Does mission-oriented funding stimulate private R&D? Evidence from military R&D for US states

Abstract

US military Research and Development (R&D) expenditures arguably represent the best example of mission-oriented policy. They are sizeable, with a clear-cut public purpose (national defense) and with the government being their exclusive beneficiary. Exploiting a longitudinal dataset linking public R&D obligations to private R&D expenditures for US states, we investigate the impact of defense R&D on privately-financed R&D. To address potential endogeneity in the allocation of funds, we use an instrumental variable identification strategy leveraging the differential exposure of US states to national shocks in federal military R&D. We document considerable "crowding-in" effects with elasticities in the 0.11-0.14 range. These positive effects extend also to the labor market, when focusing on employment in selected R&D intensive industries and especially for engineers.

Keywords: R&D · Innovation policy · Defense · Mission-oriented innovation

JEL classification: O30 · O31 · 032 · O38 · H56 · H57

1 Introduction

Firms' innovation activities play a crucial role in fostering productivity and economic growth (Nelson and Winter, 1982; Dosi et al., 1988; Romer, 1990; Aghion and Howitt, 1992; Dosi et al., 2010). Yet, R&D underinvestment is a well documented feature of contemporary economies, and governments are seeking new ways to boost research in the private sector (Bloom et al., 2019). The large presence of knowledge spillovers makes social returns to R&D considerably higher than private ones, thus, resulting in lower R&D efforts than the socially desired level (Nelson, 1959; Arrow, 1962; Lucking et al., 2019). This is exacerbated by financial constraints on innovative firms, by the inherent uncertainty associated to research investments as well as other types of barriers to innovation (Hall and Lerner, 2010; D'Este et al., 2012; Garicano and Steinwender, 2016; Pellegrino and Savona, 2017). Against this background, the effectiveness of public support in stimulating private R&D expenditures is subject to large empirical and theoretical debates and shall not be taken for granted (see e.g. David et al., 2000; Becker, 2015, for surveys on the topic). In this work, we contribute to these debates providing empirical evidence about the impact of defense-related R&D funded by the US government, and empirically assess whether it stimulates or substitutes privately-financed and conducted R&D.

Especially in the US, among different types of non-conventional innovation policies, the experience of public support to military R&D appears to be the most relevant and clearly *mission-oriented* (Mowery, 2010, 2012; Moretti et al., 2019). Mission-oriented policies are gaining increasing popularity among innovation scholars and policy makers (see e.g. Mazzucato et al., 2015).[1] For instance, Bloom et al. (2019) explicitly include them in their review of the main innovation policy levers available to governments. However, much of the empirical evidence on mission-oriented policies is anecdotal and based on historical case studies (Nelson, 1982; Mazzucato, 2015; Foray et al., 2012; Foray, 2018; Azoulay et al., 2019), while quantitative econometric assessments are relatively few and rarely focused on the estimation of causal effects.[2] As a first notable exception, Moretti et al. (2019) estimate an elas-

[1]An example is the Horizon Europe framework programme financed by the European Commission.

[2]Early studies investigating the effectiveness of public R&D in promoting private R&D and innovation lacked a causal perspective (Mansfield and Switzer, 1984; Lichtenberg, 1984, 1987). More recently, empirical papers have identified causal effects of R&D support for selected public

ticity of public R&D to private R&D in a panel of countries and industries, using defense-related R&D as an instrumental variable for public R&D. Moreover, Gross and Sampat (2020) analyze the long run impact of the Office of Scientific Research and Development (OSRD), a large mission-driven organization supporting R&D during World War II in the US. They find long-lasting impacts in the post-war period on the direction of patenting and on the rise of geographical technology clusters. Finally, Deleidi and Mazzucato (2021) find positive multiplicative effects associated to defense R&D for the US economy using the SVAR methodology.

We add to this stream of research by adopting a macro-regional perspective and focusing on US states as our unit of analysis. The focus on region-wide effects is a unique feature of our analysis and it has four distinct advantages: (i) it allows us to estimate an elasticity of defense R&D that captures potential within-state R&D spillovers among performers; (ii) this coefficient is independent from national policies (and other US-wide confounders) since these are "differenced out" using time fixed effects (Nakamura and Steinsson, 2014); (iii) given that US states are relatively more open than the US as a whole, our estimates constitutes a lower bound for its nation-wide equivalent, thus, being particularly informative (Chodorow-Reich, 2019); (iv) finally, exploiting both the geographical and time dimensions provides substantial variation to help identify the parameter of interest (Auerbach et al., 2020b)[3]. More specifically, we combine different data sources to assemble a longitudinal dataset that associates, at the US state-level, defense and non-defense federal R&D obligations to non-federally funded private R&D expenditures for the period 1968-2017, as well as to high-tech employment for the period 1998-2018. We then exploit the geographical and temporal variations in our data to estimate the elasticity of non-federally funded private R&D investment to defense R&D expenditures employing panel fixed effect regressions.

Endogeneity problems may arise in this setting primarily because military funds for R&D are not randomly assigned geographically. Their allocation may well be driven by characteristics that likely determine the amount of private R&D con-

agencies. Some examples include: Howell (2017), Azoulay et al. (2019) and Gross and Sampat (2020) for the US; Santoleri et al. (2020) for Europe; Bronzini and Iachini (2014) for Italy and Moretti et al. (2019) for a panel of OECD countries and industries. At the theoretical level, Dosi et al. (2020) test mission-oriented policies in a macroeconomic agent-based model and find positive effects on innovation, productivity and GDP growth.

[3] In this respect, our work links to the macroeconomic literature on regional and local effects of public spending (Fishback and Kachanovskaya, 2015; Auerbach et al., 2020a; Bernardini et al., 2020)

ducted in a given state. To address endogeneity concerns and infer causal effects we use a recently developed identification strategy that builds on differential state exposures to national spending shocks (Nakamura and Steinsson, 2014; Guren et al., 2020). More specifically, we leverage two inherent characteristic of defense R&D funding: (i) as for general military procurement, changes in national military R&D obligations are arguably exogenous to the business cycle and to producitivity levels, being driven by geopolitical events (Ramey, 2011; Moretti et al., 2019); (ii) the total R&D funds assigned to each state are differently sensitive (with respect to other states) to changes in national R&D budget. Drawing upon these two facts, we instrument changes in state-level defense R&D obligations using variations in national defense R&D obligations interacted with state dummies.

The empirical results show that federally-financed military R&D *crowds-in* privately-funded R&D. In particular, IV estimates are systematically higher than OLS with elasticities in the range 0.11% - 0.14% over a 4-5 year horizon. This suggests that final impact of public defense R&D on total R&D significantly exceeds its dollar value. Such stimulus also translates to employment in R&D-intensive industries and in particular for engineering occupations with elasticities between 0.05% - 0.1%. Our results are robust to a series of tests and alternative specifications including the presence of weak instruments; the inclusion of other innovation policy variables; measurement errors; corrections for outliers and missing values.

The rest of the paper is organized as follows: Section 2 motivates our focus on military R&D pointing at its mission-oriented nature; Section 3 describes our dataset; Section 4 presents the econometric specification and the identification strategy while Section 5 presents and discusses the results; finally, Section 6 concludes.

2 Public military R&D as a mission-oriented innovation policy

Mission-oriented policies refer to a set of public interventions aimed not only at promoting innovation but also at directing technical change towards the achievement of well-defined technological or social goals (Mazzucato, 2015). Identifying mission-oriented policies in empirical studies is a complex task. Major conceptual issues are involved and often a clear-cut distinction with respect to other forms of intervention is not available. Yet, public defense R&D in the US stands out as a natural example of mission-oriented innovation policy (Mowery, 2010, 2012). Military R&D programmes financed by the government are typically focused on well-defined objectives defined by the funding agency. Their rationale has little to do with the standard market failure argument in support of public R&D investments (Arrow, 1962). On the contrary, they are commonly linked to the development of innovative solutions to complex technical challenges which reflect the pursue of a general public interest (i.e. national defense). Defense R&D projects are often multidisciplinary and involve different sectors and performers with a large role played by private companies (accounting for about 65% of total spending in 2015, National Science Board, 2018) and a less relevant, but still significant, contribution by government labs and universities.

The mission-oriented nature of defense R&D is also supported by the fact that the government is the sole and ultimate user of the research outcome (Campbell, 2007). Albeit military technologies may have large civilian spillovers, the results of defense R&D, in fact, have rarely an immediate non-military application. For this reason R&D projects in this area are largely financed through contracts that are subject to strict governmental accountability. Accordingly, defense agencies use various tools to manage uncertainty and keep track of the advancements made by performers including prototyping, "technology demonstration" and the use of non-R&D procurement. Also in line with the mission-oriented interpretation, military R&D is strongly biased towards development expenditures (accounting for about 90% of total funding in 2015, National Science Board, 2018), which largely prevail over funds for basic and applied research.

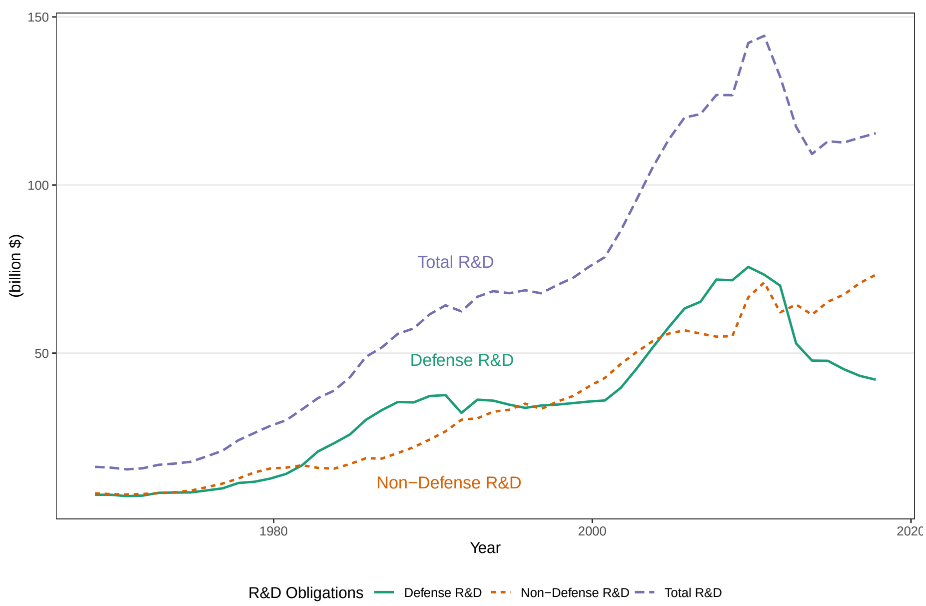
Consistently with our view, historical studies have pointed out that public defense R&D in the US played a key role in shaping both the rate and the direction of technical change in various industries, ranging from aircraft and transportation to computer and electronics (Nelson, 1982). Interestingly, it has been also argued that US military research fostered the emergence and diffusion of radical innovations and general purpose technologies (Ruttan, 2006; Mazzucato, 2015).[4] Nevertheless, it shall be noticed that, when acknowledging the mission-oriented features of defense-related R&D, one has to be cautious in generalizing the applicability of the same "model" to contemporary societal challenges, in particular climate change.

[4] As an illustrative example, consider the ARPANET project led by the DARPA agency of the Department of Defense. ARPANET is widely seen as the ancestor of the Internet (Mowery, 2010). For a recent discussion of the DARPA model see Azoulay et al. (2019).

As pointed out by Mowery (2012) – albeit key insights may be drawn in terms of competition among performers, public accountability and procurement policies – the scope for adopting the lessons from military R&D in other areas is limited as there are substantial differences regarding the characteristics of new technological challenges.

In our analysis, focusing on defense R&D has also a dual practical relevance. On the one hand, it is the largest component of the total federal R&D budget (with a share ranging from 40% to 60%, cf. Figure 1) and exhibits sizable temporal and spatial variation (across US states). On the other, changes in military expenditures are mainly driven by non-economic and geopolitical factors (Ramey, 2011). Together with some specific characteristics of their geographical distribution, this allows us to implement a clear identification strategy (cf. 4.2) which would not be available for other categories of public R&D.

Figure 1: Levels of federal R&D obligations - defense vs non-defense.



3 Data

Our longitudinal dataset comprises data for 50 US states and the District of Columbia for the period 1968-2017.[5] The main variables are described below. In Appendix A, we report figures and summary statistics concerning our dataset.

[5]Data are available from the authors upon request.

Public R&D expenditures. We employ data from Survey of Federal Funds for Research and Development led by the National Science Foundation (NSF) to measure defense and non-defense R&D spending. The survey provides annual data on federal R&D obligations disaggregated by funding agency and state of performance from 1968 onwards.[6] Federal R&D obligations represent the amounts committed in a given fiscal year regardless of when the actual payment takes place.[7] As such, they should be intended as a broad measure of public support including both R&D procurement (i.e. contracts for R&D services) and grants such as those awarded by the Small Business Innovation Research program.[8] We select only obligations by the Department of Defense to build our defense-related R&D variable. As a control variable, we also aggregate obligations from other agencies to get a proxy of non-defense R&D. The series are deflated using the price indexes (with base year 2012) respectively for federal defense R&D investment and for federal non-defense R&D investment provided by the Bureau of Economic Analysis (BEA).[9]

Private R&D expenditures. Data on private R&D expenditures come from the Business R&D and Innovation Survey (BRDIS).[10] BRDIS provides data on total private R&D expenditures by state, disaggregated by funding source. To avoid double counting and to get a reliable proxy of additional R&D investments, we only consider the non-federally financed component of private R&D. The series present

[6]Only 10 large agencies report data on the geographic distribution of obligations including: the Departments of Agriculture, Commerce, Energy, Defense, Health and Human Services, the Interior, and Transportation; the Environmental Protection Agency; NASA; and NSF. These agencies account for roughly the 97% of total R&D obligations (Pece, 2020). Survey respondents are asked to indicate the state where the research was performed by the primary contractor or grantee. In absence of this information, federal agencies should assign obligations to a specific state based on the headquarters of the performer.

[7]This implies that the actual outlays associated to a given obligations may be distributed through one or more payment tranches in subsequent periods. Unfortunately, data on federal R&D outlays are not collected at the state-level and, therefore, cannot be used for our purposes. We discuss the issue in Section 5 and provide results using national outlays to construct our instrumental variables.

[8]For detailed definition of federal obligations see the Circular A-11 by the US Office of Management and Budget which provides guidance for federal agencies on budget preparation.

[9]The price index for federal defense R&D is contained in Table 3.11.4 from the BEA website "Price Indexes for National Defense Consumption Expenditures and Gross Investment by Type". The price index for federal non-defense R&D is contained in Table 3.9.4 from the BEA website "Price Indexes for Government Consumption Expenditures and Gross Investment".

[10]This is a stratified survey jointly run by the NSF and the Census Bureau that is representative for the population of for-profit non-farm companies with five or more employees. The BRDIS initial year is 2008. The predecessor of BRDIS is the Survey of Industrial Research and Development (SIRD) which covers the period 1953-2007. According to the NSF (Wolfe, 2008), there is no evidence suggesting that the redesign of the survey from SIRD to BRDIS introduced structural breaks in the data. Nevertheless, in our analysis, potential changes affecting all states in 2008 are absorbed by the specific time dummy.

a non-negligible number of missing values for two main reasons. First, for the period 1981-1997 the survey was biannual. Second, confidentiality issues prevent publication of data for those states with a small number of surveyed firms. We linearly interpolate missing values between observations only when the gap is not greater than one year in order to minimize potential biases due to measurement errors.[11] On the contrary, no forward or backward extrapolation is performed. Private R&D data are transformed in real terms using the R&D price index (base year 2012) from the BEA.[12] Unfortunately, BRDIS data are not broken down by industry for US states, that is why we cannot estimate more granular regressions at the industry-state level.

Employment in R&D-intensive industries. We rely on the BEA Regional Accounts, which provide employment figures by state and 3-digit industries.[13]. The change in industry classification in 1997 from SIC to NAICS does not allow us to get consistent time series for the whole time span. Therefore, we focus on the period 1998-2018 which follows the introduction of the NAICS system. We focus on the 5 industries that accounts for most of the domestic R&D performance (National Science Board, 2018): chemicals manufacturing (NAICS 365); computer and electronic products manufacturing (NAICS 334); transportation equipment manufacturing (NAICS 336); information (NAICS 51); and professional, scientific, and technical services (NAICS 54).

R&D-related occupations. Data are obtained from the Occupational Employment Statistics database compiled by the Bureau of Labor Statistics. We focus on STEM occupations, in particular on those that are labeled as "Research, Development, Design, and Practitioners". Starting from 6-digit R&D-related occupations (SOC classification rev. 2010), we aggregate data at the 3-digit level and come up with the following categories: Computer Occupations 15-1100; Architects, Surveyors, and Cartographers 17-1000; Engineers 17-2000; Life scientists 19-1000 and Social Scientists and related workers 19-3000.[14]

[11] To evaluate possible distortions arising form the interpolation we report in Section 5 results for the period 1999-2017 which displays almost no missing values. Results appear to be robust to the presence of missing observations.

[12] This is available in Table 1.2.4 "Price Indexes for Gross Domestic Product by Major Type of Product" from the BEA website.

[13] For selected sectors we observe only 2-digit, whilst for other the aggregation becomes more granular at 4-digit level

[14] The 2010 SOC revision introduced some minor classification changes. In aggregating, we considered only those occupations that allows us to keep consistency at the 3-digit level before and after the revision. Notice that, in the 2010 classification, the group 15-1100 "Computer occupations"

Additional variables. We complement our dataset with data on state-level GDP and population from the BEA Regional Accounts.[15] Also, as additional control variables, we include some state-specific measures of innovation policies. First, we obtain data on defense non-R&D procurement from the Federal Procurement Data SystemNext Generation (FPDS-NG), provided by the General Services Administration (GSA). FPDS reports all primary contracts from agencies subject to mandatory reporting and for purchases above the threshold value of $\$2,500$ from 1980 onwards. Each entry is classified by funding agency and has a 4-digit Product Service Code (PSC) which allow us to rule out contracts associated to the performance of R&D (PSC codes starting with A). Second, we use data from Lucking (2019) on state tax credits, corporate income taxes and user cost of R&D capital to capture possible variations in the regional tax system.

4 Econometric specification and identification strategy

4.1 Econometric specification

To measure the effects of military R&D spending on private R&D we build a longitudinal dataset relating defense R&D obligations (i.e. our public R&D spending proxy) to private R&D expenditure (cf. Section 3). We use the geographical and temporal variation of our data to estimate the following model:

$$\Delta^h RDpriv_{i,t} = \beta \Delta^h RDdef_{i,t} + \gamma' \Delta^h \mathbf{W_{i,t}} + \alpha_i + \lambda_t + \varepsilon_{i,t}, \qquad (1)$$

where $\Delta^h RDpriv$ stands for log changes of company-financed R&D between year t and $t-h$ in state i, $\Delta^h RDdef$ denotes h-year log changes of total R&D obligations from the Department of Defense (DoD) between year t and $t-h$ in state i, and $\Delta^h W$ is a vector of state by year observables, measured in h-year log changes, used as control variables.[16] All regressions include state fixed effects (α_i) to control

coincides with the 3-digit category 15-1000. Due to the high number of missing values, we could not retrieve reliable data for the 15-2000 category "Mathematical Science Occupations".

[15] GDP series are transformed in constant dollars (base year 2012) using the US GDP deflator. Concerning population data, we also used data from the Census Bureau and find no significant differences with respect to the BEA data.

[16] As common in the empirical literature on fiscal multipliers (see e.g. Nakamura and Steinsson, 2014) we use variations in public and private spending over a time horizon of h years. For the sake of transparency, in Section 5 we report results from separate regressions for $h \in \{2,3,4,5\}$.

for state-invariant characteristics and year dummies (λ_t) to absorb US-wide shocks over time.

Notice that this model proxies a log-level specification allowing for state-specific linear trends. One needs to account for state-specific trends as U.S. states experienced rather heterogeneous trajectories in terms of R&D investments and innovation performances (Akcigit et al., 2017), as shown by Figure A.2. Hence, our specification may be rationalized as a first-order approximation of the steady-state demand for R&D from a CES production function (Moretti et al., 2019)[17]. In this setting, the parameter of interest (β) shall be interpreted as the elasticity of non-federally financed business R&D to defense R&D spending.

We take variables in per capita terms to normalize for the different population size.[18] Also, to account for the potential geographical correlation in the error structure we cluster standard errors by state.

4.2 The identification strategy

Our focus is on the identification of the β parameter associated to public defense R&D. Our baseline regressions already take into account a large set of potentially confounding factors including invariant country trends (e.g. geography, size), US-wide shocks, other innovation policy tools (i.e. non-military R&D, tax credits, non-R&D procurement), state GDP and population. Nevertheless, even after controlling for these factors, different sources of endogeneity may bias our estimates. A major concern is represented by the political nature of government R&D (Mintz, 1992). Indeed, as other forms of public spending, R&D obligations are not randomly distributed across states as the criteria adopted for their allocation are often likely correlated with unobserved state-specific characteristics that may well be determinants of R&D investing decisions by firms. For instance, politicians may pick winners (or losers), thus, financing states that are doing particularly well (or are struggling). Similarly, variations in public R&D may be accompanied by state-specific regulatory norms that influence private spending decisions. Finally, a second endogeneity concern comes from the potential measurement error affect-

[17] For the sake of comparison we also estimated a log-level specification without state-specific trends and symmetrical to the baseline model in Moretti et al. (2019). Results are very similar and reported in Table B.1 and show less conservative estimates when compared to ours.

[18] To check for potential biases arising from normalizing by population, we run regressions without dividing variables by population. Results are reported in Table B.3 and do not differ significantly from those obtained with per capita variables.

ing our spending variable. Obligations may measure imperfectly effective R&D spending as outlays occurs with some lags or because revisions and de-obligations may correct the initially obligated amount.

To deal with endogeneity we draw upon a well-established macro identification strategy (Nakamura and Steinsson, 2014, 2018; Guren et al., 2020; Cloyne et al., 2020). We leverage two fundamental characteristics of public defense R&D. The left panel in Figure 2 shows that, similarly to general defense procurement, R&D obligations by the DoD at the national level are driven by exogenous (mainly geopolitical) events underlying military buildups. For instance, for the time period covered by our dataset, we can easily find the increase in military spending and R&D during the Reagan administration and following the 9/11 terrorist attacks. Second, data suggest that US states display systematically different sensitivities to changes in national R&D spending (cf. the right panel in Figure 2). For instance, when national defense R&D rises, obligations allocated to California increase much more than in Michigan. These patterns are remarkably stable over time and suggest that state-specific variations in public military R&D display a systematic component which is arguably exogenous to current private R&D shocks. Following Nakamura and Steinsson (2014), we isolate this component by instrumenting $\Delta^h RDdef_{i,t}$ using national growth rates interacted with state dummies. Thus, our first stage is:

$$\Delta^h RDdef_{i,t} = \theta_i \Delta^h RDdef_{US,t} + \gamma' \Delta^h \mathbf{W_{i,t}} + \alpha_i + \lambda_t + u_{i,t}, \tag{2}$$

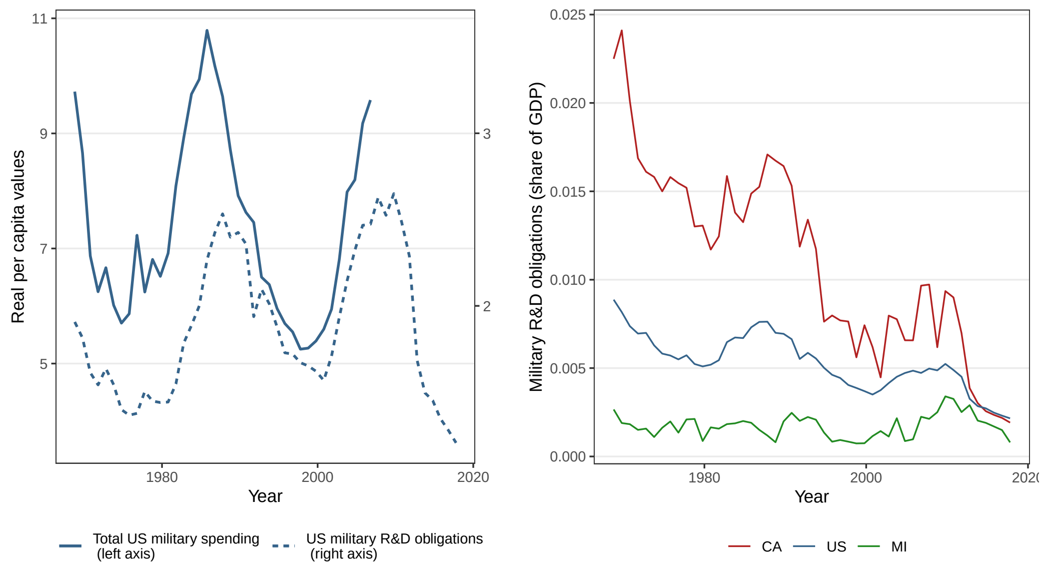
where $\Delta^h RDdef_{US,t}$ denotes log changes of US defense obligations between t and $t-h$, while θ_i represents the idiosyncratic coefficient accounting for different state-specific sensitivities to national shocks.[19]

A way to interpret this identification strategy is as an exposure research design (Goldsmith-Pinkham et al., 2020). States are differentially exposed to common national spending shocks. We identify state exposures (i.e. the idiosyncratic parameters θ_i from the first-stage regression, cf. Eq. 2) by focusing just on the systematic response to national policies, thus, arguably ruling out the influence of possible, time-varying omitted determinants of private R&D.

In this setting, US variation in DoD R&D obligations over a given time horizon represents a treatment that is assigned to states with different intensities (according

[19] The parameter theta is estimated interacting state dummies with $\Delta^h RDdef_{US,t}$. To simplify our notation we denote $\sum_{i \in I} \theta_i I_i \Delta^h RDdef_{US,t}$ with $\theta_i \Delta^h RDdef_{US,t}$, where I_i is an indicator function for state i.

Figure 2: Characteristics of defense R&D: national patterns and geographical allocation



Notes: The left panel contrasts the evolution of military spending and military R&D obligations. The former is the sum of prime military contracts as in Nakamura and Steinsson (2014). Data for this series and are available only until 2006. Defense R&D obligations are taken from the National Science Foundation. Both variables are deflated and divided by total US population. The right panel shows the heterogeneous response of California and Michigan to variations in national R&D obligations (normalized by GDP).

to θ_i). Our IV regressions estimate an average treatment response across states and years.

The exclusion restriction form this type of identification comes from the exogeneity of state exposures (Goldsmith-Pinkham et al., 2020). To put it differently, factors determining exposure of different states to national policies – after conditioning on a set of state-specific observables and state-invariant characteristics – should affect the outcome variable only via changes in $RDdef$. This assumption entails that θ_i is as good as randomly determined, conditionally on our control variables and fixed effects.

To investigate the validity of our research design, Figure B.1 contrasts the estimated exposure parameters from the first stage regression with the average log changes in $RDpriv$. Notice, first, that the estimated sensitivity coefficients (θ_i) show substantial heterogeneity, spanning considerable variation across states. Second, they are not correlated with averages of the outcome variable ($\Delta^h RDpriv$), that is, states responding more to shocks in federal defense-related R&D do not exhibit larger increases in private R&D spending. We take this evidence as bearing support to our identification strategy.

Finally, notice that the our exclusion restriction is less likely to be satisfied when (log) levels are used instead of (log) changes as the outcome variable. This possibly stems from the fact that exposure to shocks and the outcome variable are more likely to be co-determined when considered in levels (Goldsmith-Pinkham et al., 2020). That is why estimating the model in log differences would likely provide more reliable results.

5 Results

We estimate our model in Eq. 1 over different time spans (h) via both OLS and IV, employing the instrumental variables specified in Eq. 2. The estimation results are reported in Table 1. We do find positive and statistically significant effects of defense R&D obligations on private R&D over time horizons of 4 and 5 years. We progressively include controls (i.e. state GDP and non-defense R&D obligations) and show that our estimates remain remarkably stable.

A comparison between OLS and IV coefficients shows that OLS estimates are always downward biased. This may suggest that the allocation process of defense

R&D expenditures tend to favor states that are under-investing in private R&D. At the same time, "attenuation bias" due to measurement errors may also drive the downward bias. Overall, IV results suggest that a 1% increase in military R&D funding over 4-5 years crowds-in private R&D expenditures with an elasticity between 0.11% and 0.14%. Our findings, thus, indicate that the impact of defense R&D on total R&D is significantly above its dollar value, as federally financed military R&D is able to stimulate additional private R&D expenditures.

Over shorter time intervals, we do not find significant effects of defense-related R&D on private one. Quite plausibly, private R&D expenditures appear to be sticky and respond only to spending shocks occurring over sufficiently large time horizons. This may also be related to the duration of R&D projects, as well as the appointment of project managers, which is typically in the 3-5 years range (Azoulay et al., 2019). On the contrary, standard macroeconomic variables such as GDP are typically sensitive also to 2-year spending variations as found, for instance, in Nakamura and Steinsson (2014) and Auerbach et al. (2020a).

From a theoretical perspective, different mechanisms may drive these results.[20] First, defense R&D programs may lead to the formation of new bodies and agglomeration economies fostering the emergence of R&D networks among private and public entities (Gruber and Johnson, 2019). This is likely to result in additional private investments, mostly driven by localized spillovers. For instance, Gross and Sampat (2020) posit that the R&D programs led by the US Office of Scientific Research and Development (OSRD) during the World War II nurtured local innovation ecosystems and promoted the growth of technology clusters in the post-war period, with a major role played by Federally Funded Research Centers (FFRCs) and universities. Second, firms may have incentives to engage in spinoff projects with civilian applications. In this respect, direct funding by the DoD may also help relaxing credit constraints and overcoming fixed costs associated with these projects (Moretti et al., 2019).

Regarding the size of the estimate, it is very likely that our regional estimates represent a lower bound with respect to their macroeconomic, nation-wide counterparts for mainly two reasons: first, our specification embeds state-specific time trends, thus differencing out US-wide shock and policies which are likely to interact with our R&D spending variable Nakamura and Steinsson (2014); most

[20] For a detailed conceptual framework on the effects of military R&D on innovation see Mowery (2010).

Table 1: Main estimates: elasticity of non-federally funded private R&D to defense R&D obligations

Military R&D ($\Delta^h RDdef$)	*Dependent variable:* Privately-funded R&D ($\Delta^h RDpriv$)					
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
($h = 2$)	0.018	0.017	0.017	0.093	0.098	0.095
	(0.02)	(0.02)	(0.02)	(0.08)	(0.079)	(0.076)
($h = 3$)	0.023	0.022	0.021	0.07	0.067	0.066
	(0.021)	(0.021)	(0.021)	(0.058)	(0.059)	(0.055)
($h = 4$)	0.044*	0.041	0.04	0.134*	0.137*	0.138*
	(0.026)	(0.026)	(0.025)	(0.08)	(0.079)	(0.07)
($h = 5$)	0.043	0.04	0.04	0.11*	0.112**	0.109**
	(0.027)	(0.027)	(0.027)	(0.056)	(0.055)	(0.053)
Non Military R&D	✗	✓	✓	✗	✓	✓
State GDP	✗	✗	✓	✗	✗	✓

Notes: the table reports OLS and TSLS estimations. The sample period is 1968-2017. We run separate regressions for each h, where the dependent variable is the h-year log-change in private R&D (privately financed, in real per capita terms). The main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). Control variables include the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms). All regressions include state and time fixed effects. Standard errors in parenthesis are clustered by state.
*p<0.1; **p<0.05; ***p<0.01

importantly, as compared to the US economy as a whole, US states are are relatively more open economies. In this setting, production inputs, such as specialized high-skill workers, are freer to move thus lowering the effects of public spending (Chodorow-Reich, 2019).

5.1 Robustness analysis

The foregoing results may be affected by different issues which could introduce substantial biases in the estimates. In this section, we control for different potential problems resulting from weak instruments, the omission of relevant variables, measurement errors, missing values, model specification (level vs. growth rates), outliers, the influence of key states, and population normalization. We find that the main result of our empirical analysis is confirmed: defense-related public R&D

Table 2: First-stage effective F-statistics

	Effective F-statistics			
	$h = 2$	$h = 3$	$h = 4$	$h = 5$
F-stat	80.15	115.01	97.93	77.78
Critical values - Worst case bias 5%				
TSLS	30.87	33.29	33.5	34.55
LIML	16.56	24.93	24.3	27.09

Notes: the table reports for each h the effective F-statistics by Olea and Pflueger (2013) and the associated 5% critical values for the TSLS and LIML estimators. The null hypothesis is that of weak instruments. Rejections imply that the bias is not large, relative to a "worst-case" benchmark. The F-statistics refer to the first stage of the baseline model including non-military R&D obligations and state GDP as controls.

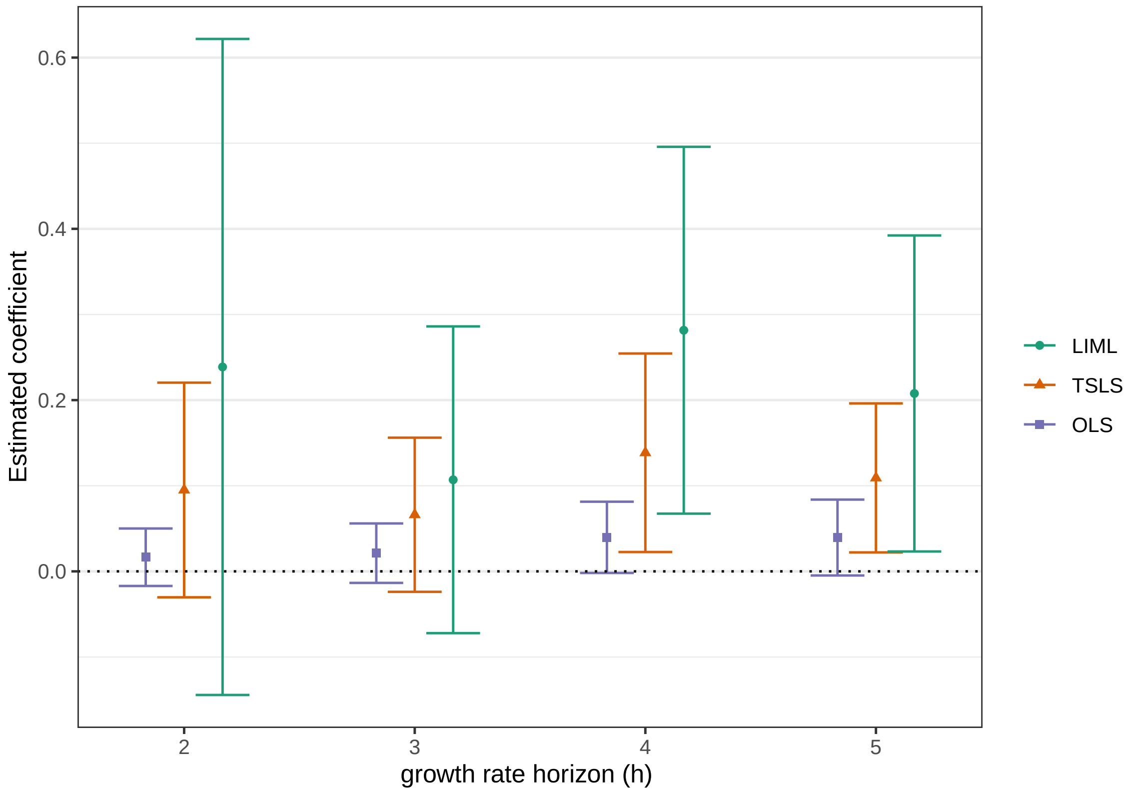
does crowd-in private R&D expenditures. In the following, we provide more details about the robustness checks we performed.

The first issue is linked to our identification strategy. TSLS estimates and the associated standard errors may not be reliable if instruments are weakly correlated with the endogenous regressor. Under weak instruments TSLS coefficients are biased towards OLS ones and standard inference procedures may not be reliable. In this work, a weak first-stage regression could also result from the many-instrument problem as we have 51 instruments (i.e. 51 state dummies interacted with national variations in defense R&D). To investigate the relevance of these concerns, Figure 3 compares the TSLS with the Limited Information Maximum Likelihood (LIML) estimator which tends to reduce biases from many and weak instruments. Estimations using LIML show higher and significant coefficients over 4-5 year variations, largely confirming our baseline results. Furthermore, we report in Table 2 the values of the effective F-statistic by Olea and Pflueger (2013).[21] At any time horizon h, we are able to reject at the 5% confidence level the null of a non-negligible bias for both TSLS and LIML. Thus, also first stage pre-screening clearly hints at the general reliability of our results.

We then consider some alternative specifications and robustness checks. Results are reported in Table 3. First, differences in tax policies across states may influence

[21]The use of the effective F-statistic is highly recommended in settings with heteroscedasticity and clustering (Andrews et al., 2019), as in our case. This is a test for the null hypothesis of weak instruments. Rejection entails that the bias of the TSLS or LIML is not large, relative to a "worst-case" benchmark.

Figure 3: Comparison across estimators: OLS, TSLS, LIML



Notes: Coefficients refer to our baseline estimation including log changes of non-military R&D obligations and GDP as controls. Confidence intervals at the 10% level are computed using standard errors clustered by state.

R&D investments and employment (Wilson, 2009; Chang, 2018; Lucking, 2019), thus, acting as a potential confounding factor in our analysis. To control for different taxation regimes, we include in our regressions state-specific R&D tax credits, corporate income tax rates and the user cost of R&D capital (which combines both).[22] Results show that the estimated elasticity between military R&D and private R&D slightly increases and remains statistically significant, as compared to our baseline specifications.

Another possible concern comes from the omission of non-R&D procurement. The magnitude and composition of government demand may indeed act as a *de facto* innovation policy (Edler and Georghiou, 2007; Guerzoni and Raiteri, 2015; Slavtchev and Wiederhold, 2016; Raiteri, 2018). This is especially relevant for defense procurement as DoD R&D contracts have been often substantially complemented by purchases of the developed product/technology (Mowery, 2010).[23] Thus, we expect military R&D obligations to be correlated with non-R&D procurement. To guard against this concern, we aggregated total non-R&D procurement by state and included it as a control in our regression. Results largely confirm our baseline estimations, albeit with a small loss in precision.

Our empirical analysis could be also biased by measurement errors due to the fact that we do not observe the effective outlays at the state level, as we can only use obligation measures. Luckily enough, data on defense R&D outlays are available at the national level. Leveraging this information we constructed our IV interacting state dummies with national variations in military R&D outlays. Under the assumption that the timing of the mismatch between national obligations and outlays is correlated with the one unobserved at the state level, this new IV estimation will correct for the aforementioned measurement error. Even with this correction, estimates appear not to change significantly, thus, suggesting that this specific form of measurement error may not play a crucial role for our analysis.

Data on private R&D display a non-negligible number of missing values in the first period of our sample. For this reason, we also estimated our model for the period 1998-2017 in which we observe almost no missing values (as the SIRD

[22]Notice that, in order to be consistent with our specification, we included the variation between t and $t + h$ of these variables. We also run regressions using levels at time t a find no substantial differences. Results are available upon request from the authors.

[23]The independent R&D program represents an even more extreme example in this respect (Lichtenberg, 1995). Overhead funds included in non-R&D procurement contracts were used by the Department of Defense to finance indirectly R&D performers.

survey becomes annual). We show that even in this restricted sample our main results hold with elasticities close to those estimated employing the whole time period.

Finally, in the Appendix B we report some additional robustness checks. First, we estimate a model in levels using the same specification in Moretti et al. (2019). More specifically, we regress levels of private R&D against lagged values of defense R&D obligations. Differently from our difference specification, in this setting state fixed effects do not absorb state-specific trends but only allow for heterogeneous intercepts. The model yields less conservative estimates (cf Table B.1) with higher elasticities of defense R&D that are in line with those reported in Moretti et al. (2019). Moreover, we assess whether our results are driven by the dynamics of single states by dropping observations of one state at the time (cf. Figure B.2). We show that estimates remain remarkably stable with North Dakota having the largest (slightly negative) influence. We also investigate the potential impact of outliers using winsorized variables and find no substantial effect (cf. Table B.2). To conclude, we ran regressions without normalizing variables by population. Results in Table B.3 also corroborate our general findings.

5.2 Employment effects in R&D intensive sectors and occupations

So far we robustly documented crowding-in effects of public military R&D funding on private R&D expenditures. Yet, higher expenditures may translate either in higher R&D employment or in increasing costs (e.g. wages and intermediate goods). Whether one of these two effects prevails may depend on the supply elasticity of R&D workers and inputs, as well as on other characteristics of the innovation system (e.g. firms organizational routines, private and public R&D networks). To shed a light on these issues, we empirically study the impact of public military R&D expenditures on employment. However, data on private R&D employment are not available at the state level. Therefore, we focus on employment in R&D-intensive industries and occupations (cf. Section 3) and we estimate the following model:[24]

[24]We focus on the top 5 R&D-intensive industries. We also run regressions for other R&D-intensive industries and find no statistically significant results except for Miscellaneous manufacturing (NAICS 339) which shows elasticities in the 0.035 - 0.05 range. Results are available upon request from the authors. Regarding occupations, we aggregated at the 3 digit level occupations classified as "Research, Development, Design, and Practitioners". More details are reported in

Table 3: Alternative specifications and robustness checks

Military R&D ($\Delta^h RDdef$)	*Dependent variable:* Privately-funded R&D ($\Delta^h RDpriv$)		
	Corporate tax	R&D tax credit	User cost of R&D capital
$h = 2$	0.102	0.119*	0.105
	(0.068)	(0.064)	(0.068)
$h = 3$	0.086*	0.104**	0.089*
	(0.05)	(0.051)	(0.049)
$h = 4$	0.14**	0.153**	0.147**
	(0.069)	(0.072)	(0.068)
$h = 5$	0.11**	0.112**	0.12**
	(0.052)	(0.053)	(0.052)
	Non-R&D procurement	Outlays	Restricted sample
$h = 2$	0.074	0.092	0.053
	(0.077)	(0.065)	(0.073)
$h = 3$	0.046	0.099*	0.061
	(0.059)	(0.056)	(0.05)
$h = 4$	0.117	0.11*	0.126*
	(0.077)	(0.06)	(0.064)
$h = 5$	0.096*	0.085	0.102*
	(0.055)	(0.051)	(0.056)

Notes: the table reports TSLS estimations for different specifications and time horizons h. Across all specifications, the dependent variable is the h-year log-change in private R&D (privately financed, in real per capita terms) while the main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). All regressions include the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms) as control variables as well as state and time fixed effects. The sample period is 1968-2017 except for the "Non-R&D procurement" case which uses 1980-2017 and the "Restricted sample" regression which uses 1998-2017. The top three specifications include respectively h-year variations in corporate tax rates, R&D tax credits and user costs of R&D capital as controls. The "Non-R&D procurement" regression includes h-year log-changes in total non-R&D procurement. The "Outlays" specification uses national variations in outlays (instead of obligations) interacted with state dummies as instrumental variables. Standard errors in parenthesis are clustered by state.

*p<0.1; **p<0.05; ***p<0.01

$$\Delta^h RDemp_{i,k,t} = \beta \Delta^h RDdef_{i,t} + \gamma' \Delta^h \mathbf{W_{i,t}} + \alpha_i + \lambda_t + \varepsilon_{i,t}, \tag{3}$$

where $\Delta^h RDemp_{i,k,t}$ stands for log changes of employment between year t and $t-h$ in state i and industry/occupation k (this is the only difference with respect to the previous model, cf. Eq. 1).

Table 4 displays the results for selected R&D-intensive industries. We find positive and significant employment effects in Computer and electronic product manufacturing (NAICS 334) and Transportation Equipment (NAICS 336). Not surprisingly, effects appear to be concentrated in sectors that receive a disproportional amount of defense R&D funds (Mowery, 2010, highlights that about 75% of defense R&D is concentrated in the aircraft and electrical equipment industries). The estimated employment elasticities are in the range of 0.08-0.1% and are lower than those of private R&D expenditures. The timing of the response is instead similar as also employment appears to respond mainly to spending shocks occurring in 4-5 year time horizons.

Results for different R&D-related occupational categories are provided in Table 5. We find sizeable effects only for the employment of engineers with elasticities between 0.05 and 0.07%. Notice that in this occupational group, a large space is occupied by jobs that are very much related to defense R&D, such as aerospace and electrical engineers. In contrast to effects at the industry level, the employment of engineers turns out to be stimulated also by 2-3 year spending shocks.

Also for employment regressions, we run a series of robustness checks controlling for confounding factors (i.e. tax policies and non-R&D procurement), measurement errors stemming from the use of obligation data, and normalization by population. Results are presented in Table B.4. They largely confirm our baseline estimations, albeit with reduced statistical significance for employment in the Computer and Electronic Products industry.

6 Conclusion

In this paper we study whether government-financed defense R&D is effective in fostering privately-funded R&D investment and employment. Our interest in military R&D is motivated by its widely acknowledged "mission-oriented" nature, that

Section 3.

Table 4: Employment elasticities of defense R&D obligations in high-tech industries

	Dependent variable: Employment ($\Delta^h RDemp$)			
Industry	$h = 2$	$h = 3$	$h = 4$	$h = 5$
Chemicals	0.049	0.054	0.06	0.045
(NAICS 325)	(0.049)	(0.054)	(0.054)	(0.052)
Computer and electronic products	0.02	0.034	0.079*	0.084*
(NAICS 334)	(0.038)	(0.047)	(0.043)	(0.044)
Transportation equipment	0.014	0.12***	0.099***	0.078*
(NAICS 336)	(0.074)	(0.024)	(0.025)	(0.039)
Information	0.005	0.017	0.026	0.026
(NAICS 51)	(0.017)	(0.017)	(0.016)	(0.017)
Professional, scientific, and technical services	-0.006	-0.006	-0.004	-0.004
(NAICS 54)	(0.007)	(0.008)	(0.009)	(0.01)

Notes: the table reports industry-by-industry TSLS estimations. The sample period is 1998-2018. We run separate regressions for each h and industry category, where the dependent variable is the h-year log-change in industry employment (normalized by state population). The main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). All regression include state and time fixed effects as well as baseline control variables, i.e. the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms). Standard errors in parenthesis are clustered by state.

*p<0.1; **p<0.05; ***p<0.01

Table 5: Employment elasticities of defense R&D obligations in R&D-related occupations

	Dependent variable: Employment ($\Delta^h RDemp$)			
Occupation	$h = 2$	$h = 3$	$h = 4$	$h = 5$
Computer Occupations	-0.061	-0.061	-0.028	-0.007
(SOC 15-1100)	(0.043)	(0.049)	(0.046)	(0.047)
Architects, Surveyors, and Cartographers	0.021	0.055	0.066	0.059
(SOC 17-1000)	(0.064)	(0.066)	(0.063)	(0.06)
Engineers	0.053***	0.066***	0.067***	0.067***
(SOC 17-2000)	(0.018)	(0.023)	(0.023)	(0.023)
Life Scientists	0.084	0.1	0.11	0.083
(SOC 19-1000)	(0.062)	(0.067)	(0.072)	(0.075)
Physical Scientists	-0.072*	-0.025	0.006	0.023
(SOC 19-2000)	(0.043)	(0.043)	(0.046)	(0.051)
Social Scientists and Related Workers	-0.046	-0.046	-0.035	-0.041
(SOC 19-3000)	(0.059)	(0.059)	(0.054)	(0.049)

Notes: the table reports occupation-by-occupation TSLS estimations. The sample period is 1999-2018. We run separate regressions for each h and occupation category, where the dependent variable is the h-year log-change in occupation employment (normalized by state population). The main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). All regression include state and time fixed effects as well as baseline control variables, i.e. the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms). Standard errors in parenthesis are clustered by state.
*p<0.1; **p<0.05; ***p<0.01

is, its ability to direct technological change towards solving tall complex technological problems (Mowery, 2010, 2012; Mazzucato, 2015). In this respect, our research may inform the policy debate on mission-oriented innovation with evidence-based results regarding the possible crowding-in effects of these policies.

We assembled a longitudinal dataset for U.S. states including R&D obligations from the DoD, private R&D expenditures, employment in R&D-intensive industries and occupations. Leveraging some characteristics of defense R&D funding, we employed a state-of-the-art IV identification strategy (Nakamura and Steinsson, 2014, 2018; Guren et al., 2020; Cloyne et al., 2020) based on differential state exposures to national shocks in order to isolate exogenous variations in defense R&D and provide a causal interpretation to our estimates.

Our results shows that an increase in defense R&D over 4-5 years crowds-in privately-funded R&D investments with an elasticity between 0.11% and 0.14%. This implies that the final impact of federally-financed military R&D on total R&D significantly exceeds its dollar value, as it spurs additional private R&D expenditures. We also find positive effects of defense-related R&D on employment in high-tech sectors and in engineering occupations, albeit with lower elasticities (i.e. 0.05-0.1 %). Such results are robust to a wide ensemble of robustness checks including additional controls (e.g. tax policies, non-R&D procurement), outliers sensitivity and alternative specifications.

The main conclusion from this work is that large mission-oriented programs can stimulate additional innovation efforts in the private sector. Nevertheless, further research is needed in order to deliver more comprehensive policy prescriptions. First, as mission-oriented programs are not all alike, we plan to investigate in a comparative fashion whether programs focused on different societal goals are equally effective in influencing private R&D spending.[25] Second, we ought to asses mission-oriented policies vis-á-vis more conventional tools such as tax credits and horizontal subsidies, as well as possible policy mixes. Finally, an investigation from a more granular geographic perspective may shed further light on some of the mechanisms underlying our results (e.g. spillovers within state).

[25]For a broad historical comparison among different mission-oriented programs see Foray et al. (2012).

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Appendix A Main variables and descriptives

Figure A.1: Defense R&D obligations per capita by state

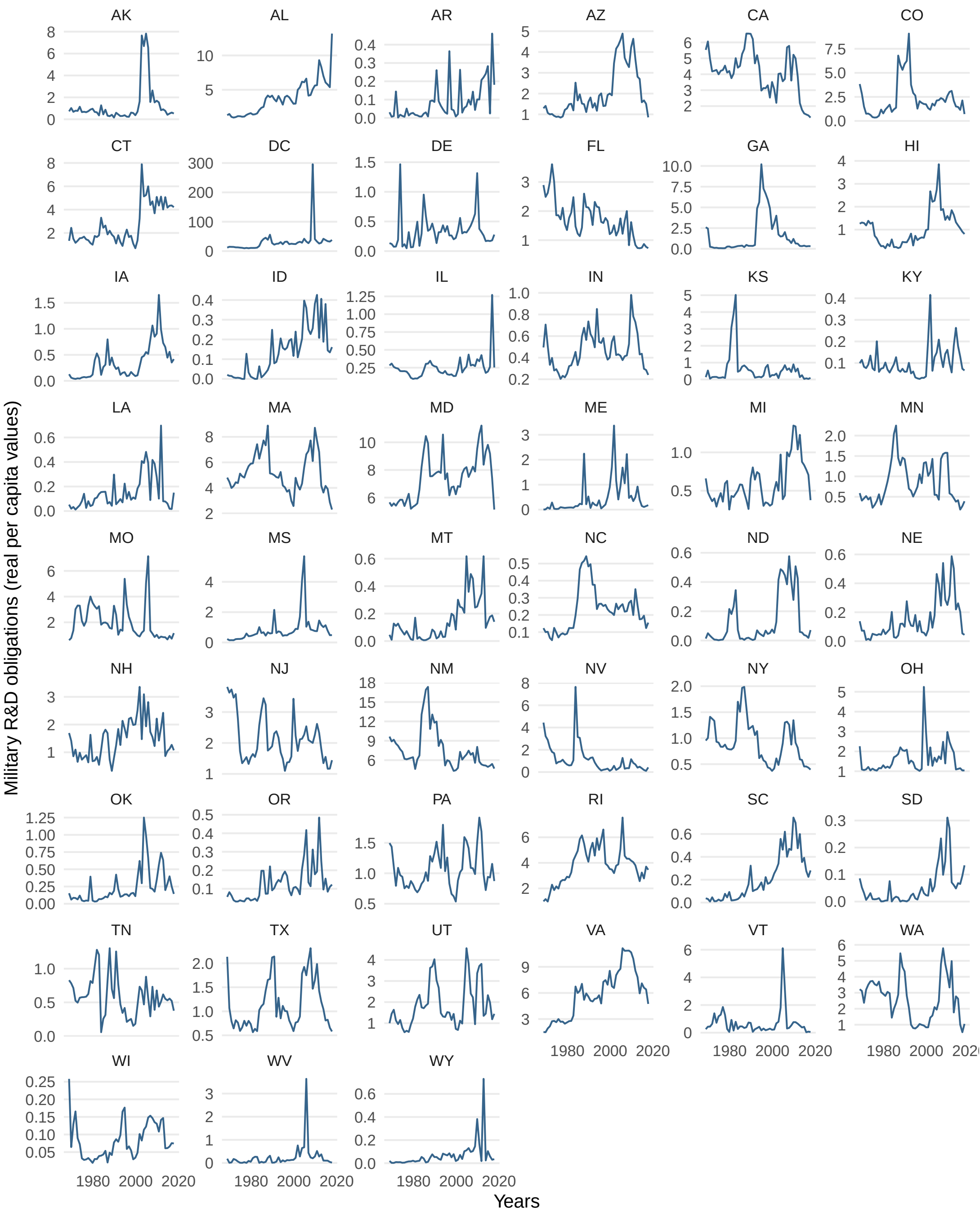
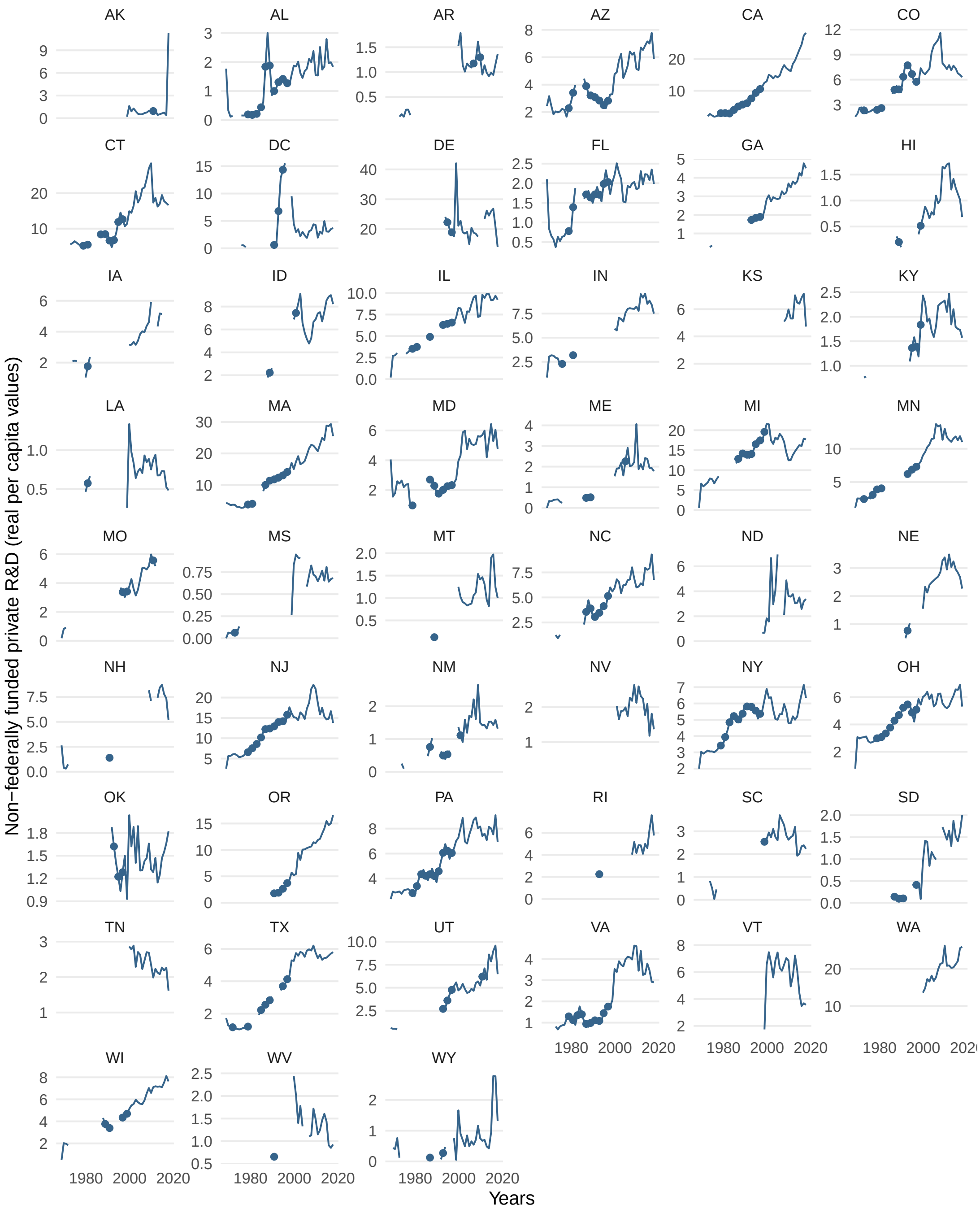


Figure A.2: Non-federally funded private R&D per capita by state



Notes: Dots represent interpolated values

Table A.1: Summary statistics by state (5-years log variations of defense and private R&D)

	Private R&D ($\Delta^5 RDpriv$)				Defense R&D ($\Delta^5 RDdef$)			
	mean	*sd*	*min*	*max*	*mean*	*sd*	*min*	*max*
State								
AK	0.08	1.10	-1.16	3.28	-0.24	1.53	-1.53	3.06
AL	0.31	0.69	-0.83	2.62	0.22	0.38	-0.55	0.98
AR	-0.00	0.33	-0.56	0.69	0.53	1.19	-1.43	2.15
AZ	0.11	0.30	-0.44	0.77	0.02	0.52	-1.19	1.08
CA	0.30	0.17	-0.02	0.69	-0.13	0.49	-1.22	0.95
CO	0.09	0.28	-0.49	0.52	-0.17	0.86	-1.96	1.56
CT	0.11	0.36	-0.56	0.97	0.11	0.68	-0.91	2.03
DC	0.05	1.24	-1.69	3.23	0.06	0.71	-1.95	2.34
DE	-0.03	0.34	-0.79	0.56	-0.09	0.58	-1.32	0.75
FL	0.08	0.35	-1.20	1.05	-0.20	0.33	-1.01	0.56
GA	0.20	0.14	-0.06	0.48	-0.56	0.85	-1.46	2.69
HI	0.17	0.45	-0.57	0.80	0.01	0.77	-0.99	1.34
IA	0.10	0.32	-0.71	0.43	0.56	0.89	-0.71	1.81
ID	0.04	0.32	-0.56	0.46	0.06	0.63	-1.08	1.23
IL	0.12	0.13	-0.09	0.40	0.07	0.57	-0.71	1.14
IN	0.12	0.32	-0.33	1.19	-0.18	0.57	-0.97	0.85
KS	0.12	0.27	-0.40	0.32	-1.78	1.19	-3.28	-0.39
KY	0.09	0.31	-0.43	0.58	0.28	0.99	-1.16	2.75
LA	-0.04	0.40	-0.59	1.04	-0.45	1.55	-3.75	2.05
MA	0.17	0.24	-0.34	0.89	-0.04	0.42	-0.86	0.78
MD	0.04	0.45	-1.11	0.92	-0.01	0.21	-0.49	0.36
ME	0.04	0.30	-0.54	0.59	-0.60	0.75	-1.64	0.75
MI	0.13	0.49	-0.42	2.66	0.05	0.64	-1.18	1.24
MN	0.19	0.22	-0.20	0.72	-0.09	0.76	-1.43	1.06
MO	0.18	0.15	0.03	0.46	-0.30	1.20	-2.23	1.98
MS	-0.02	0.29	-0.48	0.74	-0.08	0.54	-1.11	0.44
MT	0.14	0.37	-0.63	0.67	-0.18	0.88	-1.48	2.01
NC	0.14	0.23	-0.31	0.58	-0.17	0.37	-1.04	0.57
ND	0.27	0.82	-0.65	1.78	-0.51	1.94	-3.17	2.25
NE	0.09	0.22	-0.29	0.50	0.07	1.40	-2.44	2.50
NH	0.30	0.62	-0.36	1.31	-0.24	0.58	-0.82	0.49
NJ	0.12	0.24	-0.41	0.83	-0.11	0.48	-1.02	0.83
NM	0.09	0.48	-0.72	0.95	-0.11	0.29	-0.75	0.45
NV	-0.06	0.35	-0.79	0.40	-0.08	1.02	-1.89	1.68
NY	0.09	0.18	-0.32	0.45	-0.11	0.58	-1.08	1.14
OH	0.11	0.25	-0.22	1.41	-0.02	0.52	-1.14	1.28
OK	0.02	0.32	-0.44	0.71	0.13	1.12	-1.96	2.20
OR	0.44	0.28	0.11	0.99	-0.02	0.81	-1.48	1.33
PA	0.12	0.18	-0.23	0.52	-0.03	0.43	-1.06	1.05
RI	0.19	0.19	-0.03	0.45	-0.23	0.22	-0.52	0.08
SC	-0.06	0.21	-0.38	0.26	0.11	0.64	-0.93	1.17
SD	0.50	0.79	-0.57	2.59	0.29	1.51	-3.51	2.62
TN	-0.10	0.13	-0.27	0.17	0.04	0.58	-0.92	1.58
TX	0.10	0.22	-0.49	0.58	-0.06	0.60	-1.03	1.19
US	0.16	0.10	-0.03	0.35	-0.03	0.29	-0.61	0.45
UT	0.22	0.25	-0.23	0.69	0.01	0.79	-1.17	1.83
VA	0.17	0.35	-0.58	0.89	0.10	0.38	-0.60	1.00
VT	-0.06	0.46	-0.71	1.38	-0.39	1.87	-3.10	3.37
WA	0.13	0.16	-0.21	0.45	0.01	1.07	-2.24	1.30
WI	0.15	0.09	0.02	0.35	0.07	0.66	-0.80	1.35
WV	-0.14	0.27	-0.46	0.26	-0.95	1.03	-3.24	0.45
WY	0.17	1.08	-2.17	2.77	0.06	1.30	-3.03	1.95

Table A.2: Cross-correlations among main variables

	Private R&D	Military R&D	Non Military R&D	State GDP
$h = 5$				
$\Delta^h RDpriv$	1			
$\Delta^h RDdef$	0.12	1		
$\Delta^h RDnon-def$	0.17	0.1	1	
$\Delta^h GDP$	0.12	0.14	0.05	1
$h = 4$				
$\Delta^h RDpriv$	1			
$\Delta^h RDdef$	0.08	1		
$\Delta^h RDnon-def$	0.18	0.08	1	
$\Delta^h GDP$	0.06	0.1	0.01	1
$h = 3$				
$\Delta^h RDpriv$	1			
$\Delta^h RDdef$	0.04	1		
$\Delta^h RDnon-def$	0.15	0.05	1	
$\Delta^h GDP$	0.02	0.08	-0.02	1

Notes: $RDpriv$ stands for private, non-federally funded R&D. $RDdef$ represents total defense R&D obligations. $RDnon-def$ stands for total non-defense R&D obligations. GDP is total state GDP. All variables are taken in real per capita terms. Correlations are computed for log changes over different time horizons (h).

Appendix B Additional results and robustness checks

Figure B.1: State sensitivities to changes in national defense R&D vs. average log changes in private R&D

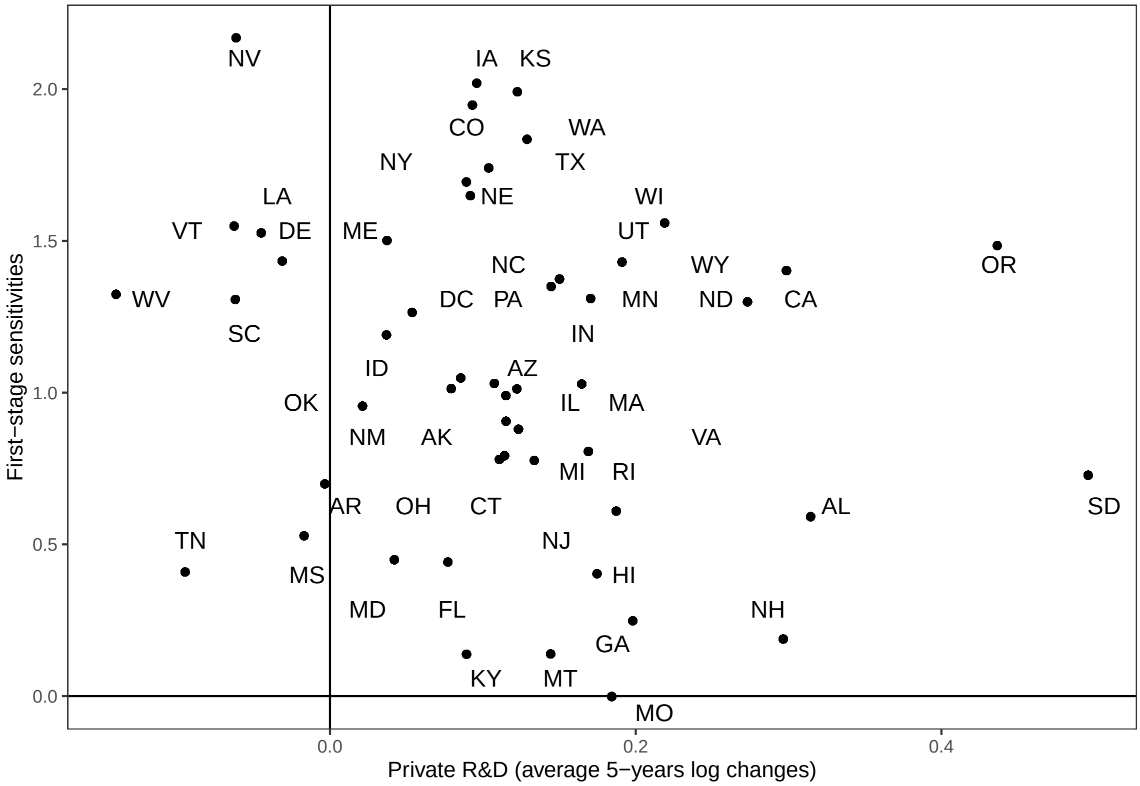
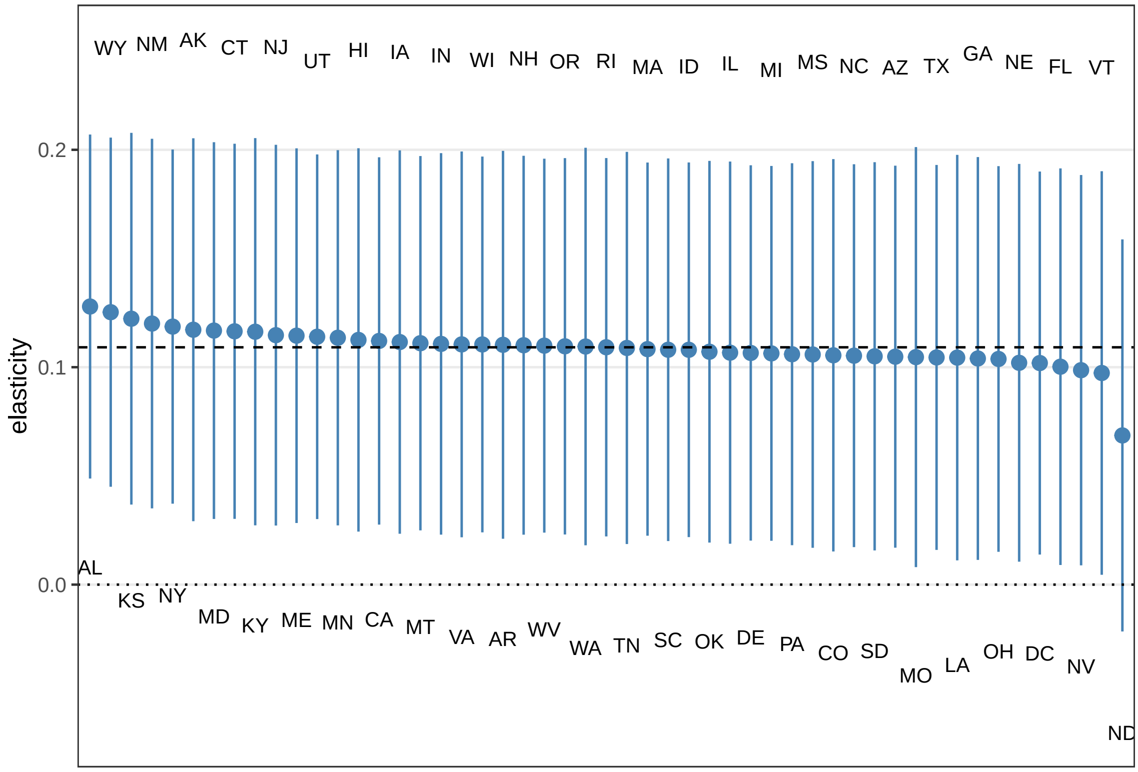


Figure B.2: Sensitivity of estimates to state inclusion



Notes: The dashed line represents our baseline IV estimate for $h = 5$. For each state i we ran the IV regression over the interval $h = 5$ excluding observations for i. The figure shows the point estimate and the associated 90% confidence interval (standard errors are clustered by state).

Table B.1: Estimates from the log level specification

	Dependent variable: Privately-funded R&D ($\ln RDpriv$)							
	OLS		IV					
			(k = 5)		(k = 10)		(k = 15)	
$\ln RDdef_{t-1}$	0.106***	0.107***	0.247***	0.249***	0.314**	0.315**	0.427**	0.423**
	(0.035)	(0.036)	(0.089)	(0.089)	(0.138)	(0.137)	(0.195)	(0.189)
Non Military R&D	✓	✓	✓	✓	✓	✓	✓	✓
Non Military R&D (lagged)	✗	✓	✗	✓	✗	✓	✗	✓
State GDP	✓	✓	✓	✓	✓	✓	✓	✓
State GDP(lagged)	✗	✓	✗	✓	✗	✓	✗	✓

Notes: OLS and TSLS estimations with state and year fixed effects. The level specification is: $\ln RDpriv_{i,t} = \beta \ln RDdef_{i,t-1} + \delta' W_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}$,. The dependent variable is the log of non-federally funded R&D expenditures. The main regressor is the lagged log of defense R&D obligations. The vector of controls include the contemporaneous and lagged logs of non-defense R&D obligations and state GDP. All variables are taken in real per capita terms. In TSLS estimations we use a simple Bartik-type of instrument, also similar to Moretti et al. (2019): $IV = share_{i,t-1} RDdef_{US,t-1}$. Where $share$ stands for a k-years moving average of the state share in public R&D and $RDdef_{US}$ is national defense R&D. We report results for three different values for k (i.e. 5, 10 and 15). Standard errors in parenthesis are clustered by state.

*p<0.1; **p<0.05; ***p<0.01

Table B.2: Outliers robustness: regressions using winsorized data (at 1st and 99th percentiles)

Military R&D ($\Delta^h RDdef$)		Dependent variable: Private R&D ($\Delta^h RDpriv$)					
		No correction			*Winsorized*		
$h=2$	*No correction*	0.093	0.098	0.095	0.102	0.107	0.105
		(0.08)	(0.079)	(0.076)	(0.074)	(0.074)	(0.071)
	Winsorized	0.082	0.086	0.083	0.091	0.094	0.092
		(0.081)	(0.08)	(0.078)	(0.076)	(0.076)	(0.073)
$h=3$	*No correction*	0.07	0.067	0.066	0.075	0.074	0.073
		(0.058)	(0.059)	(0.055)	(0.055)	(0.055)	(0.052)
	Winsorized	0.072	0.07	0.069	0.077	0.076	0.075
		(0.058)	(0.058)	(0.054)	(0.055)	(0.055)	(0.052)
$h=4$	*No correction*	0.134*	0.137*	0.138*	0.132*	0.134*	0.134*
		(0.08)	(0.079)	(0.07)	(0.073)	(0.073)	(0.067)
	Winsorized	0.139*	0.142*	0.141*	0.137*	0.138*	0.137*
		(0.083)	(0.081)	(0.073)	(0.076)	(0.075)	(0.069)
$h=5$	*No correction*	0.11*	0.112**	0.109**	0.108**	0.109**	0.106**
		(0.056)	(0.055)	(0.053)	(0.05)	(0.049)	(0.049)
	Winsorized	0.113*	0.114**	0.111**	0.111**	0.111**	0.107**
		(0.057)	(0.057)	(0.055)	(0.051)	(0.051)	(0.051)
Non Military R&D		✗	✓	✓	✗	✓	✓
State GDP		✗	✗	✓	✗	✗	✓

Notes: TSLS estimations with state and year fixed effects. The sample period is 1968-2017. We run separate regressions for each h, where the dependent variable is the h-year log-change in private R&D (privately financed, in real per capita terms). The main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). Winsorization occurs at the 1st and 99th percentiles. Control variables include the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms). Standard errors in parenthesis are clustered by state.
*p<0.1; **p<0.05; ***p<0.01

Table B.3: Regressions without normalizing by population

Military R&D ($\Delta^h RDdef$)	*Dependent variable:* Privately-funded R&D ($\Delta^h RDpriv$)					
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
$h = 2$	0.017	0.017	0.016	0.088	0.086	0.088
	(0.02)	(0.02)	(0.02)	(0.078)	(0.072)	(0.069)
$h = 3$	0.021	0.02	0.019	0.063	0.05	0.046
	(0.02)	(0.02)	(0.02)	(0.056)	(0.049)	(0.048)
$h = 4$	0.041	0.041*	0.038	0.126	0.107	0.111*
	(0.025)	(0.024)	(0.024)	(0.076)	(0.066)	(0.062)
$h = 5$	0.041	0.041	0.038	0.102*	0.099*	0.099*
	(0.027)	(0.027)	(0.026)	(0.054)	(0.054)	(0.053)
No controls	✓	✗	✗	✓	✗	✗
Only Population	✗	✓	✗	✗	✓	✗
Baseline (includ. pop)	✗	✗	✓	✗	✗	✓

Notes: OLS and TSLS estimations with state and year fixed effects. The sample period is 1968-2017. We run separate regressions for each h, where the dependent variable is the h-year log-change in firms R&D (privately financed, in real terms). The main regressor is the h-year log-change in defense R&D obligations (in real terms). Baseline controls include h-year log-changes of state population, GDP and non-defense R&D obligations (in real terms). Standard errors in parenthesis are clustered by state.

*p<0.1; **p<0.05; ***p<0.01

Table B.4: Employment regressions: robustness checks

	Dependent variable: Employment ($\Delta^h RDemp$)							
	R&D tax credit				Corporate tax			
Industry/Occupation	(h = 2)	(h = 3)	(h = 4)	(h = 5)	(h = 2)	(h = 3)	(h = 4)	(h = 5)
Engineers	0.048**	0.062**	0.062**	0.069**	0.042**	0.056**	0.059**	0.064**
(SOC 17-2000)	(0.018)	(0.024)	(0.025)	(0.03)	(0.018)	(0.023)	(0.024)	(0.029)
Computer and electronic	0.011	0.011	0.065	0.068*	0.013	0.015	0.06	0.062
products (NAICS 334)	(0.039)	(0.048)	(0.042)	(0.04)	(0.038)	(0.046)	(0.04)	(0.039)
Transportation equipment	-0.121	0.101***	0.081***	0.058	-0.142	0.1***	0.085***	0.068**
(NAICS 336)	(0.188)	(0.027)	(0.026)	(0.036)	(0.212)	(0.026)	(0.021)	(0.033)
	User cost of R&D capital				Non-R&D procurement			
Engineers	0.044**	0.059**	0.065**	0.07**	0.055***	0.068***	0.069***	0.069***
(SOC 17-2000)	(0.018)	(0.023)	(0.025)	(0.029)	(0.019)	(0.023)	(0.023)	(0.023)
Computer and electronic	0.012	0.014	0.061	0.064	0.021	0.033	0.079*	0.084*
products (NAICS 334)	(0.039)	(0.047)	(0.042)	(0.04)	(0.038)	(0.047)	(0.043)	(0.043)
Transportation equipment	-0.147	0.104***	0.09***	0.071**	0.01	0.123***	0.102***	0.074*
(NAICS 336)	(0.214)	(0.028)	(0.022)	(0.034)	(0.077)	(0.023)	(0.024)	(0.037)
	Outlays				No population normalization			
Engineers	0.019	0.02	0.039	0.049*	0.06***	0.076***	0.08***	0.082***
(SOC 17-2000)	(0.027)	(0.031)	(0.031)	(0.028)	(0.02)	(0.025)	(0.024)	(0.024)
Computer and electronic	0.045	0.045	0.073	0.072	0.014	0.016	0.059	0.065
products (NAICS 334)	(0.041)	(0.045)	(0.045)	(0.045)	(0.036)	(0.046)	(0.047)	(0.049)
Transportation equipment	0.055	0.067*	0.08**	0.066	-0.019	0.115***	0.091***	0.074*
(NAICS 336)	(0.033)	(0.034)	(0.033)	(0.043)	(0.103)	(0.023)	(0.025)	(0.037)

Notes: the table reports TSLS estimations by industry/occupation for different specifications and time horizons h. Across all specifications, the dependent variable is the h-year log-change of employment in the industry/occupation (in per capita terms) while the main regressor is the h-year log-change in defense R&D obligations (in real per capita terms). All regressions include the h-year log-changes of non-military R&D obligations and state GDP (both in real per capita terms) as control variables as well as state and time fixed effects. The sample period is 1968-2017 except for the "Non-R&D procurement" regression which uses 1980-2017. The first three specifications include respectively h-year variations in corporate tax rates, R&D tax credits and user costs of R&D capital as controls. The "Non-R&D procurement" regression includes h-year log-changes in total non-R&D procurement. The "Outlays" specification uses national variations in outlays (instead of obligations) interacted with state dummies as instrumental variables. "No population normalization" refers to a regression in which both the main regressor and the controls are not divided by population. Standard errors in parenthesis are clustered by state.

*p<0.1; **p<0.05; ***p<0.01