t-j} on the right-hand side in (1) are different). The main text, therefore, reports the contribution of state and local government structures as a percentage $(1.13/(1.13 + 0.27) \approx 0.8)$.

Figure D.10 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 peak 1.13 dollar increase in Figure D.9. 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 changes in all remaining types of state and local government infrastructure ('Other Infrastructure') are individually relatively small.

Figure D.11 provides a breakdown of the response of investment in structures by state and local governments according to the means of financing: Debt, federal transfers, or current surpluses (revenues less other spending). Note that, unlike in the previous figures, this 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 D.11 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 horizon, even dips slightly below the level predicted in the absence of the nondefense R&D shock. Figure D.11 also shows that the investment boom is not financed by increased federal transfers to state

FIGURE E.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 narrative measure of changes in nondefense R&D appropriations using the baseline specification in (1) 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 (2024). 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.

and local governments. Federal grants 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 D.11 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.

E 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.

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

Figure E.1 provides the main intuition behind the SP-IV estimation of ϕ in (6) based on the response to the narrative measure of nondefense R&D appropriations, z_t^{ND}, using the specification in (1). 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. Both figures show the impulse responses at one-year intervals that are used for the

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

	Public R&D Measure	Instruments	Intermediate η ϕ_{ND}	Intermediate η ϕ/ϕ_D	Low η ϕ/ϕ_{ND}	High η ϕ/ϕ_{ND}
[1]	Total	Exo ND	0.11^{***} (0.07,0.15)		0.11^{***} (0.07,0.15)	0.10^{***} (0.06,0.14)
[2]	Total	Exo ND, No NASA	0.11^{***} (0.04,0.19)		0.12^{***} (0.04,0.19)	0.10^{***} (0.03,0.18)
[3]	Total	All ND	0.10^{***} (0.06,0.14)		0.11^{***} (0.07,0.15)	0.09^{***} (0.05,0.13)
[4]	Total	Exo D		-0.13 (-0.36,0.11)		
[5]	Total	All D		-0.11 (-0.34,0.11)		
[6]	ND/D	Exo ND	0.10^{***} (0.06,0.14)	-0.01 (-0.26,0.25)	0.11^{***} (0.06,0.15)	0.09^{***} (0.05,0.13)
[7]	ND/D	Exo ND/D	0.10^{***} (0.05,0.14)	-0.07 (-0.35,0.21)	0.10^{***} (0.06,0.14)	0.09^{***} (0.05,0.13)
[8]	ND/D	Exo ND, No NASA	0.11^{**} (0.02,0.20)	0.20 (-0.51,0.91)	0.11^{**} (0.02,0.21)	0.10^{**} (0.01,0.20)
[9]	ND/D	All ND	0.10^{***} (0.06,0.14)	-0.03 (-0.28,0.22)	0.10^{***} (0.06,0.14)	0.09^{***} (0.05,0.13)

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 (2024).

estimation of the production function elasticity. The left panel 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 (6) imposes very specific assumptions on the lags between government R&D capital and the TFP effects. As Figure E.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 reasonable in light of 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 inverse covariance matrix of the identifying innovations weights the different impulse responses. The SP-IV estimator also applies to structural equations with multiple endogenous regressors, as in specification (8) in the main text, in which case it reduces to multiple regression in impulse response space, see Lewis and Mertens (2024).

E.2 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 (2024) show that the SP-IV estimator is equivalent to a restricted 2SLS estimator in a system of equations, 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 (2024) show that this is also the case for the SP-IV estimator. Table E.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 all NASA appropriations. For this specification, Wald-based inference points to estimates that are highly statistically significant, whereas weak-instrument-robust inference result leads to the conclusion that the instrument is uninformative. The estimates of the defense R&D capital elasticity, on the other hand, remain insignificant under Wald inference.

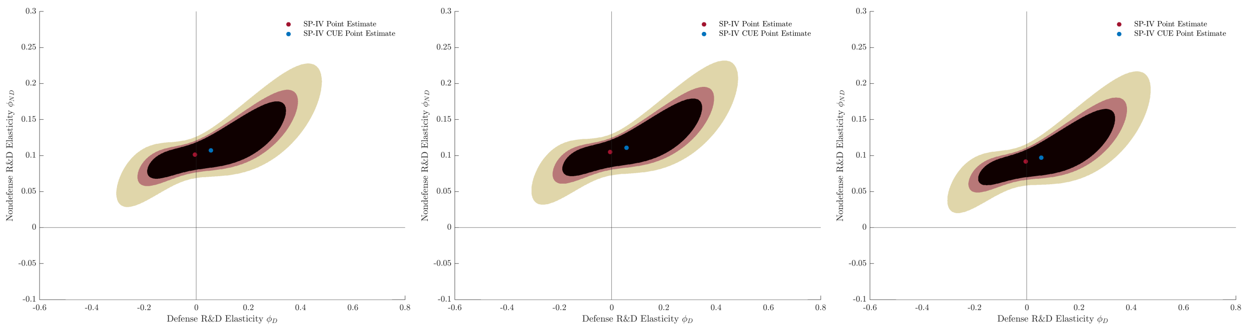
E.3 Simultaneous Confidence Sets

For the specifications with two endogenous regressors, i.e., (8) and (10) in the main text, the confidence intervals reported in Tables 1 and 2 are subvector confidence sets obtained using the projection method, see, e.g., Andrews et al. (2019). As an illustration, the panels in Figure E.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 (2024). 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 within the confidence sets. This continuously updated estimator (CUE) is marked by the blue dots in Figure E.2.

Figure E.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 intermediate 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. The simultaneous confidence sets are also very similar across specifications. The exception is the specification with the narrative measure that excludes the NASA appropriations, see panel (b) in

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

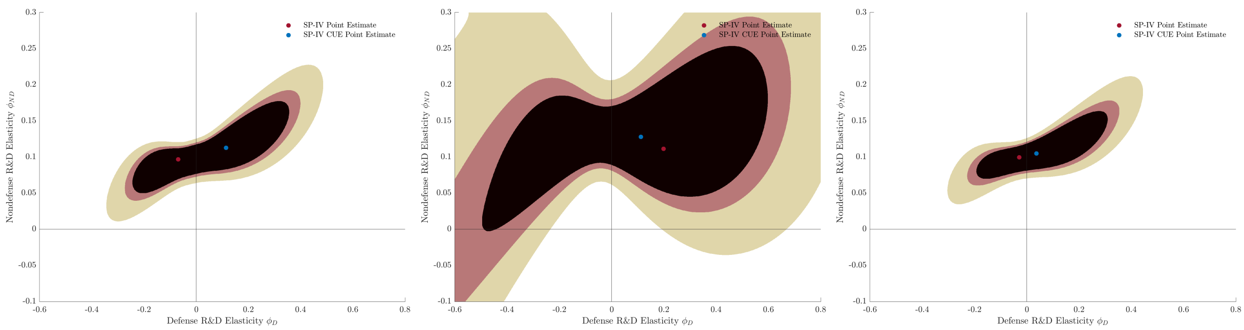
(a) Intermediate $\eta = 0.08$ (b) Low $\eta = 0.065$ (c) High $\eta = 0.12$



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

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

(a) Using Both Shocks (b) Excluding NASA (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 $\eta = 0.08$.

Figure E.3. For that specification, the confidence sets become meaningfully larger as identification is weak in that case.

E.4 Specification with Constant Elasticities

In specification (8) 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:

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

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 (E.1) are reported in Table E.2. The estimates can be multiplied by $\bar{s}_{ND} \approx 0.5$ to

Table E.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	0.06^{**} (0.01,0.12)	0.12 ($-$0.30,0.39)	0.06^{**} (0.01,0.12)	0.05^{**} (0.00,0.11)
[2]	ND/D	Exo ND/D	0.08^{**} (0.01,0.12)	-0.03 ($-$0.30,0.37)	0.08^{**} (0.01,0.13)	0.08^{*} ($-$0.00,0.12)
[3]	ND/D	Exo ND, No NASA	0.13 ($-$0.95,0.81)	-0.11 ($-2.00^{\dagger}$,0.58)	0.13 ($-$0.94,0.80)	0.12 ($-$0.95,0.84)
[4]	ND/D	All ND	0.06^{**} (0.01,0.13)	0.11 ($-$0.32,0.37)	0.06^{**} (0.02,0.13)	0.05^{**} (0.01,0.12)

Notes: Rows [1]-[4]: SP-IV estimates of ϕ_{ND} and ϕ_D in (E.1). 95 percent weak-instrument-robust intervals based on the KLM statistic of Kleibergen (2005) in parentheses. Test inversion is on a grid with endpoints -2 and 2, † denotes intervals constrained at these endpoints. Subvector inference in rows [6]-[9] uses the projection method. $*$, $**$ and $***$ denote statistical significance at 10, 5 and 1 percent levels, respectively. 'Exo ND/D': exogenous changes in nondefense/defense R&D appropriations. 'All ND/D': all changes in nondefense/defense R&D appropriations. 'No NASA': excluding all NASA appropriations. Sample: 1948Q1–2021Q4.

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 generally smaller. The only exception is in row [3], but this is also the specification for which the estimates are imprecise and weakly identified. Ignoring the results in row [3], the point estimates of ϕ_{ND} range from 0.05 to 0.08, compared to around 0.11 under the specification discussed in the main text. The estimates of ϕ_{ND} are relatively precisely estimated (except in row [3]), 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.

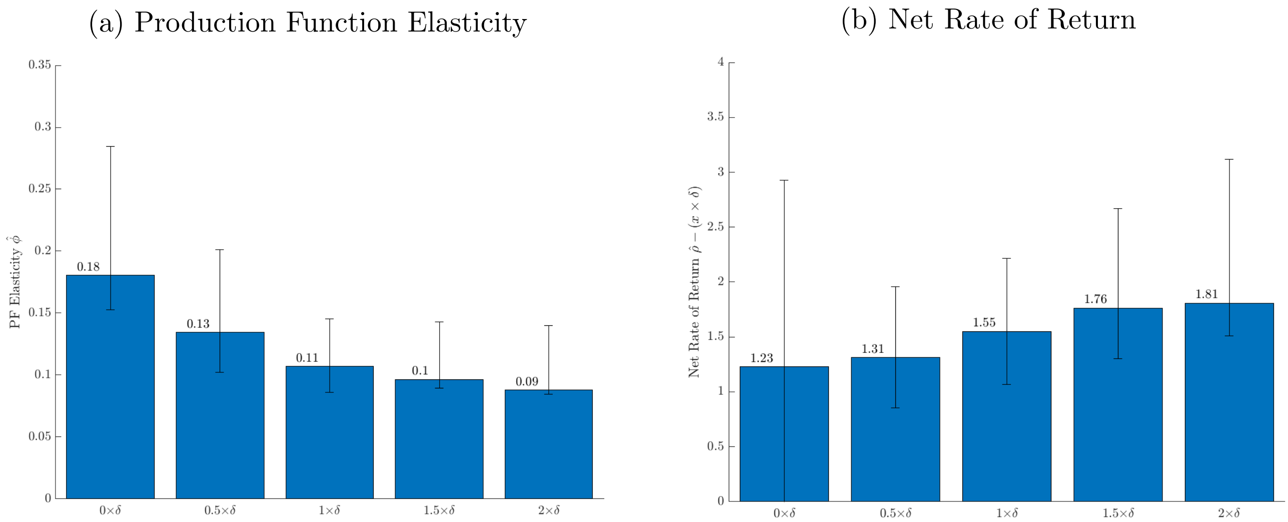
The difference in the estimates of ϕ_{ND} between the specification in equation (8) and the one in (E.1) is not too surprising, given that the share of nondefense R&D varies considerably over the estimation sample. Given that the stock of nondefense R&D capital is small in the beginning of the sample, 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 (8) 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 E.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 E.2 by 0.06 (the average ratio of government R&D capital to GDP), the implied rates of returns range from 85 to 140 percent.

E.5 Different Depreciation Rates

The quarterly measures of the government R&D capital stocks that we use throughout the analysis closely follow the methodology of the BEA, which publishes the annual totals as part of the 'Fixed

Figure E.4: Nondefense Government R&D,
Elasticity and Return Estimates Assuming Different Depreciation Rates



Notes: SP-IV estimates of ϕ (left) and rates of return ρ (right) based on (6) and (9), respectively. Estimates are based on the narrative measure of nondefense appropriations as in rows [1] of Table 1 and 2, respectively, and assuming the intermediate value $\eta = 0.08$. Error bars are 95 percent weak-instrument-robust confidence intervals based on inverting the KLM statistic of Kleibergen (2005).

Assets' tables. For certain categories of government R&D, the BEA estimates depreciation rates based on observing a progression of specific R&D investments with observable outcomes on the effective life of the R&D. For other categories of government R&D, the BEA uses the same depreciation rates as for private R&D services.

Given the inherent difficulties in measuring the obsolescence of intellectual capital, we verify how the estimates of the production function elasticities and rates of return change under different assumptions about depreciation rates on government R&D. Specifically, we capitalize the various categories of government R&D investment by multiplying the annual BEA depreciation rates for each category by a scaling factor $x = 0, 0.5, 1, 1.5$ or 2. On average across (weighted) categories and years, the BEA depreciation rate is $\delta \approx 0.16$. When $x = 0$, all depreciation rates are zero. When $x = 2$, all depreciation rates are twice as large as those used by the BEA, therefore averaging to $2 \times \delta \approx 0.32$. For simplicity, we keep the initial values of each subcomponent of the R&D capital stock constant to the 1946 values in the BEA tables.

Figure E.4 shows how the estimation results (all assuming $\eta = 0.08$) change with the assumed depreciation rates. The left panel shows the estimates of the production function elasticity, obtained exactly as in row [1] of Table 1. The right panel shows the estimates of the net rate of return, obtained by estimating the gross rate of return exactly as in row [1] of Table 2 and subtracting the (scaled) average depreciation rate. The error bars mark the 95 percent weak-instrument-robust confidence intervals.

As the left panel of Figure E.4 shows, the production function elasticity estimates are decreasing in the assumed depreciation rate. Intuitively, assuming a larger depreciation rate implies a smaller estimate of the stock of R&D capital, and therefore, a one percent increase in the capital stock corresponds to a smaller overall increase. As mentioned in the main text, the BEA depreciation rates result in elasticity estimates of around 0.11. Assuming zero depreciation raises the point estimate of the elasticity to 0.18, whereas doubling the depreciation rates lowers the estimate to 0.09. The right panel of Figure E.4 shows that the net rate of return is increasing in the assumed depreciation rate. Although the elasticity estimates are decreasing in the depreciation rate, larger depreciation rates also lower the capital stock to GDP ratio estimate, which translates to higher rates of return. Using the BEA estimates, the point estimate of the net rate of return is $(1.71 - 0.16) \times 100 = 155$ percent. This estimate drops to 123 percent when assuming zero depreciation. Doubling the depreciation rates increases the net return estimate to 181 percent. Even if one would prefer to assume a higher or lower average depreciation rate on intellectual capital, doing so would not change the main conclusion that the rate of return on nondefense government R&D is relatively high.

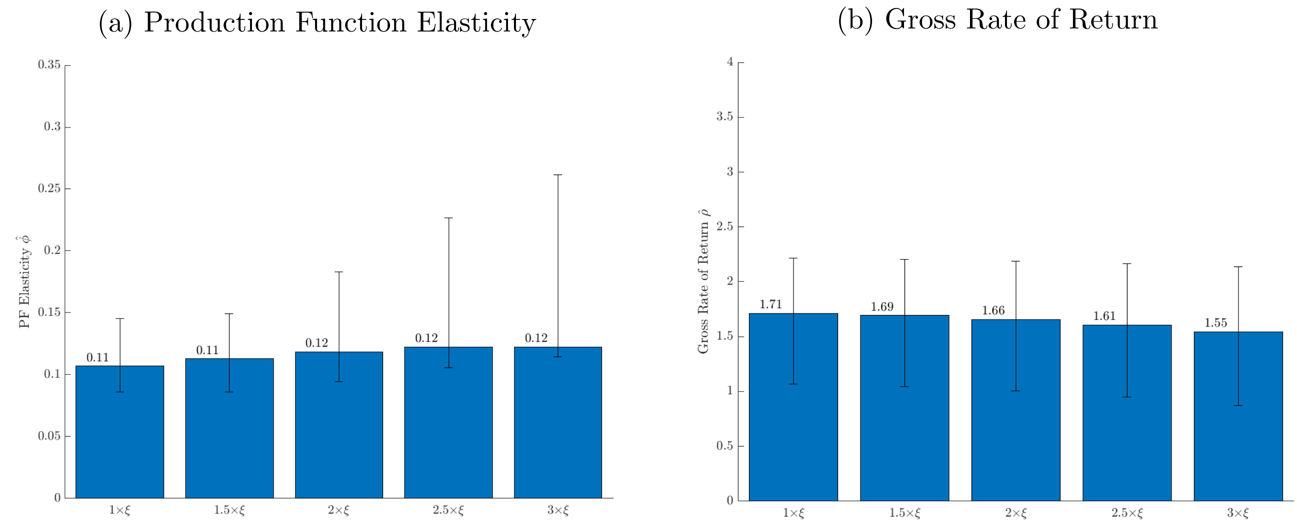
E.6 Different Elasticities to Business-Sector R&D Capital

The Fernald (2012) measure of business-sector TFP, as updated on FRB San Francisco Total Factor Productivity, accounts for the growth contribution of changes in the business-sector stock of R&D capital with a time-varying elasticity ξ. This elasticity is determined as the product of the (total) capital share of income and the weight of R&D capital in total business-sector capital derived from user cost. The resulting elasticity ξ grew gradually from 0.005 in the late 1940s to more than 0.04 in the 2020s. As explained in the main text, a potential source of bias in our estimates of the elasticity of government R&D capital is that the elasticity to business-sector R&D capital might be underestimated because of spillovers. Since a shock to nondefense appropriations crowds in private R&D capital (see Figure 9), this would result in an upward bias in our estimates of the government R&D capital elasticity as the productivity effects would be mistakenly attributed to government-funded R&D rather than R&D funded by the business sector. To illustrate that the resulting bias is likely small, in this appendix, we re-estimate the production function elasticity of government R&D capital using a range of higher production function elasticities to business-sector R&D capital. More specifically, we construct alternative TFP measures by multiplying ξ by a scaling factor $x = 1, 1.5, 2, 2.5$, or 3. This means we assume business-sector R&D elasticities that are up to $x = 3$ times as large as the original estimated value, such that business-sector R&D elasticity is as high as 0.12 in the later years of the sample, whereas $x = 1$ corresponds to the estimates in the main text.

Figure E.5 shows how our estimation results (all assuming $\eta = 0.08$) change as the assumed business-sector R&D capital elasticity takes on higher values. The left panel shows the estimates of the production function elasticity, obtained exactly as in row [1] of Table 1. The right panel shows the estimates of the gross rate of return, estimated exactly as in row [1] of Table 2. The error bars mark the 95 percent weak-instrument-robust confidence intervals.

As the left panel of Figure E.5 shows, the production function elasticity estimates change little as the business-sector R&D elasticity increases, even rising slightly to $\hat{\phi} = 0.12$ for $x = 3$. The right panel shows that the rate of return falls when x is higher, but only modestly: from 171 percent for $x = 1$ to 155

Figure E.5: Nondefense Government R&D,
Estimates Assuming Different Production Function Elasticities to Business-Sector R&D Capital



Notes: SP-IV estimates of ϕ (left) and rates of return ρ (right) based on (6) and (9), respectively. Estimates are based on the narrative measure of nondefense appropriations as in rows [1] of Table 1 and 2, respectively, and assuming the intermediate value $\eta = 0.08$. Error bars are 95 percent weak-instrument-robust confidence intervals based on inverting the KLM statistic of Kleibergen (2005).

percent when $x = 3$. We conclude that our estimation results are not sensitive to reasonable alternative assumptions regarding the business-sector R&D elasticity. The crowding-in effects on business-sector R&D, while positive, appear quantitatively too small to be a major source of bias. As we emphasize in the main text, a positive appropriations shock, to a large extent, funds R&D that is performed at private businesses and universities, see Figure 8. The relatively small amount of crowding in of privately funded R&D, therefore, does not imply that the productivity-enhancing effects of government-funded R&D do not originate from R&D activity at private businesses.

E.7 Estimates of Production Function Elasticities to Total R&D Capital

In this appendix section, we use the narrative measures of R&D appropriations to estimate production function elasticities using either the total R&D capital stock as a single endogenous regressor or the government and private R&D capital as separate endogenous regressors. The methodology is entirely analogous to that of Section 4, except that we replace government R&D capital on the right-hand side of (6) with total R&D capital, i.e., the aggregate of government and private R&D capital. Similarly, we consider the specification in (8), but replacing nondefense and defense R&D capital with government R&D capital and private R&D capital. As in the specification of the main text, we weight by shares such that elasticities across the specifications are directly comparable in size.

Table E.3 reports the estimation results. Rows [1] and [2] in Table E.3 show the results for the specification with total R&D capital (G+P) as the endogenous regressor and using the exogenous nondefense and defense narrative measures, respectively, for identification. If the elasticity to business-sector R&D capital is underestimated because of spillovers and the crowding-in effects of R&D appropriations on

Table E.3: Estimates of Production Function Elasticities of Total R&D Capital

	R&D Measure	Instruments	Intermediate $\eta = 0.08$ $\hat{\phi}^{tot}/\hat{\phi}^{tot}_G$	Intermediate $\eta = 0.08$ $\hat{\phi}^{tot}/\hat{\phi}^{tot}_P$	Low $\eta = 0.065$ $\hat{\phi}^{tot}/\hat{\phi}^{tot}_G$	High $\eta = 0.12$ $\hat{\phi}^{tot}/\hat{\phi}^{tot}_G$
[1]	Total (G+P)	Exo ND	0.14*** (0.12,0.20)		0.14*** (0.12,0.21)	0.12*** (0.10,0.19)
[2]	Total (G+P)	Exo D	−0.03 (−2.00†,0.43)		−0.03 (−2.00†,0.43)	−0.04 (−2.00†,2.00†)
[3]	G/P	Exo ND	0.20 (−0.51,0.66)	−0.25 (−2.00†,2.00†)	0.21 (−0.51,0.66)	0.18 (−0.51,0.65)
[4]	G/P	Exo ND/D	0.19 (−0.47,0.74)	−0.19 (−2.00†,2.00†)	0.20 (−0.47,0.74)	0.17 (−0.47,0.73)

Notes: G/P denotes government/private R&D capital, respectively. 95 percent weak-instrument-robust intervals based on the KLM statistic of Kleibergen (2005) in parentheses. Test inversion is on a grid with endpoints −2 and 2, † denotes intervals constrained at these endpoints. Subvector inference in rows [6]-[9] uses the projection method. $*$, $**$ and $***$ denote statistical significance at 10, 5 and 1 percent levels, respectively. 'Exo ND/D': exogenous changes in nondefense/defense R&D appropriations. 'All ND/D': all changes in nondefense/defense R&D appropriations. 'No NASA': excluding all NASA appropriations. Sample: 1948Q1–2021Q4.

private R&D capital are large, we would expect the elasticity on total R&D capital to be smaller (larger) if the direct productivity spillovers of private R&D are smaller (larger) than those of government R&D. Government R&D capital averages roughly 62 percent of total R&D capital over the estimation sample. If the crowding-in effects are small, then the elasticity on total R&D capital should be approximately $1/0.62 = 1.6$ times that of government R&D capital in the specification in the main text. As row [1] in Table E.3 shows, using the nondefense instrument yields a point estimate of $\hat{\phi}^{tot} = 0.14$ for the intermediate $\eta = 0.08$, and relatively similar estimates for alternative values of η. The estimates in row [1] are all highly statistically significant. Multiplying by the average share of government R&D capital of 0.62 yields a value of 0.09, which is slightly smaller than the estimate of the specification in Table 1 based on government R&D capital as the endogenous regressor. However, the government share of 0.62 is the *unconditional* share of government R&D capital in the data. *Conditional on a nondefense shock*, the proportional response of private R&D is 20 cents to every public dollar, as discussed above and in Section III.D. Using the *conditional* share of government R&D of $1/(1 + 0.20) = 0.83$, the estimate in row [1] implies a government R&D elasticity of $0.83 \times 0.14 = 0.12$, which is very close to our baseline estimate of 0.11. We conclude that the point estimate of 0.14 in row [1] does not indicate that there is a large upward bias.

As in Table 1 of the main text, row [2] shows the defense instrument is uninformative. Rows [3] and [4] show the results when including government (G) and private (P) R&D capital as separate endogenous regressors. If the appropriations shocks not only have a significant impact on government R&D capital but also on private R&D capital, and these effects are not perfectly collinear, then it is, in principle, possible to separately identify the elasticities to government and private R&D capital. As the results in Rows [3] and [4] show, unfortunately, the narrative measures do not contain sufficient information to sharply identify both elasticities separately.

Online Appendix References

Alexopoulos, Michelle (2011). "Read All about It!! What Happens Following a Technology Shock?" In: *American Economic Review* 101.4, pp. 1144–79.

Andrews, Isaiah, James H. Stock, and Liyang Sun (2019). "Weak Instruments in Instrumental Variables Regression: Theory and Practice". In: *Annual Review of Economics* 11.1, pp. 727–753.

Antolin-Diaz, Juan and Paolo Surico (2025). "The Long-Run Effects of Government Spending". In: *American Economic Review* 115.7, 2376–2413.

Aschauer, David Alan (1989). "Is public expenditure productive?" In: *Journal of Monetary Economics* 23.2, pp. 177–200.

Barnichon, Regis and Christian Brownlees (2019). "Impulse Response Estimation by Smooth Local Projections". In: *The Review of Economics and Statistics* 101.3, pp. 522–530.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb (2020). "Are Ideas Getting Harder to Find?" In: *American Economic Review* 110.4, pp. 1104–1144.

Cascaldi-Garcia, Danilo and Marija Vukotić (2022). "Patent-Based News Shocks". In: *The Review of Economics and Statistics* 104.1, pp. 51–66.

Cloyne, James, Joseba Martinez, Haroon Mumtaz, and Paolo Surico (2025). *Short-Term Tax Cuts, Long-term Stimulus*. NBER Working Paper 30246.

Croce, M.M., Thien T. Nguyen, S. Raymond, and L. Schmid (2019). "Government debt and the returns to innovation". In: *Journal of Financial Economics* 132.3, pp. 205–225.

Fernald, John G. (2012). *A Quarterly, Utilization-Adjusted Series on Total Factor Productivity*. Working Paper Series 2012-19. Federal Reserve Bank of San Francisco.

Fieldhouse, Andrew J. and Karel Mertens (2023). *A Narrative Analysis of Federal Appropriations for Research and Development*. Dallas Fed Working Paper 2316.

Herbst, Edward P. and Benjamin K. Johanssen (2024). "Bias in local projections". In: *Journal of Econometrics* 240.1, p. 105655.

Jordà, Òscar (2005). "Estimation and Inference of Impulse Responses by Local Projections". In: *American Economic Review* 95.1, pp. 161–182.

Kleibergen, Frank (2005). "Testing Parameters in GMM Without Assuming that They Are Identified". In: *Econometrica* 73.4, pp. 1103–1123.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman (2017). "Technological Innovation, Resource Allocation, and Growth". In: *The Quarterly Journal of Economics* 132.2, pp. 665–712.

Lazarus, Eben, Daniel J. Lewis, James H. Stock, and Mark W. Watson (2018). "HAR Inference: Recommendations for Practice". In: *Journal of Business & Economic Statistics* 36.4, pp. 541–559.

Lewis, Daniel J. and Karel Mertens (2024). *Dynamic Identification Using System Projections and Instrumental Variables*. Working Paper 2204. Federal Reserve Bank of Dallas.

Li, Dake, Mikkel Plagborg-Møller, and Christian K. Wolf (2024). "Local projections vs. VARs: Lessons from thousands of DGPs". In: *Journal of Econometrics*, p. 105722.

Mertens, Karel and Morten O. Ravn (2013). "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States". In: *American Economic Review* 103.4, pp. 1212–47.

Montiel Olea, José Luis and Mikkel Plagborg-Møller (2021). "Local Projection Inference Is Simpler and More Robust Than You Think". In: *Econometrica* 89.4, pp. 1789–1823.

Newey, Whitney K. and Kenneth D. West (1987). "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". In: *Econometrica* 55.3, pp. 703–708.

Plagborg-Møller, Mikkel and Christian K. Wolf (2021). "Local Projections and VARs Estimate the Same Impulse Responses". In: *Econometrica* 89.2, pp. 955–980.

Ramey, Valerie A. (2021). "The Macroeconomic Consequences of Infrastructure Investment". In: *Economic Analysis and Infrastructure Investment*. Ed. by Edward L. Glaeser and James M. Poterba. Chicago: University of Chicago Press.

Ramey, Valerie A. and Sarah Zubairy (2018). "Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data". In: *Journal of Political Economy* 126.2, pp. 850–901.

Shiller, Robert J. (2015). *Irrational Exuberance, 3rd ed.* Princeton, NJ: Princeton University Press.

Stock, James H. and Jonathan H. Wright (2000). "GMM with Weak Identification". In: *Econometrica* 68.5, pp. 1055–1096.

Whelan, Karl (2002). "A Guide To U.S. Chain Aggregated Nipa Data". In: *Review of Income and Wealth* 48.2, pp. 217–233.