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Buyers' role in innovation procurement: Evidence from US military R&D contracts

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Abstract

This study provides the first quantification of buyers' role in the outcome of R&D procurement contracts. We combine together four data sources on US federal R&D contracts, follow-on patented inventions, federal public workforce characteristics, and perception of their work environment. By exploiting the observability of deaths of federal employees, we find that managers' death events negatively affect innovation outcomes: a 1% increase in the share of relevant public officer deaths causes a decline of 32.3% of patents per contract, 20.5% patent citations per contract, and 34.3% patent claims per contract. These effects are driven by the deaths occurring in the 6 months before the contract is awarded, thereby indicating the relevance of the design and award stage relative to ex post contract monitoring. Lower levels of self-reported within-office cooperation also negatively impact R&D outcomes.

1 | INTRODUCTION

Government procurement of R&D services and innovative goods is a crucial activity that led to the development and diffusion of major innovations that changed our world. Classic examples include computers, large passenger jets, smartphones, semiconductors, and the Internet (see Flamm, 1987; Nelson, 1982). See Maurer and Scotchmer (2004) and Cabral et al. (2006) for overviews. Within our data set, we observe R&D contracts that lead to the patents upon which widely used products are based, such as voice-activated helpers (like Siri or Alexa) and smart household appliances (like the Roomba vacuum cleaners). Besides specific innovations, the large public demand for innovation also boosts private R&D spending (Cozzi & Impullitti, 2010; Slavtchev & Wiederhold, 2016), affects business long term (Howell, 2017), and influences the direction of innovation (Clemens & Rogers, 2020).[1] All these forces have made public procurement of innovation a central policy tool to face major societal challenges, linked to population ageing, epidemic diseases, and climate change, and to boost competitiveness and growth (OECD, 2017).

Still, Mazzucato (2013), by building on successful examples to praise the role of the State as an innovator, triggered a hot debate. Her book was criticized on many grounds, from ignoring tax revenue when claiming that the State does not reap the fruits of its investments to downplaying the crucial role of the private sector in developing new technologies into useful products (e.g., Westlake, 2014). Most relevant to this paper, several critics argued that the described cases were hand-picked successes, while little mention was made of the many wasteful projects that led to no useful innovation, if not to spectacular failures (Liebreich, 2018; Mingardi, 2015). Successes and failures are there for every policy, but, as stressed by Takalo et al. (2017), the key challenge is to identify the drivers' of successful R&D cases. Our study contributes to this debate by quantifying for the first time the importance of buyers as a determinant of the success of public procurement of innovation.

Indeed, questions have been raised on both the capacity of public procurers to manage the process effectively,[2] and the ability of governments' agencies to "pick winners" by supporting specific technologies and guiding technological development (Nelson & Langlois, 1983). When procuring innovation, public buyers play a key role toward the project' success: they make the internal and market assessment to identify the government needs and the state of potential supply, translate needs into functional requirements, design complex tenders and award mechanisms, select the most suitable contractor and manage contract execution which ends months, if not years, after the award.[3] Inefficiencies at each of these stages may significantly compromise the procurement and negatively impact the innovation process. However, despite its importance, there is limited research on the role of public buyers, as opposed to, for instance, the extensively studied issue of the efficacy of public policies (subsidies, tax benefits, etc.) for private R&D (Takalo et al., 2013a, 2013b).

There are two main measurement challenges to a quantitative assessment of public buyers' role in innovation procurement. The first is that evaluating the performance of R&D contracts is notoriously difficult. Measures typically used in the procurement of standardized goods, such as unit prices, or in the procurement of works and services, such as delays and cost overruns, have little meaning when the object of a contract is an innovation. With innovation procurement a natural possibility is to measure output through patents, but so far it has been not easy to link patent data with procurement contracts and buyer characteristics.[4] The second problem concerns how to attain a measure of the effectiveness of public buyers. The prevalent approach has been to use a fixed-effects strategy (Bandiera et al., 2009; Best et al., 2017; Bucciol et al., 2020), but this requires adequate variability in the data and leaves open the question of what exactly is driving the results. Another approach is to use surveys (Decarolis et al., 2021; Rasul & Rogger, 2016).

In this paper, we address both measurement challenges by making use of a novel data set on US federal R&D procurement contracts that combine multiple data sources. First, we use the Federal Procurement Data System (FPDS), which contains information (e.g., awarding bureau, price, product or service code, contract amount, contract type, contractor features, etc.) on every contract awarded by US federal agencies. The Department of Defense (DoD) accounts for most of R&D contracting, representing about 85% of the procurement cases in the data set.[5] Second, we use the 3PFL Database of Federally Funded Patents (3PFL), as collected by de Rassenfosse, Jaffe, et al. (2019). It links information on patented inventions (namely, the number of patents, their associated citations, and claims) induced by a US federal procurement contract of R&D. The last two data sets cover features of the awarding offices. The third data set reports fine statistical information on the entirety of the public workforce produced by the Office of Personnel Management, made publicly available through the Federal Human Resource database (FedScope). The fourth data set is the Federal Employee Viewpoint Survey (FEVS), which measures government employees' perceptions of several characteristics of their agency and specific office.

Our quantification of buyers' role in innovation outcomes exploits the variation across bureaus and time of employees' death events. We first analyze the variation in federal employees' death events relative to a comprehensive list of office and contract observable characteristics. Then, we quantify how a death event impacts procurement outcomes.[6] Clearly, the death of employees might matter through several channels: it may cause emotional distress or work overload to the remaining workers, or induce a temporary shortage of skilled workers (Warren, 2014); if it concerns managerial positions, it may create a management vacuum within the organization. Although we cannot test for all these possible mechanisms in as much detail as we would like, we analyze if deaths have different impacts on outcomes depending on the type of employee, identified by age and salary, and on the stage of the procurement process in which it occurs. Variations in the impact across employees types or procurement timing are indicative that the effect cannot be just emotional, and it is unlikely to be related to workload, as employees' load is typically spread uniformly across time.

Our main findings are as follows. The unexpected death of "relevant employees," identified by age and salary figures as those covering managerial roles, occurring in the 6 months before the contract is awarded, produces a strong negative impact on all our innovation outcome measures. An increase of 1% in relevant employees deaths causes a decline of 32.3% of patents per contract, 20.5% patent citations per contract, and 34.3% patent claims per contract. By contrast, we find a considerably weaker, though still positive and statistically significant effect of unexpected managers' deaths occurring during the contract management phase that follows the contract's award. Similarly, no effects are found when death events involve employees less likely to cover management roles. These results are robust to the inclusion of bureau and contractor fixed effects and are qualitatively stable across various modeling choices, specifications including different sets of controls and different subsamples.

These results suggest that managers deaths cause disruption of specialized human capital that is hard to replace. This interpretations is in line with practitioners' view that in procurement of innovation high technical competence is needed for managing projects. It is supported by various additional findings discussed in the paper. For instance, when we consider the different DoD departments, we find that the effects of deaths on innovation outcomes are more significant for the Army and Air Force relative to the Navy. This is consistent with the fact that the specialized literature has highlighted how the latter department relies less than the other two on project managers with technical—and not only administrative—knowledge to solicit, assign, and monitor procurement projects (Rendon et al., 2012).

In the final part of the paper, we expand the analysis to include (perceived) office characteristics. The FEVS data allow us to measure at the level of bureau-year-State features such as the self-perceived level of the bureau's skills, incentives, and within-office cooperation. We find evidence of a direct effect linking the level of cooperation to improvements in all of our innovation measures, but no interaction effects between cooperation and death events. Neither direct nor indirect effects are found for the level of skills and incentives within the bureaus. These results imply that better working environments cannot compensate for the sudden loss of specialized human capital at the center of our analysis with higher perceived levels of office cooperation, skills, or incentives.

Overall, these results shed new light on the functioning of innovation procurement. Although some of them are likely to be specific to the practices of the federal agencies in our sample, we consider the finding on the importance of the pre-award phase as consistent with the key characteristics of procurement of innovation. As discussed below, innovation procurement requires extensive work before the proper tendering stage and the coordination of large teams with interdisciplinary pieces of knowledge. This clearly points to the crucial role of management practices in the context of innovation procurement, providing additional evidence in favor of the framework proposed by Bloom and Van Reenen (2007) on the factors affecting the success of private and public organizations.

The rest of the paper is organized as follows: Section 2 sketches the DoD's R&D procurement process; Section 3 describes the data; Section 4 discusses the empirical strategy; Section 5 displays the results; Section 6 concludes.

2 | THE DOD PROCUREMENT ORGANIZATION

The US Government Accountability Office (GAO) has recently issued several reports that provide some useful background information on the DoD procurement process and management (see, e.g, GAO, 2017, 2019a, 2019b). Four important aspects are particularly relevant to our study. First, although all procurement contracts are subject to the U.S. Federal Acquisition Regulation (FAR), every single office and bureau's internal functioning still matters. Agencies and major defense acquisition programs use different approaches to organizing and leveraging support organizations. For example, the Navy programs rely on naval warfare centers to provide the engineering expertise necessary to design, build, maintain, and repair the Navy's aircraft, ships, and submarines. The Army programs reviewed by GAO rely on support organizations such as the Army Contracting Command for contracting functions, the Aviation and Missile Research Development and Engineering Center for engineering expertise, and others to provide life cycle management support. The Air Force programs rely on support organizations established within their commands. This explains the substantial variability across the DoD's different purchasing bodies that we observe in our study.

Second, the procurement of R&D at DoD is a very different acquisition process than that for goods or services, which is studied, for instance, in Carril and Duggan (2020). Strategic decisions are taken throughout all acquisitions stages, from planning to award, from administration to ex-post oversight. Governing these stages effectively requires identifying and analyzing agency-wide acquisitions ahead of 12–24 months and ensuring that needs in the budget request submission are consistent with planned acquisition strategies, the tender specifications, and the implementation plans. To manage this process effectively, the DoD relies on program officers coordinating bureaus composed of civilian, military, and contractor support personnel and cross-functional interdisciplinary teams in which key stakeholders execute the acquisition tasks. The number and composition of personnel involved in major defense acquisition programs vary considerably, ranging from 30 to 397.[7] These features of DoD suggest that a prominent role for the success of a procurement is played by the ability of the program officer to manage these teams.

Third, while the skills and abilities of the team members are surely important, it is standard practice for program officials to use contractor support when the number of government personnel allocated to the program is not sufficient to meet their needs, when the technical skills are not available, or to fulfill short-term tasks that are too brief to justify hiring government personnel.[8] This feature suggests that the availability of a skilled workforce can be achieved through well-managed outsourcing practices, even when the required technical skills are not available internally.

Finally, the procurement of R&D at DoD follows specific rules that regulate the ownership of inventions realized under a government contract and, more specifically, follows the FAR. FAR Subparts 27.2, 27.3, and 52.227 mandate that contractors should promptly disclose any invention conceived or first actually reduced to practice in the performance of work under a government contract (for experimental, developmental, or research work). The disclosure should describe the nature and the purpose of the invention and also identify any related scientific publication or public use of the invention. After the disclosure, if the invention is patentable, the contractor may elect to retain the title of the invention under the condition that it timely files a patent application at the United States Patent and Trademark Office (USPTO) and gives a nonexclusive, royalty-free license to the US government to use the invention or have the third party using it on the government's behalf. If a contractor fails to disclose an invention or fails to timely file a patent application, it risks losing all the rights in the invention (McEwen et al., 2012, p.52). Therefore, companies that perform R&D work for the DoD have a strong incentive to report any inventions realized under a government contract and to file patent applications for those inventions. These rules set out in the FAR allows us to identify patented inventions spurred by DoD contracts unambiguously. To ensure that the government retains the rights to use the patented invention, the FAR requires the contractor to include in the patent a statement acknowledging that the invention was made with government support. The statement shall include the unique identifier of the specific procurement contract underpinning the patented invention and the name of the agency awarding the contract. The 3PFL database described in Section 3 precisely exploits the contract identification number enclosed in the government interest statement in the patent document.

TABLE 1 US federal agencies and R&D contracts

Agency	No. of contracts	Percent	Contract value ($ billion)	Percent
Dep. Air Force	1034	30.15	8.77	58.47
Dep. Army	819	23.88	1.82	12.13
Dep. Navy	1103	32.16	3.65	24.33
NASA	323	9.42	0.39	2.6
Other agencies	151	4.40	0.48	2.8

Note: Contracts are grouped by DoD subagencies, NASA, and other agencies. The number of contracts awarded and their value in USD billion are reported.

3 | DATA

As alluded, the data set developed for this study combines together several sources. The level of observation is that of individual contracts, as tracked in the U.S. FPDS.[9] From this large data set, we apply a series of filters aimed at selecting R&D procurement contracts.[10] Moreover, we restrict the sample according to the following rules: R&D activity performed within US borders; award amount greater than $14,000; expected termination date before the end of the sample (to keep only completed projects we include exclusively contracts awarded until the end of 2012); no Small Business Innovation Research (SBIR) contracts and no grants.[11] This leaves us with a sample of 1750 R&D contracts awarded

TABLE 2 Summary statistics

(a) Contract level					
	Mean	**50th**	***SD***	**Obs.**	**Source**
Awarding price (in $1000)	975	245	3156	1750	FPDS
Final cost (in $1000)	6184	678	99,970	1750	FPDS
Expected duration (days)	560	370	424	1750	FPDS
Total duration (days)	928	822	594	1750	FPDS
Cost plus (dummy)	0.79	–	0.41	1750	FPDS
Negotiation (dummy)	0.36	–	0.48	1750	FPDS
Competed (dummy)	0.91	–	0.29	1750	FPDS
No. of patents	0.13	0.00	1.11	1750	3PFL
No. of citations	0.14	0.00	1.20	1750	3PFL
No. of claims	0.15	0.00	0.68	1750	3PFL
(b) Buyer level					
	Mean	**50th**	***SD***	**Obs.**	**Source**
Total employment	1962.20	1216.00	2539.00	335	FedScope
Relevant employment	930.20	445.00	1259.20	335	FedScope
Median age	7.04	7.00	0.20	335	FedScope
Median salary	7.49	7.00	1.12	335	FedScope
Cooperation	0.75	0.75	0.03	335	FEVS
Skill	0.55	0.55	0.03	335	FEVS
Incentives	0.44	0.44	0.03	335	FEVS
(c) Level					
	Mean	**50th**	***SD***	**Obs.**	**Source**
Propensity to patent	0.63	0.24	0.93	345	USPTO
Small (dummy)	0.32	–	0.45	345	FPDS
University (dummy)	0.19	–	0.40	345	3PFL

Note: *Awarding Price* and *Expected Duration* report the award amount (in $) and the expected duration (in days) of the contract at the time of award; *Final Cost* and *Total Duration* represent the actual cost and duration of the R&D projects, respectively; *Cost plus* equals 1 if the contract pricing format is cost plus and 0 if it is fixed price; *Negotiation* is a dummy variable indicating whether the contract uses negotiated procedures (i.e., the contract is awarded on the basis of a direct agreement with a contractor, after solicitation of a number of sources); *Competed* indicates the contract is available for competition; *Total Employment* reports the number of white collars in the bureau-State; *Relevant Employment* reports the number of relevant (white-collar) employees. FedScope data report bureau's *Median Age* and *Median Salary* in bins: 1 point *SD* in *Median Age* represents 5 years and category 1 coincides with "Less than 20 years"; 1 point *SD* in *Median Salary* $10,000 and category 1 coincides with "Less than $20,000." Accordingly, sample average *Median Age* and *Median Salary* are 45.15 and 84.900, respectively. *Propensity to patent* is the number of privately funded patents filed by a contractor in the period that we consider (2006–2012), divided by the average number of employees working for the contractor over the same period. *Small* is an indicator variable equal to 1 if the seller meets the small business size standard for award to a small business that is applicable to the contract. *University* is a binary variable that reports whether the contractor is a higher-education institution or not.

between 2006 and 2012, with an overall value of $10.8 billion, 11,271 offers submitted, and 345 unique winning firms. Table 1 reports how these contracts are split between federal agencies: the vast majority of the contracts in the data are awarded by bureaus belonging to one of the three ramifications of the DoD.[12]

The main characteristics of these contracts are reported in Table 2, panel (a). Contract amounts are relatively small and highly skewed: 50% of contracts have an awarding price below $245,000, while 10% of contract spending is accounted for by contracts worth more than $1,910,000. The average price is almost $1 million, but the total cost, inclusive of any subsequent modification, is more than $6 million on average. Correspondingly, the average contractual duration is 560 days, while the average final contract duration, which includes any delay, is 928 days. The substantial increase in cost, paired with relatively small delays, is explained by the cost-plus nature of most of the contracts (79%). The preponderance of cost-plus contracts in DoD procurement is well documented (Carril & Duggan, 2018; Kang & Miller, 2017). It is explained by the DoD's interest to obtain a timely completion of projects that have highly uncertain costs at the time of bidding.[13] Yet, contrary to other studies, we observe that most of the contracts are awarded through open procedures (64%) and are characterized by full and open competition (91%).

The three variables at the bottom of panel (a) are the outcome measures of innovation used in this study. They come from the 3PFL database from de Rassenfosse, Jaffe, et al. (2019), which exploits the Federal Acquisition Regulation to identify patented inventions directly related to federal contracts, as described in the previous section. The 3PFL database covers USPTO patents granted between 2005 and 2015.[14] As panel (a) of Table 2 indicates, in addition to the number of patents, the 3FPL data also allows us to measure patent-level bibliographic information which can be seen as a proxy for follow on innovation and which we recover from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT). More in detail, using the information contained in the 3PFL database, we build three different performance measures for our sample of R&D contracts: *Number of Patents*, *Number of Citations*, *Number of Claims*. The variable *Number of Patents* reports the total number of patented inventions associated with a specific federal R&D contract.[15] *Number of Citations* reports the number of patent citations received by the patents associated with a specific R&D contract in the 5 years after the patent application was filed divided by the total number of patents associated with that contract. Finally, the variable *Number of Claims* reports the number of independent claims included in the patents associated with an R&D contract divided by the total number of patents associated with that contract. Patent claims delineate the "metes and bounds" of the patent owner's legal right (Merges et al., 2003) and their count has been used as a proxy for the scope and the value of a patented invention (Bessen, 2008; de Rassenfosse & Jaffe, 2018; Harhoff et al., 2003; Lanjouw & Schankerman, 2004).[16]

One can legitimately question whether patents represent a valid measure of the public value of R&D contracts. A first concern relates to the possibility for a contractor to choose secrecy over patenting. The FAR states that the contractor should file a patent application to retain title to the invention. If the contractor fails to do so, the government has the right to file a patent application. There are thus strong incentives to apply for a patent. However, not all contractors may be aware of the regulations or may comply. In such case, secrecy would be an issue only if projects subject to unexpected death of managers during selection were more likely to choose secrecy a few years down the road, which is rather unlikely. Finally, if preference for secrecy is a firm-level variable, the fact that we control for the idiosyncratic tendency to generate patent in the regression model—and the inclusion of firm fixed effects in robustness analysis—should guard against remaining threats of omitted variable bias.

A second concern is that the Government itself may force the contractors to keep their invention secret given that the disclosure of defense-related inventions may have implication for national security. As showed in Table 3, about 70% of the contracts were explicitly awarded to conduct R&D work in the defense field. The Invention Secrecy Act of 1951 regulates this process. It enables the Patent Office to impose a secrecy order on inventions that might be detrimental for national security.[17] The imposition of a secrecy order put the patent prosecution process on hold and no patent is issued until the order is rescinded.[18] Clearly, if inventions that are connected to defense-related R&D contracts often incurred the imposition of long lasting secrecy orders, we would not be able to observe them in our data, making our measure of contract performance rather imprecise. To assess the severity of this issue, we need to determine the likelihood of such an event. According to figures from the Federation of American Scientists (FAS), between 2006 and 2012 the USPTO imposed on average 105 new secrecy orders per year on patent applications filed by different kind of entities including firms, universities, independent inventors, federal agencies and laboratories.[19] As reported in the FAS data, about 25% of these patent applications are filed by private entities and did not receive any kind of support by the US government. de Rassenfosse, Pellegrino, et al. (2019) show that in a sample of over 2800 patents with a secrecy order imposed (and later rescinded) between 1982 and 2006, the secrecy order lasted less than 3 years for about 50% of the patents, and less than 5 years for almost 70% of the patents. In addition, only about 15% of the patents applied for

TABLE 3 Federal R&D procurement categories

R&D Category	No. of contracts	No. of patents	Award value (in 1000,000$)
AB1—"Community Service/Development: Crime Prevention/ Control"	4	0	5
AB9—"Community Service/Development: Other"	32	2	59
AC1—"Defense System: Aircraft"	165	14	1051
AC2—"Defense System: Missile/Space Systems"	139	30	813
AC3—"Defense System: Ships"	9	1	7
AC4—"Defense System: Tank/Automotive"	13	0	22
AC5—"Defense System: Weapons"	95	0	252
AC6—"Defense System: Electronics/Communication Equipment"	378	83	3260
AC9—"Defense System: Miscellaneous Hard Goods"	14	1	35
AD2—"Defense Other: Services"	379	16	768
AD4—"Defense Other: Textiles/Clothing/Equipage"	11	1	6
AD9—"Defense Other: Other"	1186	100	1975
AE3—"Economic Growth: Manufacturing Technology"	20	7	31
AG9—"Energy: Other"	7	6	54
AH3—"Environmental Protection: Water Pollution"	2	0	3
AH9—"Environmental Protection: Other"	110	3	98
AJ1—"General Science/Technology: Physical Sciences"	98	18	190
AJ2—"General Science/Technology: Mathematical/Computer Sciences"	16	1	99
AJ3—"General Science/Technology: Environmental Sciences"	17	0	24
AJ4—"General Science/Technology: Engineering"	90	5	517
AJ5—"General Science/Technology: Life Sciences"	14	6	23
AJ9—"General Science/Technology: Other"	18	2	38
AN1—"Medical: Biomedical"	79	17	370
AN7—"Medical: Specialized Medical Services"	2	0	4
AN9—"Medical: Other"	4	0	1
AR1—"Space: Aeronautics/Space Technology"	128	2	124
AR2—"Space: Science/Applications"	6	18	4055
AR3—"Space: Flight"	5	0	63
AZ1—"Other Research and Development"	389	37	1087

Note: Descriptive statistics for 3-digit R&D categories are shown. We report the associated no. of contracts, no. of patents, and the overall award amount in our sample.

between 2000 and 2006 that had a secrecy order imposed and then rescinded, acknowledge support from a federal R&D contract. All in all, the number of secrecy orders issued yearly is fairly low and only a limited amount of these orders appear to target the output of federal R&D contracts. Moreover, given that a substantial proportion of the secrecy orders lasts for less than 3 years, many of these potentially unobservable inventions would resurface on time to be included in our data.

Lastly, two common issue that arise in working with patent data concern the large heterogeneity in quality across patents and the presence of a large number of contracts producing zero patents. Regarding the former issue, the majority of patents are worth little (Trajtenberg, 1990) and merely counting patents may not provide an accurate measure of R&D performance. Starting with Trajtenberg (1990) and Albert et al. (1991), a dense body of work has documented that the number of citations that a patent receives correlates with its (technological and economic) importance (for a comprehensive literature review, see de Rassenfosse & Jaffe, 2017). To account for the heterogeneity in patent quality, we have estimated the regression models on a citation-weighted patent count. This approach leads to very similar conclusions. Regarding the second issue, that of vastly more contracts with no patents than with patents, common empirical work approaches use a linear model with the log of one plus the number of patents as outcome variable or a count data model. In this paper, we prefer to stick to the linear model to prevent information loss due to the typical separation problem of count data models, discussed by Santos Silva and Tenreyro (2010). Another main advantage of using linear models is that they are less prone to bias due to the collinearity in the fixed effects. However, we consider the nonlinear model as a further robustness check in the Supporting Information Appendix. But since a linear transformation inside the log can bias the estimates, we follow Bellégo and Pape (2019) and use as dependent variable the logarithm of a small constant μ (set equal to 10^{-9}) plus the innovation counts.[20] As illustrated in the Supporting Information Appendix (Figure C.1), different values of μ affect the quantitative, but not the qualitative, finding that public official deaths affect patent outcomes.

The third source of data that we combine is the FedScope database. It contains data on nearly all federal civilian executive branch employees and we use it to construct measures of the contracting officers' and offices' characteristics. Since the data are released at the bureau-level, we merge them with the R&D contract-level data by aggregating the latter by their bureau, State of contract execution, and year of contract award.[21] Employment data include demographic characteristics along with information on appointments and tasks (e.g., length of service, occupation category, pay grade, salary level, type of appointment, work schedule, and location of each single employee).

Panel (b) of Table 2 reports summary statistics for the subset of white-collar employees. The variable *Relevant employment* in this table plays a fundamental role in our analysis. It indicates the subset of white-collar workers in each combination bureau-State who are below the median age and above the median salary.[22] In fact, although ideally one would observe which employees were involved with a specific contract as well as their health status, the data are not granular enough. Our approach to deal with this limitation is to assess the impact on innovation outcomes of shocks (i.e., death events) affecting relevant employees, whom we define as those white-collar workers whose age and salary is suggestive of their capabilities and whose death is most likely unexpected. We thus select employees having simultaneously an age below the median age and a salary above the median salary. The selection by age reduces the incidence of chronic disease on death occurrences and, more generally, the likelihood of being sick is highly reduced during the first four decades of the lifespan of a person (Gavrilov & Gavrilova, 2011).[23] Ideally, we would want to observe the death of managers. Unlike the Employment cube that distinguishes managers from other employees, the Separation cube only reports office features other than employment composition. We combine the two pieces of information to detect managers' deaths. Our strategy is selecting separating employees that are most likely to be managers, that is, having an age below the median age and a salary above the median salary relative to these variables' distributions for managers simultaneously. This implies looking at employees with a salary of $50,000 or more and an age of 45 years or less. Regarding salary, a selection above the median of the salary distribution conditional on age picks up 88% of the entire manager population and likely selects the most effective young managers. There is also strong, positive correlation between our indicator of relevant employee and higher levels of education.[24] In the next section, we will explain in details how death events occurring among relevant employees can be used to devise the empirical strategy at the heart of our analysis.

Additional measures of bureau characteristics appearing in panel (b) of Table 2 come from the fourth data source, the FEVS. They show bureau-level survey measures of the working environment. The survey, administered yearly since 2002 by the Office of Personnel Management, is the largest and most well-established source of data on federal offices' features. We will return to these data in the final part of our analysis where we discuss some potential channels through which the death of relevant managers might worsen the outcome of procurement-related innovation contracts. We will focus in particular on the three features listed at the bottom of panel (b), namely *cooperation*, *skills*, and *incentives*. These variables measure respondents' perceptions about their bureaus' strengths along these three dimensions of personnel hiring and working.[25]

Finally, panel (c) of Table 2 reports summary statistics at the seller level. Given the potential relevance of selection effects intrinsic to the procurement process, in our setting it is important to control for the contractors' ability to perform R&D. We do so by developing a measure that grasps the technological capacity of a contractor in the technological domain to which the contract is related, at the moment of the award. We collect information on all the privately funded patents applied for between 2003 and 2011 by the contractors in our sample.[26] In particular, we need to take into account the fact that different contractors may exhibit different patenting behavior irrespective of the characteristics of the R&D work they conduct for the US government.[27] To do so, we construct the variable *Propensity to patent* as the number of privately funded patents filed by a contractor in the period that we consider (2006–2012), divided by the average number of employees working for the contractor over the same period. Finally, *University* is a binary variable that reports whether the contractor is a higher-education institution or not.

4 | EMPIRICAL STRATEGY

We seek to estimate buyers' role in explaining R&D project outcomes. We do so by exploiting unexpected deaths of managers of federal bureaus active in innovation procurement. As mentioned earlier, using deaths as a source of exogeneity within organizations is a relatively common estimation strategy (Jäger, 2017), which we exploited in an earlier work that studies US federal procurement of standardized services (Decarolis et al., 2021). For this analysis, our strategy requires first isolating the death event of relevant public managers around the time of project selection. The departure of a manager for reasons related, for example, to job mobility or retirement is likely plagued by omitted variable bias. For that reason, we focus instead on cases of deaths, which are separations arguably less predictable than other mobility events—especially when it comes to younger individuals.

Based on the definition of relevant employees provided earlier, we count the number of deaths occurring among these employees in the 6 months before the contract award.[28] The ratio between this variable and the total number of relevant employees (in the bureau-State and year in which the contract is signed) is what we refer to as the share of relevant deaths and represents our main independent variable.[29] Across the 929 bureau-State-year observations in the FedScope data, the average share of relevant deaths is 0.0001, ranging from a value of 0 at the first percentile to a value of 0.0021 at the 99th percentile.

Conditional on observing at least one death case occurring (17% of observations), Figure 1 shows that the variable has a well-behaved power-law-shaped distribution. It reveals a conceivable right-skewed distribution and a major fraction of deaths lower than 0.0005. From a geographical perspective, the share of deaths does not seem to follow a clear path. Figure 2 shows the share of contracts associated with at least one relevant death across the different States.[30]

Although death-induced separations can be reasonably considered as exogenous shocks relative to procurement contract outcomes, they may not be randomly assigned across bureaus. We use a propensity score weighting approach to adjust for potential unbalancedness. Following the potential outcome literature, consider a binary variable Z_i whose value depends on whether contract i is awarded by a bureau that has experienced at least one relevant death (treated group) against none (control group). Then, conditional on covariates X_i, the propensity score describes each subject's probability of being assigned to the treatment that they received given the set of observed covariates.[31]

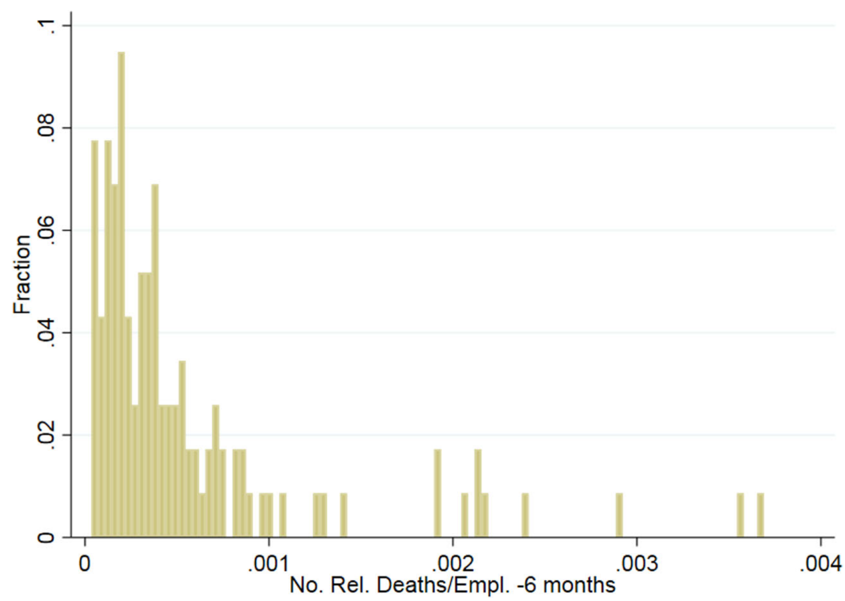

FIGURE 1 Distribution of relevant deaths. The bins represent the share of relevant deaths for the 13% of bureau/State/year triple with at least one relevant death. This figure excludes two outliers (> of 0.5% of deaths), which are *Space and Naval Warfare Systems Command* in Florida for 2008 and *U.S. Army Corps of Engineers* in Arizona for 2012 [Color figure can be viewed at wileyonlinelibrary.com]

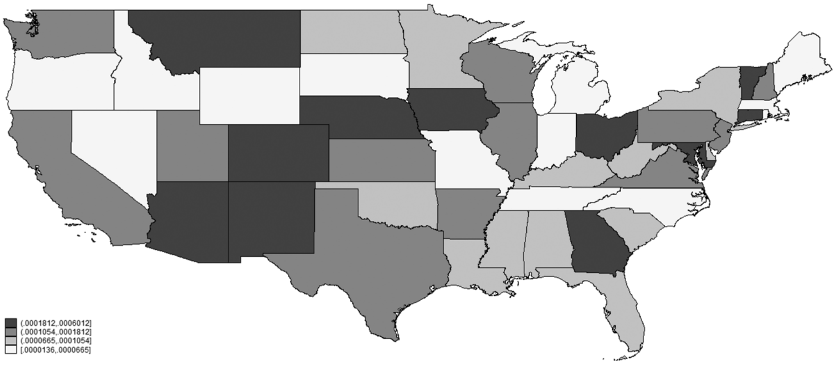

FIGURE 2 Share of contracts associated with at least one relevant death. Share of contracts by State associated with at least one relevant death

By weighting via propensity scores, we effectively compare bureaus equally likely to be assigned to each treatment group. Stated otherwise, propensity score weighting tends to make relevant deaths balanced across offices that look similar on observables. A well-recognized benefit of weighting via propensity score rather than on covariates is to reduce the curse of dimensionality and improve the estimates' precision. Similarly to Bruce et al. (2019), we use the Inverse Probability Weighting Regression Adjustment (IPWRA) method, which involves weighting the outcome measures by the inverse of the propensity score. We proceed as follows. To cope with selection on observable characteristics of buyers, we pair contracts awarded by similar triples bureau-State-year in terms of median salary, age, and the number of white-collar employees. We then perform a logistic regression of a dummy variable for relevant deaths on these characteristics and predict the propensity score $e(\mathbf{z})$.[32] Then, after weighting the outcome of treated bureaus by $\frac{1}{e(\mathbf{z})}$ and that of control bureaus by $\frac{1}{1-e(\mathbf{z})}$, we estimate the following linear model:

$$\log(\mu + Y_{ijtm}) = \beta \ ShareRelevantDeaths_{jt} + \theta X_i + \iota_j + \kappa_t + \lambda_m + \epsilon_{ijtm}, \tag{1}$$

where $Y_{ijtm} = [\#Patents; \#Citations; \#Claims]$ stands for our three contract outcomes for contract i, awarded by bureau-State j in year t and belonging to product category m. X_i represents contract and seller characteristics: in the baseline model, we include three variables capturing elements of the contract award procedure (*Cost Plus, Negotiation, Competed)* and three variables capturing firm features (*Small Business, University, Propensity to Patent*).[33] The regression models include a series of fixed effects: bureau (ι_j), calendar year (κ_t); further, λ_m which, depending on the specification, are either R&D category fixed effects or also fixed effects for the stage of R&D activity. Controlling for this latter variable is of particular importance as contracts awarded to procure basic research might be characterized by a higher level of uncertainty and a lower likelihood of being associated with a patent than applied research contracts. In some specifications, we also include fixed effects for the deciles of award price and expected duration distribution. Finally, as discussed in Section 3, for the log transformation of our dependent variable we follow Bellégo and Pape (2019) and use the logarithm of a small constant μ (set equal to 10^{-9}) plus the patent count. Our choice to set μ equal to 10^{-9} corresponds to using the largest value of μ such that the point estimate from the preferred linear model are closest to the corresponding Poisson estimate. We discuss this choice and how it affects the findings in the Supporting Information Appendix (see Figure C.1).

To explore the soundness of our IPWRA strategy, in the next section we will discuss an extensive set of robustness checks involving both linear and Poisson models, both with and without sample weighting. Before that, however, Table 4 offers additional evidence on the effectiveness of our baseline weighting strategy. It reports the estimates of a linear probability model for the probability of observing at least one relevant death in the bureau/State/year. There are no observable bureau characteristics that significantly predict the chances of observing at least one relevant death, except for variables related to age and accomplishment, which are mechanically related to the outcome variable since they measure death occurrences within a specific sub-population selected precisely based on these variables.

Lastly, before presenting the estimation results, it is useful to report in Figure 3 a graphical representation of the main relationship that we seek to uncover. In particular, this figure shows the relationships between the logarithm of the number of patents and the number of relevant deaths in the bureau/State in the 6 months before the award scaled by the white-collar workforce. The variables are residualized including as controls: contract features, seller features, along with bureau fixed effects, procurement category fixed effects, R&D stage fixed effects, project amount and duration fixed effects, and year fixed effects. The figure reports a binned scatterplot: each point represents a group of contracts sharing the same *x*- and *y*-coordinates. This means that each point represents the mean statistic of the

TABLE 4 Exogeneity test for lagged deaths

	Relevant deaths 6m before				Relevant deaths 6m before			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log Budget	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
log # Contracts	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median Age		−0.18***	−0.18**	−0.02		−0.35***	−0.45***	−0.52**
		(0.04)	(0.06)	(0.14)		(0.09)	(0.11)	(0.20)
Median Education		−0.01	−0.01	0.02		0.06	0.07*	0.08
		(0.01)	(0.01)	(0.01)		(0.04)	(0.04)	(0.05)
Median LOS		0.03	0.04	0.00		−0.01	−0.01	−0.01
		(0.02)	(0.03)	(0.04)		(0.06)	(0.06)	(0.06)
Median Salary		0.00	0.04	0.08		0.16	0.15	0.11
		(0.03)	(0.04)	(0.06)		(0.09)	(0.09)	(0.08)
Median WF Composition		0.03	0.12	−0.39		0.09	0.03	−0.40
		(0.22)	(0.26)	(0.34)		(0.37)	(0.32)	(0.51)
Accomplishment			−1.08**	−2.71***			−1.93**	−3.26***
			(0.49)	(0.60)			(0.67)	(0.84)
Appreciation			1.01**	0.78*			1.52	−0.67
			(0.46)	(0.44)			(1.01)	(0.75)
Level of Workload			−0.02	−0.52*			−0.22	0.07
			(0.31)	(0.24)			(0.40)	(0.47)
Physical condition workplace			0.26**	0.35			0.35	0.30
			(0.11)	(0.23)			(0.32)	(0.38)
Integration policy				−0.12				0.13
				(0.25)				(0.48)
Health Security				0.23				−0.05
				(0.30)				(0.66)
Good Place to work				1.19*				1.14
				(0.62)				(0.88)
Balance work/life				0.21				0.06
				(0.55)				(0.74)
Job Satisfaction				1.18**				2.40**
				(0.55)				(0.92)
Pay Satisfaction				−0.77*				−1.87**
				(0.42)				(0.84)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bureau FEs	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.02

(Continues)

TABLE 4 (Continued)

	Relevant deaths 6m before				Relevant deaths 6m before			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	669	669	669	669	669	669	669	669

Note: Four nested sets of possible predictors (1)–(4) of the bureau-year relevant death variable are presented. All ordinary least squares estimates include year fixed effects. In addition, columns (5)–(8) include bureau-State fixed effects.

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

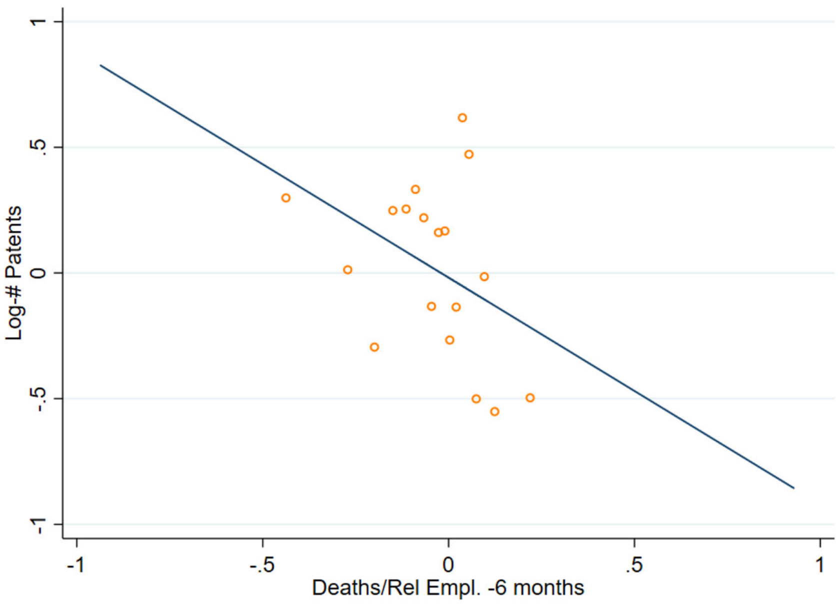

FIGURE 3 Scatterplot. Binned scatterplot. The selected number of bins is optimal in minimizing the (asymptotic) integrated mean squared error following Cattaneo et al. (2019). Each point represents a graphical representation of the relationship between the logarithm of the number of patents associated with a contract and the share of relevant deaths [Color figure can be viewed at wileyonlinelibrary.com]

residualized number of relevant deaths inside each bin. The selected number of bins minimizes the (asymptotic) integrated mean squared error following Cattaneo et al. (2019). The evidence in the figure indicates a clear, negative relationship that our baseline estimates in the next section will confirm.

5 | RESULTS

The baseline estimates of Equation (1) are reported in Table 5. For each of the three outcome measures, this table presents the estimates for four model specifications that gradually expand the set of covariates. All specifications include bureau fixed effects and R&D categories fixed effects. In addition to these fixed effects, the first model includes exclusively the share of relevant deaths.[34] The following model includes characteristics of the contractor (propensity to patent, small business and university). The third model controls for features of the contract and awarding procedure (cost plus, negotiated, competed). Finally, the fourth model also includes fixed effects for calendar year, for the stage of R&D activity, and for bins capturing the size and duration of the project. The latter model is our preferred specification.

We observe a similar pattern across all outcome variables: deaths have a negative and highly statistically significant effect. The magnitude of the estimated coefficient declines as the specification becomes richer, but the qualitative result is stable. The estimated effects imply that a 1% increase in the share of relevant deaths causes a decline of 32.3% of patents per contract, 20.5% patent citations per contract, and 34.3% patent claims per contract.

Among the other covariates, an interesting result is that the size of the contractors is associated with their propensity to innovate. Small businesses have a higher propensity to innovate along all of the three outcomes.[35]

TABLE 5 Baseline estimates

	Log # Patents				Log # 3Y Citations				Log # Claims			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Share Rel. Deaths	−0.64***	−0.60***	−0.55***	−0.39**	−0.39***	−0.36***	−0.36***	−0.23**	−0.66*	−0.61***	−0.57***	−0.42**
	(0.084)	(0.12)	(0.091)	(0.16)	(0.045)	(0.071)	(0.061)	(0.089)	(0.085)	(0.12)	(0.093)	(0.17)
Small Business		0.70**	0.64*	1.17***		0.70**	0.68*	1.16**		0.70**	0.63*	1.16***
		(0.28)	(0.34)	(0.31)		(0.31)	(0.35)	(0.44)		(0.28)	(0.34)	(0.31)
Propensity to patent		0.44	0.43	0.48		0.28	0.27	0.27		0.45	0.45	0.49
		(0.42)	(0.43)	(0.42)		(0.35)	(0.35)	(0.32)		(0.44)	(0.44)	(0.43)
University		−0.20	−0.12	0.39		−0.098	−0.026	0.28		−0.20	−0.12	0.40
		(0.37)	(0.42)	(0.34)		(0.24)	(0.30)	(0.30)		(0.37)	(0.42)	(0.35)
Bureau FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R&D category FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract features	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
R&D stage FEs	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Amount&Duration FEs	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Calendar year FEs	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.02	0.03	0.03	0.07	0.01	0.01	0.01	0.03	0.02	0.03	0.03	0.06
Observations	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00

Note: Standard errors are two-way clustered by bureau and R&D category and are in parentheses. Contract Features indicates that the model controls for features of the contract and award procedure (cost plus, negotiated, competed). Amount and Duration FEs represent deciles for contract value and duration.

*$p < .1$; **$p < .05$; ***$p < .01$.

Regarding the other two covariates—that is, the measure of whether the firm has filed for patents in the past and the dummy for whether it is associated with a university—both of them are not statistically significant.

The baseline estimates above are complemented by an extensive set of robustness checks and by a series of additional results useful to interpret and deepen the findings. Among the most relevant robustness checks, it is worth pointing out that the baseline estimates are qualitatively close to ordinary least squares estimates, thus implying that the sample weighting is not by itself a main driver of the findings, and to Poisson estimates, implemented through the Santos Silva and Tenreyro (2006) pseudo-Poisson model to account for the high-dimensional fixed effects in our favored specification. Although the magnitude of the Poisson point estimate is always larger than the corresponding IPWRA point estimate, all of the Poisson point estimates are contained within the 95% confidence interval of the corresponding IPWRA estimates. We leave a detailed discussion of the robustness checks in the Supporting Information Appendix and explore in the remaining part of this section the additional results.[36]

The first step to better understand our main findings on relevant deaths is to explore how they vary by the bureau workforce size. We find that the smaller the bureau, the more impactful the share of manager deaths is. In particular, Table 6 reports the estimates obtained by gradually excluding the larger bureaus. That is, in the estimates for the number of patents, column 1 contains the full sample, column 2 excludes from it the observations for bureau/State/year at or above the 99th percentile of the distribution of relevant employees. The next two columns further exclude observations at or above the 90th percentile (column 3) and the 75th percentile (column 4).

In terms of the size of the relevant employees, these three cutoffs correspond to 7716, 2169, and 1156 employees, respectively.[37] The same approach is adopted for the other two outcome measures and the results are reported in columns 5–12. There is a trade-off in making the sample more and more concentrated on small offices: as the precision with which we can link the death of a relevant employee to the procurement activity increases, both the chance of observing a death in the smaller offices and the chances that the (fewer) contracts awarded by smaller offices generate a patent decrease. It is therefore remarkable that, across the various subsamples explored in Table 6, the results are qualitatively stable and display a tendency toward higher magnitudes when focusing on smaller bureaus. Indeed, for all three outcome variables the estimates obtained with the smaller subsample are about twice those of the baseline sample.

The next step entails exploring the channels of the effect. In Table 7, we look both at the timing of death events relative to the stage of the contract and at the role of different employees in panel (a) as well as at the role of firms in panel (b). The estimates in panel (a) show the baseline estimates of columns 4, 8, and 12 in Table 5, but with a different measure of employees' deaths. In the baseline, we look at relevant death occurrences in the 6 months *before* the contract is awarded. This is aimed at capturing the typical period of the tendering procedure design and execution, up to the selection of the winning contractor and contract preparation. However, the post-awarding contract management phase might also be relevant if managing the contract and monitoring the private contractors can influence the likelihood that patents will originate from the contract. The first row of Table 7, by looking at relevant deaths during the 6 months *after* the contract is awarded, indicates that there is only weak evidence for this monitoring channel: the estimated coefficient in column (1) is an order of magnitude smaller than that of the baseline and with a lower statistical significance. The relatively lower importance of the ex post monitoring and contract management phase is likely linked to the intrinsic difficulty for contracting officers of to monitor the advancement of research projects, compared to more standard procurement.

The second row of the table reports the effect of white-collar deaths without conditioning on their relevance (but still in the 6-month period before contract award). Contrary to the case of the relevant deaths, there is no effect on patents or citations and a small, weakly significant effect on claims. Finally, to further explore the role of selection, we present in panel (b) of the same table estimates inclusive of firm fixed effects.[38] Relative to the baseline estimates, the smaller sample is due to the requirement of having at least two contracts per firm. Within this sample, the estimates concerning patents, citations, and claims indicate a similar effect relative to the baseline. This result implies that, even within the same contractor, being exposed to an office experiencing a relevant death leads to worse procurement outcomes in terms of innovation.

Although the main result is robust to the inclusion of contractor fixed effects, this does not rule out selection of weaker contractors as a channel through which deaths affect outcomes. Indeed, holding contractors constant merely controls for the overall quality of contractors, not for how suited a particular contractor is for a specific contract. Thus, although a contractor may look good on paper, the results might be driven by a manager's death leading to a mismatch between contracts and contractors. This misallocation could be driven by the loss of some specific knowledge of the deceased manager on some contracts.[39]

TABLE 6 Different size bureaus

	Log # Patents				Log # 3Y Citations				Log # Claims			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Share Rel. Deaths	−0.39**	−0.40**	−0.64**	−1.28***	−0.23**	−0.24**	−0.32	−1.12***	−0.42**	−0.43**	−0.68**	−1.29***
	(0.16)	(0.16)	(0.24)	(0.25)	(0.089)	(0.087)	(0.22)	(0.17)	(0.17)	(0.17)	(0.24)	(0.25)
Small Business	1.17***	1.19***	1.28***	0.82***	1.16**	1.18**	1.14**	0.96**	1.16***	1.18***	1.27***	0.86***
	(0.31)	(0.32)	(0.35)	(0.20)	(0.44)	(0.45)	(0.49)	(0.42)	(0.31)	(0.32)	(0.35)	(0.21)
Propensity to patent	0.48	0.49	0.38	−0.23	0.27	0.28	0.20	−0.29	0.49	0.50	0.40	−0.25
	(0.42)	(0.44)	(0.54)	(0.33)	(0.32)	(0.33)	(0.43)	(0.21)	(0.43)	(0.45)	(0.54)	(0.32)
University	0.39	0.41	0.062	0.99***	0.28	0.28	−0.070	0.54*	0.40	0.42	0.051	1.02***
	(0.34)	(0.36)	(0.28)	(0.19)	(0.30)	(0.31)	(0.18)	(0.28)	(0.35)	(0.36)	(0.28)	(0.19)
Bureau FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R&D category FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R&D stage FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount&Duration FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.07	0.07	0.09	0.04	0.03	0.03	0.05	0.03	0.06	0.07	0.09	0.03
Observations	1749.00	1718.00	1327.00	620.00	1749.00	1718.00	1327.00	620.00	1749.00	1718.00	1327.00	620.00

Note: Standard errors are two-way clustered by bureau and R&D category and are in parentheses. Columns 1, 5, 9 correspond to columns 4, 8, and 12 in Table 5. Then, columns 2, 6, 10 exclude all those observations pertaining bureau/State/year at or above the 99th percentile of the distribution of relevant employees; columns 3, 7, 11 exclude those at or above the 90th percentile; columns 4, 8, 12 exclude those at or above the 75th percentiles.

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

TABLE 7 Channels

(a) Outcomes on other deaths

	Log # Patents		Log # 3Y Citations		Log # Claims	
	(1)	(2)	(3)	(4)	(5)	(6)
# Rel. Deaths /Empl. +6 months	0.25		−0.92***		0.24	
	(0.17)		(0.15)		(0.17)	
# All Deaths/Empl. −6 months		0.22		−0.094		0.17
		(0.69)		(0.45)		(0.71)
Small Business	1.06***	1.01***	0.68**	1.03***	1.06***	1.02***
	(0.36)	(0.19)	(0.27)	(0.20)	(0.35)	(0.19)
Propensity to patent	0.58**	0.47	0.11	0.15	0.60**	0.48
	(0.24)	(0.36)	(0.17)	(0.22)	(0.25)	(0.36)
University	0.25	0.28	0.21	0.24	0.25	0.30
	(0.33)	(0.35)	(0.20)	(0.19)	(0.34)	(0.35)
Bureau FEs	Yes	Yes	Yes	Yes	Yes	Yes
R&D category FEs	Yes	Yes	Yes	Yes	Yes	Yes
R&D stage FEs	Yes	Yes	Yes	Yes	Yes	Yes
Contract features	Yes	Yes	Yes	Yes	Yes	Yes
Amount&Duration FEs	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.08	0.12	0.02	0.10	0.08	0.12
Observations	1749.00	1750.00	1749.00	1750.00	1749.00	1750.00

(b) Outcomes on relevant deaths—Firm fixed effects

	Log # Patents		Log # 3Y Citations		Log # Claims	
	(1)	(2)	(3)	(4)	(5)	(6)
Share Rel. Deaths	−0.43***	−0.78***	−0.23*	−0.38***	−0.45***	−0.82***
	(0.14)	(0.25)	(0.12)	(0.13)	(0.15)	(0.26)
Small Business	0.025	−0.0086	0.51	0.43	0.0078	−0.016
	(0.52)	(0.55)	(0.44)	(0.26)	(0.50)	(0.57)
Propensity to patent	0.39	−0.63	0.29	−0.66	0.40	−0.62
	(0.28)	(0.55)	(0.22)	(0.59)	(0.29)	(0.57)
Bureau FEs	Yes	Yes	Yes	Yes	Yes	Yes
R&D category FEs	Yes	Yes	Yes	Yes	Yes	Yes
Contract features	Yes	Yes	Yes	Yes	Yes	Yes
R&D stage FEs	Yes	Yes	Yes	Yes	Yes	Yes
Amount&Duration FEs	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	Yes	No	Yes	No	Yes
Adj. R^2	0.05	0.16	0.01	0.15	0.05	0.15
Observations	1614.00	1614.00	1614.00	1614.00	1614.00	1614.00

Note: Standard errors are two-way clustered by bureau and R&D category and are in parentheses. Panel (a) shows placebo regressions using relevant deaths in the 6 months after award and nonrelevant deaths. Panel (b) replicates Table 5 including firm fixed effects. In panel (b) University is excluded due to collinearity with seller fixed effects.

*$p < .1$; **$p < .05$; ***$p < .01$.

TABLE 8 Workplace characteristics

	Log # Patents				Log # 3Y Citations				Log # Claims			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Share Rel. Deaths	−1.02***	−1.03***	−0.98***	−0.64*	−0.63***	−0.63*	−0.65***	−0.52**	−1.06***	−1.06***	−1.01***	−0.68*
	(0.15)	(0.20)	(0.17)	(0.34)	(0.13)	(0.22)	(0.18)	(0.26)	(0.16)	(0.21)	(0.18)	(0.35)
Cooperation	0.77***	0.73***	0.71***	0.65**	0.66***	0.62***	0.60***	0.58**	0.76***	0.71***	0.70***	0.64**
	(0.16)	(0.19)	(0.20)	(0.29)	(0.17)	(0.19)	(0.18)	(0.24)	(0.16)	(0.19)	(0.20)	(0.30)
Skill/Incentives	0.20	0.28	0.31	0.42	−0.070	0.021	0.041	0.15	0.23	0.32	0.35	0.46
	(0.28)	(0.29)	(0.28)	(0.41)	(0.19)	(0.23)	(0.24)	(0.34)	(0.29)	(0.29)	(0.29)	(0.42)
Deaths/Empl. −6 months × Cooperation	−142.4**	−148.9**	−161.5**	−114.0	−91.3***	−96.1**	−99.5**	−88.1	−144.9*	−151.3**	−164.0**	−118.8
	(65.8)	(68.4)	(63.9)	(95.6)	(29.4)	(34.2)	(36.5)	(67.8)	(69.5)	(71.1)	(67.2)	(97.5)
Deaths/Empl. −6 months × Skill/Incentives	−14.4	−21.5	−5.29	28.0	−12.4	−16.4	−18.3	−7.45	−16.9	−24.3	−8.87	29.5
	(41.0)	(47.6)	(56.6)	(116.5)	(43.8)	(50.2)	(49.2)	(88.1)	(43.4)	(49.9)	(59.0)	(117.7)
Bureau FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R&D Category FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R&D Stage FEs	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Contract Features	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Amount&Duration FEs	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Adj. $R2$	0.03	0.03	0.03	0.07	0.01	0.01	0.02	0.03	0.03	0.03	0.03	0.07
Observations	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00	1749.00

Note: Standard errors are two-way clustered by bureau and R&D category and are in parentheses. This table reproduces Table 5 by enriching all specifications with Cooperation and Skill/Incentives and the interaction of both variables with the share of relevant deaths.

*$p < .1$; **$p < .05$; ***$p < .01$.

An interesting insight on the fact that the likely channel for the effect that we uncovered is the disruption of specialized human capital can be obtained by looking at how our estimates change between the DoD departments. Within the DoD, the acquisition process takes place differently according to Rendon et al. (2012). On the one hand, the Department of Army and the Department of Air Force solicit, assign, and monitor procurement projects at the installation level via project managers (i.e., contracting officers) with technical—and not only administrative—knowledge who also rely on project teams in managing acquisitions more often. On the other hand, for the Department of Navy, the procurement process management occurs at the regional level and is carried out by contracting officers mostly not equipped with technical skills. The role of project managers is thus more relevant for the former. In our data, this feature turns into heterogeneous effects of death within the DoD purchasing units. R&D purchases made by the Air Force and Army are more innovative as they are associated with more patents per project (0.16 vs. 0.08) and per million dollar of R&D spending (2.4% vs. 1.4%). Such relevance of the features and the organization of these purchasing units' human resources makes them likewise more exposed to death events. Technical skills are too specific to be replaced effectively and quickly after a fatal separation, and this makes the Navy less affected by the on-boarding effect of the replacements than the Air Force and Army. This is evident from an auxiliary analysis in which we replicate the baseline regression from Columns 4, 8, and 12 of Table 5 and interact relevant death with fixed effects for the Air Force and Army, Navy, Others. For all three outcomes, the interaction term hold negative and significant only with the Air Force and Army indicator: the death are disruptive in terms of less patents, less citations per patent, and less claims per patent only for the contracting units where the procurement process is managed at the installation level. This results is highly suggestive that the main mechanism behind the impact of a death event is the disruption of specialized and hard to replace human capital and not a general shock in the workload of the awarding office. Nevertheless, we shall stress that we cannot fully rule out other channels. For instance, our effects might result from a lower scrutiny of all contracts that were concomitantly under consideration for award (Table 8).

We conclude with a short description of how bureau characteristics—as measured from the FEVS—are associated with both deaths and procurement outcomes. Through a principal component analysis, we reduce the 8 questions in the FEVS section about the work unit to two new variables, one that essentially captures cooperation (as this component weights essentially only the two questions concerning cooperation) and one that covers skills and incentives. We indicate these two factors as *Cooperation* and *Skill/Incentives*. We run the same models of Table 5, allowing these two new variables to enter both directly and as interactions with Relevant Deaths. Relevant Deaths remains significant and large, even above those in Table 5.[40] The interaction terms are not significant, while the direct effect of cooperation is positive and significant across all outcomes.

These results are particularly interesting if compared to the ones in Decarolis et al. (2021). In the context of service contracts not involving R&D, they find that death events significantly interact with the FEVS measure of bureau's cooperation. This difference relative to our findings might be driven by the more limited variability in our measures of bureau characteristics: most of our data are from the DoD, while they observe a larger set of agencies and bureaus. Alternatively, it might be that for R&D procurement within-bureau cooperation is a more important determinant of successful procurement, than in the case of the procurement of simpler services. Such an interpretation would indeed be consistent with the large work-teams of individuals with heterogeneous competences that the R&D procurement activity requires and the fact that any sudden loss of human capital within such groups is harmful for innovation outcomes, regardless of the degree of bureau cooperation. That is, while cooperation by itself helps achieving better outcomes, it is not a feature that allows lessening (or bolstering) the negative impacts of a death event, with the disruption of competences that it brings. Thus, even the best-performing organizations—in terms of the FEVS measures—are affected by deaths to the same extent as weaker organizations. This fact is also particularly important to rule out the alternative explanation of a general disruption effect (e.g., because of psychological stress) due to the loss of a colleague. Indeed, if emotional distress were the main channel behind the negative effect of a death event, we would have expected that more collaborative bureaus would have fared better than less collaborative ones in coping with the disruption.

6 | CONCLUSIONS

The paper shows that public buyers play a very significant role in affecting the success of innovation procurement, as measured by the number and quality of the patents generated. Buyer's role is particularly important in the pre-award procurement design phase, although to a lower degree it also matters in the following contract management phase.

Overall, these results suggest that concerns on the ability of public buyers to effectively manage the procurement of complex innovations and to "pick winners" in technology races were well placed, and represent a preliminary but clear indication of the large potential benefits of investing in the quality of public buyers of innovation through a greater professionalization of this activity, as recently advocated by Saussier and Tirole (2015) for public procurement in general.[41]

It is rather remarkable that we found our results within an institutional setting that is typically considered well organized. The lack of resiliency to death events of even large bureaus of the DoD is troublesome as one would have assumed the presence in these organizations of adequate mechanisms to deal with this type of shocks. By finding that this is not the case, our study provides evidence on the need to develop and implement such mechanisms. Evaluating the costs and benefits of alternative mechanisms is beyond the scope of this study. Nevertheless, our findings on the timings of deaths are useful to narrow down interventions that can affect the right phase of the contract: for instance, having a speedier on-boarding of replacement managers is crucial if the death socks strikes during the design stage of the contract. Similarly, our results on bureau characteristics suggest that policies improving the cooperation levels within the office will help innovation procurement.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in public repositories and data sources as documented in the paper.

ENDNOTES

[1]Between 2006 and 2012, our own data reveal that the US federal governments spent approximately $382 billion in R&D procurement, an average of $54.57 billion per year.

[2]The World Bank has recently begun to release its Benchmarking Public Procurement, which examines the procurement process in 180 economies. The report reveals the existence of considerable heterogeneity across states. Concerns on the lack of competence of public procurers have recently been voiced by Saussier and Tirole (2015).

[3]These central roles of public buyers have recently been highlighted by the European Commission, which is pursuing a strategy in support professionalization of public procurement (European Commission, 2020).

[4]The use of patents as procurement outcome can be found in Corredoira et al. (2018), who show that federally funded patents tend to be associated with larger technological influence, in Li et al. (2017) who provide evidence that about 10% of the scientific grants awarded by the U.S. National Institutes of Health (NIH) generates at least one patent, and in Azoulay et al. (2018) who show instead that NIH grants foster the development of patents in the private sector. Regarding the studies on innovation procurement, so far they have been mainly based on surveys (Aschhoff & Sofka, 2009; Guerzoni & Raiteri, 2015), administrative meso-level data (Slavtchev & Wiederhold, 2016), and micro-level patent data (Raiteri, 2018). Within these studies, Aschhoff and Sofka (2009) find that public procurement has a positive effect on firms' innovative output, proxied by the shares of revenues coming from innovated products, whereas Raiteri (2018) shows that US federal procurement contracts that foster the development of technologies are more pervasive than a group of suitable controls. An alternative outcome measure could be the award of a follow-on contract, as this can provide useful information on the success of an R&D contract (Che et al., 2021). Unfortunately, however, FPDS data do not allow us to link it to the original contract to follow-on contracts.

[5]See Carril and Duggan (2020) for a recent study of the DoD's procurement practices involving non-R&D outcomes.

[6]For a review of this type of identification strategy see the recent application by Jäger (2017).

[7]In a review of eleven major defense acquisition programs, GAO (2019b) found that the program workforce size and composition were influenced by the degree to which the program assumed responsibility for technical development and integration, as well as the program's

stage within the acquisition life cycle. Programs that assumed more responsibility for developing and integrating key technologies generally have a larger workforce, primarily, but not only, composed of engineering and technical personnel.

[8]Using contractor support personnel to perform tasks helps to overcome the lengthy process of hiring government personnel or the possibility that the number of personnel authorizations allocated to the program by their respective command do not meet their estimated workload requirements.

[9]See: https://usaspending.gov. The data covers all federal contracting offices' transactions over $3000. They have been used extensively in previous research, including studies by Liebman and Mahoney (2017), Warren (2014), Kang and Miller (2017), Giuffrida and Rovigatti (2018), Decarolis et al. (2021).

[10]The R&D code specified in each contract comes from the variable "Product or Service Code" and is composed of two alphabetic and two numeric digits. The first digit is always the letter "A" to identify R&D; the second digit is alphabetic "A to Z" to identify the major R&D category; the third digit is numeric 1 to 9 to identify a subdivision of the major R&D category, and the fourth digit will be 1 to 7, to identify the appropriate stage of R&D with: (1) Basic Research; (2) Applied Research and Exploratory Development; (3) Advanced Development; (4) Engineering Development; (5) Operational Systems Development; (6) Management and Support; (7) Commercialization. The term "research and development" normally encompasses the first six categories. For example, the construction of recreational facilities at an installation used exclusively or generally for research and development would not normally be classified as procurement of "research and development" but is sometimes included in the sixth category to classify obligations according to the ultimate purpose of the procurement. Commercialization transactions are excluded from the analysis. R&D categories included in the sample are: Community Service/Development; Defense System; Defense Other; Economic Growth; Energy; Environmental Protection; General Science/Technology; Medical; Space; Other R&D. These categories are the only ones associated with at least one contract producing at least one patent in our data. In the Supporting Information Appendix, we show the robustness of our baseline estimates to this sample selection.

[11]The $14,000 threshold is the lowest contract value associated with a contract producing a patent in our sample. In the Supporting Information Appendix, we show the robustness of the baseline estimates to choosing different thresholds. Regarding the exclusion of SBIR contracts, these contracts are specifically intended to help certain small businesses conduct R&D activities aimed at their subsequent commercialization (Bhattacharya, 2018; Howell, 2017).

[12]We indicate as *bureaus* the sub-units of the US federal government agencies. All federal agencies, whether executive (i.e., analogous to ministers common in parliamentary or semi-presidential systems)—such as DoD—or independent—such as NASA—will be indicated as *agencies* throughout this study. Each agency has its own organizational structure according to which its power is exercised through different sub-units, the bureaus. Bureaus are charged with a specific mission depending on the agencies they are affiliated to. Bureaus undertake different tasks, including procurement, and are located in different US States.

[13]See Bajari and Tadelis (2001) for an extensive study of the trade-off between time and cost to completion induced by the contract pricing format.

[14]Having data until 2015 and considering 3 years at least on average for the patentability process to end, we exclude contracts awarded from 2013 onward. This fact is confirmed by the negligible share of contracts associated to at least one patent in the 2013–2015 time span.

[15]Among the 1750 R&D contracts in the data, the number of patents is 221. Table 3 reports the number of patents per category of federal R&D.

[16]Although the award of a follow-on contract could provide useful information on the success of an R&D contract, the data does not allow us to directly link follow-on contracts to the original contract. Moreover, follow-on contracts are often assigned by different bureaus relative to the one assigning the original contract, thus making any attempt to indirectly link contracts to their follow-on contracts prone to severe measurement errors.

[17]The US Senate passed the first Secrecy Act at the break of World War I and reissued it during World War II (Gross, 2019; Lee, 1997).

[18]If the application meets the patentability criteria, the patent office issues a *Notice of allowability* but does not issue the patent. The application disappears from public databases. A secrecy order lasts for a period of one year, but the government agency that initially requested it can have it renewed indefinitely (USPTO, 2019, at 100-10).

[19]Data available at https://fas.org/sgp/othergov/invention/stats.html.

[20]We set this value such that the estimates of the linear model and the Poisson pseudo-likelihood were the closest as possible. See Supporting Information Appendix C for a thorough discussion of the robustness of our results to alternative approaches.

[21]This is possible through an external dictionary which maps the variable "Contracting Office Agency ID" in FPDS to the variable *AGYSUB* of FedScope.

[22]In the FedScope data, the median salary and age across all federal bureaus is 50,000–59,999$ and 45–49 years, respectively. Hence, our *relevant (white-collar) workers* are those with a salary greater or equal to 50,000$ and an age below 50 years old. The median salary and age in the analysis sample differ due to the fact that only a subset of bureaus is part of it (see Table 2).

[23]Moreover, civil servants that suffer from chronic health problems, are likely to be on sick leave and excluded from the data set.

[24]For the two groups defined by our selection criteria (i.e., relevant employees and other white collar workers), a one-sided t test of the difference in means of the years of schooling between these two groups (15.60 years and 14.78 years, respectively) strongly rejects equality and confirms at least 1 year of difference.

[25]See Decarolis et al. (2021) for more details.

[26]Privately funded here means that these inventions were achieved without the support of the US federal government neither through procurement contracts, nor grants. Federally funded patents were excluded using the 3PFL database. More precisely, for every patent application we recover the patent identifier, the year of application at the USPTO, and the international patent classification (IPC) classes to which the patent application was assigned. We then produce a correspondence table that maps the PSC code assigned to a federal procurement contract into the relevant IPC classes. The IPC is a hierarchical system for the classification of patent applications according to the different technological fields to which they belong. For the task at hand we work at the class level and thus consider 129 different technological fields. For additional information on the IPC see http://www.wipo.int/classifications/ipc/en/.

[27]For instance, a specific company might be on average more likely to rely on trade secrets to protect its inventions and hence more likely to forego patent protection even when a patent application can be filed.

[28]Regarding the 6 months time window, various robustness checks are presented below. Our choice is motivated by the managerial literature according to which it takes a period between 3 months and a year for newly hired employees to gain full efficiency, so-called "onboarding effect," see Klein and Polin (2012).

[29]FedScope snapshots are taken in September, while FEVS ones in June. To account for any variation in the employment stock owing to the death occurrences before September of the same year, for contracts signed up to September, we substitute the employment stock with its lag that is unaffected by those changes. Death occurrences after June are not affecting the outcome measures, based on FEVS variables, of the current year. Outcome measures based on FEVS variables are adjusted taking their leads.

[30]Note that our sample includes only contracts awarded in States where the awarding bureau has at least one employee. This restriction ensures that we can pinpoint the bureaus' locations, local offices, and the contracts that they are likely to supervise. In the Supporting Information Appendix, Figure A.1 reports in detail the location of each bureau by indicating with an "X" the State in which they employ at least one white-collar worker. Furthermore, in Supporting Information Appendix Table A.9 we report the variation in relevant employees death events over time and bureau-state. This descriptive evidence indicates that deaths are not clustering in a few selected observations but rather scattered across multiple years and bureau-states.

[31]For causal comparisons, we adopt the potential outcome framework (Rubin, 1974). The way in which *Relevant Deaths* are built allows us to rely on the standard Stable Unit Treatment Value Assumption (Rubin, 1980), stating that the potential outcomes for each unit are unaffected by the treatment assignments of other units and each unit has potential outcomes $\{Y_i(z), z = 0, 1\}$ corresponding to the possible treatment levels, of which only one is observed: $Y_i = Z_i Y_i(1) + (1 - Z_i) Y_i(0)$. Under the unconfoundedness assumption, that is, $Y(0), Y(1) \perp Z \mid X$, we have $Pr(Y(z)|X) = Pr(Y|X, Z = z)$ for z: 0, 1, so $\tau(x)$ is the average treatment effect (ATE) conditional on x: $\tau(x) = E[Y(1) - Y(0)|X = x]$. Estimation of either comparison requires the probabilistic assignment assumption, $0 < e(X) < 1$, which states that the study population is restricted to values of covariates for which there can be both control and treated units.

[32]Specifically, we generate dummies for the quantiles of the distribution of the three variables: two quantiles for Median Age, ten for Employment and five for Median Salary. The 100 variables obtained by the interactions of these three sets of dummy variables are the regressors in the Probit model. This model specification for the computation of the propensity score is in the spirit of Dehejia and Wahba (2002). In particular, the balance is checked within each stratum by applying a t test for the equality of means. The binary covariates are not balanced for some strata (i.e., the t test is statistically significant). Hence, we divide the sample into finer strata to search for balancedness, and we specify a model with all possible interactions. This approach satisfies the balancing property mechanically (i.e., tests for mean differences in covariates between control and comparison units are statistically insignificant) at the cost of sample reduction (i.e., the logistic regression rules out combinations with no relevant death dummy variability). We also rely on common support: we force estimation of either comparison to require the probabilistic assignment assumption, $e(z)$, which states that the contract population is restricted to values of covariates for which there can be both control and treated units.

[33]Warren (2014) shows that unexpected workload changes shift various contractual/procurement terms: less competition, more cost-plus, more renegotiation, and higher prices. As these characteristics are affected by managerial workload, they are probably also affected by managerial deaths, and they are, therefore, possibly not appropriate control variables. In the Supporting Information Appendix, we explore this concern by excluding these variables from the sample specification. The findings are qualitatively the same of those in the baseline estimates presented next.

[34]In the regressions, this share is scaled up by two orders of magnitudes to interpret the unit change as 1 percentage point.

[35]There is a large debate on programs like the US SBIR that promote innovation among SMEs through public procurement, and similar initiatives have been undertaken in Europe. See Bhattacharya (2018) for an empirical study.

[36]Supporting Information Appendix C reports most of the robustness checks. For convenience, these results are subdivided in six groups depending on whether the robustness analysis involves: (1) measurement of the dependent variable; (2) measurement of the main independent variable; (3) the set of regression controls; (4) the estimation approach; (5) methods to conduct inference; and (6) sample

selection criteria. The latter set of robustness checks is also explored in Supporting Information Appendix A where we focus on the set of filters implemented to select the sample.

[37]Additional results in the Supporting Information Appendix (Table C.7) expand this analysis to a different method for splitting the sample. The results are qualitatively similar to those presented in the text in Table 6.

[38]We further expand this analysis in additional results reported in the Supporting Information Appendix. Supporting Information Appendix Table C.12 reports the baseline regressions estimated using firm fixed effects in all specifications and reporting heteroscedastic robust standard errors.

[39]This interpretation is also in line with Warren (2014) and Limodio (2021) who stress the importance of task-specific knowledge.

[40]The larger magnitude might be either an indication of the usefulness of controlling for these bureau characteristics or, on the contrary, a bias introduced by including potentially endogenous variables. Although the presence of bureau fixed effects makes the latter case unlikely, we prefer to consider the more conservative estimates in Table 5 as our main estimates.

[41]They report a recent study by the *Union des groupements d'achats publics* (UGAP, French Public Procurement Grouping Union) revealing that 63% of French public buyers do not have a legal profile and 61% of public buyers have no prior experience in the field. Only 39% of public buyers undertook some form of course or training resulting in qualification in the field of purchasing.

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