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ENABLING TECHNOLOGIES AND THE ROLE OF PRIVATE FIRMS

ABSTRACT

Investments in enabling technologies–including 5G, artificial intelligence, and the lidar technology–are important strategic decisions for firms. A common assumption is that enabling technologies have their origins in public sector projects. In contrast, we know much less about whether, and how, private firms are involved. This paper asks how inventions that private firms developed with vs without public-sector partners differ in their enabling-technology trajectory. Using machine-learning matching, we compare patented technologies generated from over 30,000 public-private relationships with comparable technologies invented by private firms alone during a 21-year period. To measure the enabling potential of a technology, we introduce a new "Enabling Technology Index." The findings show that private firm relationships with the public sector–in particular cooperative agreements and grants with mission agencies (NASA and Department of Defense)–are likely starting points for enabling technology trajectories. We thus put a spotlight on organizational arrangements that combine the breadth of exploration (agreements, grants) with deep exploitation in a particular domain (mission agency). A key contribution is a better understanding of the types of private-firm efforts that are associated with enabling technologies.

KEY WORDS: Innovation Management, Knowledge-based View, Open Innovation, Enabling Technology, Innovation, Public-Private R&D Relationship

Enabling technologies are strategically important. By definition, these technologies are novel, they enable complementary innovations (often downstream in the value chain), and become widely used across an industry or industry sectors (Teece, 2018a; Gambardella, Novelli, Heaton & Teece, 2019). The list of much-discussed "general-purpose technologies" (GPTs) is short and includes only a select few that have game-changing impact across the economy as a whole (e.g. electricity, internet; Bresnahan and Trajtenberg, 1995; Lipsey et al., 2005). In contrast, the list of enabling technologies, i.e., "junior GPTs" includes many technologies that are disruptive and growth-enabling in particular industries, but not necessarily with measurable economy-wide impact (e.g., lidar, 5G; Teece, 2018a).[1] Recent case and technology-specific evidence suggests that private (for-profit) firms are increasingly involved in the use of enabling technologies (Webb et al., 2018; Teece, 2018b), but little research has examined the enabling-technology trajectory of inventions developed by firms (Chesbrough & Appleyard, 2007; Appleyard & Chesbrough, 2017). Consequently, we ask in this study*: how enabling are the technologies developed by private firms*?

To address the research question, we evaluate the technology outcomes of over 30,000 public-private relationships and comparable private-firm-only efforts over a 21-year period from 1982 to 2002. We implement a hybrid Machine Learning - Propensity Score Matching approach to identify treatment-control pairs and to enhance causal inference. In the data, private firms' relationships with the public sector – that are traced using the government interest statement in patent documents–differ primarily by public-sector partner (i.e., who the firm partners with) and by relationship type (i.e., how the relationship is structured). We investigate variation in mission agencies vs science agencies as public-sector partners,[2] and include grants, contracts and cooperative-agreements as relationship types. Altogether, our data

[1] General-Purpose Technologies (Bresnahan and Trajtenberg, 1995) are defined as a high-end sub-set of Enabling Technologies, that is, those technologies that rise to have substantive cumulative economy-wide impact.

[2] We use Ergas (1987)'s definition of mission agencies as agencies with the goal of achieving programmatic, practical goals. Science agencies, in contrast, focus on scientific goals.

enables a comprehensive analysis of how private firms spawn enabling technologies.[3]

There are several contributions. First, we unpack how enabling the inventions created by private firms-with public partners or not- become in the long run. We find that public-private relationships that combine the breadth of exploration (agreements, grants) with deep exploitation in a particular domain (mission agency) are likely to be particularly conducive for enabling technologies. Interestingly, contracts - that agency theory designates as the most effective (see Bruce et al., 2019) - have weaker effects. For strategy, these results show that private firms can indeed create enabling technologies together with the government. Intriguingly, even when the government partner is a large end-user (e.g. mission agency) and potentially narrowly focusing on a particular commercialization (cf. Christensen et al., 2018), specific relationship types such as grants that offer greater latitude in the relationship can be a balancing force and serve as a starting point for an enabling technology trajectory.

Second, there are contributions to public policy. We add to the evidence that targeted government relations with private firms can support innovation (cf. Bloom et al., 2019). We particularly find evidence of the positive role of public-private relationships in generating enabling technologies. If the goal of policy is to support innovation that generates knowledge spillovers that enable growth within and across sectors, we have identified that agreements and grants with mission agencies in particular are aligned with this goal during the time period that we studied.

Third, there are contributions to how ecosystems evolve (Adner and Kapoor, 2016). We find that firms and their government collaborators can seed ecosystems with technologies that enable subsequent innovation by ecosystem participants and so shape how ecosystems evolve. More broadly, the results point in the direction that private firms, together with public partners, can be important in the evolution of ecosystems.

[3] Prior research often ties partner agency to relationship type but this is not necessarily accurate. For example, in our data, mission agencies are involved in contracts and agreements in ~80%, and in grants in ~20% of the cases, while in science agencies the numbers are reversed.

Finally, there are methodological contributions. We introduce a continuous *Enabling Technology Index (ETI)* and its components. Prior work has often examined specific enabling technologies, such as AI, but has yet to provide a continuous operationalization of enabling technology. Because every technology does, to some degree, enable future innovation, we introduce a continuous, tractable index that enables us to quantify enabling as a fundamental attribute of a technology. Given that many enabling technologies are rapidly generating new opportunities and strategic challenges for firms and their decision-makers, this index helps for example accurately track the potential of the firm's own efforts and those of the key organizations in the firm's ecosystem, including suppliers, competitors, collaborators, and complementors and their enabling technology potential.

Another methodological strength of our paper is a novel machine learning- propensity score matching (ML-PSM) method that enables enhanced causal inference for strategic management research (Rathje & Katila, 2019; Stuart & Rubin, 2008). Specifically, we build on advantages of supervised machine learning to intelligently expand the set of observable covariates in the matching process. The result is more precise treatment-control pairs, and a stronger push towards causality.

PRIVATE FIRMS, PUBLIC-SECTOR RELATIONS, & ENABLING TECHNOLOGIES

Prior Work on Public Sector Support of Private Firm R&D

Public sector governments have long worked in various capacities with private firms to enable R&D that benefits the society at large (Hall, 2005; Bloom, Van Reenen, and Williams, 2019). Public sector's support of private-firm R&D is based on two fundamental assumptions: (1) that the technical capabilities of for-profit firms are essential to knowledge production and economic growth, and (2) that the relatively high risk of funding high-impact, widely-usable innovation that is often of the most benefit to the society causes private firms to underinvest in them. Thus, policy makers hope to lower the costs of R&D for private firms in order to generate high-impact innovation-such as enabling technologies-that benefits not only the firm, but also other firms and the society at large.

Public sector typically uses three main types of arrangements to support high-impact R&D in private firms: university funding, tax credits, and R&D relationships. In many nations, public funding agencies fund *universities* and national laboratories to conduct scientific discovery. The results are fully disclosed and the hope is that scientific knowledge will spill over to private firms. The core idea is that this publicly available knowledge can encourage firms to further invest in developing high-impact (rather than more incremental) innovation (Jaffe and Lerner, 2001; Link, Siegel, and Van Fleet, 2011). Although not directly about enabling technologies, Azoulay, Graff Zivin et al (2019) illustrate this mechanism and find that a $10 million increase in NIH funding to academics in a research area lead to 2.7 additional patents filed by private firms. Altogether, university and national laboratory funding could thus potentially set off technology projects (including enabling ones) in private firms, but this mechanism is indirect and does not provide a direct subsidy for private firms.

Second, *R&D tax credits*[4] enable firms to decrease the cost of R&D and fund more projects, but, again, these public subsidies typically cannot be tied to specific projects. The risk is, then, that many credits are used for incremental R&D. For instance, Pless (2019) shows that tax credits increase R&D effort, particularly of small UK firms, but it is unclear whether the efforts will have wide-ranging impact. Balsmeier, Kurakina and Fleming (2018) also showed that while California firms' patents following the 1987 R&D tax credit are more highly cited by other firms--thus indicating greater public knowledge spillovers--tax credit also helped firms engage in actions that only benefit the focal firm, and not the community at large, like strategic patenting. Thus, similar to university funding, the impact of R&D tax credits is likely indirect at best, and thus uncertain.

Third, and most significantly for our paper, public sector engages in *public-private R&D relationships*.[5] In these public-private R&D relations, a public funding agency and a private firm jointly solve a complex, potentially high-impact technical problem (David, Hall, and Toole, 2000; Zúñiga-

[4] R&D tax credits are typically broad-spectrum while loans are more targeted. For example, the U.S. Federal R&D Tax Credit program on R&D expenditures covers up to 14% of *any* corporate expenditures on R&D. In contrast, federal loan programs are instituted by specific government sponsors to support specific areas of interest. For example, the U.S. Clean Energy Loan program guarantees 2% loans for B-rated firms, with loans as low as 0.375% for AAA-rated firms. The loans are granted only to firms who apply the loaned capital in the development of innovative technologies that meet the requirements as set by the public agency.
[5] The National Science Board (NSB) reported that over 60% of U.S. R&D spending is allocated to public-private R&D relationships (NSB, 2018; UNESCO, 2016).

Vicente et al., 2014), and the partner private firm often retains exclusive rights to the results (Bruce, de Figueiredo, and Silverman, 2019; Howell, 2017; Pahnke, Katila, and Eisenhardt, 2015).

Legislation typically establishes the types of R&D relationships that public sector has with private actors. In the U.S., The Federal Grant and Cooperative Agreement Act of 1977 established the distinctions between the three main types of R&D relationships: grants, contracts, and cooperative agreements. *Grants* are direct financial subsidies given to a firm by a public funding agency as an investment toward an objective specified by the agency (Congress, 1977). Grants are often used to advance a national objective, address a public problem, or to stimulate an activity desired by the government. Grants allow considerable latitude, and the grant recipient (i.e. the firm) often defines the scope of work because there are no legally binding requirements to achieve results (Rathje, 2019).[6]

By contrast, the second type of relationship, i.e. *contracts* are leader-follower relationships as the contracting agency is looking to procure a good or a service that will be of direct benefit to the government. In particular, a contract is a binding agreement between a buyer and a seller to provide goods or services in return for compensation (Rathje, 2019). Payments are often based on deliverables and milestones. Contracts also differ from grants because there is often a built-in customer. Although contracts can take many forms, the most common form is a cost-plus contract.[7] Public agencies use cost-plus contracts, as opposed to other contract forms, when they want to purchase an immature (i.e. potentially high-impact) end-product. To de-risk the firm's investment in a new technology with relatively uncertain development costs, the public agency agrees to pay both the entire cost of development and a standardized profit-margin. The profit margin may vary significantly depending on the risk of the project, but it generally stays small. For example, in the U.S., the maximum profit margin for a cost-plus contract is 15% (Arnold, Harmon, Tyson, Fasana, & Wait, 2008). Because they are commonly

[6] For example, in Pahnke et al.'s (2015) interviews, a National Institutes of Health informant described, "we are spending billions of dollars on projects – what are they producing? They produce knowledge. We fund inquiry. Following up after funding would question and undermine the whole system."

[7] Government agencies often switch between cost-plus, incentive-based, or fixed-price contracts depending on the level of technical maturity presumed in procured end-item (Ng, Maull, & Yip, 2009). Cost-plus is associated with the least mature technologies, while fixed-price is tied with the most mature products.

used for more immature technologies that involve patents, cost-plus contracts serve as the basis for our understanding of contractual relations between private firms and the public sector.

Third, *cooperative agreements* (agreements for short) are public-private relationships in which firms and public agencies agree to work side by side toward a mutual objective (Congress, 1977). They differ from grants and contracts by the degree to which the public and private entities are expected to cooperate post-award. In agreements, federal employees often are substantially involved in the execution of the work and participate closely in performing the work "side-by-side" with the private firm (Rathje, 2019). In contrast, federal agency usually takes on a purely monitoring and oversight role once, for example, a grant is awarded. Another difference is that agreements cannot be used to acquire goods or services for the federal government. They differ from contracts in that regard, and so often allow greater latitude in project scope. In cooperative agreements, the partnering firms and public agencies are free to determine their interaction pathways and schedules (Bruce et al., 2019; Ham and Mowery, 1998).[8] In other words, interaction between public and private researchers is required, but the format for interaction, unlike in contracts, is not specified ex-ante (Lerner, 2012; Mowery, 2009). Agreements can be attractive for firms because they allow collaborative, peer-to-peer working relationships between private firms and for example with a wide variety of highly capable national laboratory technical talent at low or no cost to the firm.

In general, research is inconclusive of the effects of public-private R&D relationships. Some research has found positive associations with high-impact innovation (Moretti et al., 2019; Azoulay, Fuchs, Goldstein, Kearney, 2018) while other studies have not found significant effects (e.g. Pahnke et al., 2015). Some recent work points in the direction that particular types of relationships could produce more high-impact innovation than others (Bruce et al., 2019). To sum up, whereas university-funding and tax credits are indirect, general ways of government subsidies, R&D relationships can be targeted to

[8] Other relationships that are similar to cooperative agreements but are more sparingly used include research consortia (Sematech in the U.S.; Consortium R&D project for Regional Revitalization in Japan (Nishimura and Okamuro, 2018)), innovation grand challenges, and NASA's crowd-sourcing platforms (Lifshitz-Assaf, 2017).

specific purposes and thus possibly to support enabling technologies, but their effectiveness is debated. This third category of government R&D subsidies, i.e. public-private R&D relationships, is the focus of this paper.

Gaps in prior work

To explain the occasionally conflicting findings of prior work, we focus on two major gaps in the study of private-public relationships: incorporating the variety of partner and relationship types.

Partner type. First, heterogeneity in public partner agencies deserves more attention (Dasgupta and David, 1994). Prior work has taken a homogenous view, or, focused on one agency at a time (Fuchs' 2010 work on DARPA; Howell's 2017 work on Department of Energy, Azoulay's 2019 work on NIH). This work does not pay attention to differences in partner agencies and how each agency's unique goals may impact the relationship. This is particularly significant for our paper because agency's goals are likely to influence the enabling technology trajectories that the relationship spawns. Distinguishing between different types of agencies is also significant because policy in many nations often treats agencies differently. Overall, our understanding of public-private relationships could benefit from more directly setting the agencies side by side.

The commonly-used distinction between mission and science agencies is likely to be relevant (Ergas (1987). Mission agencies are defined as programmatic agencies with the goal of achieving practical goals, i.e. they focus on "agency's mission". Ergas defines mission-oriented agencies as "closely synonymous with agencies whose goal is national sovereignty and who use radical innovations to achieve national goals and are often centrally managed" including DOD and NASA (aerospace, electronics) in the US. In contrast, science agencies including NSF, NIH and NIST are science focused (Ergas, 1987) and their goal is to provide the scientific freedom for private firms to pursue their own research goals. Another difference is that mission agencies often act as lead markets while science agencies will not.

Relationship type. Second, incorporating a full range of public-private R&D relationship types deserves more attention (Hiatt, Carlos, and Sine, 2017). By focusing on a single type of relationship in isolation--often grants--prior work is often agnostic to differences across relationship types.[9] However, different relationship types often involve very different structures of interaction between public and private organizations (e.g. grant is arms-length, but other relationships follow peer-to-peer or leader-follower structures; Flammer, 2018; Rathje, 2019). Altogether, as Bruce et al. (2019) note, considering the full range of types could be important for a comprehensive analysis of public-private relationships. Figures 1 and 2 summarize these differences that are likely to be meaningful for subsequent enabling technology trajectories.

--- Insert Figures 1-2 about here ---

Private-Public Relationships and Enabling Technologies

Core Components of Enabling Technologies. Building on Teece (2018a) we define enabling technologies as (1) pervasive, (2) novel and improvable, and (3) supportive to spawn complementary innovations. *Pervasive technologies* are those in wide use in an industry or with widespread application across multiple domains (Teece, 2018a; Gambardella et al., 2019). Take, for example, lidar. Lidar was created from a relatively simple concept—using light to measure distances between two objects (Neff, 2018). Today, the technology is used in a broad spectrum of application sectors from autonomous driving to guided weapons, and is therefore considered highly pervasive.

Second, enabling technologies are novel and capable of being continuously *improved*.[10] For instance, lidar has served as a foundational technology for many subsequent inventions, and these inventions have in turn spurred continual development in the core lidar technology. For example, mono-lidar was the fundamental technology enabling DARPA's 1985 Autonomous Land Vehicle, thought to be the world's first fully autonomous vehicle (Burns, 2018). Twenty years later, Ford engineers David Hall

[9] Grants are typically over-represented in prior work. For example, our analysis of published work in the past 30 years in journals in the intersection of private-firm strategy and public policy shows that almost 70% of articles on public-private R&D relationships focus on grants although less than 40% of the relationships are grants. We also found that grants were, on average, two to seven times more likely to be covered by each of the publications than contracts or collaborative agreements (i.e., 2.3, 7.4, 2.1, 4.7, in Strategic Management Journal, Research Policy, Management Science, and Academy of Management Journal, respectively).

[10] The concept of "capable of ongoing improvement" (e.g. Bresnahan and Trajtenberg, 1995) is also frequently used. We use novelty, given its wide-spread use and conceptualization in the R&D literature.

and Jim McBride introduced rotating lidar in DARPA's Grand Challenge, capturing lidar measurements in stereo. This advancement was widely acknowledged to be one of the most important catalysts for the creation of today's autonomous vehicle market (Kumar, 2018). Because lidar is capable of ongoing improvement and is consistently introduced in new ways, it is considered a novel and improvable technology.

Third, enabling technologies spawn uniquely *complementary innovations*, i.e. they support future innovations which cannot be supported by other supplementary technologies. For example, since lidar first flew into space in the Apollo 15 mission, dozens of lidar-based atmospheric, mapping, and communication satellites have been created and launched, paving the way for the thriving commercial satellite business of today.[11] Further, after significant technological codification and improvement, several consumer-oriented products such as the laser-based police speed gun were spawn from the original technology.

Given the attributes of enabling technologies, prior research has noted that designing a business model to capture value from enabling technologies is challenging (Arrow, 1962).[12] Because enabling technologies are intermediate inputs in the value chain, they are often commercialized by downstream firms with the required complementary assets (Teece, 2000; Teece 2018a). A prime example is the invention of float glass that drastically reduced the production cost of glass, and facilitated downstream innovations such as flat panel displays. But as Teece (2000) documents, the inventor, Pilkington Glass, received only about 5% of the benefits while the social rates of return of this new enabling technology were around 30%. In other words, pioneers in an enabling technology risk capturing only a fraction of the value that was created. This suggests that private firms may underinvest and that private firms' *joint*

[11] Lidar was primarily used in scientific experiments until the late 1980s, with the exception of military operations. The first recorded use of lidar in the military was in 1972. The "Pave Knife" laser guided bomb was used to destroy the Dragon's Jaw bridge at Thanh Hoa during the Vietnam War (Neff, 2018).

[12] Macro analysis shows that social returns from enabling technologies are two to seven times greater than private returns (Hall, Mairesse, & Mohnen, 2010; Lichtenberg, 1992). Similarly, research finds that licensing models almost always undervalue enabling technology, thus leaving much of the value with other firms—e.g., suppliers, manufacturers, competitors (Arrow, 2012). One-way knowledge leaves firms is negative knowledge spillover, in which the same collaborative R&D that leads to enabling technology development may transfer tacit knowledge external to the organization, bleeding the firm of future rents.

efforts with the government may be particularly relevant for spawning enabling technologies. Therefore, understanding how private firms are associated with enabling technologies, both together with, and without the public sector, becomes important.

HYPOTHESES

Hypotheses that follow focus on how private firms' relationships with public agencies vs the private firm's efforts alone can potentially lead the invention into a trajectory that becomes enabling. We also propose differential effects by public partner type.

Enabling Technology and Public-Private Relationships

In H1 we propose that private firm relationships with public partners have a positive impact on enabling technology emergence. First, we expect public-private relationships to be more positively associated than private-firm-only efforts with how widely the technology becomes used, i.e. pervasiveness. Technologies become pervasive through widespread application. Because the intention of public-private relationships is to ensure widespread public benefit, we expect that the relationships are likely to spawn technology that is more accessible and applicable to a broader set of segments than private firm's efforts alone. One example of potential pervasiveness is relationships between private firms and the public sector that are organized through grants. Given that grants are often based on public calls for proposals, grant applications are put out for peer review, and grant applications and final reports (at least the abstracts) are publicly available, it is likely that others can more readily build on the ideas that result from grants. Furthermore, because the data and results are encouraged to be widely disseminated (e.g., data transparency rules by NSF), we expect that inventions that result from grants can become widely used as stepping stones for new inventions and technologies thus fostering enabling technology trajectories. Cooperative agreements, in turn, can similarly increase pervasiveness because diverse R&D teams are involved (Helpman & Trajtenberg, 1994). This is because the underlying expertise in using the technology is shared across a broader set of inventors and thus likely to become accessible to and applied in a broader set of technology sectors. We thus expect that tacit knowledge of any resulting technology would permeate both the partnering agency and the firm ecosystem. Finally, although contracts are designed for a specific procurement purpose, we still expect them to spawn more pervasive innovations than private firm's efforts alone because a public-sector partner and joint efforts to make technology better understood are involved.

Second, we propose that technologies developed together with public sector partners have more potential to spawn complementary innovations than technologies developed without them. Because complementors must invest significant internal resources in learning and codifying the technology before they can take advantage of it (Teece, 2018a), having the "general public" or even a particular government agency as a default customer can be particularly helpful. For example, in contract relationships, the public procuring agency can not only act as a large lead market for enabling technologies, but also provide translational help in codifying tacit aspects of the technology for potential builders of enabling technology (cf. Arora, Fosfuri and Gambardella, 2001), thus shepherding the technology past the "valley of death" by supporting the rise of complementary technologies (David & Hall, 2000; Ahuja & Katila, 2004). Similarly, in cooperative agreements, teams that work together often include a mix of scientists and lead user practitioners which facilitates the understanding of any tacit knowledge related to the technology, and the creation of complementary innovation. While the role of the government partner is more limited in grants, grant recipients are typically asked to reflect on and outline "broader impacts" for research, which can facilitate spawning of complementary innovations relative to private firm's efforts alone.

Third, we expect that the diversity in the "team" in relationships with a government partner– relative to efforts by the private firm on its own–is likely to produce novel and improvable technologies. By definition, in the public-private R&D relations, the goal of a public agency and a private firm is to jointly solve a complex technical problem, thus increasing the diversity of perspectives (and resources) that are brought to bear on problem-solving. Cooperative agreements are particularly likely to involve diverse, interdisciplinary teams (e.g., private firm's working relationship with a national laboratory) and thus likely to use more varied knowledge that often underlies novelty (Katila, 2002). Grants and contracts also involve interactions with public funding partners and the focal firm that can be conducive to diversity in viewpoints and thus novelty. Past research also shows that teams that cross technological or geographic boundaries may increase an outcome's novelty (Ahuja & Lampert, 2001; Phene, Fladmoe-Lindquist, & Marsh, 2006) thus potentially increasing the likelihood that the technology created in public-private relationships becomes enabling. Altogether, we expect public-private relationships to have a positive impact on enabling trajectory of the technologies:

H1. Technologies that are a result of a private firm's relationships with the public sector become more enabling than technologies that are a result of a private firm's efforts alone.

Enabling Technology and Mission vs Science Agency Partners

In H1, we treated all public-private R&D relationships as homogenous and compared their effects to private-firm-only efforts. In H2, we propose that there may be differences across types of public partners – we focus on science vs mission agencies in particular- that potentially make some relationships even more likely to start enabling technology trajectories than others.

As noted above, *science agencies* including the National Science Foundation (NSF) and the National Institutes for Health (NIH) in the U.S. are science focused (Ergas, 1987) and aim to accomplish scientific goals. Science agencies also typically have access to substantial research funding internally and employ intramurally a wide variety of scientific personnel. They also own important national laboratory space, including sought-after capital-intensive research infrastructure. For example, in the U.S., science agencies control the vast majority of national user facilities, i.e., government-owned laboratory environments used by academic, government, for-profit, and not-for-profit organizations. Thus, science agencies are well equipped to support private firms' R&D activity with the intent of furthering scientific aims.

Mission agencies including the Department of Defense (DoD) and National Aeronautics and Space Administration (NASA) are, conversely, generally built to support a national externality, e.g., national security, or space travel. Their mission is to fund and purchase technology to accomplish these practice (aka mission) oriented goals. Mission agencies also differ from science agencies because they can typically provide access to "lead users" within government who can apply the novel technology to mission needs.

We argue that science agencies are more likely than mission agencies to serve as starting points for enabling technology trajectories for several reasons. Given the in-house research infrastructure, relationships with science agencies can likely support projects that cross geographical or technology boundaries and help firms engage diverse, interdisciplinary teams thus likely increasing technology's pervasiveness. Because science agencies often support deep knowledge search and help overcome underinvestment in certain R&D areas, they are also likely associated with more novel technologies. We also expect relationships with science agencies to enhance complementarity because science agencies often encourage translational efforts across sectors, not only in a specific sector. Because these attributes are associated with more enabling technologies, as noted above, it is likely then that private firms' relationships with science agencies can more positively influence the enabling trajectories of technologies than relationships with mission agencies. In contrast, the norms and goals of mission agencies are to fund demand side innovation by incentivizing the delivery of products (Edler & Georghiou, 2007; Nemet, 2009), which may limit pervasiveness, novelty and wider complementarity beyond the mission agency's lead market. We propose:

H2. Technologies that are a result of a private firm's relationships with science agencies become more enabling than technologies from relationships with mission agencies.

METHOD

Sample and Data Sources

The dataset is the full population of U.S. patented technologies assigned to private firms between 1982 and 2002. We begin the sample in 1982. This allows sufficient time for the Federal Grant and Cooperative Agreement Act (1977) that established the three standard public-private R&D relationship types (grants, cooperative agreements, contracts) to become institutionalized. We end the sample in 2002 to allow sufficient time for patent outcomes to be well understood. The final sample is 1,862,045 private-firm assigned patented technologies, 33,130 of which were the result of a public-private R&D relationship.

We chose to analyze patented technologies as they provide a useful, perhaps best, representation of private firms' technical problem-solving efforts over time (Jaffe & Trajtenberg, 2002; Katila & Ahuja, 2002). Patents by definition are both a detailed description of a complex technical problem and a solution to that problem (Walker, 1995), and must be non-trivial, original, and useful, making them a particularly appropriate data source.

We focus on patents granted by the United States Patent Office, compiled by USPTO's PatentsView.org. We utilize the complete database. These data were further cross-referenced with Google's Patent Search. Google's Patent Search was used to specifically rectify the missing dates from <1% of the PatentsView data. By combining PatentsView and Google Patent Search datasets, the final dataset includes the full population of patents and patent citations over the 30-year span, containing 4,218,252 unique patents. To focus on private firms, we further removed 1.1M patents that had no assignee (i.e. patented by an individual and not an organization) or were assigned to public organizations.[13]

We use the *federal interest statement* in patent documents to distinguish private-firm only efforts from those with the government. We supplement the USPTO data with federal contract information from USASpend.gov and cross-referenced with Google's Patent Search. Firms that file a patent in the U.S. are legally obligated to file a federal interest statement that outlines if the patent was a result of a public-private relationship. "The contractor or grantee…in applying for a patent…must add a government interest statement that discloses the government's rights to the invention" (GAO/RCED-99-242 Federally Sponsored Inventions, United States General Accounting Office, 1999: 4).

[13] We wish to thank an anonymous reviewer who noted that the focus of the data naturally limits the generalizability of our findings to private-firm inventions, and to those that are patented. For instance, future work could expand to compare to inventions that are a result of intramural efforts of the federal government. And while patented inventions are important to examine in their own right, future work could also expand the analysis to inventions that are not patented.

The federal interest statement also contains other details about the relationship, including relationship type and partner agency. Rai and Sampat (2013) find that the federal interest statements in patents are a much more accurate data source than the records maintained by the government itself (e.g. iEdison). They further note that organizations are much more likely than individuals to comply with the requirement to note federal interest, therefore making the data source appropriate for our data on firms. Corredoira et al (2018) further review court cases that show that underreporting of government sponsorship undermines the inventor's legitimacy of ownership interest in patent infringement cases involving third parties, disincentivizing hiding government interest in a patent. Failure to properly report federal funding in patent documents may lead to a forfeit of the patent title to the government, or "withholding of additional grant funds" (Corredoira et al., 2018).

Statistical Methods

We use a quasi-experiment to test the association of enabling technologies and public agency relations of private firms. A critical challenge in the comparison of private-only and public-private technologies is selection bias. An ideal approach would be to conduct an experiment by randomly assigning problems for different types of organizations and their partners to solve. As a result, selection bias would be eliminated. Unfortunately, a grand experiment of this kind is unavailable. We therefore rely on a three-step process to construct quasi-experimental conditions.

Step 1. Propensity Score Matching with Machine Learning. Matching is particularly important for a study on public-private relationships for several reasons. Azoulay et al. (2019) note that public partners may target research areas with the most potential for follow-on innovation, which could lead to a correlation between public relationships and enabling technology (patent) outcomes even if public investments were unproductive. Similarly, the complex problems solved by public-private relationships could be inherently different from the problems solved by many private firms acting on their own, and could again significantly bias the results. Matching methods attempt to address this selection bias by "controlling" for these pre-existing differences across "treated" and "control" groups (Stuart and Rubin, 2008) by identifying subsamples that are balanced with respect to observed covariates.

Coarsened exact matching (CEM) and Propensity-score matching (PSM) help address endogeneity concerns by matching treated (public-private) and controls (private-firm only) on all potentially observable confounding covariates (Rosenbaum and Rubin, 1983; Stuart and Rubin, 2008). To implement propensity-score matching, researchers typically subjectively select a set of potentially confounding covariates. Next, they use the set of confounding covariates (technology class, application year, and grant year of patents is the standard set of covariates used in patent studies; Jaffe et al., 1993; Trajtenberg et al., 1997) to generate each patent's probability of being selected into treatment – i.e., propensity score – often using logistic regression, and match patents in the treatment and control groups with similar scores. Recent research has pointed out, however, that relying on a limited set of covariates leaves researchers unable to adequately control for selection bias (Antonakis et al., 2010; Hamilton & Nickerson, 2003).

In response, we expand the confounding variable set used for matching significantly. Specifically, we use geographic location, number of inventors, and patent examiners in addition to the 3 standard covariates mentioned above (technology class, application year, and grant year), as well as their interactions.[14] Given the expanded set of confounding covariates, however, traditional PSM methods break down.[15] Second, larger amounts of covariates increase the likelihood of overfitting which can increase bias (Caliendo & Kopeinig, 2008). Overfitting can be particularly damaging because relying on overfit propensity scores can result in inflated standard errors, i.e., lack of precision (Schuster, Lowe, and Platt, 2016), over or under-estimation of the second-stage effects (Cepeda *et al.*, 2003), or lead to

[14] Patent examiners in particular are an important covariate to include in the matching process. Patent examiners are coded as a discrete variable at each patent examiner name (first_last). Patent examiners are responsible for reviewing patent applications and adding patent citations when necessary. Examiners are considered potentially confounding variables as (1) they are assigned to evaluate specific technologies for which they have unique expertise (Righi & Simcoe, 2019) and (2) vary greatly in their propensity to add patent citations (Alcácer & Gittelman, 2006). Since patent examiners may, therefore, serve as both highly correlated with treatment and outcome, they are included. There are 26,698 patent examiners and 496 technology classes in the data.

[15] Absorb command in stata is an example of a computational trick that makes regressions computationally manageable with a large number of dummy variables (see also Athey & Stern, 2002). However, the advance of ML methods is particularly in their usefulness to identify potentially significant interactions that may be confounding (e.g. potential interdependency of patent examiners, technology class and team size). Thank you to an anonymous reviewer for pushing us to clarify this.

“paradoxical associations” (i.e. significance in the wrong direction) (Concato, Feinstein, Peduzzi, Kemper, & Holford, 1996: 1373).

In response, we implement a hybrid Machine Learning - Propensity Score Matching approach. Specifically, the ML-PSM method incorporates three tenants of supervised machine learning to overcome limitations. First, *advanced stochastic optimization* overcomes intractability by exploiting online optimization, allowing us to include a much larger pool of potentially confounding dimensions. Second, *regularization* and *cross-validation* enable us to avoid overfitting. Regularization re-weights "unconfounding" covariates (i.e., those which do not influence selection) to zero and therefore removes them from the regression. Cross-validation splits the sample between “training”, “validation”, and “test” sets, using the split sample to tune the regularization and model parameters such that the most accurate predictions can be generated. Combining these approaches, we substitute traditional logistic regression for a supervised machine learning approach to calculate patent propensity scores.

Next, we construct a subset of control patents with sufficiently high propensity scores (the “matching sample”) such that they resemble the patents which were the outcomes of public-private relationships, except for receiving the treatment. To determine which propensity scores were high enough for inclusion in the matching sample, we used a global optimum nearest-neighbor matching algorithm, matching one-to-one without replacement. Given that there were over three million "control" patents to choose from, a fully matched sample can be generated (i.e., each treated patent is matched with a control). Robustness checks on various caliper[16] matching distances were run, per standard practice. The fully matched sample includes 66,260 patents, 33,130 of which are the result of a public-private relationship.

Step 2. Matched samples. We then analyzed the effectiveness of the matching. The effectiveness of the methodology to generate like distributions of technologies for treated (public-private relationship) vs control (no relationship) groups is illustrated using propensity score distribution overlap, in logit form.

[16] Caliper distances are defined as the maximum radius under which two variables are considered a "good match." For our strictest test, we use 0.02 multiplied by one standard deviation of the distribution of all matching distances (Austin, 2011), because matching with additional neighbors may increase the bias, since additional neighbors will necessarily be worse matches.

Pre-match, nearly two-thirds of the control group is not matched by the treatment group. Post-match, the distributions are almost identical. Further evidence of balance across treatment and control groups is found using distributional difference in covariates pre- vs. post-match (figures available from the authors).

Step 3. Regression Models. Using the matched sample, we then use OLS and negative binomial regressions to analyze the impact of relationships and partner agencies on enabling technology trajectories. We included fixed effects for application year, location and technology. As U.S. patent technology categories were updated across all year groups at the same time, technology remains constant within time, and year-technology interaction effects are unnecessary.

Measures

Dependent Variable: Enabling Technology. We measured enabling technology by an *Enabling Technology Index.* In order to construct the *Enabling Technology Index*, we operationalize three components of enabling technology (pervasiveness, novelty, complementary innovations) using patent data as described below.

To construct the Enabling Technology Index, pervasiveness (i.e. how wide-spread the technology becomes across multiple domains; Hall & Trajtenberg, 2006) is measured by the breadth of technical fields in which the focal patent is subsequently cited. Three-digit US patent classes are employed to measure technical fields. Citations within 15 years of the patent's grant date are used. Breadth of technical fields is measured using a Herfindahl index that ranges from zero to one (Trajtenberg et al., 1997). The greater the breadth, the more widespread the impact of the focal technology.

Novelty (i.e. the ability to be improved upon over time)[17] is measured by the breadth of technical fields of backward citations (backward citations are the patents which are cited in the focal patent). While many measures of novelty exist (Verhoeven, Bakker, & Veugelers, 2016), we utilize the well-accepted approach of Trajtenberg et al. (1997) and measure novelty by the breadth of knowledge that is cited by

[17] Trajtenberg et al. (1997) use the labels of generality and originality, respectively, for pervasiveness and novelty.

the focal patent. Novelty is calculated using a Herfindahl index and ranges from zero to one, with a score of one indicating maximum novelty. As above, technical fields are operationalized using three-digit US patent classes.

Complementarity is measured by the ratio of forward citations (citing patents) which uniquely cite the originating patent, and not its predecessors (Funk & Owen-Smith, 2017). By utilizing the local network properties of the focal patent, the complementarity measure captures the change in citation patterns of future technologies given the introduction of the focal patent.[18] If the focal patent becomes the sole patent cited by future technologies, then the technology is completely unique in supporting complementary innovations and receives a score of 1. In contrast, if the citation patterns are reinforced, and all new technologies cite both the focal patent and its predecessors, then the technology is seen as consolidating, and receives a score of -1. We calculate the index of unique complementarity at 15 years after patent's grant date. Larger values indicate greater levels of unique complementarity.

Enabling Technology Index (ETI) is calculated by loading each factor (pervasiveness, novelty, complementarity) onto a single factor using factor analysis (varimax with oblique rotation, eigenvalue >1, Cronbach's alpha > 0.7). For each patent, the resulting Enabling Technology Index is mean-centered at zero.

In order to construct the Enabling Technology Index, patents that did not receive any forward citations were excluded. To incorporate these patents in the analysis, and to provide a simple count-based measure of the general importance of the technology, we coded an alternate outcome variable, citation-weighted patents – an often-used indicator of technology importance (Bloom, Schankerman, and Van Reenen, 2013). Patent classification and year fixed effects normalize the measure. We discuss these results using Importance of technology as an outcome variable in robustness.

[18] $Unique\ Complementarity = \frac{1}{n_t}\sum_{i=1}^{n}\frac{-2f_{it}b_{it}+f_{it}}{w_{it}}\ , w_{it} > 0$ where n_t is the number of forward citations of both the focal patent and its predecessors, f_{it} is a 1 if a new patent cites the focal patent, b_{it} is a 1 if a new patent cites the focal patent's predecessors, and w_{it} is an optional weighting parameter which indexes a matrix W of weights for the focal patent, i, at time t. For simplicity, in our analysis w_{it} = 1. See Funk and Owen-Smith, 2017.

To take into account patents that receive no citations, we also ran a two-step Heckman analysis that attempts to take into account treatment effects (i.e. particular government relations could fly under the radar, or in contrast be particularly widely disseminated, possibly influencing whether a particular invention is subsequently cited; cf. Gross, 2019). Results were consistent. Because OLS performs better than the Heckman method when finding a valid exclusion restriction is challenging (Wolfolds and Siegel, 2019), we report OLS as the main analysis.

Independent Variables

As noted above, we use the mandatory federal interest statement in private firms' U.S. patents to code whether a public-private relationship underlies a technology (Bruce et al., 2019; Flammer, 2018; Selsky & Parker, 2005). We define a *public-private relationship* to exist for a patented invention if a federal interest is reported in the patent document, indicating that a tie between a public agency and a for-profit firm existed to exchange resources (e.g., financial, infrastructure, research support) and to create a mutually desired R&D outcome, i.e. the patented technology.

We use the details provided in the federal interest statement to distinguish between three types of public-private relationships. *Grant* is a binary variable that takes a value of one if the patented technology was the result of a grant-based relationship. *Contract* is a binary variable that takes a value of one if the technology was the result of a procurement contract. *Agreement* is a binary variable that takes a value of one if the technology was the result of a cooperative agreement (Congress, 1977).

We use the details provided in the federal interest statement to distinguish between two types of agency partners. *Mission agency* is a binary variable that takes a value of one if the patented technology was a result of a relationship with the Department of Defense (36% of public-private relationships in the original data) or NASA (8%). *Science agency* is a binary variable that takes a value of one if the patented technology was a result of a relationship with the NIH (23%), the NSF (10%), or the National Institutes for Standards and Technology (NIST) (.5%). The remaining category is *Other,* i.e. hybrid agencies that often share both science and mission goals (e.g. Department of Energy, 1.8%; Department of Agriculture .4%).

Controls

We control for the count of *backward citations* in each patent because fewer citations may indicate less crowded (and less mature) fields with more room for follow-on innovation (Scotchmer, 2004). We control for *number of inventors* measured by the count of the total number of inventors listed on the patent application. Larger teams working on a patentable technology likely have a larger network with which to share the innovation and more significant access to additional resources, such as knowledge and funding (Jaffe et al., 1993).

We control for the *geographical location* because local infrastructure, cultural differences, and proximity to inventor networks can influence knowledge spillovers and propensity to cite (Jaffe, Trajtenberg, & Henderson, 1993). Location is defined by the categorical variables state and country at the time of invention. We control for the three-digit patent *technology class* (USPC) for each patented invention using dummy variables to take into account differences in technology fields including the propensity to cite, build patent thickets, and protect intellectual property (Mansfield, 1986; Cohen et al., 2000). There are 496 technology classes in the data.

We include fixed effects for patent *application year* to control for technology sector dynamism, and tools and technologies available for subsequent innovators. We also control for *time-to-grant*, measured by the number of years from filing to grant of a patent, to account for time-variant changes in the Patent Office such as changes in the examination processes or possibly even the underlying complexity of the patented technology not controlled for otherwise, which may affect follow on innovation. We also control for *patent age,* measured by the number of years since a patent was granted.

RESULTS

Table 1 includes descriptive statistics and correlations. Table 2 presents the high-level associations of *enabling technology* and public-private relationships. Private-only is the omitted category. Samples before matching (models 1-2) and post machine learning-PSM matching (models 3-4) are reported for comparison. Models 2 and 4 both indicate that public-private relationships are associated with technologies that start a more enabling trajectory in comparison with the private firm's efforts alone, supporting H1.

Table 3 includes the analyses by public agency (models 1-3) to test H2. Consistent with table 2, the results show that public-private relationships have greater associations with enabling technology trajectories of technologies than private firms acting on their own, again supporting H1. However, we do not find support for H2 that predicted that science agencies as partners would result in more enabling technology trajectories than mission agencies. In fact, we find the opposite. In model 3, mission agency relationships relate to slightly more (not less) enabling technology than science agencies, thus contradicting H2.

Given the unexpected results regarding H2, Table 4 and table 5 further split the analysis by science vs mission agency, respectively, to examine the possible differences across contracts, grants, and cooperative agreements within each agency relationship. While Model 2 in both of these tables indicates that both science and mission agency relationships have a similar positive association with enabling technology trajectories (private-firm only efforts are the baseline), Model 6 shows that mission agencies engaged in cooperative agreements have the strongest positive association with enabling technology (table 5), while grants in science agencies also have positive but relatively weaker effects (table 4). Thus, *particular* types of relationships with mission agencies are particularly likely to be starting points for enabling technology trajectory which could explain the unexpected results regarding H2 above, i.e. why we find that mission agencies rather than science agencies are more likely to spawn more enabling technologies. We return to this intriguing finding in the discussion.

--Insert Tables 3-5 about here--

Robustness tests. We ran several robustness tests to increase confidence in our findings. We first bolstered confidence in our dependent variable measure. Prior work argues that private firms are *less* likely to capture value from enabling technologies (Teece, 2006, 2018a; Chesbrough and Appleyard, 2007). We thus expected our dependent variable, i.e. the enabling technology index to have a negative relation with value capture. Using knowledge spillover “reabsorption” (Belenzon, 2012) to measure value capture, our expectation is strongly confirmed (results available from the authors), thus increasing confidence in our dependent variable measure.

We then used an alternate dependent variable, i.e., Importance of technology measured by counts of forward citations (i.e. citations made to the focal patent by subsequent patents, both with and without self-cites) (Griliches, 1990). As a dependent variable, the sheer number of forward citations captures a different aspect of technology, i.e. its knowledge impact (in contrast, ET index captures the enabling technology impact). Using Importance of technology as the dependent variable, the results differ from our original ones, as expected. Grants and science agencies now have the largest positive coefficients, reflecting that they spawn highly-cited technologies captured by the forward citation counts. Altogether, these alternative tests indicate that our dependent variable, i.e. the enabling technology index indeed captures a distinctively different trajectory of a technology than other measures.

Finally, we split the enabling technology index into its three components, i.e. pervasiveness, novelty and unique complementarity (cf. Hall and Trajtenberg, 2004), and used each as a dependent variable. The results provide further confidence in our original findings: Grants, and science agencies engender higher levels of novelty, while mission agencies engender more complementary innovation which further helps parse out the main findings (results available from the authors).

DISCUSSION

Despite the rise of interest in enabling technologies, our understanding of the role of private firms in enabling technology development is limited. We started the paper with the question of how enabling are the technologies developed by private firms with and without public sector partners. Using machine learning matching, we compared technologies generated from over 30,000 public-private relationships with comparable technologies invented by private firms alone during a 21-year period. Our results shed light on this important strategic option for firms.

First, our results help unpack the enabling technology trajectories of inventions created by private firms. The findings show that technologies that are a result of private firms' relationships with the public sector - in particular cooperative agreements with mission agencies (NASA, DoD) - have a stronger association with enabling technology trajectories than private firm's efforts alone. Interestingly, contracts - that agency theory traditionally considers as the most effective - have weaker effects. The new *Enabling*

Technology Index that we introduce to measure enabling technology helps us quantify the firm's strategic decisions about enabling technology. Overall, firms are involved in enabling technologies in unexpectedly many ways, warranting a study on this increasingly important option for strategists.

Our findings also challenge two assumptions widely held about enabling technologies. The first assumption is that enabling technologies have their origins only in the public sector. The second assumption is that enabling technologies originate with science agencies. Our findings challenge both assumptions. First, as noted above, we find that private firms have an important role in enabling technology creation. Second, we contradict the belief that mission rather than science agencies may not adequately support the development of enabling technologies, but rather support narrow exploitation, given that the mission-oriented end-user would potentially narrowly focus the project towards a particular commercialization (cf. Christensen et al., 2018). Our results indicate a more nuanced interpretation. Mission agencies have the strongest overall effect when collaborative agreements are used. It seems that when the relationship type (agreement) affords more latitude, knowledge exchange, and diversity in teams with mission agency participation, technology is sent to an enabling technology trajectory. Access and joint peer relationships with mission agency partners may thus be particularly important because they likely give the firm a better understanding of the customer's unique and specialized demands—demands that may not easily be summarized in public communications from the government, such as the Statement of Objectives (for contracts). This reduced information asymmetry inherent in agreements may thus enable customer relations with the mission agency, instead of falling into a "valley of death." Overall, these results suggest that a balance of exploratory and exploitative components in a relationship may be most beneficial.

Another unexpected results was that we did not find contracts to be particularly helpful for enabling technology trajectories. One reason may be that relationships between private firms and the public sector that are organized through contracts have a pre-specific format that often involves formal channels of communication between public and private researchers in order to cement access and insight into the firm's R&D process. Contracts may thus be effective for generating prespecified types of knowledge tailored to the relationship but less helpful for enabling technologies that gain widespread use. The norms of interaction are instantiated by public agencies primarily to reduce the risk (agency costs) in the investment. This structured interaction would explain the limited positive impact of contracts on more high-impact, enabling technology. For example, in contracts, public and private researchers are assigned roles that force them to collaborate throughout the R&D process towards a specific procurement need. In other words, the public partner controls the R&D process for a specific procurement purpose, and the developed technology is possibly then less likely to be targeted for widespread use. This can limit the technology's pervasiveness. The constrained R&D process inherent in contracts will also most likely result in less novel technologies than if less restrictive types of relationships were used. Note that this may be true even if the firm had proposed to develop a more novel technology in their response to solicitation, given the restricted freedom inherent in the structure of the contract relationship, again explaining the more limited impact of contracts on enabling technologies.

The findings are also significant for public policy as they add to the evidence (e.g. Bloom et al., 2019) that targeted government relations with private firms can support enabling technologies. We particularly find the positive role of public-private relationships that generate technologies that become enabling for subsequent inventions in many sectors. If the goal of policy is to support private-firm innovation that generates spillovers that enable growth across sectors, we have identified that particular government research relations with private firms (grants, cooperative agreements, and particularly with mission agencies) are aligned with this goal.

Our results also add to the evidence about how to build technology ecosystems. We find that firms and their government collaborators can seed ecosystems with technologies that enable subsequent innovation by ecosystem participants and so shape how ecosystems evolve. More broadly, the results point in the direction that private firms, together with public partners, can be important in the creation of technology ecosystems.

Like all research, these findings should be interpreted with usual caution, and as such open up several intriguing opportunities for future work. While we focused on patented technologies, one possibility is, like Murray (2010) noted, that projects with science focus would have a lower propensity to patent in the first place. If this propensity would be particularly likely for example in grant and science agency relationships, it could potentially underestimate the grants' impact on enabling technologies if the projects that are missing would be of high ET potential. Since we find a positive relation of grants and science agencies with our data, this type of missing data would be unlikely to qualitatively change our interpretation of the findings. However, if we are missing the least promising projects, i.e. the low end of the distribution because they are not patented, and so overestimate, findings could be affected. There is however no clear theoretical reasoning why grantees would be likely to not patent projects with low ET value (one would actually expect the opposite because ETs are difficult to capture value from). Nevertheless, these issues at the intersection of public policy and private firm R&D present several interesting opportunities for follow-on work.

Finally, we also provide a methodological contribution by introducing a novel machine learning propensity score (ML-PSM) method. Extending the work that applies machine learning in strategy and economics (Athey and Imbens, 2015; Illari, Russo, and Williamson, 2011), we employed a new inference strategy that applies machine learning to matching. The machine learning techniques applied in this paper allow scholars to simultaneously increase efficiency and avoid overfitting, minimizing the potential for selection bias.

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Figure 1. Public Agencies

Classification	Definition	Examples	Contribution
Science	Goal is to increase scientific knowledge and understanding	National Science Foundation, National Institutes of Health	Freedom for scientific inquiry
Mission	Goal is to fulfill practical goals for the agency such as procure technologies	Department of Defense, NASA	Early monopsony buyer

Figure 2. Relationship types

Classification	Definition	Public-Sector Contribution
Grant	No required direct interaction with public researchers	Financial resources
Contract	Required interaction with public researchers. Format for interaction is specified ex-ante	Financial resources, Structured knowledge flows
Agreement	Requires interaction with public researchers. Format for interaction is not specified.	Financial resources, Diverse (i.e., public-private) R&D teams

Table 1 Descriptives and Correlations.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Enabling technology index	0.11	0.94										
2. Public-private relationship	0.50	0.50	0.02									
3. Contracts	0.25	0.43	0.0003	0.58								
4. Agreements	0.01	0.11	0.01	0.11	-0.03							
5. Grants	0.13	0.34	0.04	0.38	-0.15	-0.01						
6. Mission agency	0.13	0.34	0.01	0.39	0.52	0.04	-0.03					
7. Science agency	0.09	0.29	0.03	0.31	-0.09	0.04	0.61	-0.12				
8. Time to grant	2.61	1.54	0.10	-0.05	-0.07	0.02	0.12	-0.03	0.11			
9. Patent age	19.81	8.21	-0.13	0.26	0.19	-0.03	-0.03	0.13	-0.05	-0.39		
10. Number of inventors	2.45	1.65	0.05	0.01	0.01	0.05	0.08	0.00	0.06	0.15	-0.24	
11. Number of backward citations (logged)	1.77	1.09	0.04	-0.16	-0.06	0.04	-0.03	-0.04	-0.04	0.20	-0.45	0.14

Table 2. OLS Predicting Enabling Technology Using Pre-Match vs. Post-Match Samples

DV: Enabling Technology Index	Pre-Match		Post-Match	
	(1)	(2)	(3)	(4)
Public-Private Relationship		0.113***		0.103***
		(0.102, 0.123)		(0.088.0.117)
Time-to-Grant	0.037***	0.036***	0.015	0.013
	(0.032, 0041)	(0.031, 0.041)	(-0.009, 0.039)	(-0.011, 0.037)
Patent Age	-0.012***	-0.012***	-0.019	-0.021
	(-0.016, -0.007)	(-0.017, -0.007)	(-0.043, 0.004)	(-0.044, 0.002)
Number of Inventors	0.003***	0.002***	0.003	0.002
	(0.002, 0.004)	(0.002, 0.003)	(-0.001, 0.008)	(-0.003, 0.0126)
Intercept	-2.586***	-2.548**	0.245	0.310
	(-4.195,-0.978)	(-4.156, -0.940)	(-2,943, 3.432)	(-2,873, 3.493)
R-squared	0.165	0.166	0.163	0.166
Adjusted R-squared	0.165	0.165	0.156	0.159
N	1,862,045	1,862,045	66,260	66,260

*p<0.05; **p<0.01; ***p<0.001; **Fixed effects for Application year, Location, and Technology class are included in all models.**

Table 3. OLS Predicting Enabling Technology: Split by Agency

	(1)	(2)	(4)
Intercept	3.457*	3.565*	3.581*
	(-0.397, 7.311)	(-0.283,7.414)	(-0269, 7.430)
Public-private relationship		0.102***	
		(0.081,0.124)	
Mission			0.104***
			(0.079,0.129)
Science			0.101***
			(0.070,0.132)
Time-to-grant (Years)	-0.010	-0.013	-0.013
	(-0.045, 0.026)	(-0.049,0.022)	(-0.049, 0.022)
Patent Age (Years)	-0.051***	-0.052**	-0.052**
	(-0.086, -0.016)	(-0.087, -0.017)	(-0.087, -0.017)
Number of Inventors	0.002	0.0004	0.0004
	(-0.004, 0.009)	(-0.006,0,007)	(-0.006, 0.007)
Number of Backward Citations (logged)	-0.039***	-0.037***	-0.037***
	(-0.050, -0.029)	(-0.047, -0.026)	(-0.047, -0.026)
N	28,860	28,860	28,860
R	0.171	0.173	0.173
Adjusted R	0.156	0.159	0.159

*p<0.05; **p<0.01; ***p<0.001; Fixed effects for Application year, Location, and Technology class are included in all models.

Table 4. OLS Predicting Enabling Technology: Relationships with Science Agencies

OLS predicting Enabling Technology Index in Science Agencies

	Dependent variable:					
	Enabling Technology Index					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.622^{**}	3.556^{**}	3.592^{**}	3.619^{**}	3.635^{**}	3.576^{**}
	(0.504, 6.740)	(0.442, 6.670)	(0.475, 6.710)	(0.500, 6.738)	(0.520, 6.750)	(0.461, 6.691)
Science Agency Relationship		0.102^{***}				
		(0.064, 0.140)				
Contract			0.060^{*}			0.091^{***}
			(-0.007, 0.127)			(0.023, 0.159)
Agreement				0.008		0.040
				(-0.169, 0.185)		(-0.137, 0.217)
Grant					0.090^{***}	0.099^{***}
					(0.051, 0.128)	(0.060, 0.138)
Time To Grant (Years)	-0.030	-0.034	-0.030	-0.030	-0.034	-0.034
	(-0.089, 0.030)	(-0.093, 0.025)	(-0.089, 0.030)	(-0.089, 0.030)	(-0.094, 0.025)	(-0.094, 0.025)
Patent Age (Years)	-0.076^{**}	-0.077^{***}	-0.076^{**}	-0.076^{**}	-0.078^{***}	-0.077^{***}
	(-0.134, -0.018)	(-0.135, -0.019)	(-0.134, -0.018)	(-0.134, -0.018)	(-0.136, -0.020)	(-0.136, -0.019)
Number of Inventors	-0.004	-0.005	-0.004	-0.004	-0.005	-0.005
	(-0.014, 0.005)	(-0.015, 0.005)	(-0.014, 0.005)	(-0.014, 0.005)	(-0.014, 0.005)	(-0.015, 0.005)
Number of Backward Citations (Logged)	-0.039^{***}	-0.035^{***}	-0.038^{***}	-0.039^{***}	-0.036^{***}	-0.035^{***}
	(-0.054, -0.023)	(-0.051, -0.019)	(-0.054, -0.023)	(-0.054, -0.023)	(-0.051, -0.020)	(-0.051, -0.019)
Observations	10,544	10,544	10,544	10,544	10,544	10,544
R^2	0.186	0.188	0.186	0.186	0.188	0.188
Adjusted R^2	0.154	0.156	0.154	0.154	0.155	0.156
Residual Std. Error	0.835 (df = 10139)	0.834 (df = 10138)	0.835 (df = 10138)	0.835 (df = 10138)	0.834 (df = 10138)	0.834 (df = 10136)
F Statistic	5.743^{***} (df = 404; 10139)	5.812^{***} (df = 405; 10138)	5.737^{***} (df = 405; 10138)	5.728^{***} (df = 405; 10138)	5.792^{***} (df = 405; 10138)	5.784^{***} (df = 407; 10136)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5. OLS Predicting Enabling Technology: Relationships with Mission Agencies

OLS predicting Enabling Technology Index in Mission Agencies

	Dependent variable:					
	Enabling Technology Index					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.330	2.355	2.309	2.431	2.398	2.511
	(-2.452, 7.113)	(-2.420, 7.131)	(-2.470, 7.088)	(-2.353, 7.214)	(-2.383, 7.179)	(-2.266, 7.288)
Mission Agency Relationship		0.101^{***}				
		(0.072, 0.130)				
Contract			0.071^{***}			0.084^{***}
			(0.042, 0.101)			(0.054, 0.114)
Agreement				0.213^{*}		0.253^{**}
				(-0.011, 0.437)		(0.029, 0.477)
Grant					0.109^{***}	0.139^{***}
					(0.048, 0.170)	(0.077, 0.201)
Time To Grant (Years)	-0.008	-0.010	-0.009	-0.009	-0.009	-0.012
	(-0.057, 0.040)	(-0.059, 0.038)	(-0.057, 0.039)	(-0.058, 0.039)	(-0.058, 0.039)	(-0.060, 0.036)
Patent Age (Years)	-0.041^{*}	-0.043^{*}	-0.042^{*}	-0.043^{*}	-0.042^{*}	-0.044^{*}
	(-0.089, 0.006)	(-0.090, 0.005)	(-0.090, 0.005)	(-0.090, 0.005)	(-0.089, 0.006)	(-0.091, 0.003)
Number of Inventors	0.006	0.003	0.004	0.006	0.005	0.003
	(-0.003, 0.015)	(-0.006, 0.011)	(-0.005, 0.013)	(-0.003, 0.015)	(-0.003, 0.014)	(-0.006, 0.012)
Number of Backward Citations (Logged)	-0.035^{***}	-0.034^{***}	-0.034^{***}	-0.035^{***}	-0.035^{***}	-0.034^{***}
	(-0.050, -0.020)	(-0.049, -0.019)	(-0.049, -0.020)	(-0.050, -0.020)	(-0.049, -0.020)	(-0.049, -0.019)
Observations	16,046	16,046	16,046	16,046	16,046	16,046
R^2	0.186	0.189	0.188	0.187	0.187	0.189
Adjusted R^2	0.163	0.165	0.164	0.163	0.163	0.165
Residual Std. Error	0.856 (df = 15588)	0.854 (df = 15587)	0.855 (df = 15587)	0.855 (df = 15587)	0.855 (df = 15587)	0.854 (df = 15585)
F Statistic	7.818^{***} (df = 457; 15588)	7.923^{***} (df = 458; 15587)	7.860^{***} (df = 458; 15587)	7.809^{***} (df = 458; 15587)	7.833^{***} (df = 458; 15587)	7.889^{***} (df = 460; 15585)
Note:						*p<0.1; **p<0.05; ***p<0.01