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Macroeconomic Effects of Government Defense and Non-Defense R&D

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Macroeconomic Effects of Government Defense and Non-Defense R&D

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We use narrative R&D appropriation shocks to investigate the transmission mechanism of government R&D. We document that a non-defense R&D shock boosts innovation, the stock market and labor productivity while prices decrease. We show that NASA's R&D contracting during the Space Race contributes to our results, with effects concentrated in transportation, electrical and computer equipment, and even more persistent in business services. In contrast, a defense R&D shock leads to mixed effects on innovation and labor productivity and, as a military news shock, generates a hump-shaped increase in defense equipment sector production. These results are robust in the post-Korea sample. Our findings on the macroeconomic transmission mechanism of non-defense R&D are consistent with theoretical models with endogenous productivity mechanisms and learning by doing.

JEL Classification: C32, E62, H25, O30, O38
Keywords: government R&D, non-defense R&D, NASA, Space Race, local projections, narrative identification

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1. Introduction

How does the economy respond following a government R&D shock? How does this response propagate and differ when distinguishing between defense and non-defense R&D? This paper investigates the effects of public R&D, focusing on the macroeconomic transmission mechanism, in line with the fiscal policy literature on the aggregate effects of government purchases. [1]

Using U.S. narrative R&D appropriations shocks from Fieldhouse and Mertens (2024) on the post-WWII sample, we find a positive response of the patent innovation index as measured by Kogan et al. (2017), private investment in intellectual property products and private investment in information processing equipment and software following a non-defense R&D shock. We document that the response is stronger and more persistent for the business services innovation index, which includes computer programming and data-processing services.

Inspecting the mechanism, we find that non-defense R&D shocks lead to an increase in industrial production and the sectoral gross output for manufacturing, electrical equipment, and business services. To bolster our findings, we use data from the *Bureau of Labor Statistics (BLS) Discontinued Database*, including reconstructed series from historical bulletins, finding an increase in average production hours in transportation, electrical equipment, and industrial machinery. Similarly, we find an increase in employment in the business services and computer equipment sectors.

A non-defense R&D shock increases labor productivity and the stock market while prices decline. These results are consistent with macroeconomic models that include a fiscal stimulus with *learning-by-doing* as in D'Alessandro, Fella, and Melosi (2019) and Briganti (2023) or demand shock with an endogenous productivity mechanism as in Jørgensen and Ravn (2022) and Klein and Linnemann (2023).

The stock market's positive reaction aligns with Mumtaz and Theodoridis (2020)'s findings, which document a similar relationship in the pre-1980 U.S. period in which government spending had a supply expansion effect through federal R&D spending.

The effects of defense R&D shocks on innovation measures are mixed. The response patent-based innovation index shows a persistent negative response lasting for approximately five years. Similarly, the responses of the private investment in intellectual property products and the private investment in information processing equipment and software turns negative about four years after the shock. Labor productivity shows no statistically significant response, while prices tend to increase.

[1] We use throughout the paper "public R&D investment", "public R&D spending", "government R&D" or "public R&D" to denote government gross investment in Research and Development (R&D). See Crawford et al. (2014) for accounting details.

Manufacturing is one of the sectors with the largest dependence on government purchases, including defense-related spending (Ramey and Shapiro 1998; Nekarda and Ramey 2011). The potential productivity effects in the aircraft sector through *learning by doing*, as theoretically modelled by Briganti (2023), and through *learning-by-necessity*, as in Ilzetzki (2024), could explain some of our results. Nonetheless, evidence from Cox et al. (2024) suggests a role in government purchases for the Professional and Business Services sector that receives 28% of federal purchases but only 4% of private share purchases and is more related to non-defense purchases (Cox et al. 2024). [2] As expected, the importance of procurement contracts in the Business Services sector has steadily increased over time (Belenzon and Cioaca 2022). Our findings suggest that the transmission channels of government R&D extend beyond manufacturing (e.g., electrical and computer equipment, aircraft) to include business services.

We show that the aircraft sector's response to defense R&D shocks mirrors a general defense news shock with an immediate but non-persistent response. Similarly, we observe a hump-shaped pattern in the industrial production in defense and space equipment. These findings may be driven by the defense contractors' reactions during military buildups.

The effects of non-defense R&D shocks take several quarters with long implementation lags, as in the theoretical model of Schmöller (2022). Thus, non-defense R&D shocks have significant delays as for many non-defense purchases argued by Ramey (2011).

Furthermore, non-defense R&D appropriation shocks are serially correlated and may be anticipated several months before the shock. Nevertheless, alternative shocks based on recursive identification, as in Blanchard and Perotti (2002), contain measurement errors due to the construction of quarterly series from annual surveys and tend to predict shocks not consistent with the narrative evidence. Fieldhouse and Mertens (2024) narrative shocks, based on appropriations, reflect the future spending increase and are uncorrelated with measurement errors.

In line with Kantor and Whalley (2023), which document the spillover effects of the Space Race on the manufacturing sector, we provide evidence that the Space Race and, in particular, the role of NASA R&D contracting can be an important source of identification for our results, as well as one of the largest non-defense R&D increases.

While much R&D funding is provided through grants (Cox et al. 2024), both defense and NASA R&D have been mainly provided through contracts (Levine 1982; Mowery 2010; Kantor and Whalley 2023). This suggests that the role of NASA's management of procurement R&D using contracts may explain our results, as studied by Belenzon and Cioaca (2022).

[2] Cox et al. (2024) specifically refers to Professional, Scientific, and Technical Services, one of the main professional and business sectors. The other two subsectors are Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services.

Differently from the defense news shocks of Ramey (2011), Zeev and Pappa (2017) and Fisher and Peters (2010), defense R&D appropriation shocks preserve explanatory power after the Korean War, as the defense contract shocks of Briganti (2023). Following a defense R&D shock, industrial production in defense and space equipment exhibits a hump-shaped pattern that tends to be low in the post-1965 sample when both the Korean and the Vietnam shocks are excluded. Nonetheless, the response of aggregate measures of innovation and productivity is almost negative, while prices still increase.

Unfortunately, non-defense R&D narrative shocks do not have explanatory power after the Space Race. Despite the increase in National Institutes of Health (NIH) funding during the '90s, which led to one of the world's most important biomedical research institutes, we do not observe relevant fluctuations as significant as those during the Space Race. Conversely, the increasing funding of the National Science Foundation (NSF) during the American Recovery and Reinvestment Act (ARRA) was strictly endogenous and reversed by the Budget Control Act of 2011.

Our results come with some caveats. Since after the Space Race, we do not observe relevant fluctuations in non-defense R&D, our results do not inform about other possible effects of non-defense R&D funding. In particular, grants from the NSF or the Department of Energy small business innovation research program (SBIR) as studied by Myers and Lanahan (2022). Similarly, we cannot disentangle the effect of different defense R&D programs such as the Department of Defense SBIR program (Howell et al. 2025) or the impact of the Office of Scientific Research and Development (OSRD) during WWII, as in Gross and Sampat (2023a).

In the spirit of Ramey and Zubairy (2018), we use the narrative series to identify Jordà's local projections (Jordà 2005) and smooth local projections as in Barnichon and Brownlees (2019), which penalizes the higher variance associated with standard local projections at long-horizon (Li, Plagborg-Møller, and Wolf 2024; Jordà and Taylor 2025). We also emphasize methodological issues in identifying government R&D shocks.

Related Literature— Our paper contributes to three strands of the literature. First, it contributes to the literature that investigates the spillover and social returns of government R&D at an aggregate level or focusing on specific R&D programs. Fieldhouse and Mertens (2024) find long-run effects of non-defense R&D on the business sector TFP and innovation measures using a reconstructed series of narrative shocks based on appropriations. Antolin-Diaz and Surico (2025) find long-lasting effects on TFP and real GDP using the defense news shocks constructed by Ramey (2011). They find even larger effects following a public R&D shock identified using the max-share method. Lipsis et al. (2023) estimate a higher fiscal multiplier for public R&D investment. Similarly, Dyèvre

(2024) shows that public R&D can have a greater impact than private R&D investment, and government-interest patents can produce larger spillover effects.

Focusing on historical programs, Gross and Sampat (2023a) study one of the largest R&D funding during WWII, finding effects until the 70s, Kantor and Whalley (2023) explore the effects on manufacturing growth of the space race with the USSR and Ilzetzki (2024) estimates the impact on productivity using archival material on U.S. production aircraft from WWII. Azoulay et al. (2019) and Myers and Lanahan (2022) use variations in federal agency funding rules to estimate the impact of public R&D grants on innovation. While our paper is close to Gross and Sampat (2023a) and Kantor and Whalley (2023), it is different for the methodology implemented. Indeed, our time-series framework is similar to Antolin-Diaz and Surico (2025).

Second, our paper is related to the literature on the aggregate effects of government spending. Notable examples are Ramey and Shapiro (1998), Ramey (2011), Nekarda and Ramey (2011), Barro and Redlick (2011) and, in particular, Briganti (2023) and Cox et al. (2024). Most of these studies focus on total government as government purchases, while the Fieldhouse and Mertens (2024) R&D shocks are based on appropriations of the five major federal agencies. We also speak on recent literature on the inflationary effects of government spending and their transmission channel in models with learning-by-doing (D'Alessandro, Fella, and Melosi 2019; Briganti 2023) or endogenous productivity mechanisms (Mumtaz and Theodoridis 2020; Jørgensen and Ravn 2022; Klein and Linnemann 2023).

Finally, our paper speaks to the economics of innovation literature regarding the role of public R&D as mission-oriented policies (Mazzucato 2018). According to Mowery (2010), defense R&D has played an important role in innovation. [3] On this line of research, Moretti, Steinwender, and Van Reenen (2023) using country-industry panel data for 26 OECD countries finding crowd-in effects of military R&D spending on private investment. Pallante, Russo, and Roventini (2023), relying on a panel analysis for the U.S. and using an identification similar to Nakamura and Steinsson (2014), find a crowd-in effect on private investment of military R&D spending. Recently, Ilzetzki (2025) reviews the literature on military R&D externalities.

Given the role of NASA's R&D contracting during the Space Race (Levine 1982), we speak to the literature on the role of public procurement and R&D contracts. Howell et al. (2025) study the top-down versus bottom-up mechanisms for innovation procurement for the Department of defense, showing the relevant role of decentralization and openness for public R&D contracts. Indeed, starting from the '90s, defense industry experienced

[3] See Mowery (2010) for a comprehensive review on the role of military R&D and innovation. Defense R&D spending has been considered as an example of "mission-oriented policies (MOP)" which have contributed to many innovations (Mowery 2010). There is no theoretical framework on the relationship between military R&D and innovation, but there is general evidence that positive effects are registered during peacetime.

an increase in concentration driven by the merging of defense contractors (Carril and Duggan 2020).

Belenzon and Cioaca (2022) investigate the role of R&D contracts on private R&D investment, finding crowd-in effects. The transmission channel is related to a non-competitive downstream procurement channel called *guaranteed demand*. Despite the expansion of government procurement, the link between R&D contracts and downstream procurement has weakened over time, reducing firms' incentives to invest in public R&D Crespi and Guarascio (2019) use industry-level information on patent applications for 24 countries studying the relationship between public procurement and innovation, while Duque Gabriel (2024) explores the relationship between public procurement and firm credit, investment, and employment. Finally, Hebous and Zimmermann (2021) find important channels of federal procurement contracts on firms.

Structure of the paper— The paper proceeds as follows. In Section 2, we describe the data, the narrative series we have used, some historical evidence on defense and non-defense spending, and we present our econometric methodology. In Section 3, we present our main findings and inspect the mechanism behind our results. In Section 4, we assess the robustness of our results using different samples and compare them using the Ramey (2011) military shock. Section 5 presents conclusions. In Appendix A, we provide the data sources and construction, and in the Appendix, we provide additional robustness checks.

2. Data and Methodology

We use U.S. quarterly data starting in 1947:Q1. Official quarterly series on public and private R&D spending from the Bureau of Economic Analysis National Income and Product Account (BEA-NIPA) are obtained by linear interpolation of annual surveys from the National Science Foundation (NSF) (Crawford et al. 2014). [4] This aspect is relevant when discussing the identification strategy.

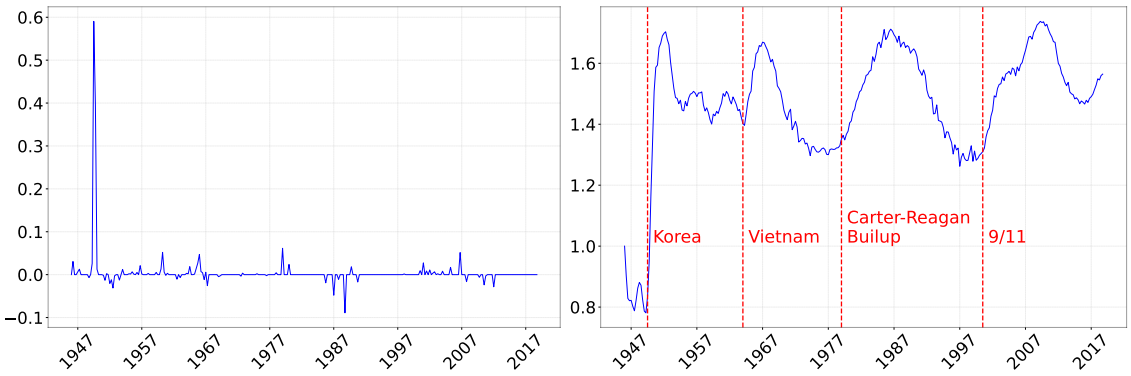
This section describes our data, including the narrative series used to identify the structural shocks. We review historical trends in defense and non-defense R&D, and we present our econometric methodology.

2.1. Data Sources and Construction

We collect data on hours of production and employment for industries using the *Bureau of Labor Statistics (BLS) Discontinued Database*. [5] The data are available at monthly frequencies

[4] Starting in 1990, the private investment R&D series is interpolated using a composite series of the U.S. Census Bureau. See Crawford et al. (2014) for details.

[5] As in Briganti (2023). We thank Edoardo Briganti for helping us retrieve the data



A. Ramey's Military News

B. Log of Real Defense Spending Per Capita

FIGURE 1

Notes: Military News Shock is from Ramey and Zubairy (2018) deflated using the GDP implicit deflator and scaled by the GDP trend using a sixth-degree polynomial. Total defense spending from BEA-NIPA is deflated using the GDP implicit deflator and expressed per capita. Red vertical lines are war dates from Ramey (2011): 1950:Q3, 1965:Q1, 1980:Q1 and 2001:Q3

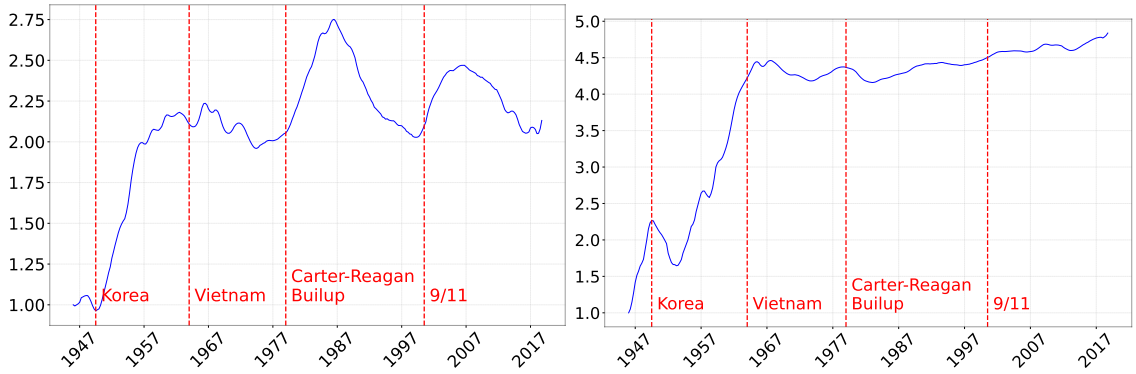
until 2003. For some missing series, we digitize data from Historical Bulletin No. 1312-12 and No. 2445 of the BLS retrieved using FRASER Digital Library and the Appendix data of the monthly Survey of Current Business released by the U.S. Department of Commerce. We leave details on the data construction in the Appendix A.

We construct gross output by industry using annual tables of historical GDP by industry from BEA from 1947 to 1997.

We use NASA's historical book to retrieve information on NASA R&D characteristics and performers. As descriptive evidence, we use Historical Tables 9.8 provided by the Office of Management and Budget (OMB) to retrieve data on NASA R&D spending and new administrative classification database of Gross and Sampat (2025) regarding NASA interest patents.

From the dataset of Fieldhouse and Mertens (2024), which covers the period from 1947:Q1 to 2019:Q4, we use: orthogonalized defense (non-defense) R&D shock, public R&D capital, private R&D capital, utilization-adjusted TFP, utilization rate, cumulated appropriations shock, and the stock market return in manufacturing, high-tech and health industries.

Private investment in intellectual property products, private investment in information processing equipment and software, industrial production, and industrial production in defense and space equipment are retrieved from BEA-NIPA using the FRED database as we described in Appendix A. The disaggregated patent innovation index for industries constructed as in Kogan et al. (2017) is retrieved from the replication files of Cascaldi-Garcia and Vukotić (2022).



A. Log of Real Government Defense R&D B. Log of Real Government Non-Defense R&D

FIGURE 2. Public R&D Spending and War Dates

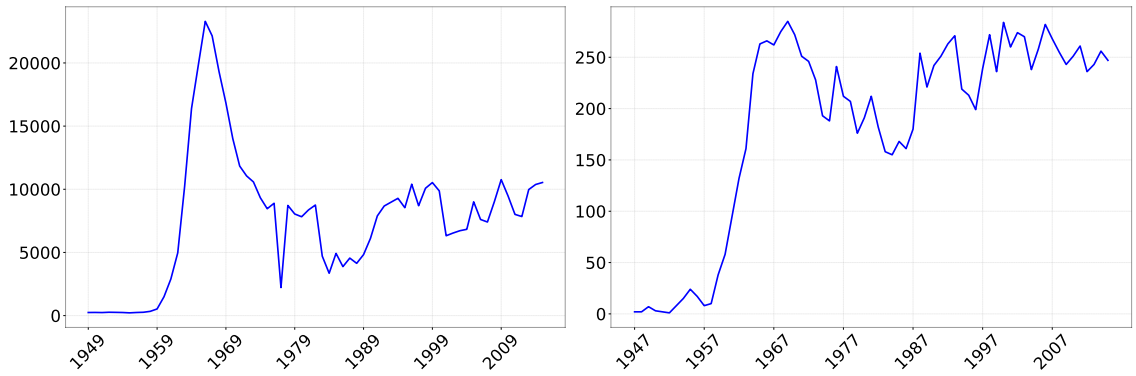
Notes: Log of Government Gross Defense and Non-Defense R&D Investment are from BEA-NIPA deflated using the NIPA price indices for federal defense and non-defense intellectual property products and expressed in per capita terms. Red vertical lines are war dates from Ramey (2011): 1950:Q3, 1965:Q1, 1980:Q1 and 2001:Q3

2.2. Descriptive Evidence

Figure 1 shows the fluctuations in aggregate defense spending following the more relevant war dates of Ramey and Shapiro (1998) and the narrative military news shock of Ramey (2011). The major increase in defense spending following the Korean War in 1950:Q3, in which *Business Week* predicted that defense spending would triple for the fiscal year 1952 (Ramey 2011). The other war events are the *Vietnam War* in 1965:Q1, the increase following the election of Ronald Reagan in 1980:Q1 (i.e. *Carter-Reagan Buildup*) and finally following the terrorist attack of the 9/11 in 2001:Q3. Given the availability of many of our quarterly series from 1947:Q1, we do not consider the WWII period, in which the U.S. government's Office of Scientific Research and Development (OSRD) sustained one of the largest public spending programs in applied R&D (Gross and Sampat 2023a).

Figure 2 shows that the largest increase in defense R&D spending follows these waves: the Korean War, Vietnam in small measure, the Strategic Defense Initiative and 9/11. A notable variation in defense R&D is also related to the Sputnik Crisis that led to the creation of DARPA. The right panel of Figure 2 reports the trend of non-defense R&D spending that saw a large increase during the period 1955-1965. Inspired by Vannevar Bush's reports (Bush 1945), in 1950, the National Science Foundation was created with the role of "*promote the progress of science, advance the national health, prosperity and health and secure the national defense*".

The Soviet Launch of Sputnik in 1957 started the "Space Race". The Eisenhower Administration created the National Aeronautics and Space Administration (NASA) in 1958. Space activities– except those related to weapons and military operations– were brought



A. NASA Real R&D Spending B. NASA Government Interest Patents

FIGURE 3. NASA Spending and Patenting

Notes: NASA R&D outlays (in Millions of 2012 Dollars) are from Table 9.8 of the OMB Budget Historical Tables (General Science, Space and Technology) deflated using the NIPA price indices for federal non-defense intellectual property products. Fiscal Year (FY) from 1949–2015.
The number of NASA Government Interest Patents filed per year is from the author's elaboration from the database of Gross and Sampat (2025). We include both title and license NASA interest patents.

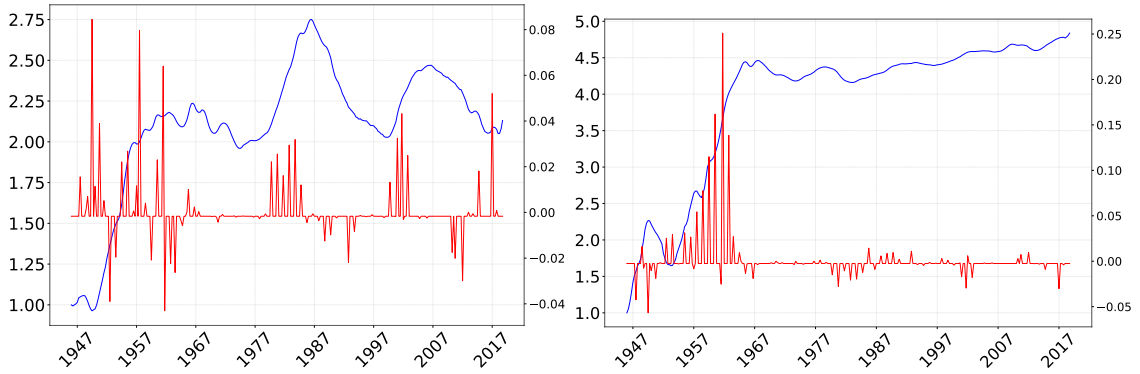
to this new civilian agency.

The Apollo program started in 1961 after JFK's speech to send a man to the moon, which led to an increase in non-defense spending concentrated in space technology and hardware, with a peak of NASA funding in 1966 close to 51 billion of real dollars (Kantor and Whalley 2023). NASA reached over 400,000 employees (Weinzierl 2018), most from NASA contractors. Figure 3 shows the real NASA R&D spending in General Space, Science and Technology and the number of new government NASA-funded patents computed using the new administrative records of Gross and Sampat (2025).

At the end of the 20th century, important shifts occurred for the NIH in which the budget was doubled, but the variation in non-defense R&D is not as significant as during the Space Race.

Identification— Our identification strategy relies on using the Fieldhouse and Mertens (2024) narrative data based on a series of changes in R&D appropriations shocks. Figure 4 shows the exogenous orthogonal R&D shocks of Fieldhouse and Mertens (2024) and the defense and non-defense R&D spending.

Appropriations are future authorizations of spending that can provide a better timing identification of the shock (Fieldhouse and Mertens 2024), in line with the literature on fiscal foresight (Ramey 2011) and the time delays of government purchases as registered from the national accounts (Brunet 2023; Briganti and Sellemi 2023). In the context of R&D, the lag structure (*outlay rate*) refers to the timing between an appropriation and an outlay of around 50% Fieldhouse and Mertens (2024).



A. Defense R&D B. Non-Defense R&D

FIGURE 4. Public R&D Spending and Narrative Shocks

Notes: Log of Defense and Non-Defense R&D are from BEA-NIPA deflated using the NIPA price indices for federal defense and non-defense intellectual property products expressed per capita. Red lines are orthogonalized defense and non-defense R&D shocks from Fieldhouse and Mertens (2024). *Sample:* 1947:Q1–2019:Q4

These series are obtained from a narrative classification of U.S. Federal *Budget Authority* considering all enacted R&D appropriations for the five major federal agencies after WWII. [6] The "exogenous" changes are classified based on a narrative analysis described in the companion analysis (Fieldhouse and Mertens 2023) not motivated by short-run economic considerations: the Sputnik Crisis, the moon mission and concerns about the adequacy of the science, technology, health and engineering base (e.g., the creation of the NSF or the war on cancer). Regarding defense R&D, the most relevant shocks are typically driven by wars (e.g., the Korean War).

An alternative identification strategy would be to use the interpolated series on defense and non-defense R&D as a structural shock after controlling for some lagged variables. This is the Blanchard and Perotti (2002) identification method as used by Lipsis et al. (2023) and similar to Antolin-Diaz and Surico (2025), both of which focus on public R&D. As we show in Section 4 when we distinguish between defense and non-defense this type of identification tends to predict shock inconsistent with the narrative evidence, and it would inherit much of the measurement errors. Fortunately, Fieldhouse and Mertens (2024) narrative series are uncorrelated with this measurement error. In Section 3, we also compare the wrong timing given by the recursive identification.

The most relevant defense R&D appropriations shocks are dated during the Korean War, the Sputnik Crises, the Strategic Defense Initiative, the 9/11 and the last two shocks dated during the Obama and Trump Administrations in 2016 and 2018, respectively. Conversely, the most relevant non-defense R&D shock is dated during the Space Race, which led to a

[6] The five major federal agencies of the U.S. account for 87 to 93% of total federal R&D spending

massive change in NASA, NSF and the Civilian Department of Energy (DoE) appropriations.

2.3. Econometric Methodology

We use the narrative series of R&D exogenous appropriations shock in local projections (Jordà 2005; Jordà and Taylor 2025) to estimate the Impulse Response Functions (IRFs) relying on a direct regression of the variable of interest in period $t + h$ on an identified shock at time t and on control variables.

In practice, we estimate the following local projections (LPs):

$$y_{t+h} = \alpha_{(h)} + \beta_{(h)} d_t + \sum_{i=1}^{p} \gamma_{i(h)} X_{it} + \varepsilon_{(h)t+h} \quad \text{for } h = 0, 1, 2, \ldots, \tag{1}$$

where y_{t+h} is the outcome variable of interest, $\alpha_{(h)}$ is the intercept, $\beta_{(h)}$ is our IRFs, d_t is the identified shock, and X_{it} include lagged control variables. In our estimation, d_t is directly the narrative series. The LPs are estimated with a series of OLS regressions of future outcomes on a present shock and controls. [7]

There is a considerable debate in the literature about VAR versus LPs. Montiel Olea et al. (2025) summarize important and practical aspects of the two methodologies. Montiel Olea and Plagborg-Møller (2021) show that *lag-augmented* LPs with heteroscedasticity-robust standard errors are asymptotically valid uniformly over the persistence in the data and for a wide range of horizons. Our concern is to capture the technological diffusion after an increase in public R&D as in Antolin-Diaz and Surico (2025). In this context, Bayesian VAR with long lags and penalized LPs become attractive (Antolin-Diaz and Surico 2025). [8]

We estimate the IRFs using smooth-local projections (SLPs) as proposed by Barnichon and Brownlees (2019) using penalized B-splines for approximating the IRFs. The B-spline parameters are estimated using a generalized ridge regression, shrinking parameters towards a quadratic polynomial. SLPs reduce the variability of the IRF estimates while preserving the flexibility of the LPs (Barnichon and Brownlees 2019). However, the econometric literature is still exploring penalized LPs (Montiel Olea et al. 2025; Li, Plagborg-Møller, and Wolf 2024), including the theoretical justification of constructing standard errors (Jordà and Taylor 2025). In the Appendix, we also use least-squares LPs with robust standard errors. We leave details on the Barnichon and Brownlees (2019) procedure in the Appendix.

[7] Since we successive lead the dependent variable, except for horizon $h = 0$, the residuals ε_{t+h} will be serially correlated since they will be a moving average of the forecast errors from t to $t + h$

[8] Montiel Olea et al. (2025) argue that an LP can be viewed as a VAR that controls for a lot of lags. The same is discussed by Ludwig (2024). Montiel Olea et al. (2025) also highlight that the bias and standard deviation of VAR estimators strictly depend on the chosen lag length, whereas the LP estimator is significantly less sensitive to this choice.

We estimate Equation (1) up to a horizon of 40 quarters, given the adoption lags following a public R&D shock. We use four lags for all the control variables and specify non-stationary variables in log levels given the robustness property of LPs to the high persistence of the data (Montiel Olea et al. 2025). We use the same baseline of control variables of Fieldhouse and Mertens (2024). We include four lags of cumulative R&D appropriations (defense or non-defense), utilization capacity, utilization-adjusted TFP (Fernald 2014), public R&D capital, private R&D capital, the stock market in manufacturing, high tech, and health industries and finally, Ramey's Military news (Ramey 2011; Ramey and Zubairy 2018) to control the predicted increase in aggregate government spending, including public R&D (Antolin-Diaz and Surico 2025). Differently from Fieldhouse and Mertens (2024), we always include lags of the shock in our control variables. Following Fieldhouse and Mertens (2024), we normalize the shock by the peak response of the public R&D capital.

3. Results

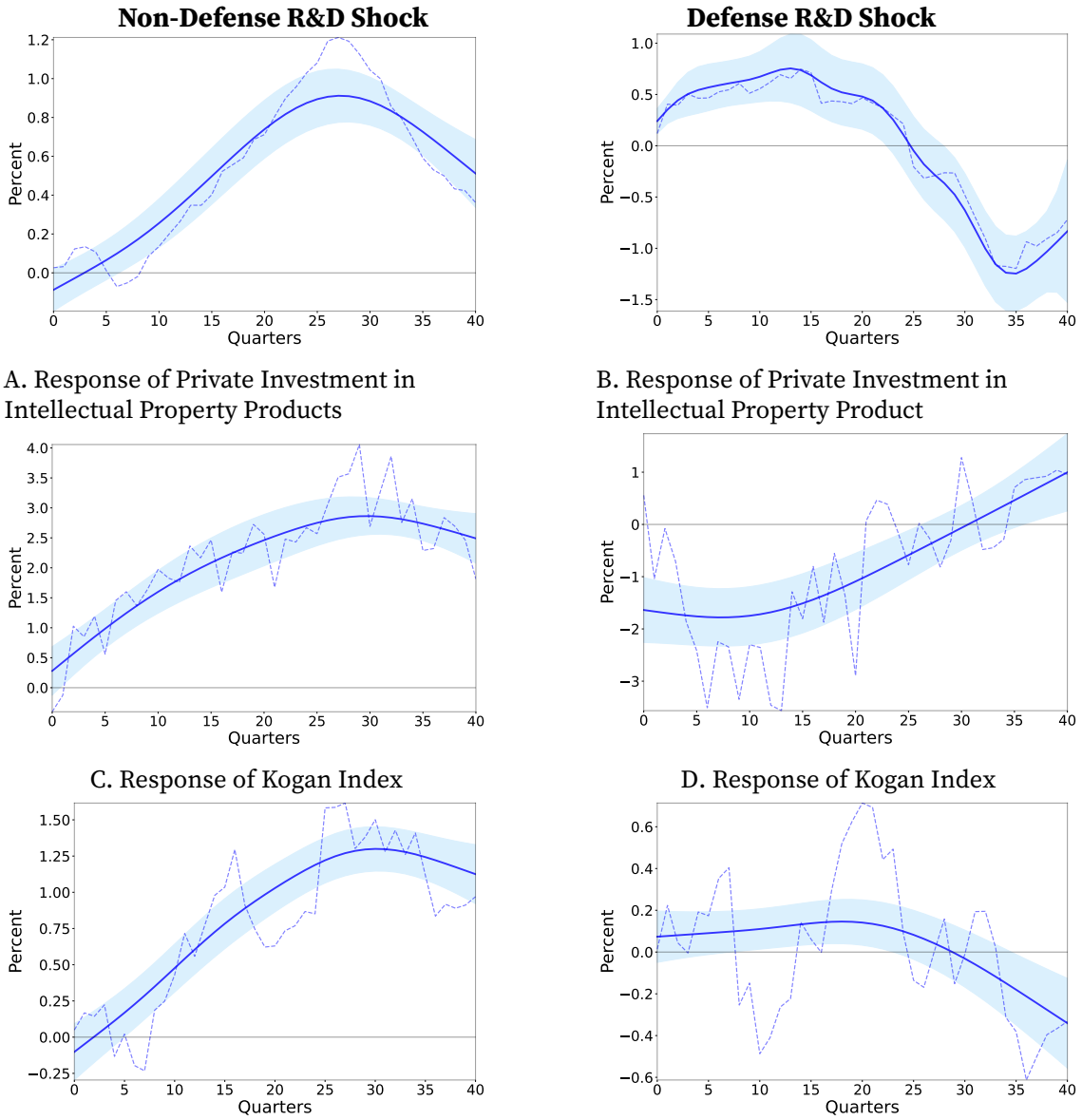
This section presents our main results using the orthogonalized version of the narrative shock of Fieldhouse and Mertens (2024). The orthogonalized shocks are the residuals of a regression of one shock (non-defense) on the other (defense). This orthogonalization can remove contemporaneous effects between changes in appropriations only on the impact. [9] Even if defense and non-defense R&D shock are correlated, and the orthogonalization may not be sufficient, we show in Section 4 that the shocks are probably driven by different sources. In the Appendix, we provide a different specification not based on the orthogonalized shock.

3.1. Baseline Results

Figure 5 reports the IRFs comparing non-defense versus defense R&D shock. For a shock that leads to a one per cent increase in public R&D capital, the private investment in intellectual property products (IPP) as measured in the national accounts, that includes R&D, software and artistic original products, increases by 1 per cent six years after a non-defense shock.

Following a non-defense R&D shock, the response of the patent-based innovation index (hereafter the Kogan Index) is sustained, with a peak increase of more than 3 % five years after the shock. The Kogan et al. (2017) Index is constructed using changes in stock market valuations of firms that obtain patent grants by combining firm-level data on patent grants with their subsequent stock price movements using firm-level datasets. The

[9] In the robustness section in the Appendix, we introduce both shocks in our SLPs.



A. Response of Private Investment in Intellectual Property Products

B. Response of Private Investment in Intellectual Property Product

C. Response of Kogan Index

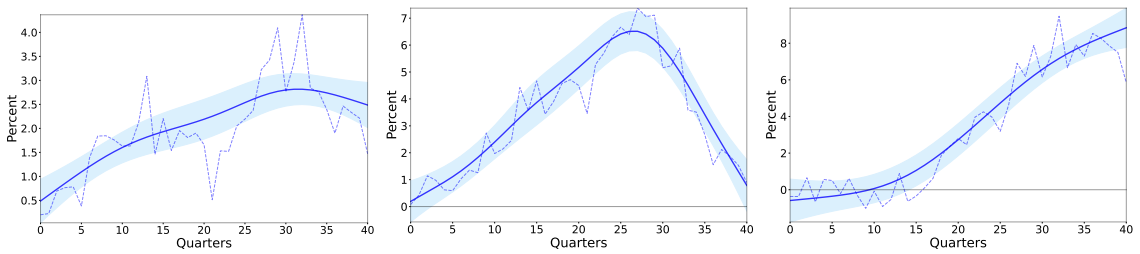
D. Response of Kogan Index

E. Private Investment in Information Processing Equipment and Software

F. Private Investment in Information Processing Equipment and Software

FIGURE 5

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Log Private investment in intellectual property product (IPP) is deflated using the NIPA index on private intellectual property. Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense appropriations, the stock market in manufacturing, high-tech, and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs *Sample:* 1947:Q1–2019Q4



A. Manufacturing Industry B. Electrical Equipment C. Business Services

FIGURE 6. Response of Disaggregated Kogan Index to a Non-Defense R&D Shock

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Disaggregated Kogan et al. (2017) is from Cascaldi-Garcia and Vukotić (2022) replication files. Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* 1948:Q1–2010:Q4

index is expressed in dollars and, therefore, can be compared across time and industries. [10]

Following a defense R&D shock, private investment in IPP responds positively on impact but turns negative after five years, while the Kogan et al. (2017) reaches positive values six years after the shock.

The bottom panel of Figure 5 shows the response of private fixed investment in information processing equipment and software. This variable is deflated using their price index since the prices of the information processing equipment and software have experienced a relevant decrease during the whole sample. This variable includes as one of the principal subcategories, computer and peripheral equipment. The response following a non-defense R&D shock is similar to the response of private investment in IPP. Following a defense R&D shock, the response is almost zero and becomes negative.

As we show in the Appendix, when using least squares *lag-augmented* LPs with robust standard errors, the results regarding defense R&D are not statistically significant.

Disaggregated Kogan Index— We evaluate the response of Kogan et al. (2017) disaggregated for industries [11]

Figure 6 shows the disaggregated response of three sectors: manufacturing, electrical equipment and business services. The industry evidence suggests that manufacturing

[10]The aggregate index represents the total value of all patents granted to the firms in our sample during a specific quarter that is then scaled by the GDP. The period can be extended using the repository available on GitHub.

[11]From 1948:Q1 to 2010:Q4. In Figure 5, the sample spans from 1947:Q1 to 2019:Q4. We verify the results are similar using a sample from 1948:Q1 to 2019:Q4. We are grateful to Danilo-Cascaldi Garcia for sharing his data.

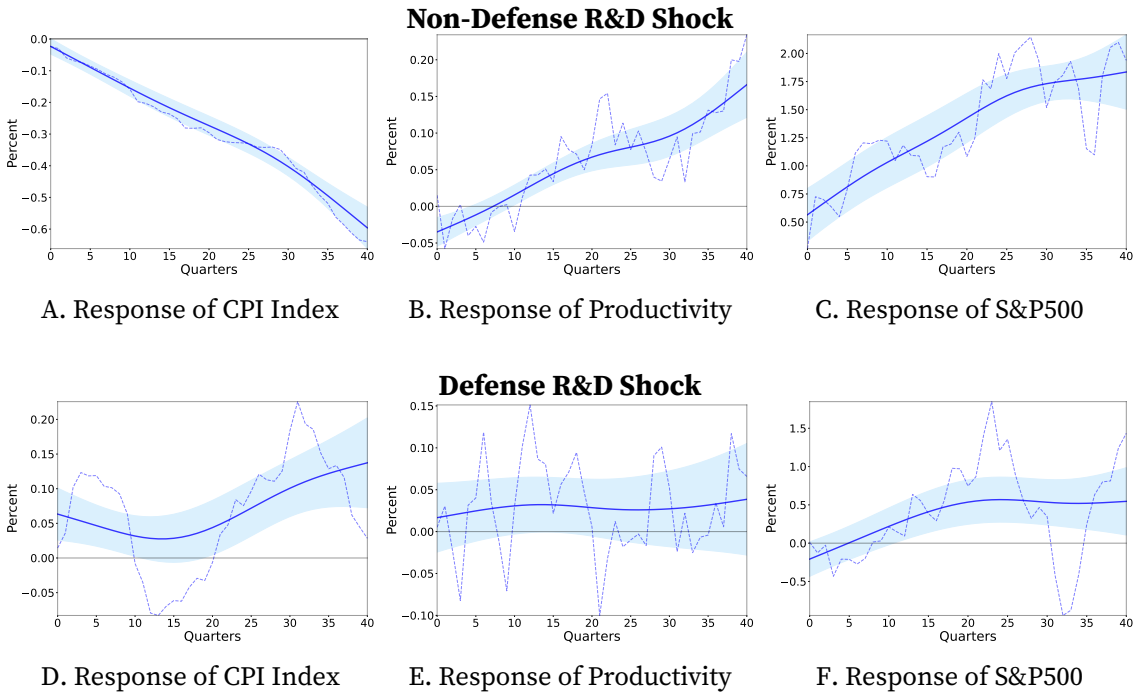


FIGURE 7

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). CPI Index is expressed in log. Productivity is log of real GDP divided by total hours. S&P500 is the log from Robert Shiller's composite index. Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* 1947:Q1–2019:Q4.

is one of the most relevant sectors for explaining the fluctuations of the index (Cascaldi-Garcia and Vukotić 2022).

Electrical equipment is one of the most important industries in manufacturing, and one of the most important sub-industries is related to semiconductors and other devices. Finally, the right panel of Figure 6 reports the response of Business Services, which represents 93 % of services patents. The main sub-sector is *Computer Programming, Data Processing And Other Computer Related Services*, which account for 80 % of the patents in business services (Cascaldi-Garcia and Vukotić 2022). The response is still sustained ten years after the shock. For a non-defense R&D shock that leads to a one per cent increase in public R&D capital, the innovation business services index increases by 8%.

Cisco and IBM are high-frequency patenting companies in the business services sector; IBM has an average of 1,384 patents granted per year (Cascaldi-Garcia and Vukotić 2022). Not surprisingly, professional and business services is a sector with a large fraction of non-defense government purchases (Cox et al. 2024).

Productivity, Prices and Stock Market— Figure 7 shows the response of the Consumer Price (CPI) Index, labor productivity measured as the log of the GDP over the total hours as in Klein and Linnemann (2023) and the S&P 500 index (in log). Following a non-defense shock, the CPI index decreases, while labor productivity and S&P500 increase. These results can be reconciled with Mumtaz and Theodoridis (2020), which find a positive response of the stock market following a government spending shock in the pre-1980 sample, during which government spending leads to an expansion in supply. Thus, they find an increase in productivity and a decrease in prices.

The potential transmission channel of Mumtaz and Theodoridis (2020) is related to the decreasing role of government R&D starting from the '80s. The diminishing significance of the endogenous growth mechanism driven by the declining effect of government on R&D on labor productivity has potentially reduced the impact of government spending on technology (Mumtaz and Theodoridis 2020).

The bottom panel of Figure 7 shows the response following a defense R&D shock. The CPI index exhibits a hump-shaped pattern initially, followed by another increase. The response of labor productivity is erratic and not statistically significant.

Interestingly, our IRF responses following a non-defense R&D shock are similar to those derived from the theoretical model of Schmöller (2022), in which fiscal support to private R&D boosts aggregate demand and TFP while inflation decreases. R&D has a long implementation lag, with a TFP peak after four years (Schmöller 2022).

3.2. Inspecting the Mechanism

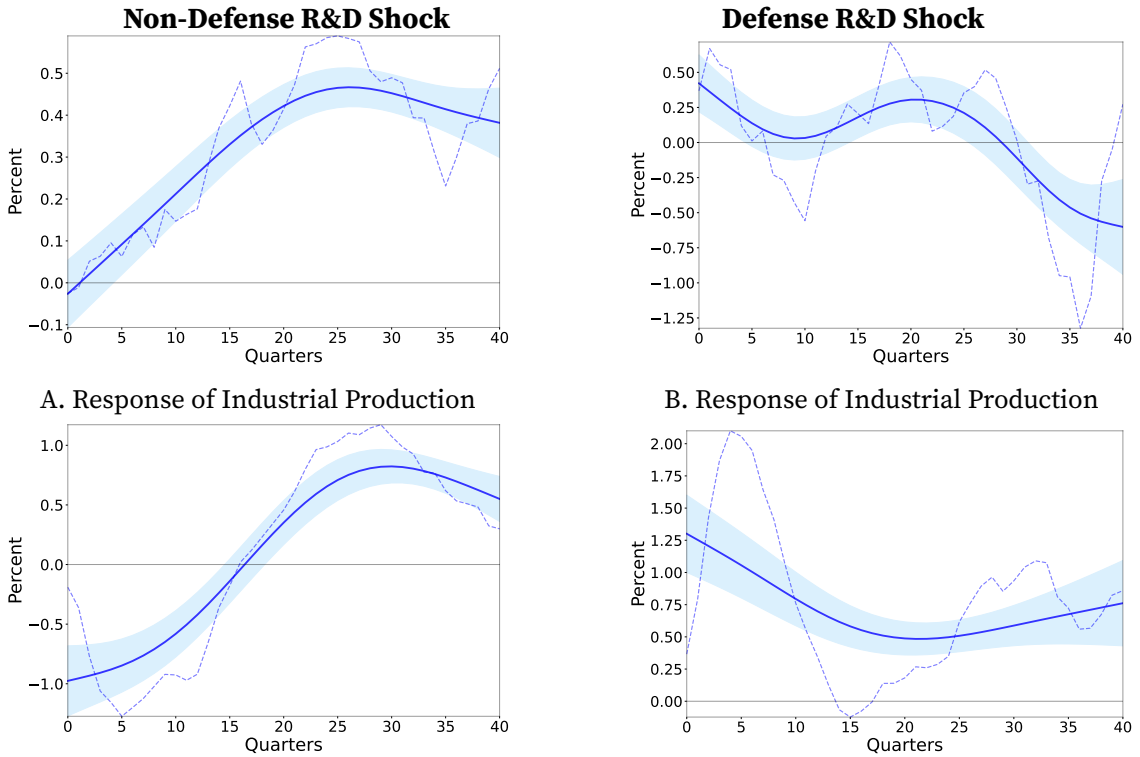
Industrial Production and Sectoral Output— Figure 8 shows the response of industrial production and of industrial production in defense and space equipment sector.

Following a non-defense R&D shock, overall industrial production increases, peaking after five years. At the same time, the response of industrial production in defense and space equipment has a negative impact, with a positive peak after five years.

A defense R&D shock leads to a hump-shaped increase in defense and space sector, similar, as we show in Section 4, to a defense news shock. We argue that this response may be driven by the defense contractor reactions as argued by Briganti (2023) following a defense contract shock. [12] This is not surprising since the largest increase in defense R&D follows military buildup, as we have seen in Figure 2.

Defense R&D is dominated by demand for weapons, and wartime mobilization led to massive demand for existing weapons (Mowery 2010). At the same time, Mowery (2010) argues there is general evidence that positive effects of military R&D are registered during peacetime. Nevertheless, identifying sources of military R&D variation unrelated to

[12] Industrial Production Source and Description Tables . Briganti and Sellemi (2023) note that this index records defense production with some delay.



A. Response of Industrial Production

B. Response of Industrial Production

C. Response of Industrial Production in Defense and Space Equipment

D. Response of Industrial Production in Defense and Space Equipment

FIGURE 8

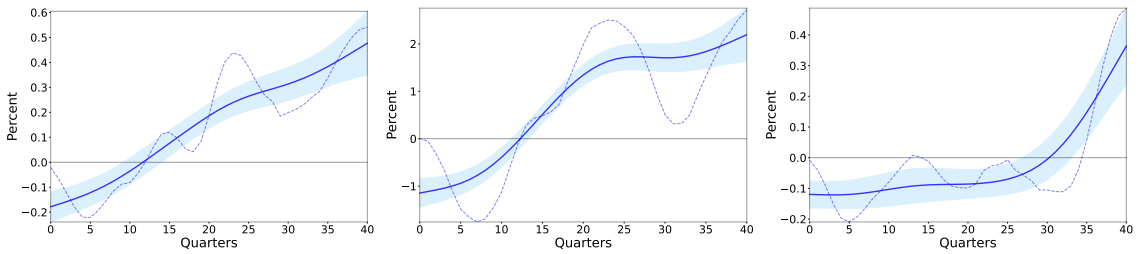
Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* 1947:Q1–2019:Q4

buildups remains challenging. As we show in Section 4, excluding the Korean and Vietnam shocks, we find no evidence of positive effects of defense R&D on innovation or other variables.

The main channels through which defense R&D influences innovation are, according to Mowery (2010) and Ilzetzki (2025), the *spinoffs* and *procurement* channels. Controversial aspects of defense R&D include its potential distortion effects on private firms' innovation efforts and the possible crowding out of privately financed R&D (Cowan and Foray 1995).

An often-used argument is related to the *dual-use* properties of defense R&D products. A similar argument for European small firms is discussed by Ilzetzki (2025).

Howell et al. (2025) investigate the role of *Open Program* for defense contractors. For instance, Anduril, a VC startup founded in 2017, beat out the traditional top defense contractors (e.g., Lockheed), which exhibit a decline in the innovation rate (Howell et al.



A. Manufacturing B. Electrical Equipment C. Business Services

FIGURE 9. Response of Gross Output to a Non-Defense R&D Shock

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* 1947:Q1–Q4

2025) and a rise in mergers (Carril and Duggan 2020).

Figure 9 shows the response of sectoral gross output from our reconstructed data from the BEA industry tables for 1947-1997. As for the disaggregated Kogan et al. (2017) index, Figure 9 shows the response of manufacturing, electrical equipment and business services. The response of manufacturing and electrical is similar, while the output in business services is negative for the first five years, then increases. [13]

Employment and Hours of Production— Figure 10 bottom panel shows the response of employment in Computer Equipment. This category is part of industrial machinery (i.e., manufacturing). For data availability reasons, we use all employment (in thousands). [14]

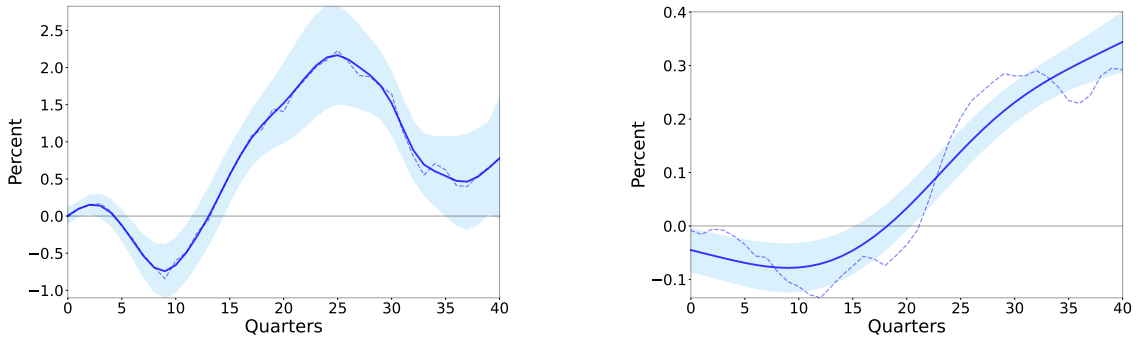
Figure 10 also shows the response of employment in professional and business services from the BLS *Current Employment Statistics*. The main subsector *professional scientific and technical services* (*NAICS 54*) includes architectural, engineering and related services; specialized design services; computer systems design and related services; and management scientific research and development services. As for the response of the Kogan et al. (2017) of business services, the response of employment is still persistent ten years after the shock.

Within manufacturing, Electronic, Industrial Machinery and Computer Equipment and Chemicals are the industries that account for 64 % of the total values of all patents in manufacturing (Cascaldi-Garcia and Vukotić 2022) of the Kogan et al. (2017) index. [15]

[13]The pattern is very similar if we use gross value added instead of gross output.

[14]The series only starts from 1958, and the IRFs are problematic if we use four lags due to a weak response of public R&D. Note that the IRFs of employment responses can be delayed due to labor market frictions (Briganti 2023) with respect to the hours of production.

[15]In the Appendix, we also report the chemical sector's response, which is particularly noisy.



A. Employment in Computer Equipment B. Employment in Business Services

FIGURE 10. Response to a Non-Defense R&D Shock

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags (Figure A two lags) of the shock, the outcome variable, cumulated non-defense appropriations, utilization capacity, utilization-adjusted TFP, public R&D capital, private R&D capital, Ramey's Military News and the Stock Market Return in Manufacturing, High Tech and Health Industries.
The IRFs are scaled by the peak response of public R&D capital. In Figure A, we use two lags.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* (A) 1958:Q1–2003:Q4, (B) 1947:Q1–2019Q4

Figure 11 shows the response of hours of production. As discussed by Briganti (2023), the use of average weekly hours of production is new in the time series framework and can be used as a proxy of capital utilization. [16] Transportation equipment, industrial machinery, and electrical equipment are all sectors related to manufacturing, particularly the space sector.

Transportation equipment includes motor vehicles, aircraft, guided missiles, space vehicles, ships, and boats. Industrial machinery includes engines, turbines, computers, office equipment, and other products related to industrial machinery. Finally, Electrical equipment is a sub-sector of electronic and electrical equipment (SIC 36).

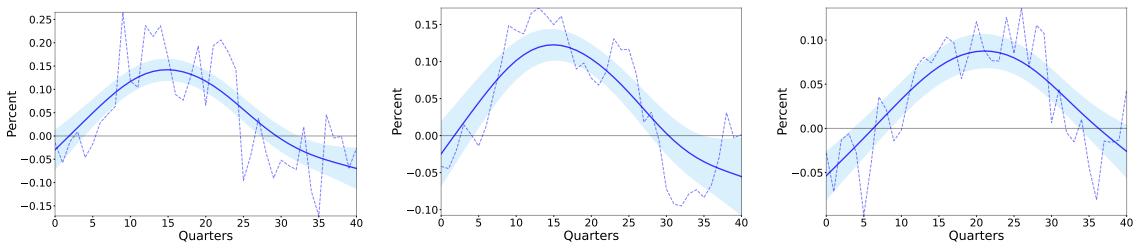
Across all three sectors, we find a similar pattern with a peak increase in average hours of production four years after a non-defense R&D shock. [17]

3.3. NASA R&D Contracting

NASA's policy was primarily to contract out much of its R&D rather than perform it in-house, and NASA R&D procurement contracts have some intrinsic characteristics related to the program (e.g., Mercury, Gemini and Apollo). Many of the largest R&D contracts

[16] Briganti (2023) using a new measure of defense contracts, finds an increase in consumption as well as an increase in hours and labor productivity, in contrast with the previous studies that attribute the finding to a missing timing of the Blanchard and Perotti (2002) recursive shock (see Ramey (2011)).

[17] We also verify that these results are robust to the post-Korea sample, meaning that they are effectively driven by the Space Race period.



A. Transportation Equipment B. Industrial Machinery C. Electrical Equipment

FIGURE 11. Response of Hours of Production to a Non-Defense R&D Shock

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, public R&D capital, private R&D capital and the stock market in manufacturing, high tech and health.
The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.
Sample: 1947:Q1–2002:Q3

were negotiated, with cases in which competition was not feasible Levine (1982). [18]

In the Mercury Project, an industry team composed of Western Electric, Bell Telephone, Bendix, IBM, Burns, and Roe developed the manned spaceflight network. Between 1966 and 1968, General Electric, IBM, Bendix, and Radio Corporation of America were all among the top ten NASA contractors. General Electric rose from tenth to second among NASA contractors.

Belenzon and Cioaca (2022) study the effects of government R&D contracts on upstream and downstream firms' R&D, finding a mechanism of *guaranteed demand* such that firms that demonstrate technological superiority in R&D races with non-competitive downstream procurement are rewarded. Thus, government R&D contracts implicitly promise potential future public procurement.

An additional consideration concerns the interaction between NASA and the Department of Defense (DoD). Indeed, defense R&D contractors tend to collaborate with NASA, as also noted by Belenzon and Cioaca (2022) for a different period. This was particularly relevant during the transition from NACA to NASA and during the Space Race, with the Department of Defense's *Advanced Research Projects Agency* (ARPA) playing a key coordinating role (Rosholt 1966), especially in aeronautical research and cooperative agreements regarding launch and tracking. The NSF, on the other hand, helped to connect NASA with the broader scientific community. Indeed, the NSF R&D shocks are highly correlated with all other agencies. This high correlation indicates the political influence of the NSF, as

[18] NASA's programs were primarily applied research (Levine 1982). The applied research division within the Office of Advanced Research and Technology (OART) conducted the basic research at NASA. For the fiscal year 1963-1968, the four distinct categories of basic research were fluid physics, electrophysics, materials and applied mathematics (Ezell 1988).

TABLE 1. Granger-test

Predicted	Predictor	F	P-value
Narrative Non-Defense R&D	Ramey's Military News	0.04	0.99
Narrative Non-Defense R&D	GDP	1.73	0.14
Narrative Non-Defense R&D	Government Spending	2.73	0.08
Narrative Non-Defense R&D	Non-Defense R&D Spending	2.39	0.05
Narrative Non-Defense R&D	Top 3 Contractors	0.60	0.66
Narrative Non-Defense R&D	Endogenous Tax	0.31	0.87

Notes: Four lags used in the Granger Test. We use series in log-first difference for real per capita GDP, real per capita government and real government defense (non-defense) R&D since the test can be problematic with non-stationary data. In the Appendix, we also report the test for narrative defense R&D.

noted by Dyèvre (2024). [19]

As reported by Belenzon and Cioaca (2022), a recent case study that illustrates the role of procurement in NASA R&D is the Human Landing System (HLS) program. NASA awarded R&D contracts to three companies -SpaceX, Blue Origin, and Dynetics. Due to budget constraints, NASA selected SpaceX as the only contractor. Blue Origin offered to cover up to $2 billion in contract costs to re-enter the competition, highlighting the importance of securing downstream procurement contracts for a firm.

3.4. Timing

Non-defense spending can be anticipated months or years before the fiscal stimulus is completed since there are long delays between the decision to increase spending and the actual increase (Ramey 2011).

Table 1 reports the results of the Granger causality test. We examine whether some lagged macroeconomic variables Granger caused the narrative shock. Nonetheless, our test cannot rule out anticipation effects occurring more than four quarters earlier.

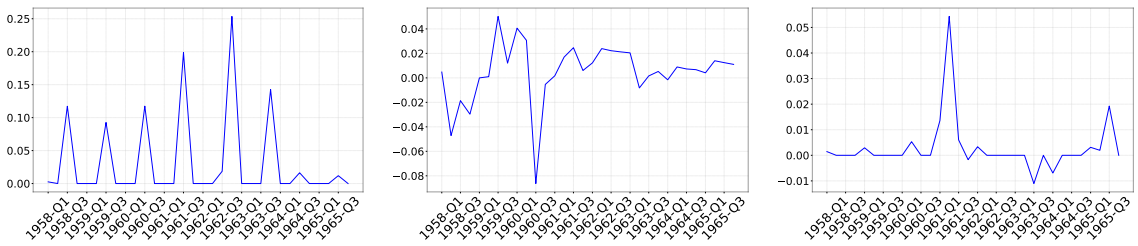
As we graphically inspect in Figure 12, the serial correlation of the R&D shock is much higher for non-defense R&D. A regression of the non-defense R&D shock on its four lags holds an R squared equal to 0.27. [20] The same regression for defense R&D holds an R squared equal to 0.07. This motivates the importance of including lags of the shock and the cumulated appropriations to purge this serial correlation.

Fieldhouse and Mertens (2024) shocks are based on future authorization of increased spending (i.e., appropriations). For instance, one of the largest changes in R&D appropriations in 1962:Q3 reflects the future increase in funding for FY1963.

Figure 12 shows some descriptive evidence during the Space Race. Non-Defense R&D shocks are Fieldhouse and Mertens (2024) scaled shock. Spending shock is the recursive

[19] We report the correlation in the Appendix

[20] Furthermore, the p-value of the F Statistics is equal to 0.0064



A. Non-Defense R&D Narrative Shock

B. Non-Defense R&D Spending Shock

C. Ramey's Military News

FIGURE 12. During the Space Race (1958-1965)

Notes: Non-Defense R&D shocks are from Fieldhouse and Mertens (2024) scaled by public R&D capital. While Ramey (2011) military news shock is scaled by the GDP trend. Average Hours of production in the aircraft and manufacturing sector are from the BLS Discontinued Database. *Sample:* 1958:Q1–1965:Q3

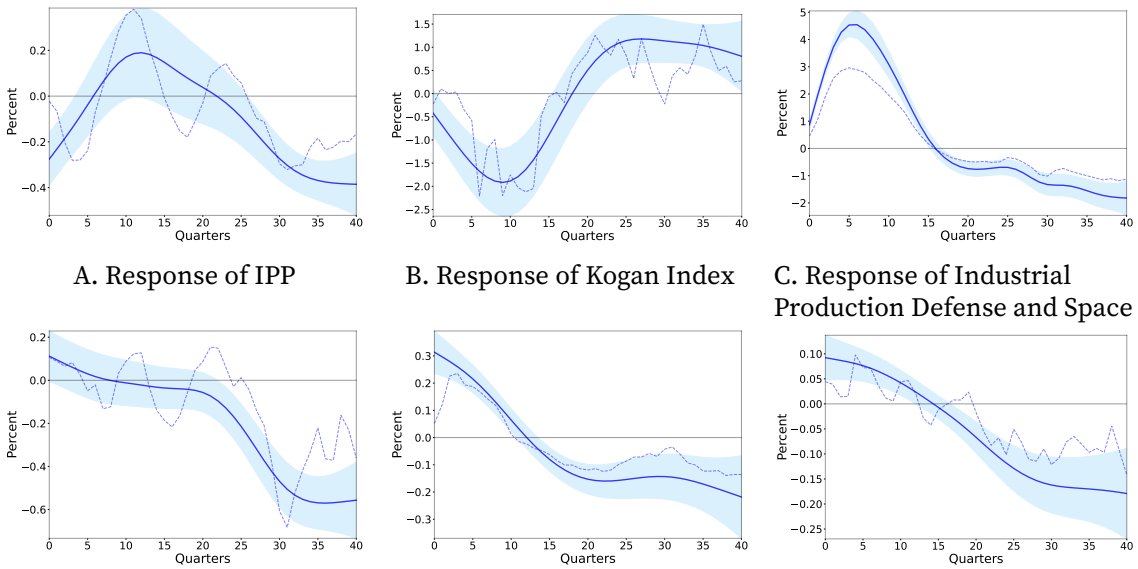
shock based on non-defense R&D spending. The shock is the residual of a regression of non-defense R&D on four lags of itself, real GDP and defense R&D. [21] The recursive spending shock predicted a negative shock in 1960, not consistent with the narrative evidence in Fieldhouse and Mertens (2024) and the identified shock of Antolin-Diaz and Surico (2025). Thus, using the Blanchard and Perotti (2002) identification method for R&D spending can lead to spurious results, especially when distinguishing between defense and non-defense. [22]

Figure 12 also shows the defense news of Ramey (2011) that includes shocks to spending on NASA in 1961:Q1 and 1961:Q2. While the Moon Program ended in 1969, the narrative R&D shocks series identifies the last relevant shock in 1964 in line with Ramey (2011)'s defense narrative, which documents that NASA's budget peaked in 1965 and then declined.

Given our concerns about the timing of Fieldhouse and Mertens (2023) shocks and the unreliability of the recursive identification, in the Appendix, we augment our control variables to include measures that can capture the fiscal foresight. Specifically, we include lagged values of Mertens and Ravn (2012) deficit-driven tax shocks, Fisher and Peters (2010) excess defense contractors, the 3-Month Treasury Bill rate, the unemployment rate, and real GDP as control variables.

[21] We obtain similar results by omitting defense R&D spending or by including defense spending or military news shock (Ramey 2011).

[22] We have reason to believe that the results of Deleidi and Mazzucato (2021) can be an example of this. We construct a new quarterly series using the annual data on non-defense R&D, and as an interpolator in Chow and Lin (1971) method, we use cumulated appropriations in levels and total government spending. While our reconstructed series presents a correlation of 0.99 with the BEA quarterly from the national accounts, when we estimate the shock, the correlation between the two shocks is around 0.24. The recursive shock is particularly noisy in the post-WWII period. In the Appendix, we also replicate the structural VAR of Deleidi and Mazzucato (2021).



A. Response of IPP

B. Response of Kogan Index

C. Response of Industrial Production Defense and Space

D. Response of Industrial Production

E. Response of CPI

F. Response of Productivity

FIGURE 13. Response to Ramey's Military News Shocks

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, real government spending (in log), real GDP (in log) and the stock market in manufacturing, high tech and health. The IRFs are scaled by the peak response of government spending. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.
Sample: 1947:Q1–2019Q:4

4. Sensitivity Analysis

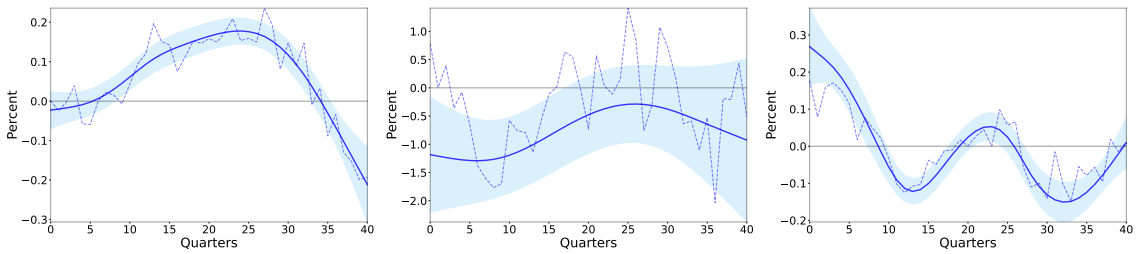
In this section, we assess the robustness of our results across different samples and compare our main findings with the defense news shocks of Ramey (2011). We also examine why non-defense R&D is a weak instrument in the post-Space Race sample.

4.1. Ramey's Military News

We compare the results of the previous sections with those obtained using Ramey's Military News Shock (Ramey 2011; Ramey and Zubairy 2018). We scale the shock by the peak response of total government spending. Following standard practice in the fiscal policy literature, we include four lags of government spending and real GDP as control variables instead of private and public R&D capital. [23]

Figure 13 reports our IRFs to Ramey's military news shock. The top panel shows the response of private investment in IPP, the Kogan et al. (2017) index. Both IRFs are negative

[23] In our baseline results, as in Fieldhouse and Mertens (2024), we do not include real GDP in control variables. We include this analysis in the robustness checks presented in the Appendix.



A. Response of Aircraft Hours to Non-Defense R&D

B. Response of Aircraft Hours to Defense R&D

C. Response of Aircraft Hours to Military News

FIGURE 14

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Aircraft Hours are in log Index. The response to Ramey's Military News shock includes control variables as in Figure 13, while the response to defense and non defense R&D include the controls described in the main text in Section 2. The IRFs are scaled by the peak response of public R&D capital for defense and non-defense R&D and by the peak responses of total government spending following Ramey's military news shock.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. *Sample:* 1947:Q1–2019:Q4.

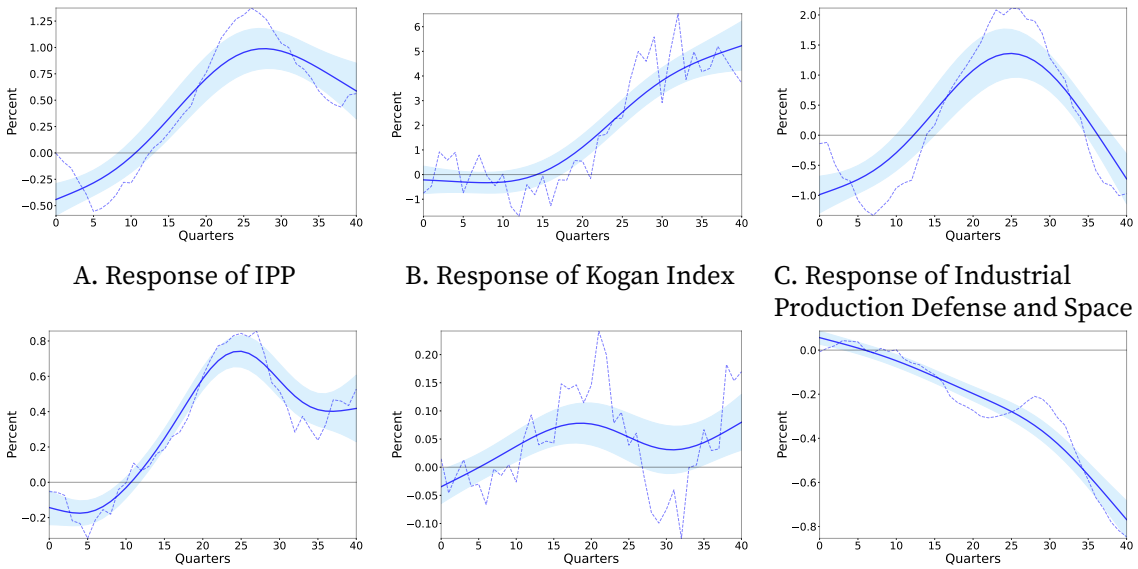
or near zero at impact and then begin to increase. The Kogan index reaches positive values after five years.

The effects of a military news shock may be concentrated among a few large firms, as discussed by Ma and Zimmermann (2023) in their comparison between monetary and fiscal policy shocks. This concern can also be true for a defense R&D shock.

The bottom panel in Figure 13 shows the response of industrial production in defense and space equipment, which increases with a peak after one year. This response is similar to that following a defense R&D shock shown in Figure 5. Following either a defense news shock or a defense R&D shock, industrial production in defense and space equipment exhibits a similar hump-shaped response. The response following a defense R&D shock is more persistent at the medium horizon, although this difference may be due to the different control variables used. At the same time, the response of overall industrial production begins to decline after four years, consistent with the pattern observed in Figure 8.

We find a slight increase in the price index during the first year, followed by a decrease. Our results differ from Jørgensen and Ravn (2022) about the inflationary effects of a government spending shock only near the impact. These findings can be driven by the inflationary effects of military buildup during the Korean and Vietnam Wars (Ilzetzki 2025). Nonetheless, in Figure 17, we find evidence of an increase in the price index in a sample starting from 1966.

The labor productivity response is positive but tends to decline and becomes negative one year after the shock. Compared to a defense R&D shock, the effects are less persistent



A. Response of IPP

B. Response of Kogan Index

C. Response of Industrial Production Defense and Space

D. Response of Industrial Production

E. Response of Productivity

F. Response of CPI Index

FIGURE 15. Non-Defense R&D Shock (Post Korea Sample)

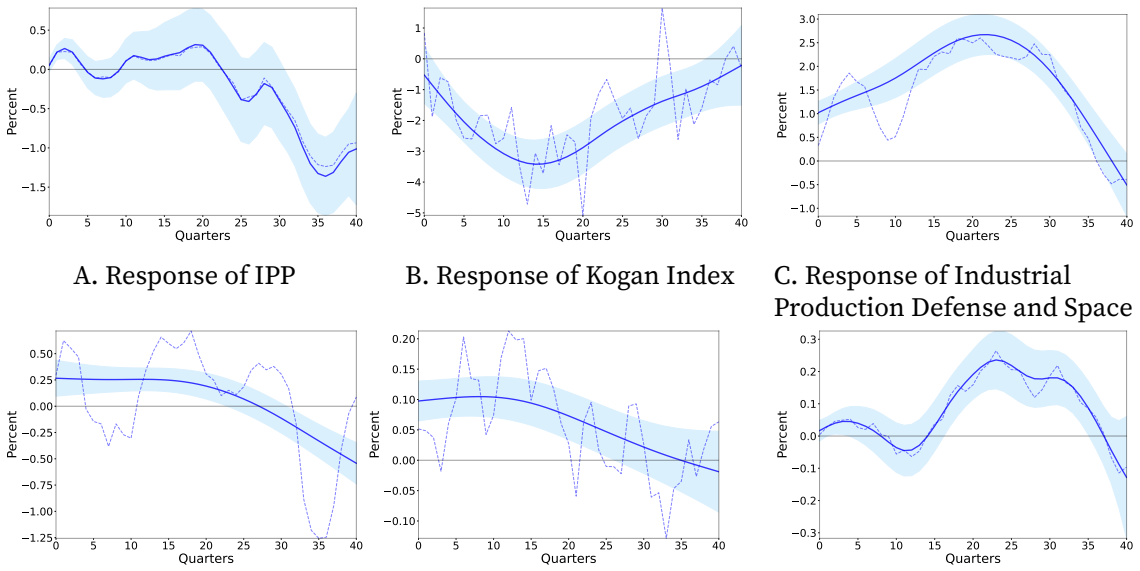
Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The Response functions are scaled by the peak response of Public R&D capital. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs *Sample:* 1954:Q1–2019:Q4

for both the CPI index and labor productivity. [24]

Aircraft Sector— In Figure 14, we compare the responses of the aircraft sector to non-defense R&D shock, defense R&D shock, and Ramey's military news. The right panel shows the response of average weekly aircraft hours to Ramey (2011)'s military news shock. The response is consistent with the evidence in Briganti (2023), which estimates an "internal instrument" VAR with a defense contract measure ordered first. The immediate response indicates the increased production following a defense contract shock. Following a defense R&D shock, hours in the aircraft sector increase by nearly one per cent but tend to decline rapidly after one year. This different response may be explained by the delay between measures of unanticipated defense shocks (e.g., Ramey's News or defense contracts) and Fieldhouse and Mertens (2024) defense R&D narrative shocks.

This result provides a rationale for the pattern of industrial production observed in Figure 8 following a defense R&D shock. While following a non-defense R&D shock,

[24] Our specification includes both the log of GDP divided by total hours and utilization-adjusted TFP. The IRFs are similar if we exclude the utilization-adjusted TFP measures. We also estimate the CPI response to a defense R&D shock by including the log of real GDP in the control variables, and the pattern remains similar.



A. Response of IPP

B. Response of Kogan Index

C. Response of Industrial Production Defense and Space

D. Response of Industrial Production

E. Response of Productivity

F. Response of CPI Index

FIGURE 16. Defense R&D Shock (Post Korea Sample)

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs *Sample:* 1954:Q1–2019:Q4

average hours increase gradually, peaking five years after the shock.

Post-Korea Sample— Our findings remain robust in the post-Korea sample for both defense and non-defense R&D, despite greater uncertainty. Regarding defense R&D, this suggests that the other three military buildups are potential sources of identification.

Figure 15 shows the responses following a non-defense R&D shock. We observe that most effects peak after five years, including the response of average hours in the aircraft sector. There is a somewhat weak response of labor productivity.

Conversely, the effects of defense R&D shock on innovation measures are broadly similar to the response following a military news shock in Figure 5. Our findings show that this pattern is not a feature of the Korean War.

Figure 16 shows the response following a defense R&D shock in the post-Korean war sample. As shown in Figure 4, the Carter-Reagan Buildup and 9/11 are still important sources of identification. Furthermore, the responses of other variables are qualitatively similar to the full-sample specification in Figure 5 and Figure 8. The response of labor productivity is slightly positive, but it becomes negative after four years.

Concerning the findings of Antolin-Diaz and Surico (2025) on the correlation between

TABLE 2. Explanatory Power of R&D Appropriations Shock on R&D Spending

	R-squared	F-statistic
Narrative Non-Defense R&D		
1947:Q1–2019:Q4	0.24	18.2
1954:Q1–2019:Q4	0.39	22.2
1965:Q1–2019:Q4	0.08	2.41
Narrative Defense R&D		
1947:Q1–2019:Q4	0.14	8.0
1954:Q1–2019:Q4	0.18	8.9
1965:Q1–2019:Q4	0.31	16.6
1966:Q1–2019:Q4	0.32	16.2

Notes: The table shows the R^2 and F-statistic from regressions of the growth of real defense or non-defense R&D spending (per capita) on current and four lags of the orthogonalized narrative R&D appropriations shock (Fieldhouse and Mertens 2024).

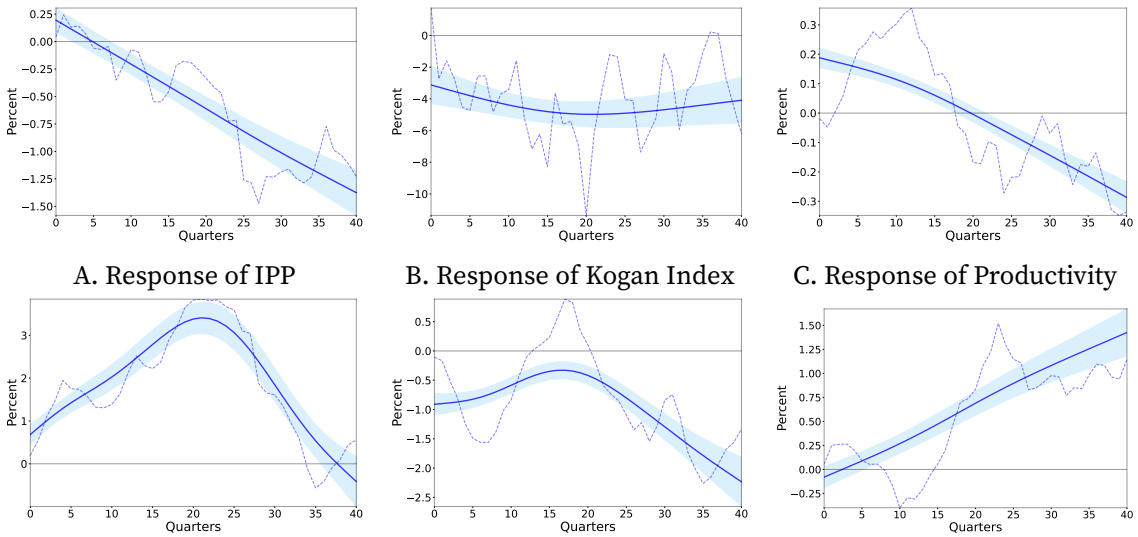
public R&D and war events, we show that excluding the Korean War period from the sample decreases the correlation between Ramey (2011)'s military news and defense R&D appropriations shocks from 0.41 to 0.11. This is close to the 0.17 correlation between public R&D shocks and military news found by Antolin-Diaz and Surico (2025), using a different identification strategy based on a max-share variance method in a Bayesian VAR framework and covering a broader historical sample beginning in 1889. These findings support the view that defense R&D does not account for the bulk of historical public R&D shocks, which likely reflect a mix of defense and non-defense influences (Antolin-Diaz and Surico 2025).

4.2. After the Space Race

Non-Defense R&D— While our results are robust in the post-Korea sample, non-defense R&D has no explanatory power after 1964. We run a regression as Ramey (2011) in which the dependent variable is the growth of non-defense R&D spending (per capita) on current and four lags of the orthogonalized non-defense R&D appropriations shock. We run the same regression for defense R&D. Not surprisingly, non-defense R&D shocks have a relatively high R-squared in the post-Korea sample, but their explanatory power falls dramatically after the Space Race, with an R-squared that drops from 0.403 to 0.08. [25] In Ramey (2011), the military news shock on the growth of government spending in the post-Korea sample has a R^2 = 0.037 with an F-Statistic equal to 1.60. Similar to the non-defense R&D in the post-Space Race sample. This suggests no other important sources of identification for non-defense R&D after the Space Race.

Defense R&D— Defense R&D shocks still have explanatory power after the Space Race

[25] We find a higher R-squared value using eight instead of four lags and use the growth of appropriations



A. Response of IPP

B. Response of Kogan Index

C. Response of Productivity

D. Response of Industrial Production Defense and Space

E. Response of Industrial Production

F. Response of CPI

FIGURE 17. Defense R&D Shock (Post 1966 Sample)

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense R&D appropriations, the stock market in manufacturing, high tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs *Sample:* 1966:Q1–2019:Q4

and Vietnam War, driven by increases during the Reagan SDI ("Star Wars") and after 9/11.

In Figure 17, we report our baseline results using a sample starting in 1966. Thus, we exclude two of the four war dates of Ramey (2011): the Korean and the Vietnam Wars. We still find a negative response of the Kogan et al. (2017) index and the private investment in IPP. Labor productivity increases with a peak three years after the shock, then declines and turns negative. The CPI index starts to increase with a peak response five years after the shock.

The exclusion of these two military buildups tends to attenuate the characteristic hump-shaped response following a defense R&D shock. Correspondingly, overall industrial production remains negative, with a positive peak coinciding with the peak response in defense and space equipment industrial production.

5. Conclusions

This paper contributes to the literature on the macroeconomic effects of government R&D by exploring the transmission mechanisms of defense and non-defense R&D shocks.

Our findings can be summarized as follows. We show that non-defense R&D shocks

stimulate private investment in intellectual property products as well as in information-processing equipment and software. We also document an increase in the patent-based innovation index of Kogan et al. (2017), with a sustained impact on the business services index, which includes computer and data programming services.

Inspecting the mechanism, we find that non-defense R&D shocks lead to increases in employment in professional business services and computer equipment sectors, along with higher average hours worked in transportation equipment, industrial machinery, and electrical equipment. These sectors are strictly connected with space-related industries, particularly NASA's primary contractors and subcontractors.

Consistent with theoretical models with endogenous productivity mechanisms and learning-by-doing, we find a decrease in the price levels and a positive response of labor productivity and stock markets as in Mumtaz and Theodoridis (2020) following non-defense R&D shocks.

In contrast, defense R&D shocks have less clear relationships with innovation measures, while they immediately increase defense and space equipment sector production, like a military buildup. Not surprisingly, major increases in defense R&D follow military buildups. We also find that these effects are similar in the post-Korea and post-Vietnam periods when narrative defense R&D shocks of Fieldhouse and Mertens (2024) still have explanatory effects. Nevertheless, our results do not shed light on the long-run impact of the OSRD during WWII— one of the largest public R&D expansions in U.S. history (Gross and Sampat 2023a,b).

Capturing all the potential spillovers of R&D funding is not straightforward in a time-series econometrics framework. Some caution should be kept regarding the spillover effects of different federal agencies' funding along the lines of Myers and Lanahan (2022) or Dyèvre (2024) that build a dynamic dataset using firm-level data from Compustat matched with government interest patents. We leave these questions for future research.

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Appendix A.

A.1. Data Sources

We use quarterly data from 1947:Q1 to 2019:Q4 unless we indicate other dates for data availability (for instance, when using data from BLS).

We use from Fieldhouse and Mertens (2024) the following series from their data:

- Orthogonalized Defense (non-defense) R&D Shocks
- Defense (non-defense) R&D appropriations scaled shock
- Public R&D Capital
- Private R&D Capital
- utilization-adjusted - TFP from Fernald (2014)
- Utilization Rate
- Stock Market Return in Manufacturing, High Tech and Health Industries are from the Kenneth French Library. Cumulative real stock market return average for manufacturing, high-tech, and health industries

From BEA-NIPA retrieved using FRED, we use the following series:

- Defense R&D Spending
- Non-Defense R&D Spending
- Private Investment in Intellectual Property Products (IPP)
- Private Fixed Investment in Information Processing Equipment and Software
- Industrial Production
- Industrial Production in Defense and Space Equipment
- Consumer Price Index (CPI)
- Nominal GDP, GDP implicit deflator (2012=100) are from BEA-NIPA obtained through the FRED Database.
- Defense investment in R&D is in line 24 of table 3.9.5 in the NIPA's account retrieved from FRED.
- Non-Defense investment in R&D is from BEA-NIPA retrieved from FRED

From other sources, including replication files:

- Patent Based- Innovation index is constructed from the updated dataset of Kogan et al. (2017) following Cascaldi-Garcia and Vukotić (2022) and Cascaldi-Garcia, Vukotić, and Zubairy (2023). The disaggregated data for manufacturing industries are retrieved from the Cascaldi-Garcia and Vukotić (2022) replication files (1948:Q1-2010:Q4)

- Military News are from Ramey and Zubairy (2018) replication files. From 2015 to 2019, we have assumed that the series have values equal to zero as Fieldhouse and Mertens (2024)
- Ramey and Shapiro (1998) military dates augmented with the 9/11 following Ramey (2011). The series takes value equal to one in 1950:Q3, 1965:Q1, 1980:Q1, 2001:Q3, and zeroes elsewhere.
- Excess Defense Contractor is from Fisher and Peters (2010) using Ramey (2016) replication files
- Tax News (Endogenous) are Mertens and Ravn (2012) anticipated tax news using Ramey (2016) replication files
- Total Hours Worked are from Valerie Ramey's website update BLS Statistics (from 1948:Q1)
- S&P500 is from Robert Shiller (S&P 500 composite index)

A.2. Construction of BLS Data on Hours and Employment

- **Professional and Business Services**
  - Current Employment Statistics (CES): All employees, thousands, professional and business services, seasonally adjusted. Monthly from 1947 to 2019. Quarterly as the average of the three-month

We use from the *BLS Discontinued Database* the following series:

- **Transportation Equipment**:
  - Average Weekly Hours of Production from 1947 to 2003, seasonally adjusted at monthly frequencies. Quarterly values are the average of the three months.
- **Industrial Machinery**
  - Average Weekly Hours of Production from 1947 to 2003, seasonally adjusted at monthly frequencies. Quarterly values are the average of the three months.
  - Employment in Thousands. From 1947 at monthly frequencies. Quarterly values are the average of the three months.
- **Aircraft**
  - Average Weekly Hours of Production from 1947 to 2003 at monthly frequencies. We compute the quarterly as the average of the three months and then seasonally adjusted using X-ARIMA 13
- **Electronic and other Electrical Equipment and Components(except Computer Equipment) SIC 36**
  - From the BLS Discontinued is available only starting from 1988. We collect monthly data from 1947 to 1984 using BLS Historical Bulletin No. 1312-12 and No. 2445. For 1984-1988, data were not available in the BLS Historical Bulletin. We

use the Appendix of the Survey of Current Business of October 1985, September 1986, August 1987 and July 1988. The data should be seasonally adjusted in the Survey. We adjust again using X-ARIMA 13.
  - Employment Thousand. Monthly from 1947. We compute quarterly values as the average of the three-month
- **Electrical Distribution Equipment (SIC 361)** Available from 1958 to 2003. For the period 1947 to 1958, we use Bulletin No.1312-12 from FRASER Digital Library and impute the value of the main categories (SIC 36 Electronic and Other Electrical Equipment and Components, Except Computer Equipment)
- **Electrical Components and Accessories (SIC 367)** Available from 1958 to 2003. For the period 1947 to 1958, we use Bulletin No.1312-12 and No.2445 from FRASER Digital Library and impute the value of the main categories (SIC 36 Electronic and Other Electrical Equipment and Components, Except Computer Equipment)
- **Computer and Office -Equipment (SIC Code 357)**
  - Data from BLS Discontinued Database are only from 1958, also in the historical bulletin. At the same time, other historical sources do not have this category. We impute the hours of production of main categories (SIC 35 Industrial Machinery and Equipment) that in the Historical Sources is "Machinery Except Electrical". We cross-check the Historical Bulletin No.2445 and the BLS Database. The series is seasonally adjusted using X-ARIMA 13. This category includes Electronic Computers, computer terminals, and Calculators.
  - Employment: data from 1958 BLS Dicontinued
- **Chemicals and allied products (SIC Code 28)** we use from 1947 to 2003. The data are available seasonally adjusted at monthly frequencies from 1947

A.3. Construction of Sectoral Data from BEA Table

We use the historical tables of BEA on Gross Output and value-added for industries. The series are linearly interpolated at quarterly frequencies.

- **Manufacturing** Gross Output from 1947 to 1997 deflated by the Manufacturing Output chain price index. Quarterly series as a linear interpolation of annual data.
- **Electrical Equipment** Gross Output from 1947 to 1997 deflated by the Electrical Equipment Output chain price index. Quarterly series as a linear interpolation of annual data.
- **Business Services** Gross Output from 1947 to 1997 deflated by Business Services Output chain price index. Quarterly series as a linear interpolation of annual data.

Appendix B. Descriptive Evidence

	Military News	DoD	DoE: Defense	NSF	NIH	NASA	DoE
Military News	1.00						
DoD	0.41	1.00					
DoE: Defense	0.00	0.27	1.00				
NSF	-0.01	0.53	0.35	1.00			
NIH	0.05	0.45	0.36	0.59	1.00		
NASA	-0.01	0.18	0.15	0.55	0.27	1.00	
DoE	-0.10	0.21	0.45	0.54	0.38	0.28	1.00

TABLE A1. Correlation R&D Shocks and Military News

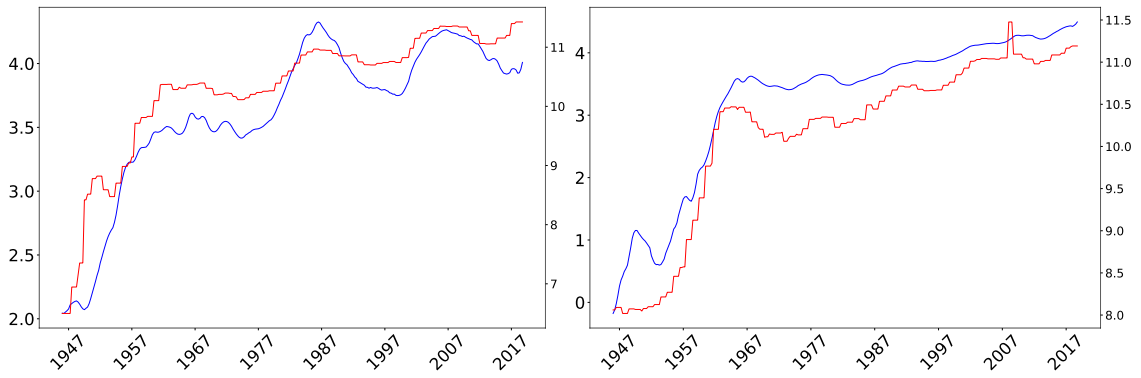
Notes: Correlation between narrative R&D appropriations shock. All agency shocks are scaled by the public R&D capital. Ramey's Military News are deflated with the one previous GDP implicit deflator and scaled by the lagged value of the trend of GDP using a sixth-degree polynomial as in Ramey and Zubairy (2018)
Sample: 1947:Q1-2019:Q4

Table A2 reports the correlation of Narrative R&D. NSF shocks have a high correlation with civilian and military agencies.

	NSF	NIH	NASA	DoE	DoE: Defense	DoD
NSF	1.00					
NIH	0.59	1.00				
NASA	0.55	0.27	1.00			
DoE	0.54	0.38	0.28	1.00		
DoE: Defense	0.35	0.36	0.15	0.45	1.00	
DoD	0.53	0.45	0.18	0.21	0.27	1.00

TABLE A2. Correlation of Narrative R&D Shock

Notes: Correlation between narrative R&D appropriations shock. All agency shocks are scaled by the public R&D capital.
Sample: 1947:Q1-2019:Q4



A. Defense R&D B. Non-Defense R&D

FIGURE A1. R&D Spending and Cumulated Appropriations

Notes: Defense and Non-Defense R&D are from BEA-NIPA deflated using the NIPA price indices for federal defense and non-defense intellectual property products. Cumulated defense and non-defense R&D appropriations shock are in log-levels from Fieldhouse and Mertens (2024)

TABLE A3. Explanatory Power of R&D Exogenous Shock on Cumulated Appropriations

	R-squared	F-statistic
Narrative Non-Defense R&D		
1947:1–2019:4	0.464	22.40
1947:1–2019:4 (**8 lags**)	0.706	20.83
Narrative Defense R&D		
1947:1–2019:4	0.706	20.83
1947:1–2019:4 (**8 lags**)	0.739	17.99

Notes: The table shows the R^2 and F-statistic from regressions of the growth of real cumulated defense or non-defense R&D appropriations on current and four lags of the orthogonalized narrative R&D exogenous appropriations shock (Fieldhouse and Mertens 2024). The F-statistic is a Wald test based on a robust variance-covariance matrix.

TABLE A4. Granger Test

Predicted	Predictor	F	P-value
Narrative Non-Defense R&D	Ramey's Military News	0.04	0.99
Narrative Non-Defense R&D	GDP	1.73	0.14
Narrative Non-Defense R&D	Government Spending	2.73	0.08
Narrative Non-Defense R&D	Non-Defense R&D Spending	2.39	0.05
Narrative Non-Defense R&D	Top 3 Contractors	0.60	0.66
Narrative Non-Defense R&D	Endogenous Tax	0.31	0.87
Narrative Defense R&D	Ramey's Military News	1.01	0.40
Narrative Defense R&D	GDP	3.03	0.02
Narrative Defense R&D	Government Spending	2.21	0.07
Narrative Defense R&D	Defense R&D Spending	1.20	0.31
Narrative Defense R&D	Top 3 Contractors	0.46	0.76
Narrative Defense R&D	Endogenous Tax	0.81	0.52

Notes: Four lags used in the Granger Test. We use series in log-first difference for real per capita GDP, real per capita government and real government defense (non-defense) R&D since the test can be problematic with non-stationary data.

B.1. NASA Contractors

B.2. Narrative Evidence on NASA

From Ramey's News.

> *Defense News Shock: Kennedy is much more a hawk than Eisenhower*.
>
> In May 25, 1961, Kennedy gives speech before joint session of Congress announcing goal of going to the moon. NYT May 31, 1961: Estimates price tag of $20 - $40 billion dollars. In July 1961, a 10 yr $35 billion space exploration program sails through Congress. Note: this was not counted as defense spending
>
> *Defense News Shock: Moon mission*
>
> **BW 7/8/1961**: "The Administration's 10-year, $35-billion space exploration program. . . is moving swiftly and almost casually through Congress. Virtually no questions are being raised about the sums involved or the usefulness of sending men to the moon." P. 41
>
> BW 11/26/1966: Budget squeeze on NASA. Probably won't get much over $5-billion for FY 1968. "NASA is spending around $5.4 billion the current fiscal year; last year it hit a peak of $5.9 billion." P. 64. in Ramey and Zubairy (2018)

From Fieldhouse and Mertens (2023). :

Congress again appropriated significant increases in both nominal and real aerospace R&D funding for FY1963, driven by President Kennedy's recent pledge to put a man on the moon as well as broader national security concerns and geopolitical rivalry with the Soviet Union.

"[...] We have tremendous potential resources on other non-military fronts to help in countering the Soviet threat: education, science, research, and, not least, the ideas and principles by which we live [...] This involves new activities by the Department of Health, Education, and Welfare designed principally to encourage improved teaching quality and student opportunities in the interests of national security." Dwight D. Eisenhower *State of the Union*

"The Kennedy administration's FY1962 budget requested a significant increase in NSF funding, proclaiming that "new scientific knowledge which stems from basic research is indispensable to the technological progress of modern industrialized society." Funding basic research and the "improvement of graduate school laboratories" were top policy priorities of the administration"

"In real terms, NASA's research and science budget peaked in FY1965 and then steadily fell for more than a decade, with funding cut nearly 60% over FY1966-76"

From NASA's Historical Book.

April 7, 1959:

$3 million

NASA Administrator T. Keith Glennan requested $3 million for research into rendezvous techniques as part of the NASA budget for Fiscal Year 1960

June 18, 1959:

NASA authorized $150,000 for Army Ordnance Missile Command studies of a lunar exploration program based on Saturn-boosted systems.

March 28, 1961:

President John F. Kennedy submitted to Congress an amended budget request for NASA which totaled $1,235,300,000. This total was $125,670,000 greater than the Eisenhower Administration's request. The increase included $56 million for Saturn research and development and $11 million for the extension of Cape Canaveral facilities.

TABLE A5. Ranking of NASA's Top Ten Contractors by Fiscal Year

Contractor	FY 1962	FY 1963	FY 1964	FY 1965	FY 1966	FY 1967	FY 1968
North American Rockwell Corp.[a]	1	1	1	1	1	1	1
McDonnell Aircraft Co., Inc.[b]	2	2	2	2	4	4	4
Douglas Aircraft Co., Inc.[b]	3	4	3	4			
Aerojet-General Corp.	4	3	8	8	8	8	8
United Aircraft Co.	5	9	–	–	–	–	–
Chrysler Corp.	6	7	6	9	9	–	–
General Dynamics Corp.	7	5	9	–	–	–	–
Ling-Temco-Vought, Inc.	8	–	–	–	–	–	–
Grumman Aircraft Engineering Corp.	9	10	5	3	2	2	2
General Electric Co.	10	8	7	2	3	3	3
Boeing Co.	–	6	4	10	7	7	5
International Business Machines (IBM) Corp.	–	–	–	–	10	–	9
Radio Corp. of America	–	–	–	–	–	7	7
Bendix Corp.	–	–	–	–	–	6	10
General Motors Corp.	–	–	–	–	–	–	–

Notes: Authors elaboration from NASA Historical databook of Van Nimmen, Bruno, and Rosholt (1988).
[a] North American Aviation, Inc. until FY 1967. [b] McDonnell and Douglas Aircraft merged to form McDonnell Douglas Corporation starting FY 1966.

Appendix C. Smooth LPs and Alternative Inference for LPs

Consider the following LPs:

$$y_{t+h} = \alpha_{(h)} + \beta_{(h)} d_t + \sum_{i=1}^{p} \gamma_{i(h)} X_{it} + \varepsilon_{(h)t+h} \quad \text{for } h = 0, 1, 2, \ldots, \tag{A1}$$

We approximate the IRF coefficients are using a linear combination of B-Spline basis functions as in Barnichon and Brownlees (2019):

$$\beta_{(h)} \approx \sum_{k=1}^{K} b_k B_k(h) \quad \text{for } k = 1, \ldots, K \tag{A2}$$

Substituting Equation (A2) into Equation (1),stacking over time and rewriting in compact form:

$$Y = X\theta + U \tag{A3}$$

Following Barnichon and Brownlees (2019), θ, the vector of B-Spline parameters $(a_1, \ldots, a_K, b_1, \ldots, b_K, c_{11}, \ldots, c_{1K}, \ldots, c_{p1}, \ldots, c_{pK})'$ is estimated using a generalized ridge regression

$$\hat{\theta} = \arg\min_{\theta} \left\{ \|Y - X\theta\|^2 + \lambda \theta' \mathbf{P} \theta \right\} = (X'X + \lambda \mathbf{P})^{-1} X'Y \tag{A4}$$

where **P** is a symmetric positive semidefinite penalty matrix that determines the penalty applied. We set **P** to shrink the IRFs towards a line. λ is the penalty parameter that controls the regularization. The penalization lowers the variance of LPs while potentially increasing the bias. The λ is estimated through a 5-fold cross-validation. Standard errors are HAC (Newey and West 1987) as in Barnichon and Brownlees (2019). The B-spline method can smooth the IRFs over various shapes. But since a tuning parameter must be chosen for regularization, the theoretical justification for constructing standard errors has not yet been developed (Jordà and Taylor 2025).

Lag-augmented LPs. We run our baseline results using *lag-augmented* whit Eicker Huber White standard errors as in **?** IRF's coefficients are smoothed using a rolling window moving average of the coefficients (Jordà and Taylor 2025). We also report the response of the public R&D capital normalized to the peak response.

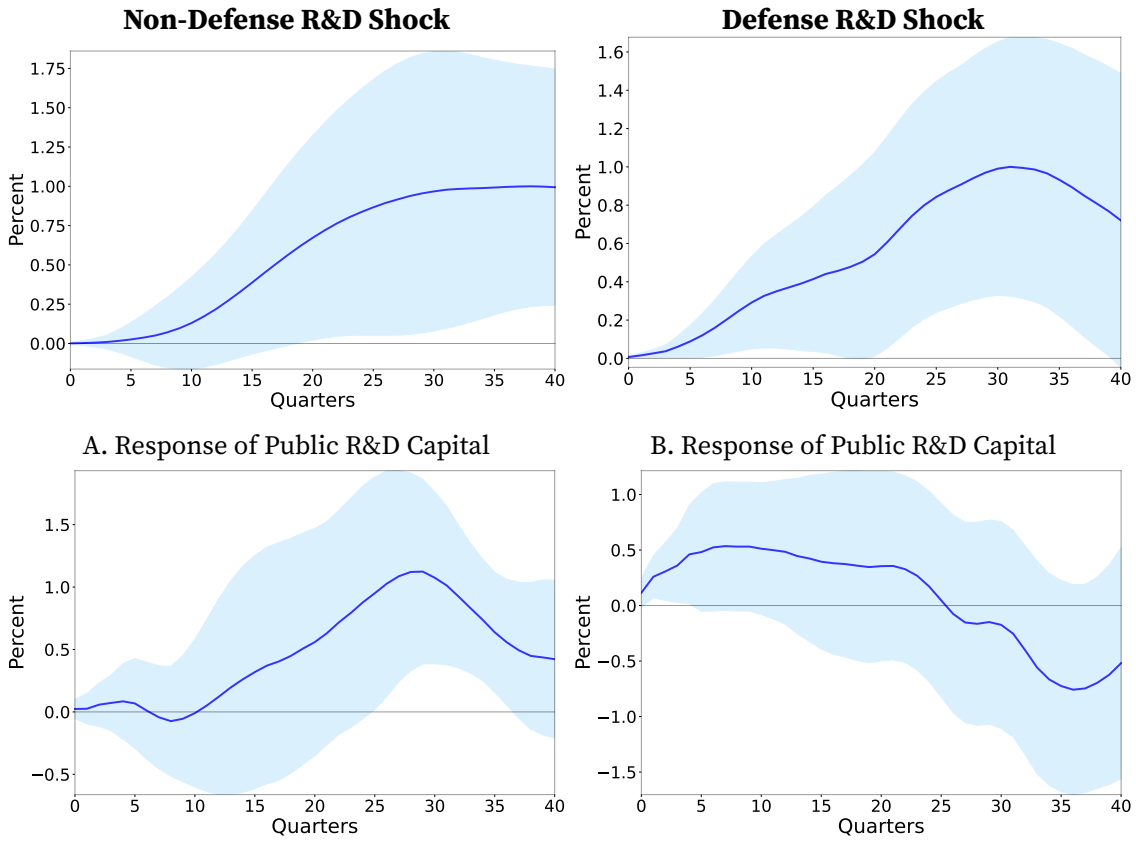


FIGURE A2. IRFs of R&D Capital and Private Investment

Notes: Estimation from a *lag-augmented* LPs. Control variables include four lags of the shock, the outcome variables, the patent innovation index, cumulative R&D appropriations, utilization capacity, utilization-adjusted TFP, public R&D capital, private R&D capital, the stock market in manufacturing, high tech and health, and Ramey's military news.
The IRFs are scaled by the peak response of public R&D capital.
Standard errors are Eicker-Huber-White following Montiel Olea and Plagborg-Møller (2021). 90% confidence bands.
Sample: 1947:Q1–2019:Q4

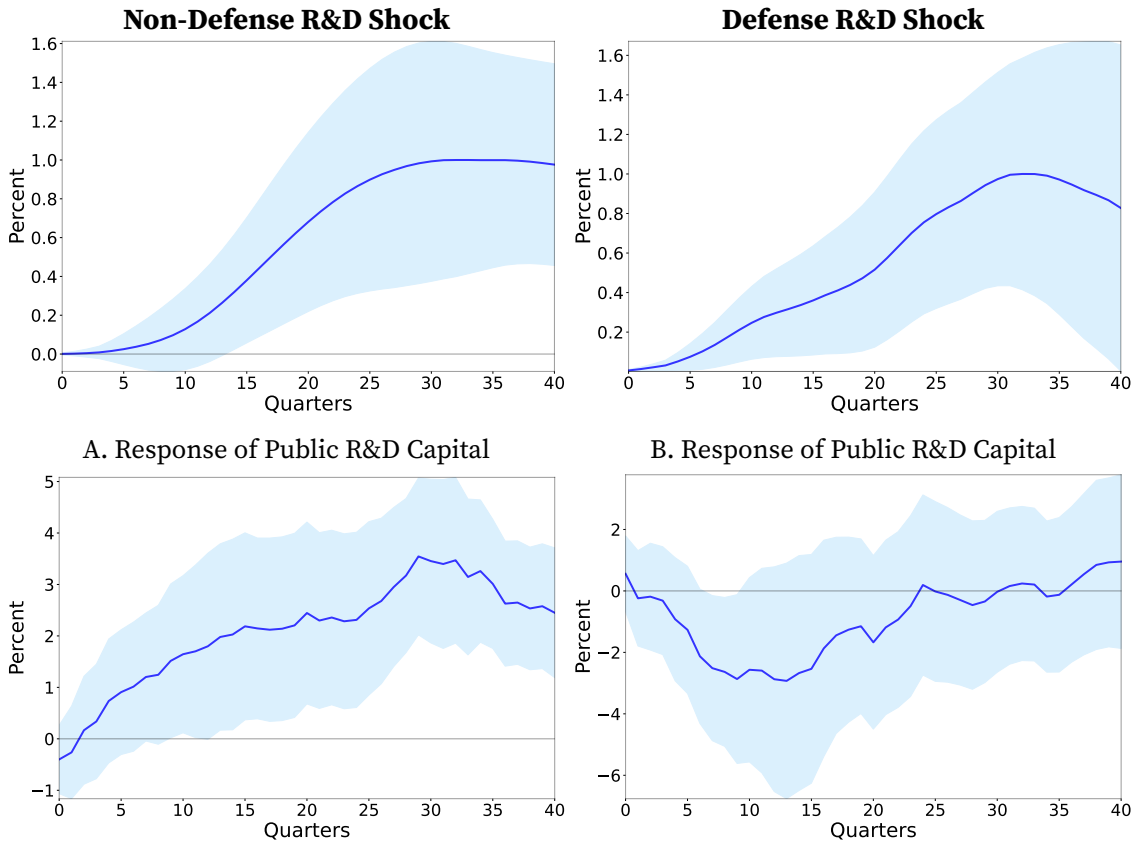


FIGURE A3. IRFs of R&D Capital and Kogan Index

Notes: Estimation from a *lag-augmented* LPs. Control variables include four lags of the shock, the outcome variable, the patent innovation index, cumulative R&D appropriations, utilization capacity, utilization-adjusted TFP, public R&D capital, private R&D capital, the stock market in manufacturing, high tech and health, and Ramey's military news.
The IRFs are scaled by the peak response of public R&D capital.
Standard errors are Eicker-Huber-White following Montiel Olea and Plagborg-Møller (2021). 90% confidence bands.
Sample: 1947:Q1–2019:Q4

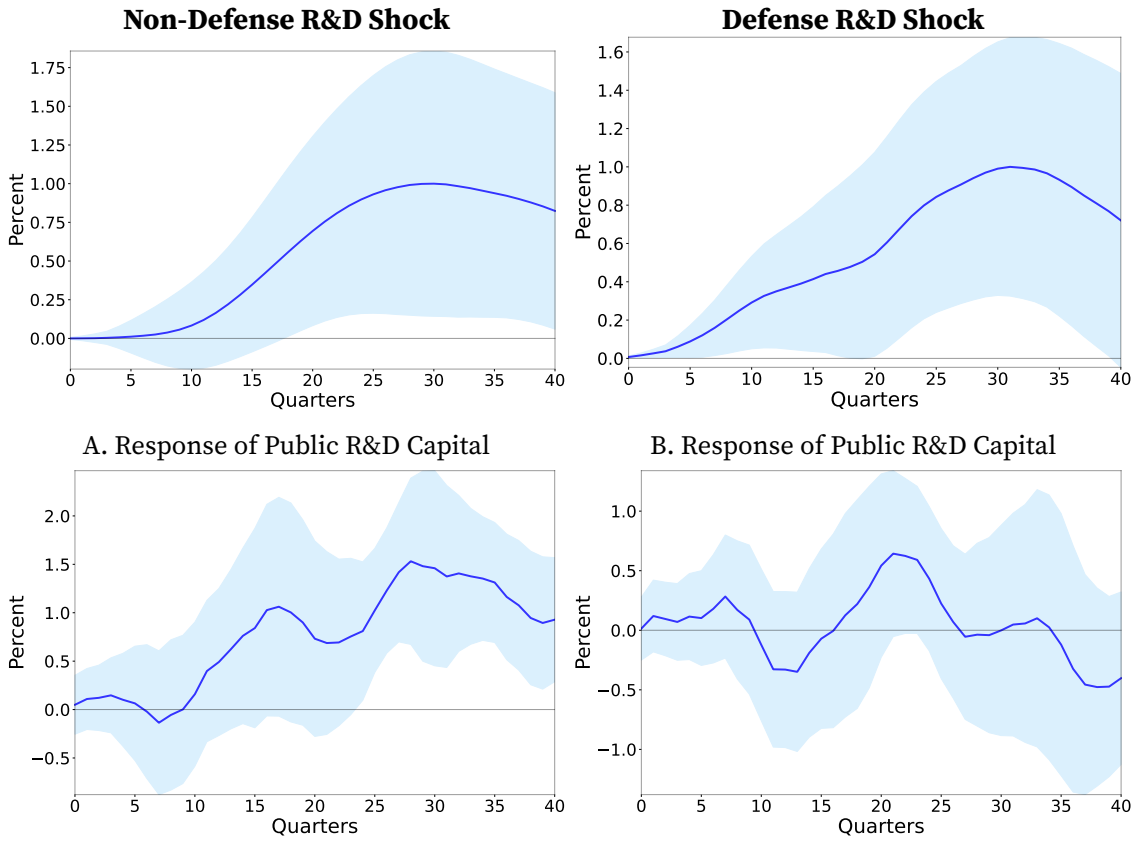


FIGURE A4. IRFs of R&D Capital and Private Investment in Information Processing Equipment and Software

Notes: Estimation from a *lag-augmented* LPs. Control variables include four lags of the shock, the outcome variable, the patent innovation index, cumulative R&D appropriations, utilization capacity, utilization-adjusted TFP, public R&D capital, private R&D capital, the stock market in manufacturing, high tech and health, and Ramey's military news.
The IRFs are scaled by the peak response of public R&D capital.
Standard errors are Eicker-Huber-White following Montiel Olea and Plagborg-Møller (2021). 90% confidence bands.
Sample: 1947:Q1–2019:Q4

Appendix D. Robustness

D.1. Additional controls and alternative specification

Differently from our baseline specification, we use the appropriations scaled shock, while in our control variables, we include lagged values of both the shocks (defense R&D and non defense R&D).

We add as control variables in our SLPs the following variables: log of real GDP, 3-Month Treasury Bill, Unemployment Rate, Fisher and Peters (2010) Excess Defense Contractors and Mertens and Ravn (2012) endogenous tax changes.

With the inclusion of these additional controls, the response of public R&D following a defense R&D shock is almost negative. The response is somewhat more positive if we exclude the pre-Korean War period.

Including these additional controls, the response of industrial production is not more negative during the first quarter, while the peak is similar to the main estimation.

D.2. Lag Length (selected results)

We report the IRFs for some of our previous results using 2 or 6 lags in our SLPs. The control variables are the same as the last section.

Appendix E. Further Results

E.1. Response of Computer Equipment and Chemicals Sectors

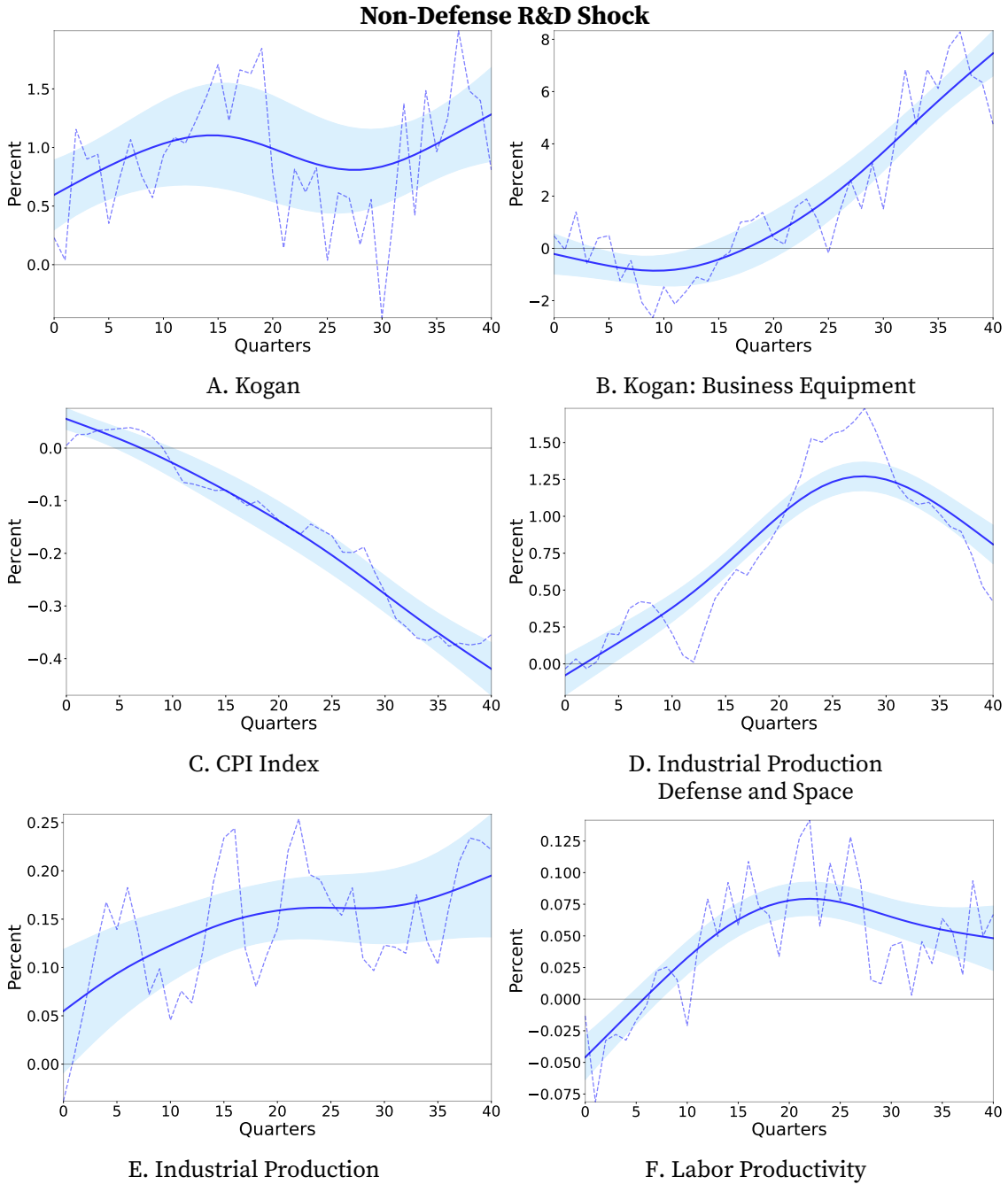


FIGURE A5. Additional Controls

Notes: Estimation from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high-tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs. For the unemployment rate, the shock is 1pt standard deviation

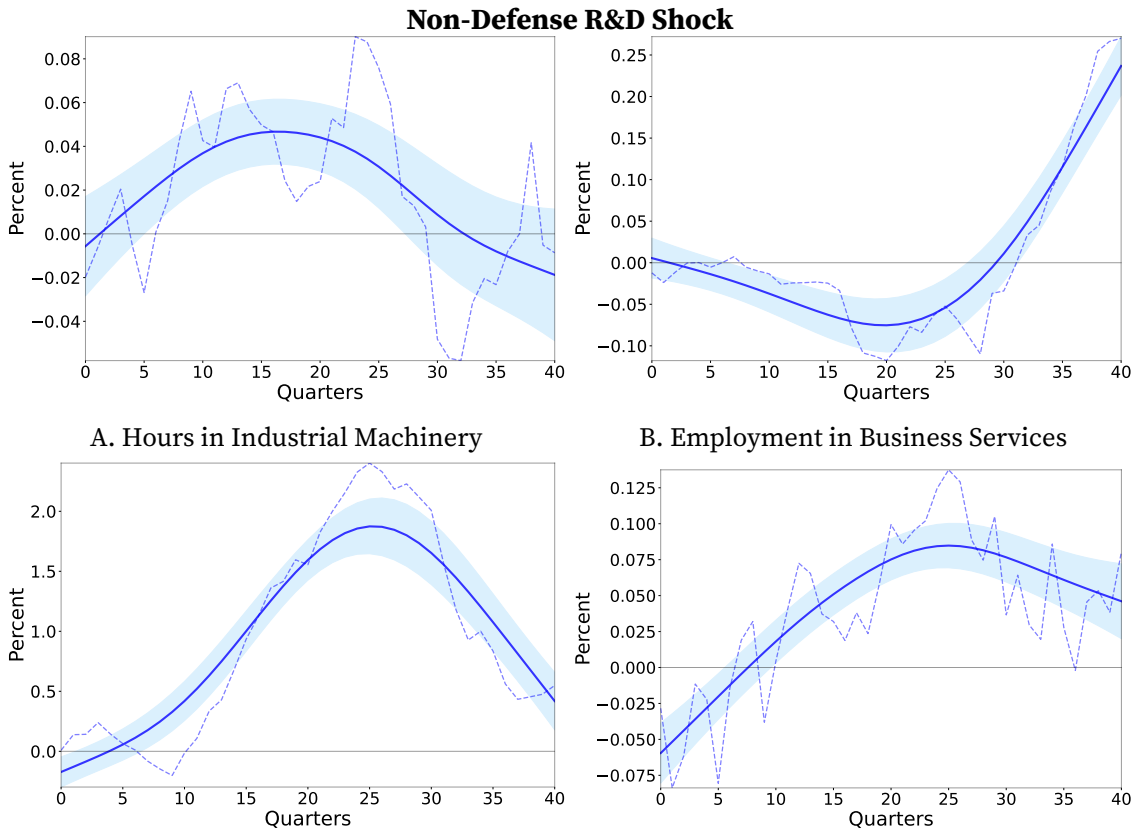
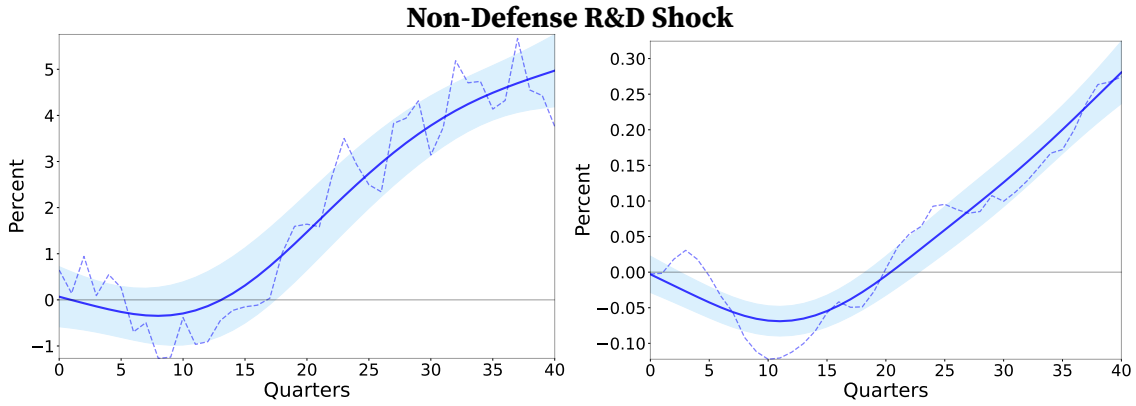


FIGURE A6. Additional Controls

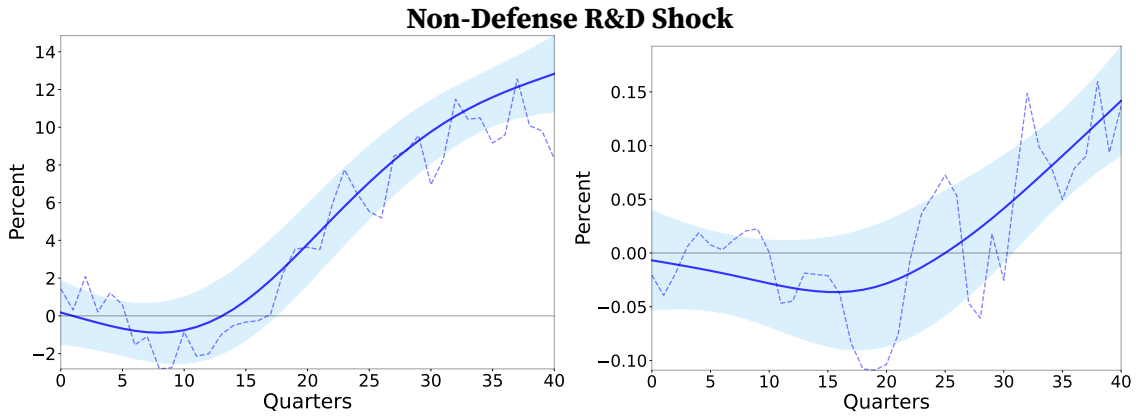
Notes: Estimation from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high-tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.



A. Kogan Index: Business Services B. Employment in Business Services

FIGURE A7. Additional Controls (2 lags)

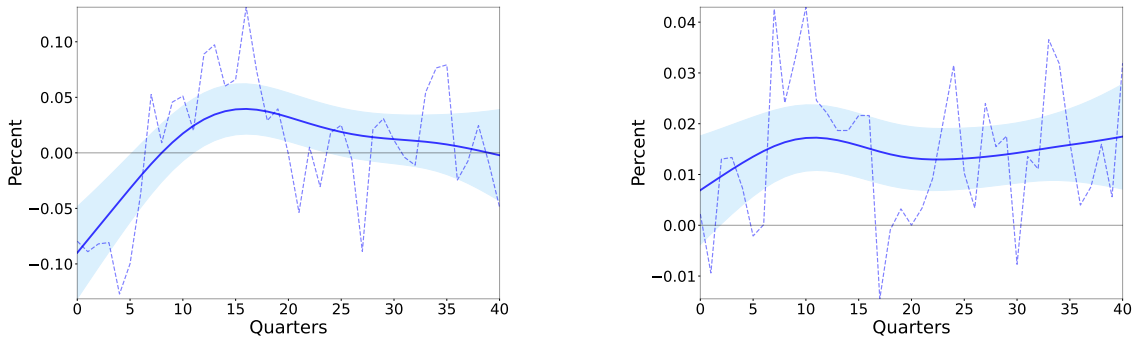
Notes: Estimation from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high-tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.



A. Kogan Index: Business Services B. Employment in Business Services

FIGURE A8. Additional Controls (6 lags)

Notes: Estimation from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, cumulated defense or non-defense R&D appropriations, the stock market in manufacturing, high-tech and health and Ramey's military news. The IRFs are scaled by the peak response of Public R&D capital. Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.



A. Computer Equipment

B. Chemicals

FIGURE A9. Response of Hours of Production to a Non-Defense R&D Shock

Notes: IRFs from Smooth Local Projections (SLPs) as in Barnichon and Brownlees (2019). Control variables include four lags of the shock, the outcome variable, utilization capacity, utilization-adjusted TFP, real government spending in log, real GDP in log, the stock market in manufacturing, high tech and health.
The IRFs are scaled by the peak response of government spending.
Standard errors are Newey and West (1987). 90% confidence bands. Dashed lines are standard (least squares) LPs.
Sample: 1947:Q1–2002:Q3

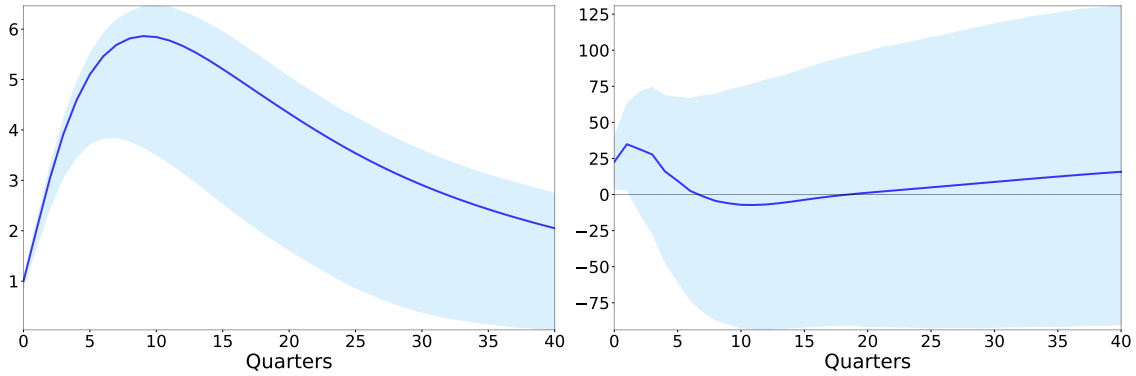
Appendix F. Replication of Deleidi and Mazzucato (2021)

Deleidi and Mazzucato (2021) have perhaps one of the highest multipliers in the literature for military R&D. An impact multiplier close to 24. A cumulative multiplier close to 11 after two years and statistically significant at 68 %, and equal to 5.7 after 32 quarters.

As Boysen-Hogrefe (2025) demonstrates, the results are not particularly robust. One of the main points of Boysen-Hogrefe (2025) is related to the idea that the estimates of the VAR with variables in first differences can remove a cointegration relationship. Furthermore, we stress that the public series on R&D spending (defense and non-defense) released at quarterly frequencies by BEA are linearly interpolated, leading to their spurious impact multipliers.

Deleidi and Mazzucato (2021) estimate a structural VAR with the following variables: military R&D, residual of government consumption and investment (i.e. G - Military R&D), private R&D and real GDP. All the variables are deflated by the GDP implicit deflator and expressed in log first-differences. Thus, they identify the structural shock using a Cholesky factorization as in Blanchard and Perotti (2002). The IRFs are cumulated to recover the response in levels, and multipliers are computed using an ex-post conversion factor close to 200.

To see how the results change when we use a different specification, we estimate the same structural VAR using all the series in log levels as suggested by Ramey (2016) (see also Sims, Stock, and Watson (1990)). Thus, we still rely on the ex-post conversion factor that can lead to inflated multipliers (see Ramey and Zubairy (2018)).



A. Response of Military R&D

B. Response of Real GDP

FIGURE A10. Response to a Military R&D Shock (Log Specification)

Notes: IRFs from a structural VAR as described in Deleidi and Mazzucato (2021) without the differentiation. All variables are entered in the VAR in log-levels. Shaded areas represent 90 % confidence bands. Bootstrap standard errors based on 10,000 repetitions.
Sample: 1947:Q1–2019:Q4

Although the impact multiplier aligns with Deleidi and Mazzucato (2021), the effects

of military R&D are less persistent when the series is not differentiated. The interpolation may affect the within-year estimate, so it would be better to focus on a year horizon when the dynamic multiplier is near zero and the standard errors are relatively large. A useful robustness check in this context is to run the model at annual frequencies.

We believe these results are sufficient to conclude that the approach to estimating these multipliers cannot lead to any conclusion, at least using quarterly interpolated data and focusing on impact multipliers.



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