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# PUBLIC CONTRACTING FOR PRIVATE INNOVATION: GOVERNMENT EXPERTISE, DECISION RIGHTS, AND PERFORMANCE OUTCOMES

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## ABSTRACT

We examine how the U.S. Federal Government governs R&D contracts with private-sector firms. The government chooses between two contractual forms: grants and cooperative agreements. The latter provides the government substantially greater discretion over, and monitoring of, project progress. Using novel data on R&D contracts and on the geo-location and technical expertise of each government scientist over a 12-year period, we test implications from the organizational economics and contracting literatures. We find that cooperative agreements are more likely to be used for early-stage projects and those for which local government scientific personnel have relevant technical expertise; in turn, cooperative agreements yield greater innovative output as measured by patents, controlling for endogeneity of contract form. The results are consistent with multi-task agency and transaction-cost approaches that emphasize decision rights and monitoring.

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## INTRODUCTION

There is a vast literature documenting the solutions to contractual opportunism in agreements between private firms. In principle, public-private contracting should be amenable to many of the same solutions. However, in practice, contracting that involves the public sector is characterized by strong rigidity (Moszoro, Spiller, and Stolorz, 2016), due both to political pressure from third parties (Spiller and Moszoro, 2014) and more general bureaucratic structures (Moe, 1990). Consequently, although many aspects of contract theory can inform public-private contracting, the distinct characteristics of the public sector – which often preclude the use of several creative contracting mechanisms implicated in such theories – suggest a more directed theoretical and empirical approach is warranted to address the peculiarities of contracting in the governmental setting.

This paper examines public-private contracting in the specific setting of public contracting for private innovation. Government entities frequently encourage the development of specific types of innovations that are deemed necessary to achieve public aims. For example, in 2016 the U.S. federal government funded $148 billion in R&D (Hourihan and Parkes, 2015), at least $30 billion of which was devoted to contracts for private innovation regarding specific goals such as preclinical trials for new pharmaceutical drugs, studies of chemical toxicity in water, and the development of systems on the Mars rover missions.[1]

Contracting for innovation faces a central problem: when a client organization pays a research firm to pursue a specific project, there is a risk that the research firm will divert the payment to pursue its own interests. If the research project fails, it is difficult for the client organization to distinguish between research-firm malfeasance and bad luck. This problem is

[1] Similarly, in 2012 the United Kingdom allocated £1.6B (18%) of its £8.7B government R&D budget to private firms (National Audit Office, 2013).

exacerbated as the uncertainty surrounding the project increases. Organizational economists offer several prescriptions to overcome this problem. However, virtually all of the proposed solutions depend on substantial flexibility in contract design: judicious allocation of property rights (Aghion and Tirole, 1994), menus of fixed fees and royalty payments (Hegde, 2014), appropriate investments in equity (Oxley, 1997), or sophisticated contractual provisions to deal with a range of contingencies that might arise (Reuer and Ariño, 2007). These solutions, however, are often precluded by the rigidities of public-sector contracting, such as the need for standardized contracts, the desire to prevent officeholders from self-dealing, the requirement for procedural adherence and transparency by agencies and civil servants, the presence of public sector unions, and the attempt to insulate the bureaucracy from the political pressures of third parties (Moszoro *et al.*, 2016). Given these constraints, how can public-private contracts for innovation overcome contractual hazards in order to create value?

We invoke and extend a solution that stems from recent analyses of privatization: government retention of specific decision rights even while the private actor retains residual control rights. Specifically, Hart *et al.*'s (1997) influential model of privatization predicts that privatized services, for which the private provider owns residual control rights including decision rights, will have lower costs but also lower quality than publicly-provided services. Yet Williamson (1999) proposes that overlapping decision-making authority between the private entity and public bureau may ameliorate quality degradation. Empirically, Cabral *et al*. (2010, 2013) find that privatized prisons in Brazil exhibit quality equivalent to that of publicly run counterparts, attributing this to the presence at each private prison of a government supervisor, or 'warden,' whose job is to review and occasionally overrule decisions about those aspects of operations that could adversely affect quality. This preserves quality as long as the government warden is motivated to make good decisions.

We extend this logic to make three predictions about public contracting for private innovation. As contracting hazards increase due to project uncertainty, the government agency is more likely to include an information exchange and decision-rights mechanism in the contract. However, this mechanism will only be implemented if the government agency has employees with the requisite subject-matter expertise to make effective and appropriate project decisions. Finally, conditional on project uncertainty and government expertise, cooperative agreements will be more successful at generating patented innovations (which are the explicit goal of such projects) because of more effective monitoring of private-sector R&D efforts by the government.

We test these predictions using a sample of more than 4,000 R&D contracts between U.S. federal agencies and private firms. Similar to many countries, U.S. law generally restricts these contracts to take one of two forms: a 'grant,' which affords the government no in-process decision rights, and a 'cooperative agreement,' in which government employees have substantial in-process decision rights. Using novel data on the technical expertise of government agency personnel located in geographic proximity to the private firm's R&D site, we find support for our theoretical predictions. Notably, 1) earlier-stage projects (which are likely to entail greater uncertainty) are more likely to be governed by cooperative agreements than by grants, 2) agencies rely on cooperative agreements more readily when they have relevant technical capabilities near the R&D site, 3) cooperative agreements perform better than grants in terms of patents generated and the citations to these patents, and 4) although cooperative agreements perform better than grants overall, those projects that were governed by grants would not have been as productive as current cooperative agreements had they been organized as cooperative agreements. We then consider a number of alternative theoretical explanations, econometric specifications, and data measurements, and find the results are robust to these approaches.

This study makes three contributions to the theoretical literature. First, whereas most analyses of privatized services have focused on the in-house vs. privatization decision, we extend the logic to consider variations in privatized governance based on different characteristics of projects. Second, whereas recent literature on hybrid governance highlights the condition that the government monitor must be *willing* to monitor effectively, we propose that, for projects that rely on highly idiosyncratic knowledge, the monitor must be both willing *and able* – i.e., must have the requisite skills to monitor and make good decisions. Third, this focus on requisite skills extends the literature on government capabilities: whereas prior research on value creation in public-private collaboration has tended to emphasize a government entity's capabilities in contracting (e.g., Klein *et al.*, 2013), we extend this to consider how a government entity's technological capabilities and expertise influence the organization of privatized services.[2] Through these contributions, we further flesh out the implications of Moszoro *et al.*'s (2016) insights about rigidity in public-private contracting.

The paper also makes an empirical contribution. We develop measures of government innovative capabilities, based upon the specific technical expertise of government scientists, engineers, doctors, and researchers as measured by 9.5 million person-year observations of government personnel data. We then geo-locate those capabilities throughout the United States, essentially creating a map of government capabilities along 59 expertise dimensions. To the best of our knowledge, this is the first time that government capabilities have been measured in such a microanalytic way.

The paper proceeds as follows. In section 2, we analyze the public-sector challenge of

[2] Relatedly, Decarolis *et al.* (2018) examine public-private procurement contracting but focus on the competencies of private firms rather than the public sector.

contracting effectively for R&D, ultimately generating predictions regarding the use of government decision rights in contracts for innovation. Section 3 provides institutional detail on the U.S. empirical setting. Section 4 introduces our data, model, and empirical strategy. Section 5 presents empirical results, and section 6 offers a brief discussion and conclusion.

## CONTRACTING FOR RESEARCH – THE PRIVATE-PRIVATE VS. PUBLIC-PRIVATE CONTEXT

### *The private-private context*

The market for technology suffers from several well-documented defects (Arora and Gambardella, 2010). The R&D process is commonly characterized by several features that create contractual hazards, including uncertainty, noncontractible effort, tacit knowledge, and appropriability concerns. Organizational economics theories generally agree that contracting difficulties rise monotonically with these characteristics. Given such difficulties, scholars have devoted substantial attention to explicating contractual mechanisms that private entities can use to efficiently govern R&D transactions.

Consider an example in which a pharmaceutical firm seeks to contract with a biotechnology firm for R&D into a new drug. The client firm pays the research firm to conduct a set of specified research tasks. But it is nearly impossible for the client firm to observe the effort that the research firm's employees actually devote to the tasks. R&D is an uncertain endeavor, so if the research firm does not generate the desired innovation, it is difficult to tell whether this was the result of insufficient effort or bad luck. Even when the innovation is developed, if transfer to the client firm requires the provision of attendant tacit knowledge, then it is difficult to monitor whether the researchers are making a good-faith effort to provide this knowledge (Hegde, 2014), especially if either firm has latent concerns that proprietary knowledge outside the scope of the contract will 'leak' to the other party during the course of the endeavor (Oxley and Wada, 2009).

Given these challenges, how might the firms successfully govern their exchange? One prescription is to judiciously assign property rights so as to elicit noncontractible effort as effectively as is feasible (Aghion and Tirole, 1994; Grossman and Hart, 1986). Lerner and Merges (1998) test this empirically by exploring the pattern of property-rights assignment in R&D contracts between pharmaceutical companies and biotechnology firms. They find modest evidence that these contracts do indeed assign more property rights to the biotech firm when projects are earlier-stage (and hence are more uncertain and require more non-contractible effort from the biotech firm). Lerner and Malmendier (2010) consider termination options that distribute rights to R&D results when projects characterized by unobservable effort also generate observable milestones, finding that such termination options also appear more frequently in contracts for earlier-stage projects than in contracts for later-stage projects.[3]

An alternative prescription is to implement a combination of fixed fees and royalty payments to align the firms' incentives. Since royalties depend on successful commercialization of an innovation, they can provide a strong incentive to the research firm to both conduct the requisite R&D and devote effort to transferring the results to the client firm (Xiao and Xu, 2012). Although reliance on royalties shifts risk to the research firm, which in many models is more risk-averse than the client firm, the benefits of incentive alignment outweigh the attendant costs for sufficiently high levels of uncertainty and noncontractible effort. In a study of biomedical invention, Hegde (2014) finds systematic patterns of complex royalty payments between

[3] A unilateral termination option for the client firm encourages the research firm to devote appropriate effort to the project, while a termination fee set at an appropriate level discourages the client firm from strategically terminating the project. This option can align incentives between client firm and research firm.

commercializing firms and inventors that are consistent with theoretical predictions.

A third prescription is to judiciously use equity investments to align incentives, direct effort, and protect knowledge (Pisano, 1990; Teece, 1986). While non-equity arrangements such as licensing contracts will suffice for high-appropriability or low-tacit-knowledge research in the presence of low uncertainty, equity joint ventures will be used to govern research agreements with higher levels of contractual hazards (Oxley and Wada, 2009). Shared ownership of the collaborative venture implies shared ownership of the attendant profits, thus aligning the firms' incentives regarding success of the venture. Equity arrangements also provide formal monitoring and, in particular, decision-making authority over the research effort (Reuer, Ariño, and Mellewigt, 2006). These predictions have been borne out in specific industry settings (Sampson, 2004a) and multi-industry studies (Oxley, 1997). Going beyond the governance-choice decision, Sampson (2004b) also finds that R&D alliances that are organized according to transaction-cost precepts generate more patented innovations than those that are organized inappropriately.

Finally, complex contractual provisions may be employed to coordinate and control effort in the face of uncertainty. Contractual features such as contingency payments can elicit effort and align incentives in contractual relationships, while provisions that specify responses to potential contingencies can restrict opportunistic behavior (Argyres, Bercovitz, and Mayer, 2007; Reuer and Ariño, 2007). Contractual clauses that thus effectively address hazards can dramatically increase contractual effectiveness (Anderson and Dekker, 2005) and facilitate resolution of disagreements (Lumineau and Malhotra, 2011). Alternatively, judicious assignment of decision rights and monitoring provisions can dramatically influence the effectiveness of incentives and the performance of the project (Arruñada, Garicano, and Vázquez, 2001; Athey and Roberts, 2001; Reuer and Devarakonda, 2016).

In general, then, contracting between private firms is frequently facilitated by a range of governance mechanisms including judicious allocation of property rights, complex royalty schemes, equity holdings, and/or sophisticated contingent contracts with attendant decision rights. These mechanisms support a substantial market for technology both within and across nations (Arora and Gambardella, 2010).

*The public-private context*

At first glance, one might expect that the above prescriptions are straightforwardly applicable to public-private contracting. However, in many countries, strict rules and processes constrain the form of public contracts for innovation. In the U.S., as in several other OECD countries, government entities are prohibited from owning property rights in the resulting innovations, paying royalties to the contracted firms, or taking equity in these firms. Strict contracting policies also hinder attempts to craft project-specific contractual provisions.[4] Thus, the most common levers available to private-private contracts for research are unavailable in public-private research contracts. These constraints reflect the stylized fact that public-sector contracts tend to be far more rigid than their private-sector counterparts (Moszoro *et al.*, 2016). This enduring feature of public bureaucracy (Boyne, 2002) is often attributed to a desire to restrict public agents' ability to engage in self-dealing (Lan and Rainey, 1992); or, alternatively, to concerns about political pressure from third parties (Spiller and Moszoro, 2014). This then leads to processes in government which are procedurally onerous and substantively transparent, often leading to inefficiency in the government by design (Moe, 1989). Because of these substantial procedural requirements and limited resources for government contracting, the government tends

[4] For example, similar to the U.S., Canada's federal contracts for R&D take the form of either grants or 'contributions,' which are largely analogous to U.S. cooperative agreements.

to favor standardized, rather than customized, contracts for many purposes, limiting the ability of the government to employ specialized terms (Miller, 1955).

This rigidity is manifest in Hart *et al.*'s (1997) incomplete-contract model of privatization. In this model, a government actor chooses between delivering a service through in-house provision or through a contract with a private provider. The service requires investment in an asset and then operation using that asset. Of particular relevance, property rights over the asset cannot be divided, but rest entirely with either the government or the firm, and payment to the firm is limited to a fixed fee that can be renegotiated upward if the quality of the service is increased. Given these blunt levers, the private firm has a strong incentive to lower the cost of provision, even at the expense of quality, while an in-house provider has little incentive to improve either cost or quality.[5] Consequently, the authors predict that privatized services will have lower costs but also lower quality than their publicly-provided counterparts. Levin and Tadelis (2010) find that municipalities are less likely to outsource services for which quality is important yet noncontractible, concluding that this is consistent with the Hart *et al*. (1997) model. This provides a pessimistic assessment of the feasibility of public-private contracting for innovation, given its reliance on noncontractible effort.

Yet Cabral *et al*. (2010, 2013) find that privatized prisons in two Brazilian states exhibit quality that is equal to or better than that of their publicly run counterparts, even while enjoying lower costs. They propose that the key quality-protection mechanism is the appointment to each private prison of a government 'warden' whose job is to monitor prison operation and ensure that it adheres to specified minimum quality standards. As long as the warden remains committed to

[5] The private firm reaps the entire benefit from cost reduction, but only incurs a fraction of the benefit to quality improvement because it must bargain with the government ex post for fee increases associated with improved quality. The private firm thus 'overinvests' in cost reduction, yielding a socially suboptimal level of quality.

her task – i.e., she is not bribed by the private firm – then this 'hybrid' form of private operation and public supervision appears to solve the problem of quality deterioration.[6]

To the extent that public contracting for innovation is characterized by the constraints embodied in the Hart *et al*. (1997) model, perhaps the sole available lever is the prospect of government supervision of the research project, analogous to the government prison warden. Yet one difference stands out in the innovation setting. Cabral *et al*. (2010, 2013) implicitly assume that the government warden understands the causal mechanisms linking cost-reduction and quality shading – in essence, she knows which actions by the private agent are good and which are bad. However, evidence indicates that an organization's possession of relevant technological capability helps it appraise the value of external research (Cassiman and Veugelers, 2006): '[t]he ability to evaluate…outside knowledge is largely a function of the level of prior related knowledge' (Cohen and Levinthal, 1990: 128).

Indeed, precisely for this reason, an organization's technological capability in a particular sphere can influence its competence at contracting in that sphere. Mayer and Salomon (2006) study an IT firm's decisions to complete client projects with in-house or outsourced teams, finding evidence that strong technological capability in, for example, mainframe technology allows the firm to outsource on mainframe-related projects in the face of contractual hazards. They conclude that the firm is better able to manage an external contract when it has technological capabilities that enable it to anticipate problems and monitor outcomes. Building on this idea, Argyres and Mayer (2007) propose that the technological (i.e., engineering)

[6] Although the Brazilian prison setting only allows comparison of public to private-hybrid prisons, it should be the case that a purely private prison would have lower costs than the private-hybrid prison. Some of this would be due to quality-shading efforts that are socially destructive. But some should be due to lower effort to invest in cost-reduction by the private-hybrid, given that the warden may sometimes erroneously negate a valid cost-reduction scheme.

expertise of a firm's employees is particularly relevant to establishing effective interfirm communication flows in research contracts. Thus, in the context of public contracting for innovation, the government supervisor must have the requisite technological expertise to know which actions are good and bad – in other words, if the supervisor is willing but not able to make good decisions, then public supervision is a hindrance.

In sum, extending the predictions concerning decision rights and monitoring above, we expect to find two patterns in contract choice: research projects that are more uncertain in outcome are more likely to be governed by contracts that afford greater public supervision (i.e., cooperative agreements), as are research projects for which the available public personnel have relevant expertise. We further expect research projects governed according to the above precepts will outperform those that are not in terms of innovative output.

## GOVERNMENT CONTRACTING FOR RESEARCH: INSTITUTIONAL DETAILS

The U.S. federal government is composed of 381 agencies, which in turn are composed of 874 bureaus. Although formally overseen by the Executive Branch of the government, agencies pursue their own research and development agendas, each determined by a variety of different considerations. To meet their required objectives, bureaus often determine that specific research endeavors would require expertise beyond that available within the Federal government.[7] In such cases, the bureau contracts with outside entities for the requisite research effort.

The process begins when a bureau's program office issues a call for research proposals, or CFP (see 'Appendix A: The Grant-Making Process' for a detailed description of the CFP process). The CFP outlines the motivation for the research project, the statutory authority for the

[7] McKenna (2006: 103-105) describes the government's strategic decision, at the beginning of the U.S. space program, to rely on external expertise rather than try to employ all necessary experts within NASA.

agency to conduct the research, a list of requirements, milestones, expectations, and objectives of the project, a list of eligibility requirements for the private contractor, and a description of how the project will be managed. The CFP may specify that the research will be conducted through a grant, a cooperative agreement, or either. As Appendix A describes, the CFP process is virtually identical across the two types of contracts. In both cases, all property rights resulting from the contracted research are owned by the contracted entity while the U.S. government receives a royalty-free license. This precludes the judicious allocation of property rights and the use of royalty schemes to elicit effort.[8] However, for the purposes of this study, there are three key differences between the governance forms.

The first difference is the degree of cooperative effort between the government agency and private firm. As stipulated in the Federal Grant and Cooperative Agreement Act of 1977 (FGCAA) and the Code for Federal Regulation (CFR), grants do not provide for 'substantial involvement' between government employees and the firm, whereas cooperative agreements do.[9] This is reinforced by each agency's own guidance documents. For example, Section 3 of the NASA Grant and Cooperative Agreement Manual (2016: 3) notes that unlike a grant, a cooperative agreement should be used if 'substantial involvement is expected between the executive agency and the…other recipient when carrying out the activity contemplated in the agreement.'[10]

The second difference relates to the disparate pattern of decision rights assigned to

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[8] Some Federal procurement agreements also involve R&D effort by the private vendor. In these agreements, called 'contracts,' the Federal government funds the vendor's R&D as 'work for hire' and receives ownership of any resulting patents. We exclude these from this study for two reasons: they are not designed to support significant R&D; and their different (although still rigid) allocation of property rights would conflate the incentives affecting contract performance.

[9] See 'Implementation of the Federal Grants and Cooperative Agreements Act of 1977, Office of Management Budget, August 18, 1978, *Federal Register* 43(161): 36860-36865. 'Substantial involvement' does not have a formal regulatory definition, but it is described variously as entailing direction and redirection of the technical aspects of the project as a whole; sharing responsibility with the firm for the management, control, direction, and performance of the project.

[10] *NASA Grant and Cooperative Agreement Manual*, Revised September 16, 2016.

private firm and government. Grants typically allow the recipient firm's principal investigator to make virtually all key decisions during the research project, subject to compliance with Federal regulations. In cooperative agreements, decision rights are more evenly distributed between government and firm personnel. Daily decisions are often jointly determined by both parties. For example, in a cooperative agreement between the National Cancer Institute (NCI) and GlobeImmune, Inc. to develop yeast-based tarmogens for cancer immuno-therapy, the NCI and GlobeImmune each had its own Principal Investigator. This role, as specified in the agreement, was to be 'person(s) designated by the Parties who will be responsible for the scientific conduct of the Research Plan.'[11]

Cooperative agreements also often provide the government with the right to terminate a project before its official completion should the government's principal decision-maker on the project determine that its progress is not satisfactory. Indeed, the Department of Energy's Model Cooperative Agreement in Energy Efficiency and Renewable Energy contains not only regular review meetings for the government, but also contains a section that grants the government 'Go/No Go Decisions' and decision-making authority at key milestones in the project.[12] In contrast, although the government can in principle decide to withhold subsequent funding payments from an in-process grant, this tactic is cumbersome to implement and rarely employed.

The third substantive difference between grants and cooperative agreements stems from the decision-rights difference, and relates to the degree of information that passes between the private firm and the government. Although a grant is awarded to a recipient firm through a

[11] 'Preclinical and Clinical Development of GlobeImmune, Inc's Proprietary Yeast-Based Tarmogens Expressing Tumor-Associated Antigens for Cancer Immunotherapy,' between the National Cancer Institute, NIH, and GlobeImmune, Inc., signed 05/08/2008.

[12] 'Model Cooperative Agreement,' Contractual Term 7D. U.S. Department of Energy, Energy Efficiency and Renewable Energy Program, 02/19/2013.

rigorous review process, during the project the recipient is only required to provide the agency with periodic (often annual) reports of progress made on the grant's objectives. After the project is completed, the recipient has a finite amount of time (usually 90 days) to file a final report of accomplishments.

In cooperative agreements, the private firm is expected to provide information to the government on a much more frequent basis. Given that decisions regarding project tasks are sometimes made as frequently as daily, information must flow almost continuously to support informed government decision-making. In those cases where government and private firm scientists work closely together, this can occur informally through the collaborative effort. In cases where this collaboration does not occur consistently, agreements stipulate formal obligations to provide for communication. Thus, in contrast to research grants where researchers provide information to the government at specified, infrequent intervals, cooperative agreements stipulate more rapid communication and flow of information.

For example, a cooperative agreement between the Department of Energy and Mascoma Corporation, for a project to demonstrate feasibility of biorefining technology using plant biomass, specified that 'in order to adequately monitor project progress and provide technical direction to the Recipient, DOE must [attend Mascoma Corporation] meetings, reviews and tests.' Presumably to protect against malfeasance, the cooperative agreement further noted, '[Mascoma Corporation] shall notify the DOE Project Officer of meetings, reviews, and tests in sufficient time to permit DOE participation and provide all appropriate documentation for DOE review.'[13]

Overall, then, research grants and cooperative agreements represent discrete structural

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[13] 'Demonstration of Biorefinery Application,' between the Mascoma Corporation and the Department of Energy, signed 09/30/2008.

alternatives for R&D contracting between the U.S. Federal government and private firms. Grants largely reflect canonical arms-length contracting, with little interaction during the research project except for intermittent progress reports and with the research firm retaining almost complete discretion over its allocation of effort. Cooperative agreements reflect contracting of the type prescribed above to effectively manage contractual hazards, with the government holding substantial monitoring authority and discretion over effort allocation and with the requisite information flow and interaction between the parties.

## DATA, MEASURES, AND EMPIRICAL STRATEGY

### *Data sources*

To empirically test the predictions in this study, we employ data on the characteristics of U.S. Federal Government research grants and cooperative agreements, characteristics of the government bureau soliciting the project (notably the degree of relevant expertise in the local bureau offices), characteristics of the firm performing the project, and measures of innovative outcomes. We obtain this data from three sources.

The first dataset contains information on the characteristics of agreements from USASpending.gov. We downloaded all government grants and cooperative agreements (termed 'assistance' in the USASpending.gov nomenclature) executed between fiscal years 2000 and 2011. Each record contains information on the governance mechanism (grant or cooperative agreement), the firm that received the funding, the principal location in which the organization would perform the research (e.g., Cincinnati, Ohio), the agency or bureau of the government that made the award (e.g., National Institute of Standards and Technology), the title and short description of the project, and other details.[14] Of particular relevance, project descriptions list a set of activities necessary for the research project. We use records for only those organizations categorized as businesses in the government agreement records.[15] We also remove cases where the funding agency was part of the Department of Defense or military due to data limitations.

We employ a second dataset of granted U.S. patents, provided by PatentsView.org, to measure patent generation. We download all U.S. patents with a 'government interest' indicated in the patent application. Per U.S. regulations, patents that have any affiliation with a government unit – including any funding from that unit – must include a government-interest statement that acknowledges this affiliation. Government-interest statements refer to affiliated grants and cooperative agreements by their unique 'funding identification numbers.' We then conduct an exact match against the data in the USASpending database using the funding identification numbers included in patent applications, thus identifying all patents that stipulated an affiliation with any of the contracts in the sample. We ultimately identified 1,544 patents. Of the 4,074 contracts in our sample, 508 (12.47%) led to at least one patent; 56 of these agreements supported five patents or more. Separately, to create control variables as discussed below, we use the PatentsView data to construct counts of aggregate patenting per year by each of the 383 private firms involved in any of the sample contracts.

To identify the level of relevant expertise available in specific government bureau offices, we rely on a third and relatively novel database from the U.S. Office of Personnel Management's (OPM) Central Personnel Data Files (CPDF). These records contain annual,

[14] A codebook for the federal assistance dataset is available at https://goo.gl/TW7QHY (last accessed February 17, 2017). To fill in some missing project descriptions, we searched the Federal Procurement Data System (FPDS) and National Institutes of Health RePORTER system for federal award IDs matched to government-supported patents.
[15] To avoid any university affiliates misclassified as businesses, we also exclude records where the word 'university' appears in the organization name.

individual-level information on nearly all U.S. civil servants during the sample period (using anonymous identifier codes), including information on work location, job title and occupation, and research-related job functions.[16] The CPDF allows us to measure the precise number of government employees in each office of each Federal bureau who perform specific jobs. The CPDF categorizes over 800 occupations into 59 occupational groups/families, as detailed in OPM's *Handbook of Occupational Groups and Families*.[17] For example, the 'Medical, Hospital, Dental, and Pubic Health Group' includes physician assistants, nurses, nurse assistants, and doctors of dentistry, medicine, and osteopathy, among other related job titles. From these data, we compute the number of personnel in each of the 59 occupational categories at every known Federal work location in the US, geocoding each employee's latitude and longitude. This occupation-location data is further disaggregated to the bureau level (e.g., the NIH is a bureau of the Department of Health and Human Services). Thus, we are able to identify how many of the NIH's employees in a particular location are in the Medical, Hospital, Dental, and Public Health Group occupational category.

Further, for each government employee who is involved in research-related activities, broadly defined, the CPDF also includes a 'functional research' category, where the set of categories includes research, development, testing and evaluation, construction, production, installation, data collection, project management, and teaching. These classifications are created by the National Science Foundation for OPM to describe the work that comprises the majority of each research employee's time. The 'research' function, for example, emphasizes early-stage research – 'systematic, critical, intensive investigation directed toward the development of new

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[16]This dataset excludes the military, U.S. Post Office, and 'sensitive' agencies (colloquially known as 'three-letter agencies') and occupations (such as U.S. Marshals). More than 70 percent of U.S. Federal Government employees work outside the greater-DC metro area.
[17] Available at: [https://www.opm.gov/fedclass/GShbkocc.pdf](https://www.opm.gov/fedclass/GShbkocc.pdf) (last accessed February 14, 2017)

or fuller scientific knowledge of the subject studied' – whereas the 'testing and evaluation' function emphasizes later stage 'testing of equipment, materials, devices, components, systems and methodologies under controlled conditions and the systematic evaluation of test data to determine the degree of compliance of the test item with predetermined criteria and requirements.[18] We are thus able to identify how many of the NIH's Medical, Hospital, Dental, and Public Health Group personnel in any location are dedicated to early-stage research, how many dedicated to development, and so on.

With data from these three sources – USASpending, PatentsView, and the CPDF database – we construct our variables.

*Variables*

Our first two predictions relate to the choice of governance for a research contract. The dependent variable for testing these predictions is *Coop Agreement*$_j$, which is a binary indicator set equal to one if contract *j* was a cooperative agreement and zero if a grant. Our third prediction relates to the innovative performance of research contracts. We employ five dependent variables to test this prediction. *Generates Patent*$_j$, is a binary indicator set equal to one if contract *j* generated at least one patent and zero otherwise. *NumPatents*$_j$ is a count of patents generated by contract *j*. *Citation-Weighted Patents*$_j$, is the sum of the patents generated by contract *j* and the subsequent citations to those patents. *Citations/Patent*$_j$ is constructed as *Citation-Weighted Patents/NumPatents*. *Citations/Patent/Year*$_j$ is constructed as *Citation-Weighted Patents/NumPatents* divided by the number of years since contract *j* was signed.

Governance. The main independent variables of interest predicting the choice of

[18] Office of Personnel Management (November 14, 2014). The Guide to Data Standards, Update 16, A159-A167.

governance are *Early-Stage Personnel*$_j$, which proxies for high-uncertainty projects, and *Personnel Expertise Ratio*$_j$, which measures the ability of government personnel to provide effective oversight on a project. For ease of explication, we discuss these in reverse order.

*Personnel Expertise Ratio*$_j$ is defined as the proportion of occupational categories required to conduct contract *j* that are available among geographically proximate client bureau personnel. We measure this using a three-step procedure. First, for each of the 59 occupational categories identified in the CPDF handbook, we create a list of distinct terms in the constituent job titles.[19] Next, we search for these terms in contract *j*'s project description. If a term from an occupational category is found in the project description, then contract *j* is coded as requiring the skills of that category. Thus, each contract is characterized as drawing on a subset of the 59 occupational skill sets, with the median contract requiring skills from eight occupational categories, the mean contract requiring skills from 12.8 occupational categories, and the standard deviation across all contracts at 15.8. Finally, for each contract *j*, we calculate the proportion of requisite categories for which the sponsoring government bureau had at least one employee within a 100-mile radius of the principal research location during the year that the contract was signed.[20] For example, if a project description signed in 2005 contained terms that occurred in occupational categories *x*, *y*, and *z*, and the sponsoring government bureau had at least one employee working in each of categories *x* and *y* that year within 100 miles of the research location, then the *Personnel Expertise Ratio* for that contract would be 0.67. We predicted that contracts are more likely to include monitoring/decision-rights provisions when the government

[19] For example, the term list for the 'Medical, Hospital, Dental and Public Health Group' includes terms such as health, scienc*, medic*, physician, autopsy*, dietitian, nutritionist, diagnost*, radiolog*.
[20] We use a 100-mile radius for our core estimations because this roughly corresponds to the maximum distance that one can drive twice in one workday (outbound and return) and still have time for a half-day meeting. We replicate all estimations with alternative radii of 200, 300, 400, and 500 miles.

has personnel who are sufficiently expert to fulfill these duties effectively; consequently, we expect the coefficient on *Personnel Expertise Ratio* to be positive.

As noted above, we expect cooperative agreements will be favored for more uncertain projects. We test this by using the functional research categories in the CPDF data to proxy for the early-stage nature of a contract. Imagine that contract *j*'s project description contains words that occur only in occupational category *x* and contract *k*'s project description contains words that occur only in occupational category *y*. If the government employees in occupational category *x* are clustered in the research function, while employees in occupational category *y* are clustered in the development function, then contract *j* is likely to cover a more early-stage research project than contract *k*.

Given this, *Early-Stage Personnel*$_j$ is defined as the proportion of a bureau's geographically proximate employees in contract *j*'s requisite occupational categories who are assigned to a research function. We measure this in a three-step process. We start with the list of relevant occupational categories for contract *j* and identify client bureau personnel in those categories within 100 miles of the location of work. We then calculate the percent of these relevant employees who are also categorized in the research function. We predicted that contracts are more likely to include monitoring/decision-rights provisions when the project entails early-stage effort; consequently, we expect the coefficient on *Early-Stage Personnel* to be positive.

*Performance*. The main independent variable of interest in the innovative performance of research contracts is the contractual form: *Coop Agreement*, defined above. We predicted that, conditional on government personnel assigning contracts according to project uncertainty and presence of relevant skills, cooperative agreements should outperform grants. Therefore, we expect the coefficient on *Coop Agreement* to be positive.

*Control variables*. We include several additional variables to control for various project, firm, bureau, and time-based characteristics. It is possible that projects with larger budgets or more firm co-funding are more likely to fall under a particular governance form or generate patents. We therefore include *Federal Funding*$_j$, defined as the dollar amount contributed by the government to support contract *j*, as well as *Firm/Total Funding*$_j$, defined as the amount contributed by the firm divided by total funding for contract *j*. Larger or higher-patenting firms might be more likely to generate a patent from the contracted research and/or be differentially likely to operate under a particular contractual form. To address this, we include *Large Firm*$_j$, which equals one if the firm is categorized by the government as a 'large for-profit enterprise' in the research contract document and zero if it is coded as a 'small business enterprise.' We also include *Prior Patents*$_j$, defined as the number of patent applications filed by the focal firm in the year preceding the signing of contract *j*. Given the skew in *Federal Funding*, *Firm/Total Funding*, and *Prior Patents*, we standardize each variable and use the z-scores rather than using the raw values.

A bureau's choice of contractual form, and the performance of its contract, might be affected by the degree to which its local office is managing several concurrent contracts. For a cooperative agreement in particular, this could affect performance if government researchers with relevant expertise are unable to devote as much attention and effort to contract *j*'s research project as would be optimal. We include *Coops Within 100 Miles*$_j$ and *Coops/Personnel Ratio*$_j$, defined respectively as the number of in-process cooperative agreements within a 100-mile radius of contract *j*'s principal research location and the ratio of these agreements to research personnel in the local bureau. Note that the *Coops/Personnel Ratio* variable obliquely proxies for the feasibility of coordination between government researchers and the focal firm; if the government researchers are stretched too thin, then they will not be able to effectively monitor or make decisions regarding contract *j*'s research project. Contracts undertaken in different years might have different forms and outcomes due to temporal pressures on personnel; to address this we include fiscal-year fixed effects. Finally, for roughly 31 percent of contracts, the project description does not yield a link to any occupational categories, which precludes identifying employees with relevant skills. In these instances, we set *Personnel Expertise Ratio* equal to 0. To separate these from the qualitatively different instances in which contract *j* is linked to occupational categories and the bureau has no relevant local personnel, we also include *No Expertise*$_j$, a binary variable set to one if contract *j*'s project description is not linked to any occupational categories and to zero otherwise.[21]

Table 1 provides summary statistics for our sample. As noted above, 12.5 percent of our sample contracts generate at least one patent. Almost one-quarter of the contracts are cooperative agreements. Slightly more than one-quarter of the contracts involve a large firm. The average number of concurrent cooperative agreements managed by the local relevant bureau is nearly six, which equates to nearly 0.5 agreements per local research employee. The average cooperative agreement is five times as likely to generate a patent as the average grant, and is more likely to entail early-stage effort. The average cooperative agreement is also more likely to be performed by a large, high-patenting organization in conjunction with a bureau that has relevant local expertise. Correlation matrices for the sample are provided in Table B1 of Appendix B.

[TABLE 1 ABOUT HERE]

[21] We further address the issue of missing values in the Data section of Appendix B.

*Empirical strategy*

To appropriately estimate the models we employ a two-stage econometric technique that first estimates the probability of selecting into a grant or cooperative agreement governance mode and then estimates the effect of this cooperative agreement 'treatment' on patenting, using information from the selection model to correct for the non-random nature of the treatment model. The first stage provides a test for our governance predictions while the second stage provides a test for our performance predictions.

This estimation approach requires an instrumental variable for contract form in the first-stage selection model. Our instrument is *Personnel Expertise Ratio*. As described above, when there are fewer government research personnel with relevant expertise in the geographic area of a research location, the government bureau is less able to accurately evaluate progress in the research project. Thus, allocating decision rights and monitoring rights to the government will provide little governance benefit and will merely impose bureaucracy costs on the project; therefore, cooperative agreements will be negatively correlated with the number of geographically proximate government personnel with relevant technical expertise. At the same time, the presence of local government research personnel with expertise *per se* is unlikely to be correlated with patenting, to the extent that firm and government scientists are effectively substitutes in production. We address the robustness of this assumption in the Robustness Checks section of Appendix B.

One complication in our setting is that both selection and treatment models have dichotomous dependent variables. Consequently, several conventional two-stage approaches are inappropriate because they are only robust in linear settings (Chesher, 2010; Wooldridge, 2010).

Our preferred method is the inverse probability weighting regression adjustment method (IPWRA) (Angrist, 1998; Angrist and Pischke, 2009). Appendix B provides a more detailed explanation of the IPWRA method, along with an assessment of its strengths and weaknesses. In short, this method is appropriate when a researcher wants to estimate treatment effects from observational data combining regression adjustment with inverse probability weighting. It is also appropriate when the choice of treatment is endogenous (e.g., whether to use a cooperative agreement or grant agreement) and there is a dichotomous variable in the second stage outcome equation (e.g., whether an agreement yields a patent). Finally, it is attractive because it allows both the treatment and control groups to have their own set of second-stage coefficients, recognizing that those in each group may be differentially affected by the covariates.

We believe that the IPWRA approach is the most relevant and most accurate statistical approach for this research question and this data set. Nevertheless, we re-estimate the models using alternative approaches, including the single stage ('naïve') probit, the two-stage least squares linear probability model, the bivariate probit, the instrumental variables probit, and the full-information-maximum-likelihood (FIML) approach with joint normality in the error terms.[22] The results of these robustness checks are reported in Appendix B. Virtually all results using these methods are qualitatively identical to the results discussed in the next section.

## EMPIRICAL RESULTS

The central results of this paper are reported in Table 2. Model 1 presents the first stage IPWRA results that emanate from the governance predictions in the theory. Models 2A and 2B present

[22] All of these estimation approaches are appropriate conditional on the government funding a project. If one instead assumes that the government decides among grant, cooperative agreement, and not funding the project at all, then a multi-level treatment model would be appropriate. However, we cannot observe non-funded CFPs.

the second stage IPWRA results that arise from the contract performance predictions of the theory. The first stage of this model includes all exogenous predictors as well as the instrument, *Personnel Expertise Ratio*, which predicts selection into a cooperative agreement rather than a grant. The second stage incorporates the inverse of the predicted probability of selection from the first stage as a weight in the estimation as well as regression adjustment.

[TABLE 2 ABOUT HERE]

We begin with the first-stage results in Model 1, for which the dependent variable is *Coop Agreement*. Of particular importance, the coefficient on *Personnel Expertise Ratio* is positive, statistically significant ($p = 0.000$), and of substantial magnitude. Research contracts are more likely to be organized as cooperative agreements when the sponsoring bureau has relevant skills in its geographically proximate offices. The marginal effect of a bureau having personnel in all relevant areas for a project leads to an 11 percent increase in the likelihood of a contract being organized as a cooperative agreement rather than as a grant. This is also consistent with the theoretical prediction that public-private contracts will be more likely to entail ongoing public supervision when the public client possesses sufficient technical expertise to effectively exert its supervisory responsibilities.

Consistent with our prediction, the coefficient on *Early-Stage Personnel* in the first stage is positive and significant ($p = 0.000$), indicating that earlier-stage projects are more likely to be governed by cooperative agreements. If all the personnel with expertise in areas relevant to a project's required expertise work in early-stage research positions, an agreement is 16 percent more likely to be organized cooperatively than if none of them does. Early-stage projects, which are typically considered to be more uncertain and hence entail more unobservable effort, are thus associated with high-monitoring, high-client-decision-rights governance.

As for the control variables, contracts involving larger firms are more likely to be organized as cooperative agreements. The amount of federal funding is not associated with governance form, but the proportion of firm funding to total funding is positively associated with cooperative agreements. Finally, projects that do not identify any areas of expertise were roughly 11 percent less likely to be organized as cooperative agreements, suggesting the government may prefer arms-length financial support for narrowly-defined projects.

We now turn to the second-stage results, for which the dependent variable is *Generates Patent*. Model 2A presents the estimated coefficients for contracts that were governed as cooperative agreements, while Model 2B presents these for contracts that were governed as grants. Both second-stage models rely on the results from the first stage. We have converted the coefficient on the treatment variable, *Coop Agreement,* to a marginal effect. Thus, the coefficient on *Coop Agreement* in Model 2A reflects the marginal effect of being a cooperative agreement vs. being governed by a grant, for those contracts that were actually governed by cooperative agreement, while its counterpart in Model 2B reflects the effect of being a cooperative agreement vs. a grant, for those contracts that were actually governed by grant. The coefficient in Model 2A is 0.278, indicating that the average cooperative agreement in our sample was nearly 28 percent more likely to generate a patent than it would have been if it were organized as a grant, holding all other variables at the mean. In contrast, the coefficient in Model 2B is 0.083, indicating that the average grant in our sample would have been eight percent more likely to generate a patent had it been organized as a cooperative agreement. Put differently, consistent with our prediction, cooperative agreements are associated with higher innovative output than are grants, controlling for the other independent variables; this effect is more pronounced for contracts that actually were organized as cooperative agreements than for contracts that actually were organized as grants.

In model 2A, several other variables influence the likelihood that a cooperative agreement generates a patent. Of particular note, *Coops/Personnel Ratio* is negatively related to *Generates Patent;* this is consistent with the notion that as a bureau's scientific personnel gets stretched thinly, they are less able to engage in smooth coordination of effort with firm personnel, thus lowering research productivity. No coefficients on the control variables are significant at conventional thresholds except for Prior Year Patents.

Turning to Model 2B, which focuses on contracts that were organized as grants, the coefficients on *Large Firm* and *Firm/Total Funding* are both positive and significant ($p = 0.033$ and $p = 0.046$, respectively). This indicates that larger organizations are more likely to generate patents and, consistent with incentive theory, firms that have 'skin in the game' are also more likely to generate patents.

Taken together, the above results suggest that the presence or absence of relevant expertise influences the governance of research contracts, such that cooperative agreements are substantially more likely when the sponsoring government bureau has relevant skills in geographically proximate offices. In addition, early-stage projects are more likely to be governed as cooperative agreements. In turn, cooperative agreements are more likely than grants to generate patents. Had the average cooperative agreement been governed as a grant, it would have had a 28 percent lower probability of generating a patent. That said, those projects organized as grants would not have enjoyed a comparable increase in probability of patent generation since they are qualitatively different than the projects organized as cooperative agreements. Had the average grant been governed as a cooperative agreement, it would have had an eight percent higher probability (from a lower initial baseline) of generating a patent.[23]

*Extensions: The magnitude of innovative performance*

The above estimation focuses on a binary measure of innovative performance—whether or not a research contract generates at least one patent. It is possible that other measures of innovative output will indicate different impacts of contract structure. As noted above, we constructed alternative measures of innovative output, notably *Num Patents*, *Citation-Weighted Patents, Citations/Patent,* and *Citations/Patent/Year*. Table 3 presents results for IPWRA estimation of models with these four dependent variables. The Table only shows the second-stage results because the first-stage results are identical to those of the IPWRA estimation in Table 2's Model 1, by definition.

[TABLE 3 ABOUT HERE]

For each measure of innovative output, the coefficient on *Coop Agreement* is uniformly positive and statistically significant ($p$ = 0.000 in all models). In all four cases, this coefficient is substantially higher for contracts that actually were governed by cooperative agreements than for contracts that were governed by grants; the coefficient ranges from roughly five times larger to as much as 15 times larger. (The largest differences occur because cooperative agreements

[23] This raises a question: If the average grant would enjoy a positive (albeit small) increase in probability of patent generation if it were organized as a cooperative agreement, then why isn't it governed by a cooperative agreement? The negative coefficient on *Coops/Personnel* ratio implies that each cooperative agreement imposes a negative externality on other geographically proximate cooperative agreements due to a congestion effect. Hence, for a wide range of values, the modest bump in research productivity from converting a focal grant to cooperative agreement will be offset by the declining productivity of nearby cooperative agreements. See Appendix B for a further discussion of this point.

simultaneously generate more patents and more citations/patent, affecting Models 3–8.) This consistent pattern of coefficient sign and magnitude matches the core results above. Because of the extreme skewness of the dependent variables used in Table 3, we include in Appendix B the coefficients on the second-stage *Coop Agreement* variable for identical models using logged dependent variables (addressed as item seven in the robustness checks below and Table B8 in Appendix B). The results for all eight models retain their sign and significance ($p = 0.000$ in all models).

*Robustness checks*

There are several concerns that may arise from the specification and estimation strategies we employ. They include: 1) sensitivity of results to the IPWRA approach or to the chosen geographic radius for *Personnel Expertise Ratio*; 2) omitted variable bias related to temporal variance, e.g., changes to the Federal budget thanks to the American Recovery and Reinvestment Act of 2009 (ARRA, a.k.a. the Federal 'stimulus package'); 3) unobserved heterogeneity at the bureau level and/or firm level; 4) the empirical appropriateness of the instrumental variable; 5) skewness of patenting and citation rates; 6) the possibility that the performance results reflect more effective coordination between government and private sector scientists when they work on cooperative agreements; and 7) unobserved heterogeneity in project quality assigned to grants and cooperative agreements. We address in detail each of these concerns in appendices to the paper; the first six concerns are addressed in the Robustness Checks section of Appendix B, and the final concern is addressed in Appendix A. To summarize briefly: Across numerous estimation methods and a wide range of geographic radii, the results illustrated in Table 2 remain materially unchanged. Results also remain largely the same when a dummy variable to identify

ARRA contracts is included, when bureau and firm effects are included, and when logged patenting and citations are used as dependent variables. Finally, after controlling for endogeneity in contract choice to the best of our ability, the results remain qualitatively unchanged.

## DISCUSSION AND CONCLUSION

Governments throughout the world spend tens of billions of dollars annually on contractually sourced research. Yet the challenge of public contracting for private innovation, although of substantial importance, is not well understood. In this paper, we shed light on this topic. Conventional prescriptions from the ‘contracting for innovation’ literature do not apply straightforwardly to government contracting because of restrictions that preclude the judicious use of property rights, equity investment, royalty payments, or complex contractual provisions to align parties’ incentives in the face of unobservable effort. Put differently, public contracting for private innovation is an excellent setting in which to examine one particular mechanism to induce effort: allocation of decision rights.

We predict that public retention of decision rights is more likely to be used in the face of high project uncertainty and when the available government personnel have project-relevant technical expertise. We also predict that the use of monitoring and decision rights will positively influence the likelihood that a project results in a patented innovation. We then test these predictions with data on U.S. Federal government contracts for innovation by private firms, which are generally constrained to take one of two forms: grants, in which the government retains virtually no decision rights, and cooperative agreements, in which the government retains ongoing decision rights and attendant monitoring rights.

We find empirical support for the above predictions: cooperative agreements are more likely to be used for early-stage projects than for later-stage projects, and cooperative agreements are more likely to be used when local government personnel have relevant technical expertise. Similarly, after accounting for endogeneity in governance choice due to project uncertainty and personnel expertise, we find cooperative agreements are indeed associated with higher innovative output than are grants. We interpret these results as evidence consistent with the idea that a principal chooses to govern more-uncertain projects, where the problem of noncontractible effort is higher, by retaining more decision rights and enforcing greater monitoring over the project. However, when the principal lacks the relevant know-how to properly evaluate project progress, it is preferable to leave decisions in the hands of the agent.

These results contribute to our understanding of value creation involving public organizations. Specifically, as public actors strive to generate valuable innovations to serve government needs or more broadly enhance social welfare, this study's insights may help these actors overcome the constraints of contractual rigidities. More generally, these results contribute to the literature on public contracting (Moszoro *et al.*, 2016) and to the debate over management of noncontractible quality for a privatized service (Hart *et al.*, 1997; Williamson, 1999), notably for 'hybrid' public management (Ménard, 2004; Rangan, Samii, and Van Wassenhove, 2006). Whereas prior literature has identified the importance of incentives for the government overseer of a hybrid (Cabral *et al.*, 2010, 2013), this study highlights the importance of that overseer's ability to evaluate the effort of the private provider.

At the broadest level, recent research on contractual governance has assessed the distinct roles of coordination mechanisms vs. control mechanisms (Malhotra and Lumineau, 2011; Oxley and Wada, 2009; Ryall and Sampson, 2009). For example, Lumineau and Malhotra (2011) distinguish between contractual clauses that emphasize control and those that emphasize coordination, and find that coordination-related clauses are associated with smoother functioning of contracts in the face of interfirm friction. In a review of this literature, Lumineau (2017: 1561) concludes that 'a strong controlling focus may raise a constant policing…of the partner's performance…. Such a 'carrot-and-stick' approach with a strict oversight may create rigidity and over-monitoring.' Our study indicates that the relationship between rigidity and reliance on control mechanisms may also flow in the opposite direction: in institutional contexts that impose contractual rigidity, control mechanisms may be more feasible than coordination mechanisms.

This study also makes an additional empirical contribution in developing a measure of government personnel skills at a far more microanalytic level than has been done in the past. We can thus measure the precise level of skills or capabilities, across 59 occupational categories and 19 functional areas, possessed by the personnel of a given U.S. government bureau at a precise geographic level such as an office location, town, or any geographic radius. To the best of our knowledge, no other measure of government technical expertise exists at such a level of granularity. More generally, although the capabilities literature focuses theoretically on capabilities with specific uses, data constraints have tended to restrict empirical measurement of capabilities to features such as patenting productivity (e.g., Tortoriello, 2015) or prior experience in a particular industry (e.g., Klepper and Simons, 2000).

There are limitations to this study. First, we have excluded from our analysis pure outsourcing arrangements, in which the government rather than the firm owns the property rights to the innovation. It would be interesting to explore whether and how our theories and empirical methods might apply to these very common arrangements. Second, our paper measures innovative output as patents. One could imagine a situation where the government might value other outputs, such as jobs, regional economic development, or a variety of political criteria.

Those aspects of a potential government utility function are outside the scope of this paper. Third, we take contractual form as endogenously determined by the government, but without the influence of firms who did not win. To the extent that non-winning applicants for innovation contracts with the government influence contract form, our analysis will not capture that influence. Finally, while our theoretical framework aspires to be universal, the empirical work is particular to the institutional details and structure of government contracting for innovation in the United States. We believe that exploring applications of the theory to other countries would be a fruitful avenue for research.

There exist a number of further unexplored questions in this vein. Does government funding enable a firm to deepen its current expertise, or to broaden its technological portfolio and capabilities? How do the human-capital capabilities of the government affect the effectiveness of private sector research beyond patents? These questions are part of a vibrant avenue for future research on innovation and appropriation at the nexus of the government and private-firm R&D.

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Table 1. Descriptive statistics for variables used in primary analysis

| | All contracts (N=4,074) | | | | Cooperative agreements only (N=916) | | | | Grants only (N=3,158) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | S.D. | Min. | Max. | Mean | S.D. | Min. | Max. | Mean | S.D. | Min. | Max. |
| Generates Patent | 0.125 | 0.330 | 0 | 1 | 0.326 | 0.469 | 0 | 1 | 0.066 | 0.249 | 0 | 1 |
| Num. Patents Generated | 0.322 | 1.963 | 0 | 59 | 1.096 | 3.964 | 0 | 59 | 0.097 | 0.439 | 0 | 6 |
| Citation-Weighted Patents | 1.815 | 23.513 | 0 | 1082 | 7.480 | 49.073 | 0 | 1082 | 0.172 | 1.817 | 0 | 61 |
| Citations/Patent | 0.496 | 3.607 | 0 | 100.333 | 1.793 | 7.050 | 0 | 100.333 | 0.120 | 1.323 | 0 | 61 |
| Citations/Patent/Year | 0.045 | 0.252 | 0 | 6.271 | 0.146 | 0.475 | 0 | 6.271 | 0.015 | 0.112 | 0 | 3.813 |
| Coop Agreement | 0.225 | 0.418 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Personnel Expertise Ratio | 0.059 | 0.159 | 0 | 1 | 0.117 | 0.217 | 0 | 1 | 0.042 | 0.134 | 0 | 1 |
| Early Stage Personnel | 0.009 | 0.070 | 0 | 1 | 0.013 | 0.078 | 0 | 1 | 0.008 | 0.068 | 0 | 1 |
| Federal Funding[a] | 0 | 1 | -2.331 | 31.400 | 0.214 | 1.342 | -0.609 | 21.336 | -0.062 | 0.871 | -2.331 | 31.400 |
| Firm/Total Funding[a] | 0 | 1 | -0.354 | 4.101 | 0.870 | 1.546 | -0.354 | 4.101 | -0.252 | 0.561 | -0.354 | 4.101 |
| Large Firm | 0.268 | 0.443 | 0 | 1 | 0.750 | 0.433 | 0 | 1 | 0.128 | 0.334 | 0 | 1 |
| Prior Year Patents[a] | 0 | 1 | -0.316 | 16.323 | 0.483 | 1.392 | -0.316 | 16.323 | -0.140 | 0.801 | -0.316 | 16.323 |
| Coops/Personnel Ratio | 0.459 | 1.839 | 0 | 25 | 1.093 | 2.917 | 0 | 24 | 0.275 | 1.322 | 0 | 25 |
| Coops within 100 Miles | 5.703 | 10.553 | 0 | 68 | 12.503 | 14.771 | 0 | 65 | 3.730 | 7.945 | 0 | 68 |
| No Expertise | 0.312 | 0.463 | 0 | 1 | 0.084 | 0.278 | 0 | 1 | 0.378 | 0.485 | 0 | 1 |

*Note*. All variables calibrated to 100-mile distance.

[a] *z*-score standardized

Table 2. Two-stage IPWRA probit estimation of patent generation

| | First-stage model | Second-stage models | |
|---|---|---|---|
| | Model 1 | Model 2A (subsample: Coops) | Model 2B (subsample: Grants) |
| Personnel Expertise Ratio (IV) | 0.651** | | |
| | (0.165) | | |
| Coop Agreement | | 0.278** | 0.083** |
| | | (0.032) | (0.006) |
| Early Stage Personnel | 1.007** | -3.660 | 0.700 |
| | (0.275) | (2.155) | (0.385) |
| Federal Funding | 0.038 | 0.046 | 0.061 |
| | (0.035) | (0.046) | (0.035) |
| Firm/Total Funding | 0.286** | 0.077 | 0.148* |
| | (0.031) | (0.046) | (0.069) |
| Prior Year Patents | 0.005 | -0.171** | -0.025 |
| | (0.024) | (0.058) | (0.066) |
| Coops/Personnel Ratio | -0.003 | -0.090* | -0.079 |
| | (0.014) | (0.046) | (0.048) |
| Coops within 100 Miles | 0.018** | 0.005 | 0.005 |
| | (0.003) | (0.007) | (0.006) |
| Large Firm | 1.270** | 0.239 | 0.304* |
| | (0.068) | (0.154) | (0.152) |
| No Expertise | -0.663** | 0.057 | -0.152 |
| | (0.090) | (0.284) | (0.152) |
| Fiscal Year Fixed Effects | YES | YES | YES |

*Note*. N = 4,074 in Model 1, 916 in Model 2A, and 3,158 in Model 2B. Heteroskedasticity-robust standard errors are reported in parentheses. Models specified using 100-mile distance variables. Coefficients on *Coop Agreement* in Models 2A & 2B are interpreted as marginal effects; i.e., conditional on being a cooperative agreement or grant, respectively.
* $p < .05$, ** $p < .01$

Table 3. Second-stage IPWRA results of patent generation and quality outcomes

| | Num. patents generated | | Citation-weighted patents | | Citations/patent | | Citations/ patent/year | |
|---|---|---|---|---|---|---|---|---|
| Variable | Model 1 Coops | Model 2 Grants | Model 3 Coops | Model 4 Grants | Model 5 Coops | Model 6 Grants | Model 7 Coops | Model 8 Grants |
| Coop Agreement | 0.666** | 0.145** | 4.516** | 0.273** | 1.506** | 0.169** | 0.121** | 0.022** |
| | (0.090) | (0.016) | (0.819) | (0.063) | (0.230) | (0.031) | (0.018) | (0.003) |
| Early Stage Personnel | -1.285 | 0.072 | -6.281* | 0.098 | -1.699* | 0.035 | -0.160* | 0.003 |
| | (0.663) | (0.121) | (2.976) | (0.268) | (0.803) | (0.098) | (0.077) | (0.014) |
| Federal Funding | 0.208* | 0.101* | 0.781* | 0.031 | 0.099 | -0.006 | 0.011 | -0.001 |
| | (0.098) | (0.040) | (0.394) | (0.035) | (0.059) | (0.010) | (0.008) | (0.002) |
| Firm/Total Funding | 0.060 | 0.107* | 1.184 | 0.148 | -0.062 | 0.042 | 0.001 | 0.006 |
| | (0.064) | (0.046) | (0.632) | (0.173) | (0.112) | (0.060) | (0.010) | (0.009) |
| Prior Year Patents | 0.174 | -0.038 | 1.658 | -0.167 | 0.029 | -0.063 | -0.004 | -0.009* |
| | (0.143) | (0.037) | (0.958) | (0.091) | (0.124) | (0.033) | (0.009) | (0.005) |
| Coops/Personnel Ratio | 0.042 | -0.054* | 0.034 | -0.050 | -0.039 | -0.014 | -0.005 | -0.002 |
| | (0.107) | (0.021) | (0.158) | (0.041) | (0.021) | (0.016) | (0.002) | (0.002) |
| Coops within 100 Miles | -0.009 | 0.003 | -0.079 | -0.008 | -0.008 | -0.003 | -0.001 | -0.000 |
| | (0.021) | (0.004) | (0.054) | (0.006) | (0.007) | (0.002) | (0.001) | (0.000) |
| Large Firm | 0.609 | 0.136* | -0.244 | 0.512* | 0.291 | 0.204 | 0.033 | 0.032* |
| | (0.320) | (0.059) | (1.133) | (0.257) | (0.210) | (0.115) | (0.021) | (0.015) |
| No Expertise | 0.481 | 0.031 | -1.329 | -0.099 | -0.106 | -0.069 | 0.012 | -0.001 |
| | (0.381) | (0.036) | (1.247) | (0.135) | (0.245) | (0.085) | (0.031) | (0.006) |
| Year Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |

*Note*. N = 916 in odd-numbered models and 3,158 in even-numbered models. Heteroskedasticity-robust standard errors are reported in parentheses. Models specified using 100-mile distance variables.
* $p < .05$, ** $p < .01$

## APPENDIX A: THE PUBLIC CONTRACTING PROCESS FOR INNOVATION

The public contracting process for innovation operates similarly for grants and for cooperative agreements. The process unfolds as each government agency strives to accomplish its research agenda, which itself is driven by the agency's strategic plans, input from scientific review boards, legislative mandates, and/or current exigencies. An agency is allocated funds from Congress. Some of these funds are earmarked for specific research areas; the bulk are to be allocated at the agency's discretion. Given its agenda, the agency identifies a particular research project of interest and posts a Request or Call for Proposals (CFP) to the public. The CFP usually specifies the nature of the research, the desired deliverables, the general process for oversight, and the anticipated maximum amount of the grant/cooperative agreement. Firms (and other organizations) then submit proposals; coincidentally, the funding amount specified in almost all submitted proposals is exactly the anticipated maximum amount in the CFP. The proposals are then evaluated by agency personnel according to the criteria specified in the CFP, which includes metrics on the ability of the proposed researchers to successfully meet the objectives of the CFP. Agency personnel can choose to award a single project (to a single applicant), or multiple projects (to multiple applicants) that work along different paths towards the same goals. In both grants and cooperative agreements, the proposal must specify the researchers, equipment, and facilities to be used. Although there can be some modest "revise and resubmit" interaction around these proposals, they normally do not entail extended negotiation/lobbying between firm and agency.

Although there is little room for negotiation between firm and agency once a CFP is released, it is possible that firms lobby the agency to encourage CFPs in certain broad areas of research. (That said, the firm would still need to be awarded the proposal in a competitive process.) Also, although these projects are intended to support an agency's overall research agenda, it is possible that agency researchers favor CFPs in certain fields because this allows them to pursue their pet research. For the purposes of our study, the main question is: would such distortions affect the governance or performance of research projects in a way that conflates our results?

For example, if innovative firms are influential and also prefer cooperative agreements, then we might find that cooperative agreements yield more patenting than grants simply because "better" firms are lobbying the agency for projects that will be governed as cooperative agreements. We offer partial assurance here. Theoretically, if a firm is influential enough to affect the subject matter of a CFP, one might expect that it is also influential enough to affect the governance choice. Which governance form would a firm prefer – the grant, in which it has great freedom to operate, or a cooperative agreement, in which it operates under the eye of government personnel? Most theoretical lenses suggest that the firm would prefer the lower-monitoring grant form. This would bias against the results that we find. Empirically, in a robustness check that includes firm random effects, we find that cooperative agreements still outperform grants at a level comparable to that of the main results. Although neither of these is dispositive, it suggests that firm influence/preferences are not driving our results.

Alternatively, if agency personnel prefer to govern research contracts as cooperative agreements when the projects involve high-status firms or high-upside projects, then again we might find that cooperative agreement generate more patents because "better" projects are set up as cooperative agreements. As noted above, our robustness test with firm random effects suggests that our main results are not driven by better firms. As for better projects, two questions arise. Are better projects routed to cooperative agreements? Why doesn't the agency permit all research to be governed by cooperative agreements and credit claim over all innovation if then funds?

There are a number of reasons why this is an unlikely outcome, and that grants and cooperative agreements are sorted appropriately based on government research contribution. First, legislation specifies that cooperative agreements must have a "substantial" contribution by the government agency. The contribution of the government in research must be specified in writing in the proposal. This, in turn, requires researchers who are qualified to conduct the research, which the government may not have. Thus, there are *ex ante* gates, before the research begins, to ensure that substantial government cooperation is featured in the research. Second, although there is no clear criteria in the legislation or regulations specifying how "substantial" involvement is measured, government officials who merely claim collaboration when such collaboration is lacking, risk running afoul of the law and becoming subject to severe penalties. Auditing of researcher time certification, whistleblowing, and inspector general investigations are all mechanisms by which such illegal behavior would be discovered. Third, in a career concerns model, government officials are generally risk averse and extremely concerned about downside outcomes. If a research project unravels and receives substantial negative press, the researchers in the agency who are supposed to be (but are not really) engaged in the purported collaborative agreement, will be found equally culpable of research failures as the researchers who were engaged in the project, subjecting them to lower probabilities of promotion. The latter two critiques might be remedied if the researchers had time to engage in each research project in a significant way. However, researchers encounter time constraints to their involvement, as noted in the paper. In fact, in Table 2, we control for the time effects by including a measure of the number of collaborative agreements to the number of personnel. Overall, it is unlikely that government researchers would have the incentive to classify projects as cooperative agreements without their substantial contribution to the direction and content of the work.

<u>Cited:</u>

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## APPENDIX B: DATA, METHODS, AND ROBUSTNESS CHECKS

This appendix provides additional details about the data and methods used in this study. It then provides additional details about a series of robustness checks designed to further test our predictions and to test alternative explanations. It is divided into three sections: Data, Methods, and Robustness Checks.

### Data

Correlation matrices

The correlation matrices for our sample appear in Table B1.

Missing Project Descriptions

As discussed in the text, 31.2% of funding agreements (i.e., 1,271 of 4,074) lack a match with any of the 59 knowledge areas identified using OPM job titles. There are two reasons this may be the case: (1) either there was text in the description field of a project's record that did not include any of the keywords used to identify subject matter expertise (24% of missing cases), or (2) a description was entirely missing (76% of missing cases). When we initially downloaded the agreement data from USASpending.gov, a considerable number of project descriptions were missing. To address this, we searched the Federal Procurement Data System (FPDS; www.fpds.gov) ATOM feed, a searchable Application Programming Interface (API) for government spending records, for project descriptions based on the federal award ID number included in the agreement records. We also searched the NIH RePORTER system (https://projectreporter.nih.gov/), a similar system for several other agencies. While this improved our data coverage, roughly 900 contracts continue to omit descriptions.

In the analyses presented in the paper, we control for the lack of match to any of the 59 areas of expertise by including the dummy variable No Expertise (coded 1 for no match found), but this does not discriminate between the two sources of non-matching discussed above. To ensure that the type of non-matching does not materially affect the outcomes reported, we re-estimated all models under two alternative specification: (1) including a second dummy variable to indicate whether or not any text was included in the project description field from USA spending; and (2) after dropping all cases without text in the description field. Under both specifications, substantive results remain consistent with those reported in the main paper: for example, the coefficient on Personnel Expertise Ratio in the first-stage = 0.618 and 0.617 in the respective models ($p < 0.001$), and the marginal effect of Cooperative Agreement in the second stage for contracts that are organized as cooperative agreements = 0.189 and 0.184, respectively ($p < 0.001$).

**Methods**

Explanation of inverse probability weighted regression with adjustment (IPWRA)

Here we outline the general approach to IPWRA.[24] Consider each agreement that is chosen for treatment, $t \in \{0,1\}$. The potential outcome of the treatment is denoted as $y_t$. As researchers, we are interested in three parameters: the mean potential outcome, $\alpha_t = E(y_t)$; the average treatment effect, $\tau_t = E(y_t - y_0)$; and the average treatment effect on the treated $\delta_t =$

[24] A more detailed discussion of the conceptual and mathematical underpinnings can be found in Greene (2012), Cameron and Trivedi (2009), Imbens and Wooldridge (2009), and Angrist and Krueger (2001)..

$E(y_t - y_0|t = 1)$.[25] To derive these values, we need to implement estimating equations for the treatment equation and outcome equation. Estimating equations solve systems of equations to computer the estimates of these parameter values, based on the functional forms for the probit. In particular, if $\mu(x, t, \beta_t)$ is the conditional mean for the outcome $y$ conditional of covariates x and treat level $t$, then $E(u|x, t) = \mu(x, t, \beta_t)$ where $\beta_t$ are the paremeters of the condition mean model given the treatment model given the treatment $t$=1. For both of these equations, we use probit models where the functional form for outcome model (see Stata 2014 Reference Manual).

The estimators are derived through the estimating equations for the treatment model and outcome model using quasi-maximum likelihood approaches. There are two general approaches to solving these models. The first is regression adjustment methods. Regression adjustment estimators estimate the effect parameters using the means of the observation-level predictions of the condition means on the outcome. The second method, using inverse probability weighting, develops estimators to determine the effect parameters using the means of the observed outcomes weighted by their inverse probability of being treated. We incorporate both methods using the inverse probability weighting with regression adjustment used by Cattaneo (2010) and Cattaneo *et al*. (2013).

These types of treatment models have additional attractive properties for our purposes. First, they allow for different models predicting the treatment and outcome. Second, they are econometrically identifiable from both functional form and instruments. In our case, we have an instrument which is predictive of the choice of agreement form, but uncorrelated (except through agreement form) with the probability of obtaining a patent. Third, these models are "double robust." This means that even if one of the treatment or outcome models is not fully specified,

[25] The no-treatment level is zero.

the estimates are still consistent. Fourth, they allow for different estimates of the variables of interest in the treated and non-treated group. This would seem to be important as projects which are selected into cooperative agreements may have different characteristics than those that are chosen for grant agreements. The effect of each of the variables in the treatment equation may be different in each circumstance.

**Robustness Checks**

Alternatives to the IPWRA method

We argued above that the IPWRA method possesses numerous qualities that make it the most appropriate statistical method for our research question and data. Nevertheless, to demonstrate that the results are not an artifact of this statistical approach, we present results using alternative econometric methods. Each model we discuss is successively closer to the type of estimation procedure our data require. However, each entails tradeoffs that make them second-best alternatives.

We begin by considering single-stage, "naïve" probit models, both with and without year fixed-effects, present in Table B2. In both models, *Cooperative Agreement* is positive as expected ($p = 0.000$). These models are straightforward, but risk being misidentified due to endogeneity between the treatment (agreement form) and outcome (patenting) variables. To alleviate concerns over endogeneity, we next turn to alternative two-stage estimation methods, more analogous to the IPWRA method we employ in the paper. These results are presented in Table B3.

The first two-stage candidate is two-stage least squares (2SLS) with instruments. This estimation procedure linearizes the probability function in both the first stage and second stage.

However, when applied to binary outcome data, this method produces increasingly incorrect parameter estimates as the probability mass moves away from the center of the probability distribution (Wooldridge 2002). In our setting, the mean for the patent-creation probability distribution is 0.13, indicating that the probability mass is beginning to get into the tails of the probability distribution. Nevertheless, in Table B3, Model 1, we provide estimates for the both stages of a two stage least squares (2SLS) linear probability model (LPM) estimation. The coefficient on *Coop Agreement* becomes indistinguishable from zero. In the first-stage, the coefficient on *Personnel Expertise Ratio* remains positive and significant ($p = 0.001$). We note that the mean for cooperative agreement is 0.23, substantially closer to the center of the probability distribution.

A second approach is to use a two-stage probit model with instrumental variables. This method cannot derive unbiased or consistent point estimation of coefficients except under a set of very restrictive assumptions (Chesher, 2010). One solution to this problem is to linearize the first stage of the regression and use instrumental-variables probit for the second stage.[26] Of course, linearizing the first stage is problematic, for the reasons noted above. Nevertheless, Model 2 in Table B3 presents the results using this estimation procedure, following the three-step approach outlined in Wooldridge (2010) and Adams *et al*. (2009). The instrument *Personnel Expertise Ratio*, employed in a single-stage probit, is positive and significant ($p = 0.000$) in predicting cooperative agreement adoption. The effect of *Coop Agreement* on patent generation is positive and significant ($p = 0.002$).

A third statistical approach is to use bivariate probit estimation. The bivariate probit

[26] The converse is infeasible; if one uses a probit estimation in the first stage and then OLS in second stage, then the coefficients in the second stage will be incorrect. This is popularly known as the "forbidden regression" (Angrist and Pischke, 2009: 109).

allows for correlation between the first- and second-stage error terms (Greene, 2012). Moreover, similar to the IPWRA model, instruments in the first stage lead to a more precisely estimated coefficient in the second stage. Although the bivariate probit also has several attractive features, not least of which is that its statistical properties are well understood, it does have some limitations. The relevant concern in our setting is that it assumes (i.e., forces) the treatment effect to be equal across both the treated and untreated groups, providing only one set of second stage coefficients (Lokshin and Sajaia, 2011). Model 3 presents results from a bivariate probit estimation. Again, *Personnel Expertise Ratio* is positively related to cooperative agreement selection, and again *Coop Agreement* is positively related to patent generation.

A final emerging estimation technique for binary choice models with endogenous binary regressors with instruments is to use FIML (Lokshin and Sajaia, 2011). This technique relies on joint normality of the error terms in the treatment and outcome equations. Lokshin and Sajaia (2011) show that, with good instruments in the first stage, this method produces estimated coefficients that are very close to the true coefficients in Monte Carlo simulations. This method also allows for the treatment effects to differ across the treated group and untreated group. Model 4 presents results of a FIML model, known as a "switch probit" in Stata parlance. Again, *Personnel Expertise Ratio* is positively related to cooperative agreement selection, and again *Coop Agreement* is positively related to patent generation.

Overall, then, three out of four alternative two-stage empirical methods generate results that are qualitatively similar to those of the IPWRA method. Given that the method that did not replicate the results is also the least suitable for our data, we conclude that the core results of the paper are generally robust to alternative estimation procedures.

Alternative cutoffs for geographic proximity

Another potential concern regarding our analysis is that our results may depend on the geographic range we consider when identifying relevant, local government personnel. Four of our independent variables and our instrumental variable are all based on geographic proximity, which necessitates an arbitrary decision regarding what distance is "proximate" – a day's roundtrip by a government scientist (4 hours of driving). We rely above on a radius of 100 miles from the focal location of research work as the default distance – that is, the personnel counted as potentially relevant to the agreement being carried out must work for the sponsoring agency within 100 miles of the principal worksite indicated in the agreement. Perhaps 100 miles is an overly stringent or optimistic threshold for collaborative work on a contract-research project. We therefore re-estimate our primary model, the two-stage IPWRA probit reported in Models 2A and 2B of Table 2 (main paper), using variables based on thresholds of 200, 300, 400, and 500 miles. The coefficients on Coop Agreement are presented in Table B4, along with the first-stage coefficients on our instrumental variable in the selection model.

In every model, the coefficient on *Coop Agreement* remains positive and significant ($p$ = 0.000 in all models). The magnitudes of the coefficients remain relatively consistent, and close to the increased probabilities of 27% for cooperative agreements and 8% for grants reported above. The coefficient on the instrument, *Personnel Expertise Ratio*, retains similar magnitude throughout all models. In unreported models, we also re-estimated the non-instrumented single-stage probit model reported in Model 2 for 200-, 300-, 400-, and 500-mile specifications. Our core result is robust against geographic manipulation in multiple model specification methods.

Appropriateness of instrumental variable

To be a valid instrument, *Personnel Expertise Ratio* must be correlated with the endogenous regressor, *Coop Agreement*, and orthogonal to the error term in the main equation. Table B5, Model 1 reports a single-stage probit model predicting patent generation with coefficients converted to marginal effects, which is identical to Model 2 in Table B2 except that it includes the instrument as an independent variable. The coefficients on all of the variables common to the two models are little. Of particular importance, though, is that *Personnel Expertise Ratio* exhibits no direct relationship with *Generates Patent*. Indeed, the BIC for Table B5, Model 1 is slightly larger than the BIC for Table B2, Model 2, showing that including the personnel expertise variable worsens model fit rather than improving it. In every two-stage model specification reported in this paper, *Personnel Expertise Ratio* continues to be a positive and significant predictor of *Coop Agreement* ($p < 0.003$ in all models).

As discussed in the main paper, we elected to employ inverse-propensity weighted regression adjustment (IPWRA) in our primary analysis to account for covariate imbalance. IPWRA is a "doubly robust" estimation method, in that it gives "the analyst two chances to 'get it right'" (Morgan and Winship, 2015: 234). Furthermore, on the chance that agreement type (cooperative versus grant) is endogenous to our main outcome variable (patent generation), we include an instrument for selection into the cooperative agreement format – a continuous measure of locally available government personnel in the relevant bureau with the relevant expertise. Nevertheless, one might wonder what if any of our first-stage independent variables are correlated with this instrument. Based on the correlations presented in Table B1, three right-hand side variables are correlated above 0.3 with our instrument: No Expertise, Coops-to-Personnel Ratio, and Early Stage Personnel.

As long as the instrument (Personnel Expertise Ratio) is not correlated with the errors of our final outcome of concern (patent generation), it remains a valid instrument, known as a "conditional instrumental variable" (Morgan and Winship, 2015: 298–299) in the presence of correlation with other first-stage variables. The minimal correlation between the variables and the lack relationship between *Personnel Expertise Ratio* and *Generates Patent* in Table B5 indicates this assumption is valid.

However, we can model the data under the assumption of endogenous regressors for the instrument in addition to a potentially endogenous treatment variable using an extended regression models (ERMs). ERMs allow for multiple, simultaneous equations to be estimated accounting for both endogenous treatment assignment and endogenous predictors of an instrumental variable (Wooldridge, 2010). We fit a three-equation model using the same functional setup as Table 2 in the main paper, but include an additional equation specifying that Personnel Expertise Ratio be regressed on No Expertise, Coops-to-Personnel Ratio, and Early Stage Personnel under the assumption of endogeneity; heteroscedasticity-robust standard errors are included as an additional precaution. Results are reported in Table B6.

Functionally, the results do not change. First, the instrument remains positive in predicting treatment assignment ($p = 0.000$). Second, the treatment (cooperative agreement form) remains a positive predictor of patent generation ($p = 0.000$). Furthermore, using Stata's post-estimation commands, we can estimate that the average treatment effect on the treated (ATET) is a 28.2% increase in the likelihood of patent generation ($p < .001$), which is slightly larger than the effect reported in Table 2 (main paper). Finally, the ERM method also evaluates error correlations between dependent variables; important for our concerns is that the errors for personnel expertise are uncorrelated with patent generation, further supporting our use of this variable as an instrument.

Temporal Variance

Although there are multiple paths to analyzing the data, we opt for a strategy that minimizes variation between observations (via inverse-probability weighting in the first stage of our two-stage models) in order to achieve covariate balance between cooperative agreements and grants. An alternative is to examine within-firm and/or time-period specific changes. We do this in part in our current analyses by including fiscal year fixed effects in all primary analyses. These year fixed effects capture variance due to government-wide or economy-wide events due to the time period, such as the economic recession and government response in 2008-2009. In the first-stage Model 1 (Table 2, main paper), the yearly coefficients are indeed negative during FYs 2008-2010, suggesting the government was more likely to issue grants over cooperative agreements (which was the case throughout, shown by the higher proportion of agreements that were grants).

However, a major initiative of the federal government during this time was to stimulate spending via the American Recovery and Reinvestment Act (ARRA). This stimulus package was distributed over multiple fiscal years, and so might have effects not captured by year dummy variables, in particular in the choice of issuing grants rather than cooperative agreements (i.e., the ARRA could be an omitted variable in our first-stage, treatment-assignment model). While this is not a concern as long as our covariate balance estimates are valid *or* as long as our instrumental variable is valid, it is possible to determine if the ARRA had an effect in our data, as agreement records indicate whether or not they were funding via the ARRA specifically. In our sample, 291 agreements (7.14%) were flagged as stemming from the ARRA. Of those, 210 (72.16%) were cooperative agreements, rather than grants. Including a dummy variable (coded 1 if an agreement was supported by the ARRA) in the first and second stage models does not materially affect any of our results, and is not statistically significant at $\alpha = 0.05$ in predicting agreement form ($\beta = -0.239$).

Bureau-Level Differences

Another concern that may arise is that governmental units ("bureaus" in our discussion, which correspond to the level of government just below agencies; e.g., the Centers for Disease Control and Prevention is a bureau of the Health and Human Services agency) may influence results in a manner not adequately captured without bureau fixed-effects. We are unable to use bureau fixed-effects in our analysis because it introduces too much missing data. In the treatment effects setup, models are fit separately (but relatedly) to the treatment and control conditions, so if a bureau does not have sufficient coverage on all variables in both conditions, we do not observe a sufficient number of both treatment and control cases in for each variable in our model to accurately estimate a treatment effect under this specification. This is, fundamentally, the problem of causal inference caused by missing data in non-experimental studies (Rosenbaum and Rubin, 1983).

One method for addressing causal concerns in the presence of missing and unbalanced data is entropy balancing (Hainmueller, 2012; Hainmueller and Xu, 2013). Entropy balancing overcomes observational differences in a manner similar to propensity score weighting, but with increased flexibility and greater use of information. Important for our concerns, "Since the entropy balancing weights vary smoothly across units, they also commonly retain more information in the preprocessed data than other approaches" (Hainmueller and Xu, 2013: 2), which is indeed the case in our analysis.

We estimate entropy-balancing weights based on the first-stage covariates reported in (main paper) Table 3, with the addition of indicators for each agency. This accounts for not only the first-stage variables' differences across grants and cooperative agreements, but also the different likelihood of any bureau to use one form of support over the other. We lose 133 cases for which entropy balancing was not possible (N = 3,941). Rather than estimating a two-stage model, we then estimate a single-stage probit including these weights as probability weights. Table D6 reports the results of this estimation, including the Personnel Expertise Ratio instrument.

There are several takeaways from Table B7. First, as in the paper, the coefficient for cooperative agreements is positive and significant ($p = 0.000$), indicating that cooperative agreement structure does enhance the likelihood of patent generation for those that were cooperative agreements. The difference in predicted outcomes by support structure is a 21.5% increase in the marginal likelihood that an agreement generates a patent, holding all other variables at their mean value (this effect is equivalent to the average treatment effect, computed using Stata's 'margins' command). Furthermore, our instrument is not distinguishable from zero in this model, which is equivalent to a second-stage regression in the two-stage least-squares framework. This lends further support that it does not have a relationship to the final outcome, a key concern in using it as an instrument.

Skew in patent and citation measures

It is well known that patenting and citation rates often are highly skewed. Our dependent variable Generates Patent addresses this because it is a binary measure of at-least-one-patent. Nevertheless, to explore whether our results for the other dependent variables, which are based on patent and citation counts, are driven by skew, in Table B8 we re-estimate the basic models using the natural logs of these dependent variables. The results are materially unchanged.

<u>Heterogeneity in Scientist Coordination Across Grants and Cooperative Agreements</u>

As noted above, one alternative explanation for our predicted pattern of results is that contract choice and innovative performance are both driven by government scientists' ability to collaborate with firm scientists. Specifically, when government personnel with relevant skills are locally available, project tasks can entail greater collaboration; since federal policies stipulate that high-collaboration endeavors be managed under cooperative-agreement contracts, then if collaboration yields greater innovative output, cooperative agreements will be correlated with innovative output as an artifact of collaborative activity. Although we cannot identify the specific degree of collaboration that occurs in each research project, *Coops-to-Personnel Ratio* proxies for the feasibility of collaboration by measuring the other demands on government researchers' attention. The positive relationship between *Coop Agreement* and *Generates Patent* is unaffected by inclusion of this proxy, thus indicating a salutary effect of cooperative-agreement governance on innovative output beyond mere coordination in a project.

<u>Firm Differences</u>

A final concern is that unobserved heterogeneity among firms may correlate with performance of the contracts. We are unable to obtain convergence using firm *fixed* effects with either IPWRA or entropy balancing due to sparseness of the data. We thus turn to random-effects estimation, as this relaxes the model assumptions and makes fuller use of the data. A single-stage random-effects model predicting patent generation is presented in Table B9. As in our primary analysis, cooperative agreement increases the likelihood of patenting.

An alternative form of time-varying heterogeneity across firms relates to firm experience in contracting with the government. In Table B10 we re-estimate the probability that a contract is governed as a cooperative agreement, controlling for the number of prior contracts the firm had with the specific agency funding the focal contract (Model 1) or any agency (Model 2). We further disaggregate this into prior grants and prior cooperative agreements in Models 3 and 4. Models 1 and 2 indicate that contracts are more likely to be organized as grants the greater number of prior contracts that a firm has had with the government. Models 3 and 4 show that a firm's current contract mode is likely to be similar to the mode of its prior contracts, suggesting perhaps that there is a class of firm that is more likely to be awarded grants and another that is more likely to be awarded cooperative agreements, or perhaps that agencies favor a modal form that firm has experienced before. Of particular note, the inclusion of these variables does not qualitatively change the magnitude of *Personnel Expertise Ratio*, and reduces the magnitude of *Early Stage Project* by up to one-half in some models.

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## Table B1: Correlation Matrices

Panel A: Spearman Correlation Matrix – All Agreements

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Generates Patent | 1.000 | | | | | | | | | | |
| 2. Coop Agreement | 0.329 | 1.000 | | | | | | | | | |
| 3. Personnel Expertise Ratio | 0.043 | 0.180 | 1.000 | | | | | | | | |
| 4. Federal Funding[a] | 0.179 | 0.189 | -0.035 | 1.000 | | | | | | | |
| 5. Firm/Total Funding[a] | 0.216 | 0.495 | 0.085 | 0.157 | 1.000 | | | | | | |
| 6. Prior Year Patents[a] | 0.102 | 0.390 | 0.121 | 0.046 | 0.300 | 1.000 | | | | | |
| 7. Large Firm | 0.277 | 0.587 | 0.123 | 0.131 | 0.462 | 0.551 | 1.000 | | | | |
| 8. No Expertise | -0.171 | -0.265 | -0.358 | -0.013 | -0.137 | -0.244 | -0.248 | 1.000 | | | |
| 9. Coops/Personnel Ratio | 0.074 | 0.298 | 0.556 | -0.053 | 0.147 | 0.184 | 0.271 | -0.242 | 1.000 | | |
| 10. Early Stage Personnel | 0.055 | 0.164 | 0.502 | 0.007 | 0.083 | 0.083 | 0.106 | -0.235 | 0.284 | 1.000 | |
| 11. Coops within 100 Miles | 0.151 | 0.416 | 0.261 | -0.021 | 0.271 | 0.289 | 0.346 | -0.386 | 0.606 | 0.192 | 1.000 |

Panel B: Spearman Correlation Matrix – Cooperative Agreements Only

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Generates Patent | 1.000 | | | | | | | | | | |
| 2. Coop Agreement | . | . | | | | | | | | | |
| 3. Personnel Expertise Ratio | -0.102 | . | 1.000 | | | | | | | | |
| 4. Federal Funding[a] | 0.229 | . | -0.132 | 1.000 | | | | | | | |
| 5. Firm/Total Funding[a] | 0.035 | . | -0.028 | 0.054 | 1.000 | | | | | | |
| 6. Prior Year Patents[a] | -0.148 | . | -0.022 | -0.139 | 0.100 | 1.000 | | | | | |
| 7. Large Firm | 0.133 | . | -0.082 | 0.032 | 0.196 | 0.320 | 1.000 | | | | |
| 8. No Expertise | -0.010 | . | -0.278 | -0.090 | -0.046 | 0.021 | -0.061 | 1.000 | | | |
| 9. Coops/Personnel Ratio | -0.153 | . | 0.229 | -0.143 | -0.077 | 0.039 | 0.048 | 0.039 | 1.000 | | |
| 10. Early Stage Personnel | -0.118 | . | 0.537 | -0.051 | -0.049 | -0.010 | -0.201 | -0.153 | 0.043 | 1.000 | |
| 11. Coops within 100 Miles | -0.096 | . | 0.031 | -0.105 | 0.042 | 0.310 | 0.111 | 0.018 | 0.357 | 0.110 | 1.000 |

**Table B1: Correlation Matrices (continued)**

Spearman Correlation Matrix – Grants Only

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Generates Patent | 1.000 | | | | | | | | | | |
| 2. Coop Agreement | . | . | | | | | | | | | |
| 3. Personnel Expertise Ratio | 0.087 | . | 1.000 | | | | | | | | |
| 4. Federal Funding[a] | 0.065 | . | -0.040 | 1.000 | | | | | | | |
| 5. Firm/Total Funding[a] | 0.063 | . | 0.052 | 0.013 | 1.000 | | | | | | |
| 6. Prior Year Patents[a] | 0.033 | . | 0.091 | 0.021 | 0.137 | 1.000 | | | | | |
| 7. Large Firm | 0.096 | . | 0.109 | 0.001 | 0.301 | 0.426 | 1.000 | | | | |
| 8. No Expertise | -0.134 | . | -0.545 | 0.072 | 0.019 | -0.189 | -0.138 | 1.000 | | | |
| 9. Coops/Personnel Ratio | 0.088 | . | 0.469 | -0.095 | 0.100 | 0.153 | 0.145 | -0.357 | 1.000 | | |
| 10. Early Stage Personnel | 0.091 | . | 0.495 | -0.002 | 0.063 | 0.031 | 0.129 | -0.230 | 0.185 | 1.000 | |
| 11. Coops within 100 Miles | 0.130 | . | 0.300 | -0.114 | 0.137 | 0.182 | 0.174 | -0.413 | 0.791 | 0.190 | 1.000 |

[a] *z*-score standardized

**Table B2: Single-Stage Probit Estimation**

| Variable | Model 1 | Model 2 |
|---|---|---|
| Cooperative Agreement | 0.705** | 0.763** |
| | (0.075) | (0.075) |
| Federal Funding | 0.069** | 0.061* |
| | (0.026) | (0.026) |
| Firm/Total Funding | 0.009 | 0.033 |
| | (0.026) | (0.027) |
| Prior Year Patents | -0.075* | -0.064* |
| | (0.031) | (0.028) |
| Coops/Personnel Ratio | -0.051** | -0.054** |
| | (0.019) | (0.019) |
| Coops within 100 Miles | 0.005 | -0.002 |
| | (0.003) | (0.003) |
| Early Stage Personnel | 0.242 | 0.375 |
| | (0.377) | (0.378) |
| Large Firm | 0.445** | 0.462** |
| | (0.075) | (0.077) |
| No Expertise | -0.472** | -0.254** |
| | (0.075) | (0.095) |
| Fiscal Year Fixed Effects | NO | YES |
| Observations | 4074 | 4074 |
| BIC | 2662.019 | 2602.842 |
| Pseudo $R^2$ | 0.159 | 0.210 |

*Note*. Heteroskedasticity-robust standard errors are reported in parentheses.
* $p < .05$, ** $p < .01$

**Table B3. Methodological Robustness Checks: Comparison of Two-Stage Estimation Procedures**

| Variable | First-Stage Models Model 1 2SLS | Model 2 2S/3S IV | Model 3 Bi-probit | Model 4 Switch Probit |
|---|---|---|---|---|
| Personnel Expertise Ratio | 0.160** | 0.113** | 0.673** | 0.656** |
| (Instrument) | (0.047) | (0.029) | (0.163) | (0.175) |
| Federal Funding | 0.016 | 0.007 | 0.041 | 0.034 |
| | (0.012) | (0.006) | (0.035) | (0.034) |
| Firm/Total Funding | 0.089** | 0.050** | 0.277** | 0.289** |
| | (0.008) | (0.005) | (0.030) | (0.032) |
| Prior Year Patents | -0.002 | 0.001 | 0.008 | -0.001 |
| | (0.008) | (0.004) | (0.025) | (0.025) |
| Coops/Personnel Ratio | -0.001 | -0.001 | -0.002 | -0.007 |
| | (0.004) | (0.002) | (0.014) | (0.014) |
| Coops within 100 Miles | 0.006** | 0.003** | 0.017** | 0.020** |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| Early Stage Personnel | 0.186** | 0.175** | 1.033** | 0.792** |
| | (0.067) | (0.048) | (0.266) | (0.256) |
| Large Firm | 0.362** | 0.324** | 1.272** | 1.280** |
| | (0.021) | (0.021) | (0.068) | (0.066) |
| No Expertise | -0.128** | -0.111** | -0.663** | -0.634** |
| | (0.017) | (0.014) | (0.088) | (0.083) |
| Fiscal Year Fixed Effects | YES | YES | YES | NO |

| | Second-Stage Models Model 1 2SLS | Model 2 2S/3S IV | Model 3 Bi-probit | Model 4A Switch Probit Coops | Model 4B Switch Probit Grants |
|---|---|---|---|---|---|
| Coop Agreement | -0.118 | 1.726** | 0.240** | 0.281** | 0.081** |
| | (0.258) | (0.545) | (0.142)[a] | (0.079)[b] | (0.074)[b] |
| Federal Funding | 0.026** | 0.043 | 0.069* | 0.070 | 0.059 |
| | (0.010) | (0.029) | (0.028) | (0.038) | (0.037) |
| Firm/Total Funding | 0.035 | -0.057 | 0.095** | -0.035 | 0.057 |
| | (0.025) | (0.060) | (0.026) | (0.074) | (0.075) |
| Prior Year Patents | -0.017** | -0.062* | -0.060* | -0.055 | -0.090 |
| | (0.006) | (0.028) | (0.027) | (0.036) | (0.055) |
| Coops/Personnel Ratio | -0.014** | -0.051* | -0.053** | -0.067** | -0.014 |
| | (0.004) | (0.020) | (0.018) | (0.029) | (0.026) |
| Coops within 100 Miles | 0.001 | -0.008 | 0.002 | 0.001 | 0.005 |
| | (0.002) | (0.005) | (0.003) | (0.006) | (0.005) |

| | | | | | |
|---|---|---|---|---|---|
| Early Stage Personnel | 0.079 | 0.145 | 0.541 | -2.039 | 0.772* |
| | (0.099) | (0.405) | (0.364) | (1.101) | (0.373) |
| Large Firm | 0.213* | 0.067 | 0.745** | 0.371 | 0.201 |
| | (0.096) | (0.255) | (0.071) | (0.439) | (0.191) |
| No Expertise | -0.053 | -0.077 | -0.391** | 0.003 | -0.260* |
| | (0.041) | (0.149) | (0.093) | (0.268) | (0.128) |
| Year Fixed Effects | YES | YES | YES | NO | NO |
| Observations | 4,074 | 4,074 | 4,074 | 4,074 | |

*Note*. Heteroskedasticity-robust standard errors are reported in parentheses.
[a] *t*-statistic of difference in predicted probability of patent generation by agreement type
[b] *t*-statistic of difference in estimated treatment effect by agreement type
* $p < .05$, ** $p < .01$

**Table B4. Two-Stage IPWRA Probit Results, Sensitivity to Different Thresholds for Geographic Proximity**
(dependent variable: *Generates Patent*)

| | 100 Miles | | 200 Miles | | 300 Miles | | 400 Miles | | 500 Miles | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Co-ops | Grants | Co-ops | Grants | Co-ops | Grants | Co-ops | Grants | Co-ops | Grants |
| *Coop Agreement* | 0.278** | 0.083** | 0.269** | 0.085** | 0.272** | 0.083** | 0.273** | 0.084** | 0.264** | 0.085** |
| | (0.032) | (0.006) | (0.031) | (0.006) | (0.029) | (0.006) | (0.029) | (0.006) | (0.028) | (0.007) |
| First-stage Personnel | 0.651** | | 0.471** | | 0.346** | | 0.572** | | 0.639** | |
| Expertise Instrument | (0.165) | | (0.137) | | (0.123) | | (0.109) | | (0.109) | |

*Note*. Heteroskedasticity-robust standard errors are reported in parentheses. All independent variables from Table 2 are included in estimation, but coefficients are not reported.
** $p < .01$

**Table B5. Single-Stage Probit Estimation of Patent Generation, With Instrument as Independent Variable**

| Variable | Model 1 |
|---|---|
| Coop Agreement | 0.125** |
| | (0.012) |
| Personnel Expertise Ratio | -0.030 |
| | (0.028) |
| Federal Funding | 0.010* |
| | (0.004) |
| Firm/Total Funding | 0.005 |
| | (0.004) |
| Prior Year Patents | -0.010* |
| | (0.005) |
| Coops/Personnel Ratio | -0.009** |
| | (0.003) |
| Coops within 100 Miles | -0.000 |
| | (0.001) |
| Early Stage Personnel | 0.065 |
| | (0.061) |
| Large Firm | 0.083** |
| | (0.015) |
| No Expertise | -0.041** |
| | (0.013) |
| Year Fixed Effects | Yes |
| N | 4,074 |
| Pseudo $R^2$ | 0.211 |
| BIC | 2,610 |

*Note*. Heteroskedasticity-robust standard errors are reported in parentheses.
* $p < .05$, ** $p < .01$

**Table B6: Three-Equation Endogenous Treatment Extended Regression Model**

| Model | Variable | Coefficient | Robust SE | *z*-statistic | *p*-value |
|---|---|---|---|---|---|
| Final-Stage Model (Predicting Patent Generation = 1) | Federal Funding | 0.050 | 0.026 | 1.93 | 0.054 |
| | Firm/Total Funding | -0.018 | 0.035 | -0.51 | 0.610 |
| | Prior Year Patents | -0.061 | 0.028 | -2.19 | 0.029 |
| | Coops/Personnel Ratio | -0.054 | 0.019 | -2.79 | 0.005 |
| | Coops within 100 Miles | -0.005 | 0.004 | -1.54 | 0.123 |
| | Early Stage Personnel | 0.253 | 0.374 | 0.68 | 0.498 |
| | Large Firm | 0.241 | 0.120 | 2.01 | 0.045 |
| | No Expertise | -0.154 | 0.103 | -1.50 | 0.134 |
| | Coop Agreement | 1.330 | 0.253 | 5.26 | 0.000 |
| Treatment Assignment Model (Predicting Cooperative Agreement = 1) | Personnel Expertise Ratio | 0.735 | 0.233 | 3.15 | 0.002 |
| | Federal Funding | 0.036 | 0.035 | 1.04 | 0.300 |
| | Firm/Total Funding | 0.291 | 0.033 | 8.96 | 0.000 |
| | Prior Year Patents | 0.002 | 0.024 | 0.08 | 0.937 |
| | Coops/Personnel Ratio | -0.004 | 0.014 | -0.28 | 0.777 |
| | Coops within 100 Miles | 0.019 | 0.003 | 5.74 | 0.000 |
| | Early Stage Personnel | 0.940 | 0.280 | 3.36 | 0.001 |
| | Large Firm | 1.267 | 0.068 | 18.66 | 0.000 |
| | No Expertise | -0.650 | 0.093 | -7.03 | 0.000 |
| Predicting Personnel Ratio IV | Early Stage Personnel | 0.147 | 0.049 | 2.98 | 0.003 |
| | Coops/Personnel Ratio | 0.003 | 0.001 | 2.84 | 0.005 |
| | No Expertise | -0.082 | 0.004 | -22.68 | 0.000 |
| | Constant | 0.082 | 0.004 | 22.34 | 0.000 |

*Note*. N = 4,074

**Table B7: Entropy-Balanced Probit Estimation Predicting Patent Generation**

| Variable | Coefficient | Robust SE | *z*-statistic | *p*-value |
|---|---|---|---|---|
| Coop Agreement | 0.215 | 0.029 | 7.39 | 0.000 |
| Personnel Expertise Ratio | 0.029 | 0.071 | 0.41 | 0.684 |
| Federal Funding | 0.019 | 0.005 | 4.11 | 0.000 |
| Firm/Total Funding | 0.031 | 0.012 | 2.63 | 0.008 |
| Prior Year Patents | -0.023 | 0.015 | -1.52 | 0.129 |
| Coops/Personnel Ratio | -0.015 | 0.008 | -1.92 | 0.055 |
| Coops within 100 Miles | 0.002 | 0.001 | 1.86 | 0.063 |
| Early Stage Personnel | 0.177 | 0.139 | 1.28 | 0.202 |
| Large Firm | 0.004 | 0.045 | 0.09 | 0.930 |
| No Expertise | -0.048 | 0.038 | -1.24 | 0.213 |

*Note*. Year fixed-effects included. N = 3,941

**Table B8. Second-Stage IPWRA Results of Logged Patent Generation and Quality Outcomes**

| | Num. Patents Generated | | Citation-Weighted Patents | | Citations/Patent | | Citations//Year | |
|---|---|---|---|---|---|---|---|---|
| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
| Cooperative Agreement | 0.293** | 0.079** | 0.459** | 0.086** | 0.352** | 0.070** | 0.082** | 0.017** |
| | (0.032) | (0.007) | (0.044) | (0.011) | (0.037) | (0.008) | (0.010) | (0.002) |

*Note*. Heteroskedasticity-robust standard errors are reported in parentheses. Odd-number models report point estimates for cooperative agreement analyses; even-number models report point estimates for grant analyses.
** $p < .01$

**Table B9:**

**Single-Stage Probit Predicting Patent Generation with Firm Random-Effects**

| Variable | Coefficient | Robust SE | *z*-statistic | *p*-value |
|---|---|---|---|---|
| Coop Agreement | 0.192 | 0.020 | 9.46 | 0.000 |
| Fed. Funding | 0.016 | 0.006 | 2.56 | 0.011 |
| Firm-to-Total Funding | 0.001 | 0.007 | 0.19 | 0.851 |
| Prior Year Patents | -0.027 | 0.012 | -2.21 | 0.027 |
| Coops-to-Personnel Ratio | -0.004 | 0.005 | -0.77 | 0.440 |
| Coops within 100 Miles | 0.000 | 0.001 | 0.16 | 0.873 |
| Early Stage Personnel | 0.075 | 0.123 | 0.61 | 0.539 |
| No Expertise | -0.067 | 0.025 | -2.67 | 0.008 |

*Note*. Year fixed-effects included. 4,074 observations/383 groups. Coefficients are predicted marginal effects.

**Table B10:**
**Probit Estimation of Cooperative Agreement = 1 with Prior Agreement Counts**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Personnel Expertise Ratio | 0.642** | 0.636** | 0.496** | 0.501** |
| | (0.158) | (0.159) | (0.162) | (0.162) |
| Fed. Funding | 0.037 | 0.037* | 0.040* | 0.039* |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| Firm-to-Total Funding | 0.255** | 0.254** | 0.237** | 0.236** |
| | (0.027) | (0.027) | (0.027) | (0.027) |
| Prior Year Patents | 0.006 | 0.006 | -0.026 | -0.026 |
| | (0.025) | (0.025) | (0.025) | (0.025) |
| Research Personnel Prop | -0.133 | -0.137 | -0.091 | -0.092 |
| | (0.255) | (0.255) | (0.256) | (0.256) |
| Coops-to-Personnel Ratio | 0.005 | 0.006 | -0.021 | -0.021 |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Coops within 100 Miles | 0.018** | 0.018** | 0.009** | 0.010** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Early Stage Personnel | 0.870* | 0.853* | 0.574 | 0.562 |
| | (0.341) | (0.341) | (0.366) | (0.365) |
| Major Organization | 1.082** | 1.075** | 1.081** | 1.064** |
| | (0.073) | (0.073) | (0.074) | (0.074) |
| No Expertise | -0.457** | -0.457** | -0.463** | -0.461** |
| | (0.089) | (0.089) | (0.091) | (0.091) |
| Prior 1-Year Agency Contracts | -0.013** | | | |
| | (0.002) | | | |
| Prior 1-Year Contracts (Any Agency) | | -0.013** | | |
| | | (0.003) | | |
| Prior 1-Year Agency Grants | | | -0.026** | |
| | | | (0.004) | |
| Prior 1-Year Agency Coops | | | 0.103** | |
| | | | (0.013) | |
| Prior 1-Year Grants (Any Agency) | | | | -0.026** |
| | | | | (0.004) |
| Prior 1-Year Coops (Any Agency) | | | | 0.100** |
| | | | | (0.013) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |

N = 3,724; only cases from 2001 onward used. Heteroskedasticity-robust standard errors are reported in parentheses. Results are substantively unchanged by using a longer time window.
* $p < .05$, ** $p < .01$