Estimating spillovers from publicly funded R&D: Evidence from the US Department of Energy*

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Abstract

In this paper, we quantify the magnitude of R&D spillovers created by grants to small firms from the US Department of Energy. Our empirical strategy leverages variation due to state-specific matching policies, and we develop a new approach to measuring both geographic and technological spillovers that does not rely on an observable paper trail. Our estimates suggest that for every patent produced by grant recipients, three more are produced by others who benefit from spillovers. Sixty percent of these spillovers occur within the US, and many of them occur in technological areas substantially different from those targeted by the grants.

JEL Codes: O31, O33, O38

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1 Introduction

The spillovers of research and development (R&D) are one of the most cited motivations for government intervention in the markets for innovation. Ideas generated by one inventor may lead other inventors to create other new ideas; this is a phenomenon that can lead to suboptimal investment in R&D (Nelson 1959; Arrow 1962). Understanding the magnitude of R&D spillovers and how they permeate geographic space (across inventors and firms) and technological space (across ideas) has been a longstanding empirical question with many theoretical and policy implications (Griliches 1992; Bloom et al. 2019; Arora et al. 2021).[1] Despite this importance, empirical evidence on the magnitude and nature of R&D spillovers has been remarkably thin.

In this paper, we provide novel evidence on the magnitude and nature of R&D spillovers by analyzing the US Department of Energy (DoE) branch of the Small Business Innovation Research (SBIR) program. The DoE SBIR program is emblematic of many governments' venture-like R&D subsidy programs: the funding agency announces priority technologies that they would like to see developed, and then awards competitive grants to the most promising small businesses that apply.[2] At the DoE, these priorities range from light sensors, to fuels, to high performance computing software, and are described in Funding Opportunity Announcements (FOAs). Notably, all DoE SBIR applications must respond to a specific FOA. To measure how grants awarded via FOAs ultimately lead to new ideas, we follow a long line of related work (Griliches 1998) and use patenting rates at the US Patent and Trademark Office (USPTO) as our focal measure of inventive output.

We identify the magnitude of spillovers across geographic and technological space by estimating how SBIR grants ultimately lead to new patents that are (1) produced by inventors and firms located further and further away from a grant recipient, and (2) focused on technologies more and more different from the technologies targeted by FOAs. Our results indicate that, for every one patent produced by grant recipients due to a marginal increase in SBIR funding, we expect three additional patents to be produced by other inventors across the US and around the world (none of whom directly received a grant). Our results imply that US-based firms and inventors are responsible for roughly 60 percent of the net patents gener-

[1] Such spillovers may be due to externalities (e.g., uncompensated knowledge spillovers or business stealing) or market-based transactions (e.g., licensing contracts). Externalities are important since they can distort R&D investments (Jones and Williams 1998; Bryan and Lemus 2017). All spillovers are important when examining the diffusion of ideas across geographic or technological space (Keller 2004).

[2] A focus on small firms can be linked to the unique frictions they face (Holmstrom 1989; Lerner 2009) or the outsized role of young firms in the economy (Haltiwanger et al. 2013). A focus on specific technologies can be linked to distortions in how firms choose the direction of their research (Bryan and Lemus 2017).

ated by this program. Moreover, many of these new patents are topically quite distant from the technologies initially targeted by FOAs. Taken together, these results suggest that the R&D spillovers from these government grants have a wide impact across both geographic and technological space.

Our empirical approach is designed to address two of the primary challenges to estimating R&D spillovers: measurement and identification. To illustrate the measurement challenge: say that a firm in New Hampshire received an SBIR grant to develop a tool for detecting hazardous waste underground. What observable data could tell us how other inventors and firms benefitted from the R&D performed by that grant recipient?[3] Prior approaches to this problem have largely relied on one of two methods. The first uses citation linkages between patents as a proxy for spillovers (e.g., Jaffe 1986; Jaffe et al. 1993). The second approach relies on spillover matrices that use other observable data (e.g., inventors' locations) to impose structure on the way in which firms' R&D influences others along dimensions of geographic, technological, or product market proximity (e.g., Bloom et al. 2013).

We offer a new approach by drawing on methods from the spatial economics literature (Clarke 2017; Feyrer et al. 2017; James and Smith 2020) along with natural language processing tools to capture spillovers more flexibly. Our key advantage is that we construct a dataframe where the units of observation are areas of technological space. That is, we estimate technology-level regressions that relate the flow of patents to the stock of R&D grants across technologies.[4] We identify technological spillovers by using the similarity of the text in (1) patents abstracts and (2) the research objectives of the grants as described in the FOAs. We identify geographic spillovers by comparing the marginal product of funding when we focus on the patent output from different groups of firms and inventors (e.g., only grant recipients, all US-based firms and inventors, etc.).

Importantly, our approaches to measuring both geographic and technological spillovers require no paper trail of citation linkages and make no a priori assumptions about how "far out" in geographic or technological space spillovers from SBIR grants may permeate. For comparison, we also estimate our model using the traditional approach of requiring citation linkages; the results indicate that this misses roughly half of the spillovers that we identify with our more flexible approach.

[3] In this actual case, the New Hampshire-based firm, Subsurface Insights LLC, received this SBIR grant and ultimately expanded from a focus on hazardous waste into other areas including thermal energy storage in aquifers (suggestive of technological spillovers) and became involved in projects across the US and Europe (suggestive of geographic spillovers). See www.subsurfaceinsights.com and split.to/sbirsubsurface for more.

[4] Popp (2002) may be one of the first to estimate technology-level regressions that relate inputs and outputs within some predefined portions of technology space. Azoulay et al. (2019) also estimate a technology-level production function, though their technologies are grouped around biomedical topics.

The identification challenge revolves around handling the endogeneity of R&D investments. In our setting, neither the technological areas targeted by FOAs nor the firms awarded the federal grants are randomly selected. There are likely unobservable differences in the supply of and demand for technologies that the DoE prioritizes. Moreover, firms of higher unobservable productivity will likely be able to obtain more SBIR funding.

We isolate plausibly exogenous variation in R&D funding by leveraging the presence of non-competitive SBIR matching policies that vary across states and time. In some US states, when a firm wins a federal SBIR award, their state government automatically awards them additional funds (Lanahan and Feldman 2015). We use variation in these policies to identify what we term "windfall" investments into technological areas that are arguably unrelated to any (unobservable) supply or demand shocks also driving R&D investments and patenting rates. To illustrate, consider two equally productive firms that are located in different states. Further, assume these firms respond to two separate FOAs focused on two different technologies, where the supply of and demand for both technologies are the same. If both firms win an SBIR award, but one firm is located in a state with a match policy, then additional funds will be invested (exogenously) in the technology pursued by that firm. We show evidence that this thought experiment plays out in practice – states with match policies do not appear to be disproportionately populated by especially productive (or unproductive) firms pursuing especially productive (or unproductive) technologies.

We are not the first to tackle the aforementioned measurement and identification challenges associated with R&D spillovers. The two most closely related papers are Bloom et al. (2013) and Azoulay et al. (2019). Bloom et al. (2013) focus on a sample of large, publicly-traded firms, and leverage state-level R&D tax credits combined with the type of spillover matrices described above to test for both positive R&D spillovers (across technologies) and negative R&D spillovers (within product markets).[5] Azoulay et al. (2019) are not focused on estimating R&D spillovers directly, but their empirical approach – which isolates windfalls of public R&D funding targeted to specific biomedical topics – uncovers that, in academic biomedical research, spillovers across biomedical topics account for a substantial share of the ways in which publicly funded R&D translates into realized inventions. We contribute to this line of work by offering a new methodology for capturing R&D spillovers while focusing on the increasingly important energy sector.

Our preferred estimates suggest that SBIR-funded firms are capturing anywhere between

[5]Product and revenue data is not available for the vast majority of the firms and inventors in our analyses, so we cannot fully investigate product market rivalries. However, our estimates do incorporate any business stealing effects that occur up to the patenting stage of R&D (e.g., if, after one firm successfully obtains a patent, another withdraws R&D efforts that would have otherwise led to a patent).

25–55% of the net patent-based value their R&D is generating. These magnitudes are on par with a very short line of empirical studies using macro- and microeconomic methods to estimate the private and social returns to R&D (Jones and Williams 1998; Bloom et al. 2013; Azoulay et al. 2019; Zacchia 2020). This suggests that our best estimates of the wedge between the private and social returns to R&D are not primarily driven by any specific methodology or setting.

In addition to a number of specification and robustness tests, we also provide support for our research design by benchmarking an intermediate estimate we obtain from our approach: the amount of SBIR funding necessary to spur one additional patent by (only) grant recipients. Fortunately, we have a solid benchmark with which to compare; Howell (2017) uses a sharp regression discontinuity to identify clear evidence that these same grants enable firms to innovate.[6] A conservative interpretation of Howell's (2017) estimates implies a marginal cost per patent that is very close to our estimate; this gives us further confidence in our empirical design. Still, the nearly four-fold difference between this cost (of spurring one patent by grant recipients) and the cost of spurring a patent by *anyone* suggests that ignoring spillovers in program evaluations of R&D subsidies may yield very different conclusions.

We proceed as follows. Section 2 provides detail on the setting and primary data sources. It also outlines how we use natural language processing tools to connect the inputs (grants) and outputs (patents) of the focal production function we estimate. Section 3 describes the empirical model, which builds on the knowledge production function first introduced by Griliches (1979). We first describe how we use the noncompetitive state matching polices to isolate windfalls of funding and then how we incorporate spillovers across geographic and technological space into the model. Section 4 reports the main results on the size of R&D spillovers and where they occur. Section 5 focuses on the *value* of patents spurred by these grants and some implications the results have for understanding the private and social returns to R&D. Section 6 concludes by connecting our findings to ongoing literatures and offering some economic and policy implications.

2 Setting and Data

This section describes the setting, policies, and data used in our empirical analysis. We detail: the DoE SBIR program including how they solicit applications and grant funds (Section 2.1); the State Match programs that award extra noncompetitive funding to federal

[6]Other studies of the SBIR program, most of which do not address spillovers, include Lerner (2000); Wallsten (2000); Audretsch (2003); Gans and Stern (2003); Link and Scott (2010); Lanahan and Feldman (2018); National Academies of Sciences, Engineering, and Medicine (2020), and Lanahan et al. (2021).

SBIR winners (Section 2.2); the US Patent and Trademark Office (USPTO) patent data and the classification scheme used to categorize patents (Section 2.3); how we use natural language processing to merge the SBIR and patent data (linking inputs to outputs) and create technology-level data for empirical analysis (Section 2.4); and finally, summary statistics of the multiple data sets (Section 2.5). Appendix B details additional data sets we use to observe or estimate geographic distances, travel costs, and other characteristics of countries and US counties.

2.1 The US SBIR Program and the Department of Energy

Since its enactment in 1982, the US SBIR program has allocated over $40 billion to support early-stage innovation by small businesses. It is emblematic of R&D subsidy programs administered by many countries worldwide.[7] The DoE is one of eleven federal agencies participating in the SBIR program and awards roughly 250 firms a total of about $200 million per year. The DoE SBIR program is comprised of twelve offices,[8] whose focus spans a broad range of energy-related initiatives including those that may not immediately come to mind when thinking of "energy," including high-performance computing, cybersecurity, and precision measurement tools.

The DoE SBIR solicitation and award processes are as follows. One to three times per year, the DoE releases a Funding Opportunity Announcement (FOA) that outlines technological areas of interest, referred to as "topics." Each year, the FOAs include about 50 unique topics altogether. Topic descriptions are roughly five to ten paragraphs of text outlining the specifics of the technology that the DoE is interested in developing. Each office within the DoE is responsible for producing a set of topics contained in an FOA. To be eligible for funding, applicants must align themselves with the objectives of a particular topic in an active FOA.

Only private US-owned firms with less than 500 employees are eligible to apply for SBIR funding. Proposals are subject to an internal review to ensure there is sufficient alignment between the proposed activities and the FOA topic the firm is responding to. Then follows a competitive, external peer review process where at least three industry experts review the proposal's technical and commercial merits. Recipients receive the first award, a Phase I grant that provides six months of support and typically $50,000–250,000, which is intended

[7]Upwards of 17 countries have copied some structures of the SBIR program (see: tny.sh/sbirworldwide).

[8]The offices participating in our data include: Electric Delivery and Energy Reliability, Energy Efficiency and Renewable Energy, Environmental Management, Fossil Energy, Nuclear Energy, Defense Nuclear Nonproliferation, Advanced Scientific Computing Research, Basic Energy Sciences, Biological and Environmental Research, Fusion Energy Sciences, High Energy Physics, and Nuclear Physics.

to support development of a proof of concept. Phase I recipients are then eligible to compete for Phase II grants, which offer two years of support and typically $750,000–1 million.[9]

The process of selecting FOA topics and recipient SBIR firms is not random. DoE program managers attempt to solicit applications for developing technologies that have a significant potential for impact. Conditional on the set of applicants, the peer review process attempts to direct funds toward firms with the most potential success. This likely leads to endogeneity issues, which we attempt to circumvent by leveraging the presence of the matching programs that are active in different states.

2.2 SBIR State Match Programs

Since 1984, some US states have enacted policies intended to complement the federal SBIR program by awarding additional funds to firms that receive an SBIR grant. Lanahan and Feldman (2015) outline the origins of these match programs and how they operate. Following their methodology, we identify the SBIR match programs for all states up to 2018.[10]

Figure 1 documents the growth of these policies over time, with 15 states having a program in 2018. Most states tend to maintain the program after initial adoption. On average, 7 percent of DoE SBIR grant recipients are eligible for a state match, though with program diffusion in recent years, this increased to 17 percent in 2018. The size of these matches ranges from $25,000–105,000 for Phase I awards and $50,000–500,000 for Phase II awards.

These noncompetitive state policies are at the core of our research design. We discuss how we use them in combination with some plausible, data-supported assumptions to isolate exogenous variation in R&D funding in Section 3.2 below.

2.3 Patents and Technology Indexing

We follow a long line of economic studies of invention and rely on patent activity as our measure of technological progress. We source the universe of USPTO patents from 1997 to 2018 using the USPTO's PatentsView database. This contains patent details such as the

[9]Roughly eight percent of grants are awarded via the Small Business Technology Transfer (STTR) program, which requires a partnership between the small business applicant and a nonprofit research institution. We lack a strategy for separately identifying the effect of grants via this channel, so we aggregate all funding through both the SBIR and STTR channels into a single measure of funding.

[10]We exclude a small number of states' programs that involve competitive elements (e.g., peer review) since our identification strategy assumes that these matching funds are automatically awarded to all federal grant winners. Despite much effort, we cannot observe the actual amount of match funds awarded to firms since states' records are very incomplete. Still, we know how much match funding a recipient should have received, which motivates our interpretation of the empirics as an intent-to-treat analysis.

application year, the title and abstract text, and disambiguated tables of individual inventors and firm assignees as well as their geographic locations.[11]

Accounting for all firms in the PatentsView data and the five largest federal SBIR agencies,[12] roughly 49 percent of firms that ever receive an SBIR award ever obtain a USPTO patent between 1997 and 2018 (before or after the SBIR award). However, roughly 1 percent of firms ever assigned a patent receive an SBIR award at some time.

Importantly, PatentsView also contains data on the unique Cooperative Patent Classification (CPC) terms assigned to each patent. This classification scheme is used to organize patents according to the technical features of their content. The CPC terms effectively discretize technological space into over 250,000 unique concepts that are organized into a five-level hierarchy. Of use to our design is the feature that the USPTO retroactively assigns the most recent and detailed CPC scheme (as of 2018) to all prior patents. For reasons we detail in Appendix A, we use the main group level of the hierarchy as the units of analysis in our regressions. At this level of the scheme there are 10,686 unique terms, which we refer to as groups for simplicity. On average, a patent is assigned five to eight CPC groups.

2.4 Technology-level Data on R&D Investments and Patents

Our empirical model relates the aggregate investment of SBIR funds targeted at particular technologies to the eventual aggregate flow of patents that are related to those same technologies. Our approach centers on using the CPC scheme to index technological space much like how US ZIP codes index geographic space into discrete units. However, also much like ZIP codes, the CPC scheme was not developed with empirical researchers in mind. Therefore, our approach attempts to avoid relying on the CPC scheme in a manner that may produce spurious results (e.g., Thompson and Fox-Kean 2005).

As discussed in Section 2.1, the DoE invests in technologies through their use of FOAs and the topics described therein. Moreover, as discussed in Section 2.3 all patents are assigned CPC groups that describe their technical content. Since patents are already assigned CPC groups, our goal is to infer which CPC groups most closely align with each FOA topic. With this information in hand, then, loosely speaking, if we observe $1 million awarded through

[11]Patents are often used as a proxy for innovation in policy communities, and a recent in-depth case study supports the assumption that patents are useful metrics of "real" technological progress (Igami and Subrahmanyam 2019). Furthermore, they are often referenced as a primary measure of success by the SBIR program itself (e.g., see slide 4 of the SBIR program overview slides here: tny.sh/sbirprogramslides).

[12]These agencies – DoE, Department of Defense, National Aeronautics and Space Administration, National Institutes of Health, and National Science Foundation – account for approximately 85 percent of federal SBIR funding over our study timeframe.

a particular FOA topic, we know in which CPC groups to look for new patents.

We detail our approach to linking FOA topics to CPC groups in Appendix A. What follows is a brief summary. First, we use a combination of standard optical character recognition software and hand coding to digitize DoE's FOAs and parse each FOA into the separate topics. In the second step, we take the five to ten paragraphs of text that describe the objectives of each FOA topic and compare the textual similarity of these descriptions with the abstracts from all USPTO patents applied for between 1997 and 2004.[13] Using methods now commonplace in text analyses (term frequency–inverse document frequency weighted n-gram cosine similarity), we estimate a numerical similarity score between each FOA topic and each patent. This approach assumes that if an FOA topic and a patent abstract both use words that are very uncommon elsewhere in each corpus, then the two are likely referencing the same technologies. Throughout the paper, we refer to technological distance as the inverse of this similarity.[14] Appendix A.3 contains three examples of FOA topics and the most similar CPC groups matched to those topics.

An important assumption of our approach is that CPC groups describe the entirety of technological space. Motivated by Thompson and Fox-Kean (2005), we deviate from prior work (e.g., Jaffe et al. 1993) and do not assume that the specific hierarchical structure of the CPC scheme contains any information. In other words, we do not assume that two groups located next to each other in the CPC hierarchy are more technologically similar than other groups.

By instead using natural language processing techniques, we offer a new methodological approach to estimating patent-based R&D spillovers that is less dependent on the structure of the patent classification system. This methodology could be applied to any setting where the researcher observes input and output data that are not classified in the same way, but where text descriptions of the units of observation can be used to generate a crosswalk.

[13]The choice of this timeframe poses the possibility of a precision-bias tradeoff: using more years, and more recent years, in this text analysis should incorporate information that truly reflects the underlying connection between each word in the FOA topics and each CPC group. However, it also increases the risk we might incorporate information that arises endogenously. For example, when an SBIR grant recipient writes the abstract of their patent, they may use verbiage from the FOA topic related to their grant even though those words may not actually reflect the technical content of the invention. We are not very concerned with this particular issue because (1) patent applicants face legal threats if they incorrectly describe the nature of their invention, and (2) our discussions with DoE SBIR program staff never raised such a concern. Still, we use only the first eight of our 22-year sample to estimate these similarity scores to avoid the likelihood of such problems, obtaining very similar results when we vary this window.

[14]This approach of using text similarity to connect units in technology-space has been shown to be an effective way to quantify economically meaningful concepts (e.g., Azoulay et al. 2019; Myers 2020).

2.5 Summary Statistics

Table 1 contains summary statistics of the DoE SBIR program, state match programs, and patent activity. We report annual averages for our full sample, which spans 1997–2018. The Federal DoE SBIR program releases about 50 FOA topics annually, typically awarding roughly \$1.7 million per topic. Conditional on receiving any award, firms receive about 1.8 awards per year, totaling roughly \$780,000. Approximately one-quarter of DoE SBIR awards are Phase I grants and three-quarters are Phase II grants.

Approximately 7 percent of firms winning awards are eligible for a state-based match, with roughly 18 percent of FOA topics awarding a grant to one of these firms in a match state.[15]

Roughly half of all firms that ever receive an SBIR award ever obtain a patent, and roughly 1 percent of all firms in the USPTO record ever receive an SBIR award. Focusing only on years after a firm's first SBIR award, grant recipients average 0.5 patents per year, with all patent flows showing a high degree of skewness.

Across the roughly 10,000 CPC groups we focus on, SBIR firms make up a very small percentage of the total patents within each group (approx. 0.2%). However, counting all of the firms and inventors located in the same US counties as SBIR grant recipients, which includes about 700 of the roughly 3,000 counties, covers roughly 90% of US-based patents.[16] The domestic-foreign split of firms and inventors receiving USPTO patents over this period is roughly 50–50.

3 Research Design

Our goal is to estimate the magnitude of the R&D spillovers created by the DoE's SBIR program. To do this, we estimate the marginal product of funding, in terms of producing patents, and compare how the marginal product depends on (1) whether the patents are produced by SBIR grant recipients, or inventors and firms some geographic distance away from the recipients, and (2) whether the patents are closely aligned with the technological

[15] To investigate how firms use this funding, we examined a survey administered to state match recipients from North Carolina, which is the only such data we are aware of. With the caveat that the survey was based on firms receiving SBIR awards from all federal agencies (not just the DoE), firms reported that roughly 50% of the matching funds are spent on wages, which is in line with Howell and Brown (2020). About 25% of funds are spent on equipment, supplies, or facilities. It also appears that no more than 5% of these state match funds are spent on patent-related costs. As far as we can infer from these data and other states' regulations, it does not appear that receiving state matching funds changes any incentives or costs surrounding patenting.

[16] For more on the geographic distribution of US inventive activity, see Forman et al. (2014).

objectives of an FOA topic, or the content is some technological distance away from those objectives. If it appears that SBIR funding is absolutely more productive (i.e., the SBIR-$ cost per patent declines) as we expand the set of firms and inventors or technologies included in our analyses, we infer that to be the result of R&D spillovers.

3.1 Baseline Model

We focus on estimating a knowledge production function (Griliches 1979), which relates an annual flow of patents to a stock of R&D investments. Researchers have been regressing patent rates on R&D inputs for decades, but unlike most prior work where the units of analysis are firms or inventors, our units of analysis are the technological areas where firms and inventors operate, which are indexed by the CPC groups.

We use a Poisson model to describe the expected count of ultimately successful patent applications Y in each CPC group j during year t as a function of the current stock of public R&D investments K (i.e., the DoE's SBIR grants and/or the state-based matching grants):

$$\mathbb{E}[Y_{jt} \mid K_{jt}] = \exp\big(\log(K_{jt})\beta + \tau_t + \omega_{jt}\big) \ , \tag{1}$$

where β is the focal productivity parameter to recover and τ_t are year-specific intercepts that condition out aggregate year-to-year fluctuations and also handle the right censoring of our data (investments in year t can only lead to more patents in the current and $2018 - t$ succeeding years). ω is a parameter that captures productivity shocks that are unobservable to us (e.g., the value of patenting in each CPC group at a particular time).[17]

We construct the stock of public R&D investments K_{jt} using standard perpetual inventory methods. In our main specifications, we do not discount to produce conservative estimates. To construct the flow of patent output in each CPC group, Y_{jt}, we divide one by the number of CPC groups assigned to each patent (which typically ranges from five to eight) and sum over all patents by each CPC group. Thus, $Y_{jt} = 1$ indicates a flow of one "patent's worth" of output in CPC group j in year t, which ensures that our marginal product estimates are always with respect to the production of one patent (regardless of how many CPC groups it might be assigned).[18]

[17] Eq. 1 does not structurally describe firm- or inventor-level production, but rather aggregates these decisions into a technology-level relationship to estimate the magnitudes of spillovers across both technological and geographic space.

[18] In Appendix E.4, we report additional results based on (1) an alternative discounting assumptions to provide some suggestive evidence as to the degree of production lags, and (2) an alternative approach to allocating patent counts to CPC groups, which yields very similar estimates of spillover magnitudes as our preferred approach.

As previewed in the introduction, we face two econometric challenges for estimating Eq. 1: (1) accounting for the endogenous allocation of SBIR funds that would give rise to a correlation between K_{jt} and (the unobservable) ω_{jt}; and (2) capturing spillovers across geographic and technological space. The remainder of this section describes how we handle these challenges and calculate the implied magnitude of R&D spillovers in this setting.

3.2 Identification with Windfall Funding from the Match Programs

The DoE's SBIR investments are not made at random, but rather with some knowledge about their expected productivity (i.e., the probability they will lead to new patents and spillovers). In our model, these (unobservable) shocks are reflected in the ω_{jt} term. If these shocks are correlated with SBIR investments (i.e., $\mathbb{E}[\,\omega_{jt}\,|\,K_{jt}\,] \neq 0$), then we cannot recover an unbiased estimate of β.

To circumvent this concern, we make use of the aforementioned noncompetitive State Match programs. The varied presence of these policies across states and over time generates variation in the amount of state-based R&D funding that ultimately is invested in each CPC group-year observation. We argue that a subset of this variation yields windfalls of R&D funding across CPC groups only because of their differential exposure to the match policies. The key identification assumption we make is that the firms located in states when an SBIR match program is in place are not abnormally productive compared to firms in other state-years, and are not responding to FOA topics that are focused on technologies with abnormal underlying supply or demand. If this is true, then we can isolate these windfalls for estimating of Eq. 1 and recover an estimate of β that is less likely to be biased by endogenous selection of R&D funding. The following three subsections overview our approach by: (1) describing how we isolate windfall investment; (2) providing evidence supporting our assumptions that these policies are plausibly exogenous; and (3) discussing the interpretation and generalizability of this approach.

Estimating the Windfall Funding

The state match programs operate by multiplying endogenous federal investments. Thus, we must separate which of the state-based investments are a direct function of certain FOA topics receiving more federal dollars versus the windfall dollars that arise only because of a differential exposure to certain state match policies.

We isolate these windfalls of funding by treating them as residuals in a FOA topic-level regression that predicts total state-based funding as linear, year-specific functions of federal funding. Appendix C.1 outlines this approach in detail. In short, FOA topics and their corresponding CPC groups receive larger (or smaller) windfalls of funding if the total amount of state-based funding was above (or below) the average amount of state-based funding one would expect given the amount of federal funding observed.

We denote the stock of these windfall investments with W_{jt}. Because the windfalls are residuals, W_{jt} takes on both positive and negative values. Thus, the standard logarithm transformation of this stock of investments is not possible. To circumvent this problem, we approximate the logarithm transformation by dividing R&D stocks by the sample average. Formally, our main estimating equation is now:

$$\mathbb{E}[Y_{jt} \mid W_{jt}] = \exp\left(\frac{W_{jt}}{\overline{W}}\theta + \tau_t\right) , \tag{2}$$

where $\overline{W}$ is the sample mean of the stock of windfalls (W_{jt}). Our approach of dividing the stocks by the sample average approximates a log transformation in terms of the coefficient estimated (i.e., $\theta \approx \beta$).[19] Equation 2 no longer includes the unobservable ω_{jt} term because it is, by assumption, uncorrelated with the windfall funding.

Evidence of State Match Exogeneity

Our identification approach relies on the fact that the CPC groups that the DoE invests are differentially exposed to the state matching policies. Specifically, the key assumption is that these policies are not more or less prevalent amongst states with either: (1) particularly more or less productive firms; and/or (2) firms operating in CPC groups that are particularly more or less productive.

To explore these assumptions, we perform two empirical tests. First, we estimate the association between the presence of a matching policy in a state and the amount of federal SBIR funds per capita awarded to firms in that state. The results from these regressions are in Appendix C.2. Across all specifications, we cannot reject a null of no differences. Whether we examine across- or within-state variation, there does not appear to be a meaningful difference in the flow of total SBIR funds between states with and without the matches, nor between states with different match rates.

Second, we assess whether the program solicits selection concerns among firm behavior. Because these match policies technically increase the expected size of an SBIR award, firms may move to states that enacted these policies. However, with match amounts ranging from

[19] A one unit increase in $\frac{W_{jt}}{\overline{W}}$ describes a 100% increase in investments from the mean. See Appendix B for more on this approximation.

$25,000–500,000, and federal-level success rates reported at roughly 15%–20%, this is likely not a meaningful change in the expected benefit of moving across state lines, especially compared to the costs of relocation.

Still, we explore this possibility of firm movement being correlated with these policies by constructing a panel data set of the locations of all SBIR grant recipients from the major federal agencies.[20] We test whether these firms are more or less likely to move into states after a matching program is enacted. If the enactment of these policies significantly altered the value of SBIR program participation, or were perhaps correlated with meaningful economic shocks, we would expect to identify an association between the beginning of the policy and the movement of SBIR grant recipients into (or out of) the state. The results of this analysis are presented in Appendix C.2 and show no meaningful evidence that grant recipients are more or less likely to move into states after these policies are enacted. This is consistent with the findings of Lanahan and Feldman (2018), the first to use these policies to identify plausibly exogenous public R&D funding, as well as work on the location choices of new firms more generally (e.g., Stam 2007; Li et al. 2016).

Interpretation and Limitations of the Windfall Funding

While our identification approach gives us confidence that we are focusing on useful (and plausibly exogenous) variation in R&D funding, we acknowledge that it is not without some important caveats and limitations. As we outline below, we believe that these limitations generally push us towards more conservative productivity estimates when relying on the state match windfalls.

The windfall funding amounts are much smaller than total funding levels, typically 1–10% of what the DoE directly invests in each CPC group. On the one hand, the small relative size of these investments raises some concerns about measurement error in the independent variable, which would bias our estimates toward zero (yielding conservative estimates). On the other hand, from the perspective of the firms, these windfalls are a 50–100% increase in funding, which is certainly economically meaningful.

Two other factors may lead us to overly conservative estimates. First, we cannot observe the actual amount of state-based match funding each grant recipient receives because this data is virtually nonexistent. This frames our approach as an intent to treat analyses. Second, while we assume constant returns to scale in our empirical model (which aggregates output across

[20] This includes SBIR grants from the Department of Defense, National Institutes of Health, National Science Foundation, and National Aeronautics Space Administration. Firm locations were found via match (with an 80% match rate) to the National Establishment Time Series.

many firms), it would be very reasonable to assume that each firm has decreasing returns to scale. In this case, the marginal funding from state matches would be less productive than the inframarginal funds from the DoE.

More broadly, few policies are truly random, and in their description of these match programs, Lanahan and Feldman (2015) note that they are associated with a range of factors. They find that, among other things, states with greater budget slack, those with below average high-tech employment, and those with neighboring state adopters of the program are more likely to have a program in place.

Additionally, many of the exceptionally inventive states, including California, Massachusetts, and New York, do not have matching programs in our sample. This confluence of factors is perhaps why the analyses above do not suggest that states with programs are especially unique in terms of total SBIR funding or small firm movement.[21] Still, we acknowledge that our design is based on policies present in a relatively modest subset of the US R&D enterprise as illustrated in Figure 1. And given the highly skewed nature of innovative inputs (much of which are flowing into states that do not have match policies), this may lead us to underestimate the extent to which a matching program in these states might generate spillovers.

3.3 Incorporating Spillovers into the Empirical Model

This section describes how we modify our baseline model to allow for the possibility of R&D spillovers across geographic and technological space. In overview, first we allow for spillovers across geographies by estimating multiple regressions that include the patent output from regions where it is more and more costly to travel to grant recipients following Feyrer et al. (2017). Here, we compare the marginal costs implied by *different dependent variables* across regressions models to identify geographic spillovers. Second, we allow for spillovers over technologies by combining natural language processing with methods developed by Clarke (2017) and James and Smith (2020). Here, we compare the marginal costs implied by *different independent variables* within regressions models to identify technological spillovers.

Spillovers Across Geographic Space

For a spillover to occur, information needs to be transmitted. Geographic distances have led to sizable costs of this transmission. So, it is no surprise that a large line of research, spurred

[21] Anecdotally, discussions with State Match administrators indicated that firms were unaware of the policy in their state until the firms received notification from the state that they would be receiving additional matching funds.

in large part by Jaffe et al. (1993), has documented evidence consistent with geographic distances being a constraint of R&D spillovers.

For the purposes of capturing geographic spillovers across firms and inventors, we take the straightforward approach of estimating separate regressions that increase the size of concentric circles that successively include patents from firms and inventors further and further away from DoE SBIR grant recipients in the dependent variable (Feyrer et al. 2017).[22] The first, exclusive regression corresponds to counting only patents awarded to firms that receive DoE SBIR grants, which effectively replicates a traditional firm-level analysis of the program (e.g., Howell 2017). For the most inclusive regression, we count all USPTO patents, regardless of where the firm or inventor is located.

To explore how spillovers play out in between these extremes, we rely on concentric circles based on weighted travel costs for US activity. This offers a more precise construct to assess geographic spillovers given that the costs of human travel, rather than geodesic distances, constrain the flow of ideas (Agrawal et al. 2017; Catalini et al. 2020). The relevant policy levers here are related to subsidizing (or taxing) travel.

We compute travel costs within the US by focusing on county-to-county pairs as a rich yet computationally tractable set of regions. We estimate the cost of making a round-trip from every county in the US to all counties where an SBIR grant recipient is located. For this cost, we use the minimum cost of either driving directly, or driving to/from the nearest airports and flying. We detail the computation of this metric in Appendix B.

Motivated by gravity models of trade, we construct our final measure of weighted travel costs by dividing these costs by the product of the total amount of SBIR funding that flows into the destination county and the populations of the origination and destination counties. Just as a gravity trade model would predict a large exchange of goods between two large, neighboring counties, so too do we predict a large exchange of ideas between two large counties with cheap travel connections. Appendix B documents this process in further detail.

Returning to our focal knowledge production function, instead of a single dependent variable describing total patent flows Y_{jt}, we examine multiple patent flows denoted by Y_{jt}^d, where the

[22] James and Smith (2020) raise an important issue with this approach that arises when the dimension on which these concentric circles are drawn is correlated with variation in the independent variable. In Feyrer et al. (2017), the units of analysis and the dimension of spillovers are both geographic, and their independent variable is not random across geographies. However, the unit of analysis in our study is technologies, which combined with the fact that we are leveraging the state match policies for identification, leaves us unconcerned with James and Smith's (2020) critique. However, their critique is very relevant for our approach to capturing technological spillovers, which is why we employ a version of their solution when tackling spillovers in that dimension.

superscript d denotes different thresholds for patents to be included in the dependent variable based on the location of the inventors or assignee firms. Instead of a single regression, we estimate a series of regressions indexed by d:

$$\mathbb{E}[Y_{jt}^d \,|\, W_{jt}] = \exp\Big(\frac{W_{jt}}{\overline{W}}\theta^d + \tau_t^d\Big) \ , \tag{3}$$

where the vector of θ^d estimates describes how the output elasticity changes as the base of firms and inventors whose patents are included in the dependent variable count expands. We estimate versions of this where we include USPTO patents from: only grant recipients, all firms and inventors in the same counties as grant recipients, all US-based firms and inventors within each decile of the weighted travel cost metric, and lastly, all firms and inventors worldwide.

Spillovers Across Technological Space

In our setup, identifying technological spillovers amounts to estimating peer effects. Our approach is motivated by Clarke (2017) and James and Smith (2020), who include regressors that indicate the treatment status of nearby units.[23] In those papers, "nearby" refers to geographic distances. Here, we use the similarity scores generated from our mapping of FOA topics to CPC groups. Just as travel costs constrain the flow of ideas over geographies, we expect the cumulative nature of R&D to constrain the flow of ideas over technologies.

To incorporate this into our empirical model, first recall that we construct investment flows and corresponding stocks (W_{jt}) that describe the dollar amount of SBIR funds allocated to CPC group j in time t. Even more specifically, we can construct bins of investments flowing into each CPC group as a function of how similar that group is to the FOA topic from which the investment originates. Let $b \in \{1-5, 6-10, \ldots 96-100\}$ index these bins, giving W_{jtb} such that, for instance, $W_{jt,b=6-10}$ describes the stock of investments in group j at time t originating from FOA topics where group j is in the 6th to 10th percentile of technological distance.

Substituting these bins of investments into the main production function, and allowing their effect on patent rates to vary, yields:

$$\mathbb{E}[Y_{jt}^d \,|\, W_{jtb}] = \exp\Big(\sum_{b\in\mathcal{B}} \frac{W_{jtb}}{\overline{W}}\theta_b^d + \tau_t^d\Big) \ , \tag{4}$$

[23] See also the statistical literature for more on estimating causal effects in the presence of interference (e.g., Toulis and Kao 2013).

where $\mathcal{B}$ is a set of technological distance bins.

To summarize, Equation 4 represents multiple regressions indexed by the superscript d, one for each concentric set of firms and inventors whose patents are included in Y. Within each regression, we obtain multiple output elasticity estimates indexed by the subscript b, one for each bin of investments. We will use our estimates of θ_b^d from *the same regression*, holding d fixed, to investigate spillovers across technological space, and we will use our estimates of θ_b^d from *different regressions*, holding b fixed, to investigate spillovers across geographic space.

This approach is more flexible (albeit more demanding) than the spillover matrix approach to estimating R&D spillovers, since those methods impose structure on the magnitudes of spillovers across spatial dimensions. Our approach, however, estimates the structure of spillovers from the data.

Boundaries of Technological Spillovers

As noted by Manski (1993), identification here can be obtained only with assumptions about connections of units in the network. In our setting, this amounts to identifying some technological distance beyond which we must assume no spillovers occur. In other words, $\mathcal{B}$ cannot include all technological distance bins. Practically speaking, we must identify some boundary of similarity scores between an FOA topic and CPC group beyond which it is reasonable to assume that investments originating in the FOA topic have no effect on output in that CPC group.

We search for this boundary using the data-driven procedure proposed by Clarke (2017). This frames the issue as an optimal bandwidth problem, and uses cross-validation to identify the boundary of spillovers that best fits the data. Appendix D reports further details and the results of this procedure. In short, the results suggest a boundary of the 60th percentile of technological distance when focusing on grant recipients, and a boundary of the 40th percentile when focusing on all other groupings of firms and inventors. After making these assumptions, our estimates of θ_b can then be used to infer the marginal product of SBIR funding, when the focal output is patents on technologies that are some distance from an FOA topic described by b.

Calculating the Magnitude of R&D Spillovers

With estimates from Eq. 4, we calculate the implied magnitude of spillovers across geographies and technologies. For example, if we estimate that an additional $1 million would spur one additional patent from SBIR grant recipients, but the same amount would spur three patents from all firms and inventors (including grant recipients), then we would say that SBIR grant recipients are responsible for only 33% of the net patent output of the program. In this hypothetical case, we would deem geographic spillovers to be twofold, since for every one patent produced by the grant recipients, two more are produced by others.

Still, we need to estimate the marginal product of SBIR investments in a way that reflects the realities of the DoE's investment choices – they invest in FOA topics, not CPC groups. Thus, we use our elasticity estimates to construct FOA topic-level marginal products (in terms of additional patents) based on the distribution of observed FOA topics and which CPC groups are targeted within. Appendix B.3 details our approach, which also accounts for the flow nature of our dependent variable. We report the average of these topic-level estimates (along with the 5th and 95th percentiles).

4 Main Results on R&D Spillovers

4.1 Results at Geographic Edge Cases

We begin by reporting the results based on the patent flows from four geographic edge cases: grant recipients, all firms and inventors in the same US counties as grant recipients, and then all US-based and finally all inventors and firms worldwide. We use the empirically derived boundaries of technological spillovers, and start with a simple case where we use a single stock of investments that spans the entire technological distance over which we expect spillovers; that is, in the notation of our main equation (Eq. 4), we use a single bin b in the set $\mathcal{B}$.[24]

Table 2 reports the regression estimates of the output elasticities for the four edge cases. Appendix E.1 plots the raw data underlying these estimates, which support our assumption of a constant elasticity. We also report our conversion of these estimates into average marginal products (in terms of patents per \$1 million – the approximate size of a Phase II SBIR grant), which are intended to represent the average return on additional investment in an FOA topic. In all cases, we cluster standard errors at the CPC group level.[25]

[24]The estimating equation for each of the four d is: $\mathbb{E}[Y_{jt}^d \mid W_{jtb}] = \exp\left(\frac{W_{jtb}}{\overline{\overline{W}}}\theta_b^d + \tau_t^d\right)$, where $b = \mathcal{B}$ and is defined as the "technology boundary" in Table 2.

[25]While we have the universe of data on DoE SBIR grants and can observe all USPTO patents, we are still concerned with design-based uncertainty (Abadie et al. 2020). When a CPC group receives additional investment in a given year, that flow of variation persists in the stock of investments in that CPC group for all future years.

Focusing first on the patents produced by DoE SBIR grant recipients, columns 1–3 of Table 2 illustrate the different estimates we obtain when focusing on total funding (federal plus state match), just the match funding, and then just the windfall portion of the match funding. We estimate an elasticity of roughly 2.3 when including total SBIR funding in the model (col. 1), but hypothesize that a significant portion of this variation is driven by the selection bias discussed previously. Focusing just on the state match funding yields an elasticity close to 1.0, which corresponds to 4 patents per $1 million (col. 2). But we are still concerned with the possibility of selection bias since match funding, on average, is a direct effect of federal funding.

Column 3 reports the results from our preferred specification. Here, we focus just on the windfall funding generated by the match programs, which yields an elasticity estimate of 0.134. This magnitude corresponds to about 0.5 patents per $1 million. It appears that not accounting for the endogenous allocation of funding overstates the productivity of these grants by an order of magnitude.

Columns 4–6 of Table 2 shift the focus geographically outward from grant recipients. We continue to estimate average elasticities between 0.12 and 0.13. But because the base of patent flows grows quickly with each successive grouping (while the elasticity does not decline), we estimate much larger marginal products on a patent-per-dollar basis: 1.4, 1.7, and nearly 3 patents per $1 million for the same-county, US-wide, and worldwide sets of inventors and firms, respectively. These magnitudes suggest that grant recipients might be responsible for only one sixth of the net patent output created by these grants – the R&D spillovers in this setting could be as large as five-fold. In the next section, we relax our assumption of a single bin of investments (by introducing multiple bins b in the set $\mathcal{B}$) to more flexibly estimate spillovers over technology-space.

4.2 Net Spillovers Across Geographies and Technologies

The results in Table 2 suggest the potential for geographic spillovers is large. But how closely do these new patents align with the DoE's objectives as expressed in the FOA topics? And how concentrated are those geographic spillovers within the US? Here we report the results from our full and most flexible model described by Eq. 4.

Figure 2 reports the elasticity estimates based on Eq. 4 using the same four geographic edge cases as before. Each panel is based on a separate regression, and we plot the estimates of $\theta^{d,b}$, where d indicates the geographic set of patents used in the regression and b indicates the technological distance bin. As before, and still based on our data-driven search for the boundary of technological spillovers, we estimate b-specific elasticities up to the 60th percentile of technology distance when focusing only on patents from grant recipients and up to the 40th percentile for all other cases.

In each case, we observe a clear and intuitive trend: the productivity of SBIR funding is the highest within the CPC groups that are closest in technology space to the objectives of the FOA topic through which that funding flows. The elasticities decrease roughly monotonically until we estimate a series of null effects. This pattern of estimating relatively precise zero elasticities at the same point where the data-driven choice for the threshold of spillovers gives us further confidence in our approach.

We use the elasticities reported in Figure 2 (as well as further unreported regressions based on different sets of within-US firms and inventors) to generate our full set of marginal product estimates. Figure 3 plots these estimates, focusing on spillovers across just technological space (Fig. 3a), across just geographic space within the US (Fig. 3b), and within the US and abroad (Fig. 3c).

Focusing first on technological space, Figure 3a illustrates how spillovers along this dimension are not exactly monotonic. Up to the 25th percentile of technological distance, we estimate roughly equal output per dollar.[26]

Figures 3b and 3c help illustrate spillovers across geographic space. Within the US, grant recipients themselves are responsible for nearly half of all US-based patents. The estimates suggest that grant recipients generate roughly 0.75 patents for every $1 million they receive. In Appendix E.2, we walk through some simple math that indicates this estimate is well within a reasonable range one would expect based on Howell's (2017) sharp regression discontinuity evaluation of this program – our confidence intervals do not reject Howell's (2017) results.

The remainder of US-based patents are almost entirely due to firms and inventors in the closest 10% of US counties (per travel costs), with output dropping essentially to zero for the vast majority of counties. This concentration is consistent with prior work on the geographic distribution of inventive activity in the US (Forman et al. 2014).

Comparing domestic and foreign patenters, Figure 3c indicates that US-based firms and

[26] This pattern does not align with the more monotonic elasticity estimates shown in Figure 2 because the CPC groups that receive the largest amount of high-match funding (as in, lower technology distance percentiles) also tend to have patent flow rates that are below average. Although we cannot investigate this result further with our research design, this is consistent with the notion that the government is directing funding towards technologies where it is more difficult to patent, which is in line with the theoretical motivation for these subsidies.

inventors are responsible for about 60% of net patent output, with the remaining 40% due to foreign firms and inventors. We are unaware of previous attempts to directly estimate this domestic-foreign split of the returns to public R&D investments (in terms of patent production), which indicates that international R&D spillovers can be large.

Figure 3d plots the joint distribution of output across both geographic and technological dimensions. Within the US, grant recipients are responsible for most of the patents that are technologically the closest to the DoE's objectives (1st–10th percentile of technology distance), with nearby firms and inventors responsible for the vast remainder of the within-US spillovers. Foreign firms and inventors tend to focus on relatively close technologies, although we find meaningful effects out to the 25th percentile of technological distance.

Table 3 summarizes all of these results succinctly. We report the average marginal products and costs and decompose the net patent output of these grants along both the geographic and technological dimensions. We find that grant recipients are responsible for only about one quarter of the net patent output, which indicates geographic spillovers are on the scale of 3× – for every patent they produce, we expect three more from other firms and inventors around the world. Similarly, we find that the nearly two-thirds of net patent output is related to technologies that are not very similar to the original objectives of the DoE's FOA topics – technological spillovers are on the scale of twofold.

One notable difference between geographic and technological spillovers is that it appears spillovers permeate geographic space much further than technological space. On the geographic dimension, we find that countries all around the world benefit from these grants (a result we explore further in Appendix F). However on the technological dimension, it appears that spillovers permeate only about 40% of technology-space. In other words, it appears the costs of taking an idea around the world are much lower than the costs of using an idea related to one technology to advance a completely different technology. This is consistent with related work that suggests the adjustment costs of changing the direction of research are large (Myers 2020). We further discuss the implications of these magnitudes and patterns in Section 6.

4.3 Robustness and Alternative Specifications

We estimate a number of additional regressions to explore (1) the robustness of our key identification assumptions and (2) the sensitivity of our results to any of the choices made in our data construction. Below, we highlight some of these findings, with the full set of results included in Appendix E. Overall, we obtain very similar results across the range of alternatives.

Robustness to Controlling for Technology-specific Time Trends

Our identification strategy relies on an assumption that each CPC group's exposure to windfall funding from the state-based match programs is orthogonal to any underlying shocks in the supply of or demand for the technologies related to that group. We discuss this assumption and evidence supporting it in detail in Section 3.2. But as a robustness test, we also estimate two models that include a series of time-varying fixed effects at aggregated levels of the CPC scheme. These fixed effects remove time-varying variation in patent flows and SBIR funding that is common to aggregations of CPC groups, some of which may be due to (unobservable) supply or demand shocks.

Appendix E.3 reports and discusses the results of these regressions. Overall, we obtain relatively similar, though sometimes more conservative, estimates when including these controls for technology-specific time trends. Almost all of the estimates are within the confidence intervals of our preferred specification. There is some attenuation, but some of this is to be expected given that these sorts of fixed effects tend to bias production function estimates towards zero (Griliches and Mairesse 1995).

Alternative Data and Regression Specifications

Appendix E.4 reports results from seven different regressions that focus on alternative specification choices either in the data construction process (e.g., related to the similarity score calculations or the technological distance threshold) or in the regression model itself (e.g., whether zero-valued observations are included, the range of sample years, or the use of a negative binomial instead of a Poisson model). All of these alternative specification choices yield very similar results, which suggests that no single decision in our empirical approach is driving our main estimates.

We also investigate our assumptions about the discount rate on the stock of funding, which is relevant for getting a sense of production lags. As shown in Appendix E.4, we estimate a similar pattern of point estimates when we introduce non-zero discount rates, with larger discounting depressing the estimates towards zero. The magnitude of this compression towards zero is suggestive of production lags on the scale of five to seven years. We interpret these results cautiously, since the stock-and-flow empirical model we use is not well suited to investigate these lags in depth.

4.4 Additional Results

Comparison to Citation-based Paper Trail Linkages

Here, we compare our approach to the traditional front-page citation approach of capturing spillovers.[27] We explore two approaches to making the citation linkages. First, we take the popular approach of using what we term "one-degree" citations, as in direct citations, to grant recipients' patents as links. Second, we use what we term an "all-degree" approach and include any patent that can be connected by any degrees of citations to a grant recipient's patent.

Appendix E.5 reports the full results of these tests. We find that requiring citation linkages results in significantly lower spillover estimates. The one-degree approach yields spillover estimates that are 55% smaller than our preferred model, and the all-degree approach yields estimates that are 43% smaller.

This finding suggests that not much more than half of the R&D spillovers we identify are reflected in front-page citation trails. Despite the many aforementioned critiques of front-page citations, this result is, to our knowledge, the first to quantify how much may be missed when forced to rely on paper trails. Given the pervasive use of these citation linkages as proxies for R&D spillovers, we hope these results highlight the value of our alternative approach. However, one large upside of relying on citation data is the ability to investigate the specific lag structures of knowledge production, which can be long and complex (Azoulay et al. 2019).

Inventors Versus Firms as Conduits of Geographic Spillovers

Our main specification puts equal weight on individual inventors and firms (assignees) in terms of where patents are produced in geographic space. At the boundaries of our geographical sets – focusing just on patents from grant recipients and focusing on all USPTO patents – this distinction is irrelevant. However, for the intermediate cases, attributing patents entirely to inventors or to firms can shed some light on which entity appears more important for mediating spillovers over geographic space. An important caveat is that inventor and firm locations are fairly highly correlated.[28]

[27] Although survey evidence suggests citations can reflect meaningful knowledge flows (Jaffe et al. 2000), econometric analyses suggest a significant portion of citations are strategic and/or are in response to unobservable shocks (Alcácer et al. 2009; Arora et al. 2018). See Bryan et al. (2020) for recent work exploiting the, likely more informative, "in-text" citations as evidence of spillovers.

[28] 83% of all inventor-assignee pairs are from the same country. Amongst pairs where one is located in the US, 50% are located in the same state and 31% are located in the same county.

Appendix E.5 reports the results from these alternative approaches, and in general we do not estimate substantially different results whether we assign locations entirely to inventors or firms. This suggests there may not be dramatic differences in their relative importance as conduits of spillovers. There is some evidence that firms may be more important for facilitating geographic spillovers over very short distances and that individual inventors may be more important for facilitating international spillovers.[29] But again, we detect no major differences.

Regional Correlates of Spillovers

In Appendix F, we report the results of a purely descriptive search for the correlates of R&D spillovers. We cannot make any causal statements, but our setting and data provide a unique opportunity to (1) estimate how specific regions (e.g., US counties, foreign countries) are more or less likely to benefit from spillovers, and then (2) regress these estimates on features of each region to explore what is more or less correlated with the level of spillovers into that region.

In addition to features motivated by prior work, we focus on the degree to which a region appears to *exploit* knowledge produced by SBIR firms and focus on technologically similar inventions versus using that knowledge to *explore* technological space and focus on technologically distant inventions. We term this feature simply the "exploit-explore index" of a region. The notions of exploitation and exploration are pervasive in innovation economics and typically posed as a tradeoff (e.g., Manso 2011). But the importance of these alternative strategies, and whether such a tradeoff exists, has not received much attention in the context of R&D spillovers.

The results indicate that the size of spillovers across regions varies closely with features that reflect the supply of and demand for energy technologies in those regions. Interestingly, few features consistently explain more variation in a region's ability to capitalize on spillovers than their exploit-explore index. Even after conditioning on large vectors of other relevant controls, regions that appear more willing to focus on the same technologies that the SBIR firms pursued are more likely to create patents. In the case of domestic spillovers, the exploit-explore index is the fourth most important feature (out of 50 possible), with only industry clusters in IT, production technologies, and oil and gas appearing more important. At the international level, the index is found to be the most important feature (out of 83 possible). Altogether, the results suggest a need for continued work on why different groups

[29]The importance of individuals for international spillovers is consistent with Griffith et al. (2006), who find that UK firms with large inventor bases in the US appear to differentially benefit from spillovers.

of innovators are more likely to exploit or explore technology space, especially after they learn new knowledge from others.

5 Private Versus Social Value

An important question remaining is what share of these spillovers is due to externalities – what is the wedge between the private and social returns to R&D? We cannot answer this question in general, but we can answer a closely related question: how much of the total *patent-based value* stimulated by these R&D grants is captured by the grant recipients themselves?

Our analyses thus far have implicitly treated all patents spurred by these grants as equally valuable to the different sets of firms and inventors that obtain them. That is, one could assume that the marginal patents produced by grant recipients are equally as valuable as the spillover-based patents produced by non-grant recipients, on average. If this assumption is true, then it implies that the share of patent-based value captured by any group of firms or inventors is simply equal to their share of the net patent output produced by these grants. As outlined in Table 3, we estimate grant recipients are responsible for about 25% of the net patent output. This would imply they capture roughly 25% of the patent-based value their own R&D ultimately generates.

To relax this assumption, we assess whether the SBIR grants have any effect on the *quality* of new patents. To do so, we estimate another series of regressions using the main specification with the number of forward citations per patent as the dependent variable. While we noted in detail above the drawbacks of using patent citations to proxy for spillovers, they are currently still the most accessible proxy for value. Many studies have shown that forward citations are strongly correlated with the private value of patents to firms (e.g., Harhoff et al. 1999; Hall et al. 2005; Kogan et al. 2017). Thus, this regression allows us to investigate whether there is any important difference in the average citation-proxied value of patents spurred by SBIR funding.

Appendix G reports the results of these regressions, which show a clear pattern that the marginal patents produced by grant recipients (due to the SBIR funding) are cited much more often than average. This result alone is interesting in that it suggests the SBIR funding is enabling R&D that is increasing the quality of the firms' inventions in terms of their private value, but also (to the extent these citations are reflecting externalities) their social value.

When we expand the set of firms and inventors in the regression though, there are only very minor increases in the average citation-based quality of patents. In other words, the effect of SBIR funding on the quality of patents appears important only for grant recipients themselves, with the spillover-based patents appearing to be very close to average quality.

This pattern suggests that our initial estimate – that grant recipients capture 25% of the net patent value they generate – is likely an underestimate. How much of an underestimate might this be? This depends on many factors, but for simplicity and given our data constraints, we focus on one key factor: the relative value associated with a marginal patent versus the value associated with a marginal citation to a patent. That is, we assume that the only difference in expected value across patents is based on the number of forward citations each patent receives. With this assumption, if we know how valuable a marginal patent is compared to a marginal citation, we can estimate the share of patent-based value each group of firms and inventors captures, while incorporating this quality-margin effect.

Figure 4 plots the distribution of patent-based value captured by the grant recipients over a range of assumptions about the relative value of citations versus patents. This range spans from zero to one third and is based on estimates from prior work to value patents and citations (Harhoff et al. 1999; Hall et al. 2005; Kogan et al. 2017). Obviously, if no value is assigned to citations, we revert back to the quantity-only based 25% estimate. Using the upper end of the relative value of citations suggests that grant recipients may be capturing upwards of 50% of the net patent-based value stimulated by these grants.[30]

Figure 4 also plots the share of patent value captured by all US-based firms and inventors. Our range of estimates spans from about 60% (when all patents are treated equal on average) up to roughly 75%. This suggests that international spillovers might allow foreign countries to capture anywhere from 25–40% of the patent-based value generated by the DoE's SBIR grants.

To our knowledge, this is one of the first direct estimates of the domestic share of returns to public R&D investment. Macroeconomists have used equilibrium models and aggregate data to estimate how much foreign countries benefit from domestic technological advances (Eaton and Kortum 2002; Coe et al. 2009). We cannot directly map our estimates to theirs for comparison, but continued work that can link these micro- and macroeconomic estimates is worthwhile.[31]

[30] In Appendix G.2, we take an alternative approach and estimate the effect of funding on both the quantity and quality margins at the same time using citation-weighted patent counts as dependent variables. As we discuss there, these approaches put significantly more weight on citations than patents, which yields a larger range of estimates of the private value captured by the grant recipients (between 38–75%).

[31] For example, Eaton and Kortum (2002) estimate that when the state of US-based technology increases,

Comparison to Prior Estimates of Private and Social Returns to R&D

If we take our estimates of patent value capture as reflecting the wedge between the private and social returns to R&D, our results suggest that the marginal social returns to R&D in this setting are anywhere from about 100–300% of the marginal private returns. While seemingly large, this order of magnitude is very much in line with the few firm-level studies that have focused on large public firms (Bloom et al. 2013; Zacchia 2020) and macroeconomic studies (Jones and Williams 1998) that have estimated this same wedge.

This conclusion should be interpreted with caution as it is based on a number of large assumptions that generally imply we are considering an upper bound of this wedge.[32] Continued empirical work to more precisely estimate this wedge will certainly be important.

6 Discussion

The presence of R&D spillovers across geographic and technological space are a key motivation for government intervention in markets for innovation. Here, we provide another set of results in the still very short line of causal estimates of the magnitude these spillovers (Bloom et al. 2013; Azoulay et al. 2019; Zacchia 2020). In a new setting with a new methodology, we again find that R&D spillovers are very large. The firms that receive SBIR funding from the US Department of Energy obtain only 25% of the net patents that their R&D ultimately stimulates. For every one patent they produce, three more patents are produced by others who benefited from their R&D. Even after accounting for marginal differences in patent quality, our estimates suggest that, at most, SBIR firms may appropriate only half of the patent-based value their R&D creates. We provide another piece of evidence that the marginal social returns to R&D may be orders of magnitudes larger than the marginal private returns.

Our focus on smaller firms is important since many governments worldwide have R&D policies that target subsidies to small firms. Our focus on public subsidies in the energy sector suggests that this increasingly important sector is fertile ground for the diffusion of new inventions. And while our findings provide another important data point suggesting a large

the relative magnitude of welfare gains for each major foreign country (due to spillovers) is often between 10% to 20% of the US's welfare gains.

[32] This includes (at least) the following assumptions: (1) product market rivalry spillovers after the patenting stage are negligible; (2) the marginal private costs of producing these patents is equal for all firms and inventors; and (3) none of the spillovers are due to market transactions (e.g., via patent licenses). On last point, Arque-Castells and Spulber (2019) show that ignoring markets for ideas can lead to overestimating the social returns to R&D by a significant amount.

wedge between the private and social returns to R&D, continued work that disentangles externalities and spillovers is essential since it has direct implications for the optimal level of R&D subsidies.

Our results also have implications for program evaluations of R&D subsidies. Recent work has continued to improve the methodologies used to study public R&D investments (e.g., Einiö 2014; Howell 2017), but rarely are spillovers accounted for. In our setting, even if we ignore international spillovers and focus only on patents from US-based firms and inventors, we would have missed more than half of the net patent output from the SBIR program.

On the methodological front, our use of text analyses to connect the units of inputs (the funding opportunities) to outputs (patent groups) could be applied in a variety of other contexts. In our case, it frees us from relying on any citation linkages between patents, which much of the related literature to date has been forced to do. Our results suggest that relying only on these paper trails might overlook a substantial amount of patent-based R&D spillovers. However, abandoning the paper trail does limit our ability to investigate the lag between R&D investment and outputs which has been shown to be long and complex (Azoulay et al. 2019). Outside of our context, it is commonplace that the inputs and outputs of a production function are not indexed at the same unit of analysis, but our approach could be used to generate a useful data frame that directly incorporates spillovers across various units of observation.

As noted throughout the text, there are a number of important caveats to our research design and the interpretation of our results. An important limitation is that our focus on the state match policies mechanically narrowed our focus to firms and inventors in a subset of the US that excludes many of the more historically productive regions (e.g., Silicon Valley, Seattle, New York City), where the effect of these grants may be larger. Likewise, since the match policies are awarding marginal funds on top of the federal grants, our estimates will be lower than the causal effect of the federal grants if there are decreasing returns to scale at the firm level.

Another tradeoff we make in focusing on these match policies is that we are confident that the estimates do not reflect selection effects in terms of firms applying to the SBIR program. This helps with the internal validity, but likely narrows our external validity. The firm location analysis described in Appendix C.2, along with discussions with managers of the state match programs, indicate that it is highly unlikely that firms are making any decisions based on the presence of the match policies. However, if the entire SBIR program were to announce that all grants would be larger, we expect this could lead to marked changes in the composition and number of applicants. How this might ultimately affect the productivity of these public R&D investments would be a very interesting counterfactual to pursue.

Ultimately, we do not take a normative stance on which patents produced by this program should or should not count. Instead we highlight how the costs of spurring a patent vary widely depending on how seriously spillovers are appreciated. In our setting, counting all patents as relevant would lead to a large overestimate of the program's effectiveness if specific technologies are of interest. Conversely, focusing only on grant recipients would lead to a large underestimate of the program's effectiveness if the output of other firms and inventors is of interest.

Overall, our results offer new evidence on how the visible hand of the government can influence the rate and direction of R&D. We have shown that the output of publicly funded R&D can vary widely on the extent to which spillovers across technological and geographic space are appreciated. We hope future work continues to investigate the magnitudes and determinants of these spillovers to better inform both economic theories and innovation policies.

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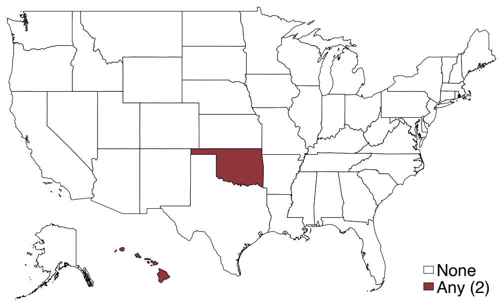
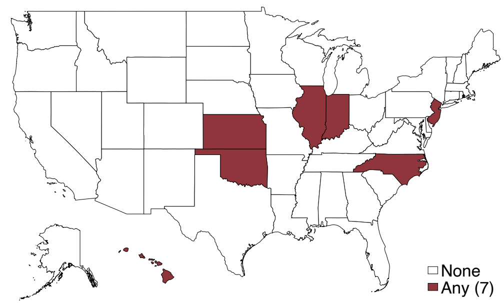
Tables & Figures

Figure 1: State Match Programs

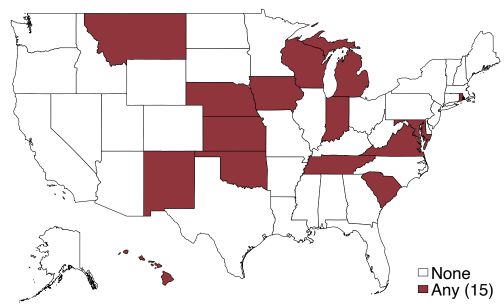
(a) 1997



(b) 2007



(c) 2018



(d) Match Amounts

Phase I

Amount, $K	N State-Years
25–45	39
50–65	56
75	45
100–105	17

Phase II

Amount, $K	N State-Years
50–75	12
100	20
250	11
500	37

Notes: Figures 1a-1c indicate which states had any matching policy in particular years. Figure 1d tabulates the sizes of the matches awarded depending on the Phase of the award.

Table 1: Summary Statistics

	Type	mean	s.d.	min	$p50$	$p99$
Federal DoE SBIR Program						
Phase I \$, total	Dol., M	47.5	13.9	26.6	43.9	77.2
Phase II \$, total	Dol., M	152.0	45.0	100.1	132.6	240.7
Firms with awards	Count	255.6	47.0	195	257	379
Awards per firm	Count	1.86	1.89	1	1	10
\$ per firm	Dol., M	0.78	1.05	0.02	0.28	5.11
FOA Topics	Count	54.0	9.92	38	55	72
FOA Topics with awards	Count	51.4	9.90	35	52	68
\$ per FOA Topic	Dol., M	1.71	1.87	0.02	1.04	9.20
State Match Programs						
Awards with match \$	Count	39.5	40.4	1	27	133
Match \$, total	Dol., M	3.74	3.91	0.07	3.29	12.4
Firms with match \$	Share	0.07	0.06	0.00	0.05	0.17
FOAs with match \$	Share	0.18	0.14	0.01	0.18	0.39
USPTO Firm-level Patent Flows						
Ever-SBIR firms ever patent, whole sample	$\{0,1\}$	0.49				
Ever-patent firms ever SBIR, whole sample	$\{0,1\}$	0.01				
Patents per SBIR firm, post-1^{st}-award	Count	0.51	2.62	0	0	9
Patents by all SBIR firms, post-1^{st}-award	Count	487.5	167.8	146	485	727
USPTO CPC group-level Patent Flows						
Unique focal CPC groups, whole sample	Fixed	10,686				
SBIR firms	$[0,\infty)$	0.06	0.49	0.00	0.00	1.23
Counties of SBIR firms	$[0,\infty)$	9.01	52.2	0.00	0.75	147.4
All US	$[0,\infty)$	10.3	56.3	0.00	1.00	161.5
Worldwide	$[0,\infty)$	20.8	106.7	0.00	2.13	347.4

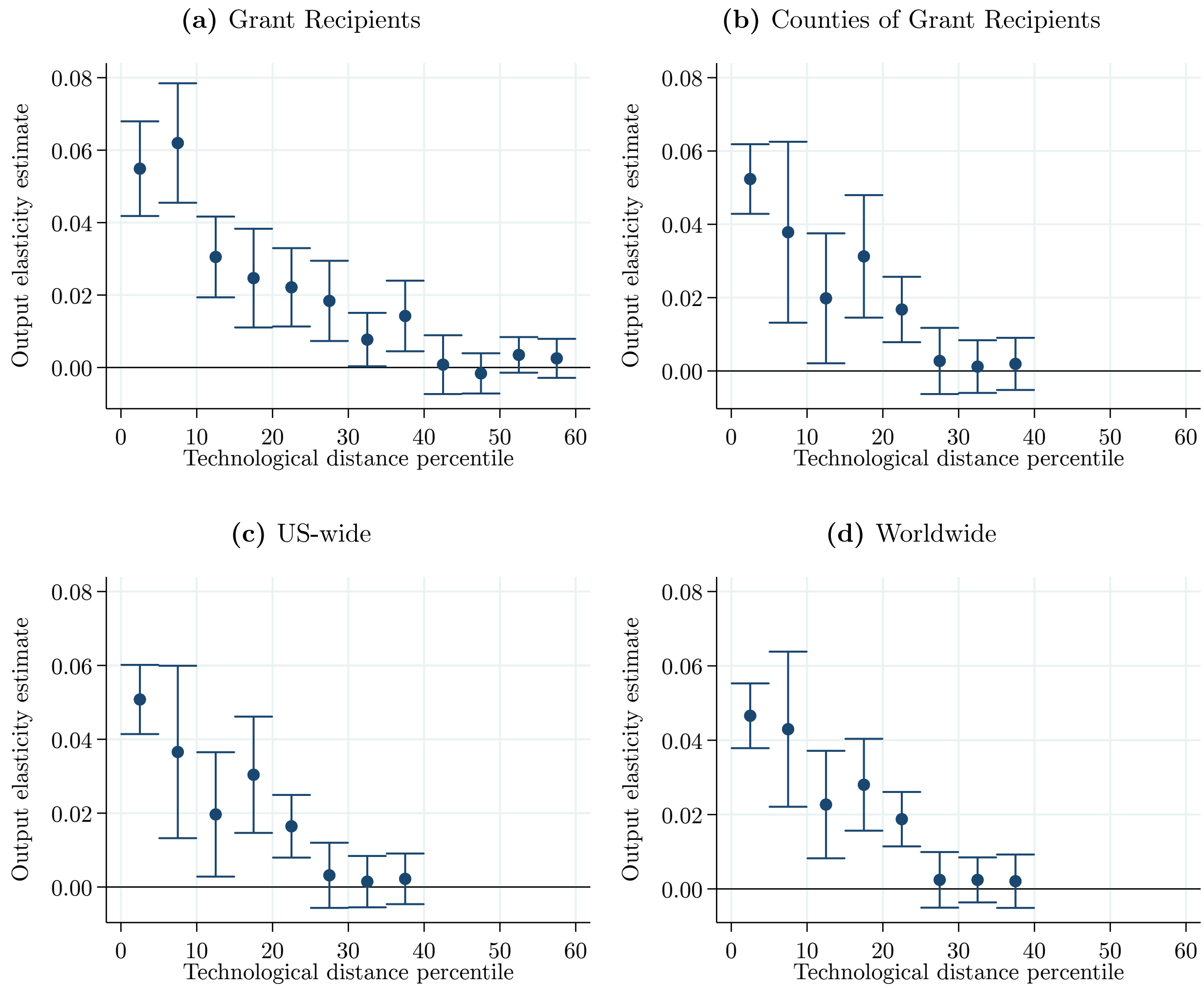
Notes: All statistics based on the annual averages for the years 1997 to 2018 unless otherwise indicated by "whole sample."

Table 2: Results at Geographic Edge Cases

	Grant recipients			Recipients' counties	US-wide	Worldwide
	(1)	(2)	(3)	(4)	(5)	(6)
Total $	2.275					
	(0.196)					
State Match $		1.015				
		(0.094)				
Windfall $			0.134	0.125	0.123	0.130
			(0.021)	(0.016)	(0.015)	(0.014)
$\frac{\partial \text{ patent}}{\partial \text{ \$1M}}$	9.28	4.14	0.54	1.40	1.73	2.97
	[9.0–10.2]	[4.0–4.5]	[0.5–0.6]	[1.2–1.6]	[1.5–1.9]	[2.5–3.3]
N obs.	235,406	235,406	235,406	235,384	235,384	235,384
Tech. boundary	$p60$	$p60$	$p60$	$p40$	$p40$	$p40$
Year F.E.	Y	Y	Y	Y	Y	Y

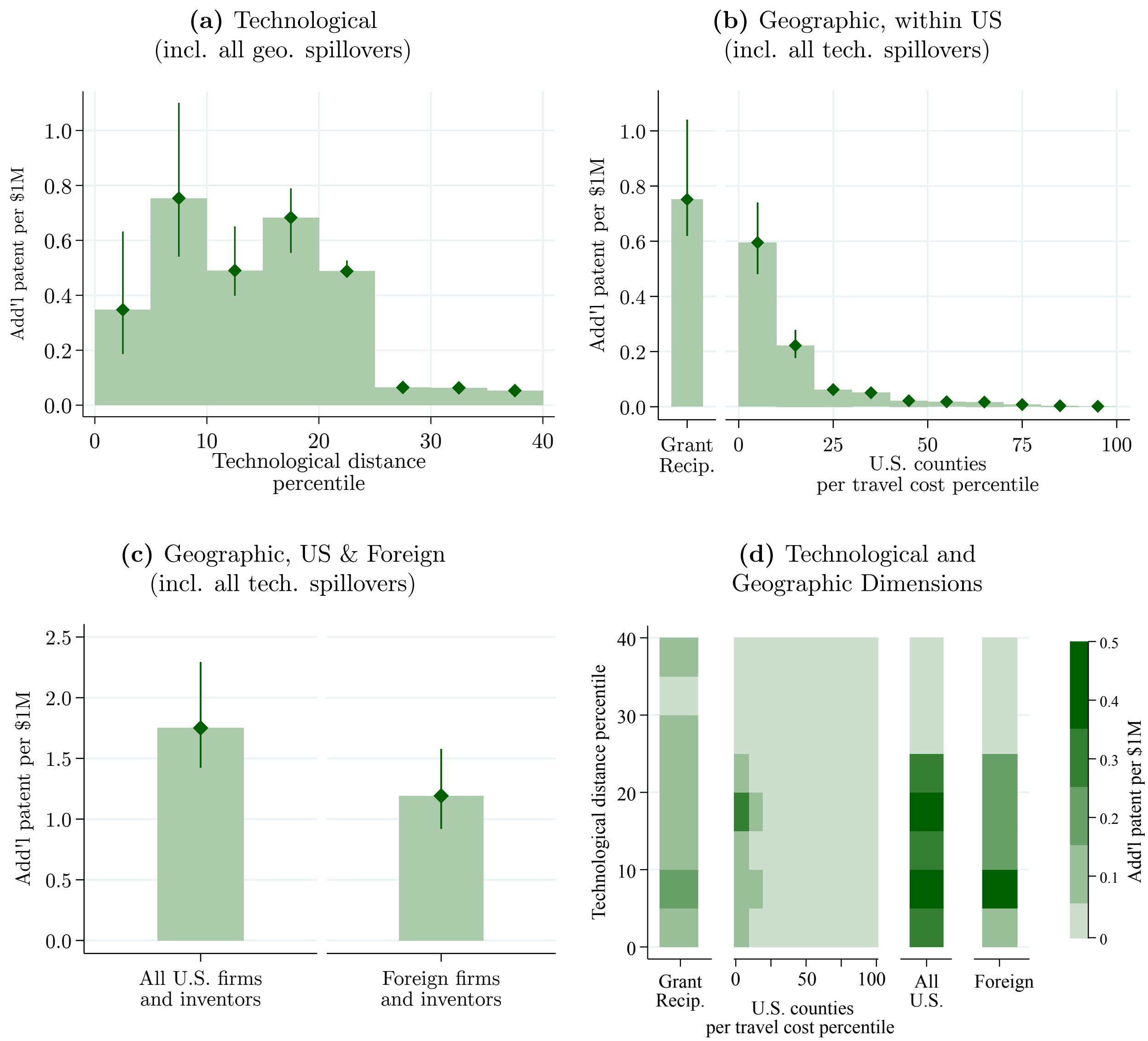
Notes: Reports the output elasticity estimates from regressions using the simple model that aggregates all technological spillovers into a single bin."Tech. boundary" indicates the boundary of technological spillovers in terms of the percentile of technological distance between the CPC group and the Funding Opportunity Announcement topic. Standard errors clustered at the CPC group level are reported in parentheses. "$\frac{\partial \text{ patent}}{\partial \text{ \$1M}}$" reports the additional patents expected from a $1 million dollar investment, averaging across all Funding Opportunity Announcements, with the fifth and ninety-fifth percentiles reported in brackets.

Figure 2: Patent Output Elasticity Estimates



Notes: Plots the estimates of θ_b^d from Eq. 4. d corresponds to geographies and varies across the four panels, with different panels corresponding to different regressions (where the dependent variable successively includes patent output from firms and inventors further and further from grant recipients). b corresponds to the technology distance bin and varies within each panel (where the bins include investments made via FOA topics that are less and less similar to the focal patent class). All estimates are based on windfall investments from state match policies. 95% confidence intervals based on standard errors clustered at the CPC group level are shown with brackets.

Figure 3: Marginal Products across Geographic and/or Technological Dimensions



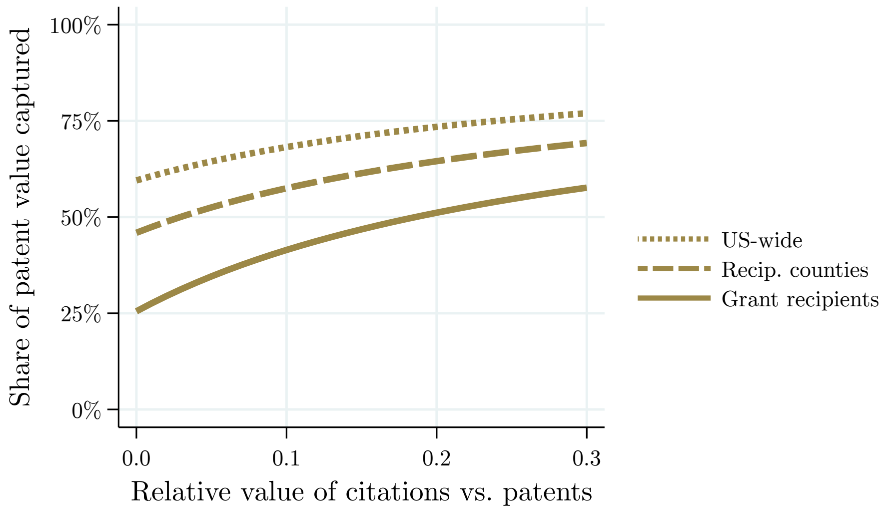
Notes: Plots the the net patents from specific subsets of firms and inventors to be expected from a $1 million dollar investment, averaging across all Funding Opportunity Announcements, with the fifth and ninety-fifth percentiles of the FOA topic-level statistics shown by the vertical lines.

Table 3: Summary of Outputs and Costs

	% of net patents	$\frac{\text{patents}}{\$1\text{M}}$	$\frac{\$}{\text{patent}}$
Counting all USPTO patents and...			
...only grant recipients	26%	0.75	$ 1,330,000
...only non-recipient firms & inventors nearby recipients	20%	0.60	$ 1,680,000
...all US firms & inventors	60%	1.75	$ 571,000
...all foreign firms & inventors	40%	1.19	$ 839,000
Counting all firms & inventors, only USPTO patents that are...			
...very similar to grants' tech. objectives	37%	1.10	$ 908,000
...somewhat similar to grants' tech. objectives	40%	1.17	$ 852,000
...least similar to grants' tech. objectives	23%	0.67	$ 1,496,000
Counting all USPTO patents, all firms & inventors	100%	2.94	$ 340,000

Notes: Reports average marginal products and costs when focusing on a particular set of patents or firms and inventors. The bottom row defines output and costs when all patents are considered, so "% of net patents" is 100% by construction. "patents / $1M" reports the net number of patents expected from a marginal investment (awarded only to grant recipients) of $1 million. "$ / patent" reports the marginal cost expected to produce one additional patent.

Figure 4: Share of Net Patent Value Captured
by Different Firms and Inventors



Notes: Plots the share of net patent value captured by successive aggregations of firms and inventors (y-axis) based on a range of assumptions (based on the existing literature) about the relative average value of an additional patent compared to the average value associated with an additional forward citation to a patent (x-axis).

Online Appendices

A Construction of CPC-level Data

This section describes how we convert the patent and SBIR data into an input-output data set. For reference, the level of observations and key variables in the raw data sets are as follows:

1. Patent Record
    - Observation level: Patent–Inventor or Firm Assignee–CPC group
    - Key variables: year application submitted and granted; inventor and firm assignee location
2. SBIR Award Data
    - Observation level: Year–Funding Opportunity Announcement (FOA) Topic–Firm
    - Key variables: dollar amount of grant
3. SBIR FOA Data
    - Observation level: Year–Topic
    - Key variables: text of Topic description

The overall flow of the data construction is as follows:

1. Standardize CPC groups
2. Compute similarity of patent abstract text to FOA topic text
3. Collapse patent-Topic similarity scores to CPC group – FOA topic similarity scores
4. Allocate funds awarded via each Topic (to firms) into each CPC group as a function of CPC group – FOA topic similarities
5. Collapse patent flows to CPC groups

A.1 Choosing a CPC Class Level

The first major decision is choosing a level of aggregation of the CPC. Each CPC code has what is referred to as a "main trunk", which consists of five units of the form:

[1 letter][2 numbers][1 letter][1-3 numbers](/)[2-6 numbers],

i.e., A01B33/08. We could, in theory, use the full code or splice the main trunk at any of the four breaks to generate different levels of aggregation of the hierarchy. To get a sense of the range of aggregation possible, there are nine different 1-digit codes, 128 different combinations for the three digit codes, 662 combinations for the four digit codes, about 10,000 codes if spliced at the "/", and over 220,000 codes if all digits are used. For simplicity, we refer to these as Level 1-5 codes, respectively.

For example, we could group all patents together if they are labeled with the Level 2 code for "Basic Electrical Elements." Or, we could separate these patents out into the fourteen Level 3 codes within, relating to "Cables", "Resistors", "Magnets", etc. Or, we could further separate out, for example, "Magnets" into another seventeen Level 4 codes, each of which has yet another dozen or so Level 5 codes within.

If we aggregate less, then we have a larger sample size and we rely less on the idiosyncrasies of the CPC hierarchy. Conversely, the traditional advantage to aggregation is related to the Stable Unit Treatment Value Assumption (SUTVA) necessary to make causal statements from statistical models. The idea is that if the researcher aggregates units together which, for instance, are most likely to experience spillovers or substitution from treatment, then the SUTVA should hold for the newly aggregated set of units.[1]

But because we are intent on identifying the magnitude of across-technology class spillovers and do not want to rely too much on the CPC's hierarchy, we lean towards less aggregation. We choose to work with the Level 4 codes of the CPC, which we term "groups." We think this suitably balances the need to avoid reliance on the CPC hierarchy in ways that can lead to misspecification (Thompson and Fox-Kean 2005), without dividing the data into units so small that patent counts are too rare to prove useful in our analyses.

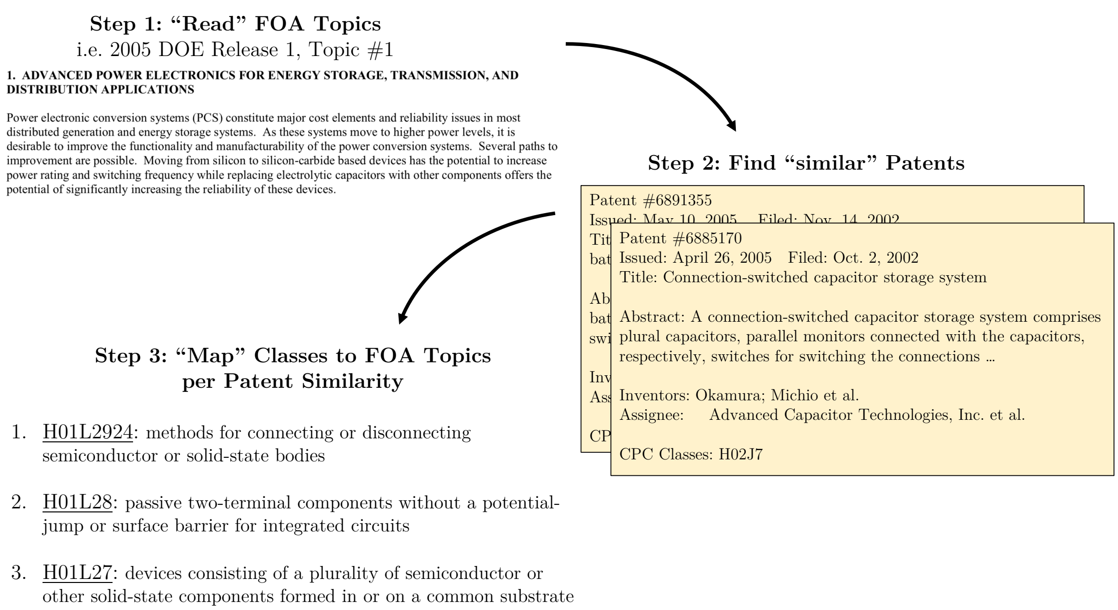
[1] However, this approach does not permit the researcher to tease out the extent to which treatment effects are "direct" or driven by spillovers across units within these aggregations.

A.2 Mapping Grants to CPC Groups

Thankfully, all patents are automatically labeled with CPC groups by the UPSTO. Our challenge then is to determine how each SBIR grant maps to a particular CPC code. We need to identify what technologies the government invests in. Our overall approach is outlined in Figure A.1.

We leverage the fact that we can connect each SBIR grant to the corresponding FOA topic that the grant application responded to. The text of these FOA topics is the key source of data we use to answer the following: if a grant recipient patented an invention that was in line with the stated goals of the topic they responded to, what CPC groups would that patent be assigned? If we know the answer to this question, then we know the dollar value of all grants awarded through each FOA topic has been "invested" in these corresponding CPC groups.

Figure A.1: Mapping Funding Opportunity Announcements to CPC Groups



We tackle this prediction problem in a series of steps that include textual similarity analysis and some simple summations and averaging. What follow are the steps of how we assign the grant dollars awarded via each FOA topic indexed by k, into the relevant CPC groups indexed by j. Following the outline, we motivate and describe the steps in further detail.

1. Estimate the text similarity S between the description of each FOA topic k and the abstract of each patent p: $S_{kp} \in [0, 1]$

2. Calculate the mean similarity $\overline{S}$ for each FOA topic to each group j based on the groups assigned to each patent, where $\mathcal{P}_j$ is the set of patents assigned group j and $N_{\mathcal{P}_j}$ is the number of patents in that set:

$$\overline{S}_{kj} = \frac{\sum_{p \in \mathcal{P}_j} S_{kp}}{N_{\mathcal{P}_j}} \tag{A.1}$$

3. Calculate percentile bins b of $\overline{S}_{kj}$, summing to create $\overline{S}^{b}_{kj}$, using either:
   - all $\overline{S}_{kj}$ values, or
   - $\overline{S}_{kj}$ values de-meaned at the FOA topic level
4. Calculate the twenty ventiles b (five percent groupings) of the $\overline{S}^{b}_{kj}$ distribution, and assume that below some percentile bin $\bar{b}$ threshold, spillovers do not occur across technology groups. (See Appendix D for more on this threshold.)
5. Evenly divide the total amount of SBIR awards given out via each FOA Topic, I_k, to all ventiles b above the percentile threshold $\bar{b}$, to give the topic-class level investment I^{b}_{kj}
6. Sum I^{b}_{kj} investments to the b and j level to obtain I^{b}_{j} – the total amount invested into group j from awards given via FOA topics that are in percentile b of similarity.

(Step 1) Text Similarity between FOA Topics & Patents: Our key assumption for this exercise is that if a patent abstract and an FOA use the same terminology, and especially if few other documents use that terminology, they are likely referring to the same technologies. This approach of exploiting the similarities between texts to link units of data has become increasingly common in economics. A number of studies leverage this approach to map "scientific space" by comparing the similarity of words used in publication abstracts (Azoulay et al. 2019, Myers 2020) and "product space" by comparing the similarity of words used in product descriptions (Hoberg and Phillips 2016). We follow the norms of modern natural language processing approaches. This includes removing "stop words" (i.e., a, the, and, etc.) and "stemming" words to remove common prefixes and suffixes. We use the commonly employed cosine function to calculate the similarity between text pairs. We also follow norms in using n-grams to identify terms, and weight these terms using the term-frequency-inverse-document-frequency (tfidf) method. We use 1-, 2-, and 3-grams in all of our specifications, which creates terms from all unique 1- 2- and 3- word combinations. Beyond 3-grams, we approach computational challenges given the size of the matrices created.[2]

(Steps 2–3) Averaging and Shrinking Similarity Scores: Ideally, Step 1 would have been to relate FOA text directly to some description of each CPC group. However, the definitions in the CPC scheme tend to be very short pieces of text not well suited to this sort of similarity analysis. Hence, we rely on the patent abstracts. To account for the fact that these CPC-level average scores are generated from a wide range of patent documents (i.e., some CPC groups are assigned to one patent, some to thousands), we employ a standard Bayesian shrinkage estimator that compresses CPC-level means with high variances towards the overall mean.

(Step 4) Accounting for Spurious Text Correlations: Interpreting the cardinality of these scores leans rather heavily on assumptions about linguistic choices across FOAs. To avoid making inferences based on any spurious use of texts across FOAs, we undertake two alternative strategies. One is to demean the similarity scores ($\overline{S}_{kj}$) at the FOA topic level (k) and use the residuals to form the similarity percentiles. The other is to use the FOA-specific ordinal score rankings to determine the similarity percentiles. These approaches remove any variation in similarity connections that might arise purely based on how certain DoE program managers or offices write the text of the Topic descriptions. The demeaning process is our preferred approach as it does not eliminate all of the variation in scores. Though results shown in Appendix E show that using the rank approach yields very similar findings.

(Step 5) Setting the Spillover Threshold: This sort of assumption is necessary to identify the peer effects as shown by Manski (1993) and others. Appendix D details our data-driven approach to this decision in detail.

(Steps 6–7) Aggregating to Similarity Bins at the Group Level: Clearly, we need to aggregate investments to the CPC group level because this is the level of our outcome (patent flows). We use the similarity bins to identify heterogeneity in the degree to which across technology spillovers occur. We have good reason to think that, even within the assumed threshold of spillovers, the magnitude of these spillovers is likely to be an increasing function of the similarity between two groups. With these separate bins of investments, we can include multiple stocks in the production function and recover similarity-bin-specific estimates of the returns to investment, which can then be used to quantify the magnitude and shape of spillovers.

As a simple example, consider the following scenario:

[2] To avoid the endogenous use of terminology by patenters or the DoE, we use patents from before our sample, 2001-2004, to estimate the similarity scores.

- there is one FOA topic (k=1),
- there are one hundred unique CPC groups ($j = \{1, 2, ..., 100\}$),
- one grant of \$50,000 is awarded via the topic (I_k=\$50,000),
- we use two bins of size 50 ($b = \{100 - 51, 50 - 1\}$),
- we set the spillover percentile threshold to $\underline{b} = 51$, i.e., only the groups in $b = \{100-51\}$, the most similar 50% of groups, are allowed the possibility of spillovers.

Here, I_j^b =\$1,000 for $b = \{100 - 51\}$ for the 50 groups most similar to the topic and \$0 otherwise, and I_j^b for $b = \{50 - 1\}$ is \$0 for all groups.

A.3 Crosswalk Examples

Figures A.2–A.4 each provide the text of a specific FOA topic as well as exemplary CPC titles that are matched to these topics per our methodology, sorted by their technological distance from the FOA topic description.

Figure A.2: FOA Example #1–Solar Energy

(a) FOA Text

2. ADVANCED SOLAR TECHNOLOGIES

Solar energy is our largest energy resource and can provide clean, sustainable energy supplies, including electricity, fuels, and thermal energy. The President's economic recovery package emphasized solar energy, among others, as a key element in combating global climate change. However, the cost-effective capture of the enormous solar resource is problematic. This topic seeks to develop novel, commercially feasible, solar systems and production techniques.

Grant applications submitted in response to this topic should: (1) include a review of the state-of-the-art of the technology and application being targeted; (2) provide a detailed evaluation of the proposed technology and place it in the context of the current state-of-the-art in terms of lifecycle cost, reliability, and other key performance measures; (3) analyze the proposed technology development process, the pathway to commercialization, the large potential markets it will serve, and the attendant potential public benefits that would accrue; and (4) address the ease of implementation of the new technology.

Phase I should include (1) a preliminary design; (2) a characterization of laboratory-scale devices using the best measurements available, including a description of the measurement methods; and (3) a road map with major milestones, leading to a production model of a system that would be built in Phase II. In Phase II, devices suitable for near-commercial applications must be built and tested, and issues associated with manufacturing the units in large volumes at a competitive price must be addressed.

Grant applications are sought in the following subtopics:

a. Manufacturing Tools for Reliability Testing—Grant applications are sought for the development of tools that can be used to conduct reliability testing in PV module manufacturing environments. For example, tools such as light soaking equipment are used to prepare modules or components for accelerated lifetime testing, which is frequently conducted in-house at the module manufacturing facility or by service companies before sending for official third party certification. New tools are needed for the testing of components (e.g., modules, inverters) or subcomponents (e.g., cells, microinverters, individual layers of a module), and should combine high performance, low cost, and a small floor footprint.

Questions – contact: Alec Bulawka (Alec.Bulawka@ee.doe.gov)
James Kern (James.Kern@ee.doe.gov

b. Module and System Manufacturing Metrology and Process Control—The rapid scale-up of the manufacturing of photovoltaics, particularly for new thin-film technologies, is challenging the possibility of using conventional technologies to make real-time non-destructive measurements of material characteristics in high-volume, high-production-rate environments and then using this information to implement real-time process control of the manufacturing process. Therefore, grant applications are sought for the development of novel, advanced, real-time non-destructive materials characterization tools for use in high-volume manufacturing lines for photovoltaic systems.

Questions – contact: Alec Bulawka (Alec.Bulawka@ee.doe.gov)
James Kern (James.Kern@ee.doe.gov

c. Photovoltaics (PV) System Diagnostic Tools—The current rapid growth of the PV industry has led to diverse and innovative product designs, which frequently require non-traditional tests for reliability and performance. Examples of these non-traditional tests include performance testing and tracking requirements for concentrating PV modules, and software-based system diagnostic tools. Grant applications are sought for innovative methods to monitor PV system and component performance, in order to identify failures and loss mechanisms and to minimize system down time. Approaches of interest include the development of diagnostic tools that are process-oriented and internal to the system components, or those that can be integrated – i.e, "piggy-backed" – through ancillary application.

Questions – contact: Alec Bulawka (Alec.Bulawka@ee.doe.gov)
James Kern (James.Kern@ee.doe.gov

(b) Titles of Relevant CPC Classes

Technology Distance ptile.	Example CPC Titles
1	Apparatus for processing exposed photographic materials
	Generation of electric power by conversion of infra-red radiation, visible light or ultraviolet light
	Plasma technique; production of accelerated electrically-charged particles
10	Electric heating; electric lighting
	Static electricity; naturally-occurring electricity
	Cyclically operating valves for machines or engines
20	Cranes; load-engaging elements or devices for cranes
	Locomotives; motor railcars
	Wireless communication networks

Notes: Topic #2 from the FY2010 Release 1 Funding Opportunity Announcement.

Figure A.3: FOA Example #2–Geothermal Energy

(a) FOA Text

4. GEOTHERMAL ENERGY TECHNOLOGY DEVELOPMENT

This topic is focused on the development and innovation required to achieve technical and commercial feasibility of EGS. Because of the complexity of these systems, grant applications are expected to focus on a component or supporting technology of EGS development that would enable improvements to the overall system. The unique function and innovation of the targeted subsystem or supporting technology must be clearly described and its function in relationship to the greater EGS system must be expressed clearly. Approaches can be targeted at any of the multi-step project stages for technology development: from design concept, through scale model development (if applicable), to laboratory testing, field testing, and commercial scale demonstrations.

Grant applications are sought in the following subtopics:

a. High Temperature Downhole Logging and Monitoring Tools—Challenging subsurface conditions are one of the barriers to an accelerated ramp-up of geothermal energy generation. To address this challenge, grant applications are sought to develop logging and monitoring tools that are capable of tolerating extreme environments of high temperatures and pressures. The instruments of interest include, but are not limited to, temperature and pressure sensors, flow meters, fluid samplers, inclination and direction sensors, acoustic instruments (high and low frequency), resistivity probes, natural gamma ray detectors, epithermal neutron scattering gauges, rock density gauges (gamma and sonic), casing monitoring devices (e.g. cement bond logs and casing collar locators), fluid conductivity, pH indicators and well dimension probes (caliper). The target temperatures and pressures for these logging and monitoring tools should be supercritical conditions (374° C and 220 bar for pure water), and the tools may be used at depths of up to 10,000 meters.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov.

b. Cements for EGS Applications—While conventional geothermal wells experience large temperature rises during production, EGS wells experience large temperature drops at the bottom of the well during the stimulation process, due to the cooling effect of the injected water. This temperature drop may be in the neighborhood of 350°F. This unique situation causes significant stress and potential failure of the cement sheath if conventional cement systems are utilized. To address this issue, grant applications are sought for the research, design, development, testing, and demonstration of a cement system for the high temperature and stress conditions of an EGS wellbore. Proposed approaches may define cement formulations that would be used by the geothermal industry to place the cement within a long string of casings; such approaches should focus on preventing a premature set and maintaining a strong seal at the shoe (so that stimulations may be performed through the casing).

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov.

c. Drilling Systems—High upfront costs, largely due to high drilling costs, are a major barrier to expanded geothermal energy production in the United States. Therefore, grant applications are sought to reduce drilling costs by developing a drilling technology (horizontal and/or directional) that is capable of drilling three times faster than conventional rotary drilling. Approaches of interest include, but are not limited to the design and development of improved drilling fluids (to reduce frictional viscosity and remove cuttings), high-performance bottom-hole assemblies (e.g., collars, bent subs, drill bits), and downhole motors (to control wellbore orientation). Proposed approaches must demonstrate reliable operation and equipment durability that exceeds the performance of conventional equipment at depths up to 10,000 meters and temperatures up to 300°C.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov.

d. Fracture Characterization Technologies—Subsurface imaging is an important part of creating a productive EGS reservoir, which requires visualization before, during, and after creation. In order to advance technology and reduce the upfront risk to geothermal projects, more robust subsurface imaging technologies must be developed. Grant applications are sought to develop improved downhole and remote imaging methods to characterize fractures. Fracture characterization includes prediction of fracture and stress orientation prior to drilling (needed to properly orient horizontal wells); determination of fracture location, spacing, and orientation (while drilling); and determination of the location of open fractures (after stimulation), in order to identify the location of fluid flow pathways within the enhanced geothermal reservoir. Proposed approaches should address robust methods for interpreting and imaging the subsurface, including but not limited to, the development of active or passive seismic, processing software, and joint inversion of geophysical techniques.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov.

e. Working Fluids for Binary Power Plants—Binary power plants are rapidly becoming a major part of the geothermal industry, due to increased development of lower temperature geothermal resources. To address cost barriers associated with the working fluids in these binary power plants, grant applications are sought to (1) identify non-azeotropic mixtures of working fluids for improved utilization of available energy in subcritical cycles; (2) characterize the composition and thermophysical and transport properties of those mixtures; (3) identify working fluids for supercritical cycles and trilateral cycles; and (4) characterize the composition, thermophysical, and transport properties of those working fluids. Proposed approaches may address working fluids or mixtures of working fluids with the potential for greater energy conversion efficiency than conventional working fluids, such as isobutane or refrigerants.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov.

f. GHP Component R&D—High initial costs have been identified as a key barrier to widespread GHP deployment. To address this barrier, applications are sought to improve GHP components to increase efficiency as well as energy savings as compared to conventional systems. Applications may address but are not limited to: variable-speed (VS) components, advanced sensors and controls (including water flow sensing), electronic expansion valves, heat exchange (HX) design and fluids, system optimization, unit control algorithms, and load management tools.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov

g. Innovative System/Loop Designs—One of the main barriers in GHP technology is the high cost of drilling and loop installation. Applications are sought for innovative system/loop designs that reduce the costs of system and/or loop installation, through new design layouts, system components, materials, and/or methods.

Questions – Contact Raymond Fortuna, 202-586-1711, raymond.fortuna@ee.doe.gov

(b) Titles of Relevant CPC Classes

Technology Distance ptile.	Example CPC Titles
1	Geophysics; gravitational measurements
	Positive-displacement machines for liquids; pumps
	Collection, production or use of heat
10	Electric heating; electric lighting
	Static electricity; naturally-occurring electricity
	Cyclically operating valves for machines or engines
20	Installations or methods for obtaining, collecting, or distributing water
	Computer systems based on specific computational models
	Vehicles, vehicle fittings, or vehicle parts

Notes: Topic #4 from the FY2010 Release 1 Funding Opportunity Announcement.

Figure A.4: FOA Example #3–Data Management

(a) FOA Text

38. DATA MANAGEMENT AND STORAGE

a. Green Storage for HPC with Solid State Disk Technologies: From Caching to Metadata Servers—Most solid-state storage devices (SSDs) use non-volatile flash memory, which is made from silicon chips, instead of using spinning metal platters (as in hard disk drives) or streaming tape. By providing random access directly to data, the delays inherent in electro-mechanical drives are eliminated. The common consumer versions, known as flash drives, are compact and fairly rugged. Advantages attributed to SSDs include higher data transfer rates, smaller storage footprint, lower power and cooling requirements, faster I/O response times (up to 1000 times faster than mechanical drives), improved I/O operations per second (IOPS), and less wasted capacity.

Furthermore, upcoming processor chip designs from Intel and AMD will include SSD/FLASH controllers built on-board the CPU chip, in order to improve integration for laptop and embedded applications. Such technology is likely to enable a localized checkpoint-restart capability to mitigate increased transient failure rates on future ultra-scale computing systems. This increased level of hardware integration makes it clear that x86 server nodes, which incorporate SSD directly onto the node, are on the horizon.

In view of these developments, the DOE seeks to improve its understanding of the implications of SSDs for large-scale, tightly-coupled systems in High Performance Computing (HPC) environments. Therefore, grant applications are sought to further develop SSD technology as a cost-effective and productive storage solution for future HPC systems, including, but not limited to:

1) **Categorization of SSD failure modes** - The rate of deployment of SSDs in HPC environments will be artificially slowed until a better understanding of the failure modes of this new class of storage is achieved. Proposed approaches should categorize the type of failure (wire bond, cell wear-out, or other failure) and determine how the failures would be detected and/or repaired in a composite device fielded in an HPC environment.

2) **Use of SSD for node-local storage, for faster (localized) checkpoint/restart (CPR)** - If transient failures cause nodes to die, then SSD could be a viable approach for fault-resilience. However, for nodes subjected to hard-failures, the use of SSD could produce an even higher node failure rate, due to the inherent failure characteristics of the SSD; in this case, the SSD approach would not be viable for CPR. Approaches of interest should collect and analyze data on the known failure modes of existing SSD components vis-a-vis node failure modes, in order to determine if SSD presents an effective alternative to the checkpoint/restart of a shared file system.

3) **Use of SSD for scalable out-of-core applications** - Although node-local disk systems have been used to support some applications that use out-of-core algorithms (such as some components of NWChem), the failure rates of spinning disks have rendered this practice unfeasible. Rather, central file systems are used to support these out-of-core applications, greatly affecting their scalability. Approaches are sought to determine whether local SSD might be reliable enough to enable a scalable approach to out-of-core processing.

4) **Use of SSD for metadata servers -** Metadata servers subject disk subsystems to many very small transactions, a feature that is very difficult to support with existing mechanical/spinning-disk based systems. SSDs might respond better to the random-access patterns required for metadata servers, but may not perform as well for write functions. Approaches of interest should analyze the data access patterns of a typical HPC Lustre metadata server and, using an SSD performance model, determine how well an SSD-based system would respond to a metadata server load.

5) **Use of SSD for accelerated caching for the front-end of large-scale disk arrays** – The use of SSDs in caching for large-scale disk arrays is an emerging technology that is not well understood. Approaches are sought to determine of both its performance potential when subjected to real workloads and its fault resilience.

b. Data Management Tools for Automatically Generating I/O Libraries—Database-like, self-describing, portable binary file formats, such as Network Command Data Form (NetCDF) and Hierarchical Data Format (HDF), greatly enhance scientific I/O systems by raising the level of abstraction for data storage to very high-level semantics (of data schemas and relationships between data objects stored) rather than low-level details of the location of each byte of the data stored in the file. However, both NetCDF and HDF5 still rely on very complex APIs to describe the data schema, and many performance pitfalls can arise if the APIs are not used in an optimal manner. Consequently, application developers must invest considerable effort in creating their own "shim" I/O APIs that are specific to their applications, in order to hide the complexity of the general-purpose APIs of NetCDF and HDF5.

Grant applications are sought to develop software tools that not only would enable rapid prototyping of high-level data schemas but also would automatically generate a high-level API for presentation to application developers, thereby hiding the complexity of the low-level NetCDF and HDF5 APIs for managing the file format. Such tools also might use auto-tuning techniques to find the best performing implementation of an I/O method.

c. Integration of Scientific File Representations with Object Database Management Systems—Scientific file formats like Network Command Data Form (NetCDF) and Hierarchical Data Format (HDF5) have capabilities that closely match those of commercial Object Database Management Systems (ODBMS); yet, commercial ODBMSs provide much more sophisticated data management tools than are available to users of NetCDF and HDF5. Unfortunately, ODBMSs are not designed to accommodate parallel writes to the same data entry from multiple parallel writers. Furthermore, database storage formats are opaque and non-portable, and no file standard exists to facilitate the movement of data from one database system to another. By contrast, NetCDF and HDF5 both offer open, standardized formats and portable, self-describing binary formats for storing data represented as Object Databases.

(b) Titles of Relevant CPC Classes

Technology Distance ptile.	Example CPC Titles
1	Electric digital data processing
	Apparatus or arrangements for taking photographs or for projecting or viewing them
	Transmission of digital information, e.g. telegraphic communication
10	Information and communication technology adapted for specific application fields
	Radio-controlled time-pieces
	Secret communication; jamming of communication
20	Presses in general
	Production of cellulose by removing non-cellulose substances
	Methods of steam generation; steam boilers

Notes: Topic #38 from the FY2010 Release 1 Funding Opportunity Announcement.

B Other Estimation & Data Notes

B.1 R&D Stock Construction

We use standard perpetual inventory methods to construct the stock of R&D investments: $K_{jt} = I_{jt} + (1-\rho)K_{j(t-1)}$ where I_{jt} is the investment flow and ρ is the discount rate. In our preferred specifications we use no discounting, as it gives us the most conservative estimates. All dollar values are adjusted for inflation using the 2018 Consumer Price Index. Results under alternative discounting assumptions are shown in Appendix E.4.

B.2 Approximating Elasticities when Negative Numbers are Present

The following demonstrates the usefulness of the "demeaning" transformation to handle the fact that our focal independent variable, the stock of state match windfall investments, can take on negative values. For the purpose of clarity, consider the following "log-log" linear regression model that is analogous to our preferred specification:

$$\begin{aligned} \log(Y_j) &= \alpha + \log(X_j)\beta + \epsilon_j, \\ \beta &= \frac{\partial \log(Y_j)}{\partial \log(X_j)} = \frac{\partial Y_j}{\partial X_j}\frac{X_j}{Y_j}; \end{aligned} \tag{B.2}$$

$$\begin{aligned} \log(Y_j) &= \tilde{\alpha} + \frac{X_j}{\overline{X}}\theta + \tilde{\epsilon}_j, \\ \theta &= \frac{\partial \log(Y_j)}{\partial \frac{X_j}{\overline{X}}} = \frac{\partial Y_j}{\partial X_j}\frac{\overline{X}}{Y_j}. \end{aligned} \tag{B.3}$$

Below the regression models, which relate the dependent variable Y to the independent variable X, we also define the coefficients of interest: β and θ. Eq. B.2 shows the useful result that average elasticities are estimated directly when using the log-log transformation. In the case of Eq. B.3, a similar coefficient is estimated, although now instead of estimating a "mean elasticity" given by β, the θ coefficient describes the elasticity across all values of Y_j, but at the sample mean of X_j, denoted here by $\overline{X}$.

In practice, we assume that any difference between these two parameters is negligible. To motivate this assumption, the following shows that θ approximates β. Substituting a first order

Taylor series approximation of $\log(X_j)$ around $\overline{X}$, $\log(\overline{X}) + \frac{X_j - \overline{X}}{\overline{X}}$ into Eq. B.2 yields:

$$
\begin{aligned}
\log(Y_j) &\approx \alpha + \left(\log(\overline{X}) + \frac{X_j - \overline{X}}{\overline{X}}\right)\beta + \epsilon_j, \\
\log(Y_j) &\approx \left[\alpha + \log(\overline{X})\beta - \beta\right] + \frac{X_j}{\overline{X}}\beta + \epsilon_j,
\end{aligned}
\tag{B.4}
$$

where $\left[\alpha + \log(\overline{X})\beta - \beta\right] \approx \tilde{\alpha}$, mapping to Eq. B.3.

B.3 Calculating Implied Marginal Products

Our regressions yield estimates of the output elasticity of SBIR funding based on variation across CPC groups over time. But this variation is not due to the DoE directly choosing to invest in a CPC group per se, but rather it is due to their decision to invest in certain FOA topics (which are in turn connected to different CPC groups). Thus, when we use these elasticities to estimate the marginal product of additional investments, we do so in a way that reflects the FOA topic-level source of variation.

Our approach to obtaining marginal products is as follows: first, note that given patent flows Y, R&D stocks K, and single elasticity estimate θ, the implied group-year (jt) level marginal product of a dollar is: $\theta \times Y_{jt} \times \frac{1}{K_{jt}} \equiv MP_{jt}$.[3]

Next, we make use of the fact that we know which CPC groups each FOA topic directs funding towards. Let w_{jk} be an indicator variable that equals one if CPC group j is deemed relevant to the funding from FOA topic k per our text similarity approach (as in, within the boundary of technological distances we consider). With these weights w_{jk}, we can estimate a k-specific weighted average of MP_{jt} for each FOA topic: $\sum_{jt} MP_{jt} w_{jk} / \sum_{jt} w_{jk}$. Then, by averaging over the roughly 1,000 FOA topics in our data, we can arrive at value that more closely approximates the true average marginal product of increased funding.

Lastly, we accommodate the fact that we have multiple θ estimates, one for each technological distance bin in Eq. 4, and also for the fact that our goal is to arrive at an estimate of the marginal cost per patent (not the marginal cost of increasing the annual patent flow rate by one). To the first point, the additive separability of the production function implies that we can simply sum over the multiple MP_{jt} values calculated for each bin. However, since our data construction approach evenly divides funding across all bins, we modify MP_{jt} to be: $\theta^b \times Y_{jt} \times \frac{1}{K_{jt}^b} \times \frac{1}{N^b}$, where b indexes bins and N^b indicates the number of bins. This captures the fact that when the DoE invests a marginal dollar, our data construction funnels equal portions of that dollar into each of the N^b bins. In the final step, we convert marginal increases in flow rates into total patent output by simply summing up the net increase in patent flows to be expected if we followed the observation for the remainder of the sample period. This mimicks a firm-level analysis of how SBIR funding would increase the stock of patents a firm produces (e.g., Howell 2017).

[3]This clearly is undefined for zero-valued patent flows or investment stocks, but elsewhere in the Appendix we report results where we estimate the θ parameters using only non-zero observations and obtain very similar estimates, which indicates that our assumption of a constant elasticity is reasonable.

B.4 Estimating Within-US Travel Costs

Although geographic distance separates inventors, the implication of much empirical work on the geographic distribution of invention (e.g., Agrawal et al. 2017) is that the costs of human travel, not geographic distance per se, constrains the flow of ideas. It is beyond the scope of this paper to estimate highly accurate travel costs given the high dimensionality of the data and numerous modes of transportation possible. However, we make strides in this direction by: (1) focusing on US county-to-county pairs as semi-dense yet computationally tractable set of regions to focus on; (2) using US Internal Revenue Service (IRS) driving mileage rates to approximate driving costs between all counties[4]; (3) using the Department of Transportation (DoT) Airline Origin and Destination Survey (DBIB) to obtain negotiated airfare rates between all US airports; (4) NBER Place Distance Database; and (5) solving for the minimum cost of traveling between each county pair in the US using the minimum of either these approximate costs of driving directly, or driving to the nearest airports and flying.[5] Then, by taking the set of counties where DoE SBIR grants (that focus on a particular technology group) are awarded as the focal set of counties, we can calculate the average cost of making a round trip to these focal counties for individuals in all other counties.

We define the mode of transit based on the proximity of the origin and destination county to an airport. This defines four possible paths: (i) origin county with an airport to destination county with an airport; (ii) origin county without an airport to destination county with an airport; (iii) origin county with an airport to destination county without an airport; and (iv) origin county without an airport to destination county without an airport. For (i), we simply use the average annual market fares reported in DB1B to compute the travel cost. For the paths that include a county without an airport, we add the cost of driving from the center of a county without an airport to the center of the closest county with an airport. We rely on the mileage – as reported by NBER – and the IRS standard mileage reimbursement rate to compute this driving cost. For the total cost, we add the ground and air transportation accordingly. For all cost measures, we adjust for inflation using the 2018 CPI adjusted index.

We impute fares using observed data as follows: for airports a and b, we estimate the cost of a round trip flight using the following regression:

$$\text{fare}_{ab} = \alpha_a + \beta_b + \text{geographic distance}_{c(a),c(b)}\delta + \epsilon_{ab}, \tag{B.5}$$

[4] As well as an estimate of the conversion between geographic distance and driving distance.

[5] DoT data is available at: http://bit.ly/2RSwkG1. NBER data is available at: http://bit.ly/2U6TtHk. IRS data is available at: http://bit.ly/37wuVvl.

where α and β are airport fixed effects, $c(\cdot)$ defines the county that an airport is located in, and the parameter δ describes how fares grow with the distance traveled. Then we use the estimated values of α, β, and δ to predict fares both in-sample (where we observe fare_{ab}) and out-of-sample (where we do not observe fare_{ab}, but we do observe at least two fares for a and/or b). We use these imputed fares, combined with population levels, to create the population-weighted geographic distance groupings that we use in our main analyses.

B.5 Additional Data Sources

The following outlines data used in the search for correlates of spillovers at the domestic and international levels as discussed in Appendix F.

B.5.1 BEA Economic Area Data

US Cluster Mapping: The majority of features we use to describe US economic areas was obtained from the US Cluster Mapping project (www.clustermapping.us; Delgado et al. 2016)

Universities and colleges: Location and average total annual R&D funding for major US universities and colleges was obtained from the National Science Foundation's Higher Education Research and Development Survey (HERD; www.nsf.gov/statistics/srvyherd).

Federally Funded R&D Centers (FFRDC): The locations of all FFRDCs was obtained from the National Science Foundation (www.nsf.gov/statistics/ffrdclist).

Nuclear reactors: The locations and types of all operating nuclear reactors was obtained from the Nuclear Regulatory Commission (www.nrc.gov/info-finder/reactors/index.html).

Travel costs: See B.4.

B.5.2 International Data

World Development Indicators (WDI): The majority of features we use to describe countries was obtained from the World Bank's WDI (datacatalog.worldbank.org/dataset/world-development-indicators).

Geography and travel: Geographic and travel distances between countries was obtained using the *GeoDist* database created by the Centre d'Études Prospectives et d'Informations Internationales (Mayer and Zignago 2011).

Trade: Bilateral trade flows between all in-sample countries and the US was obtained via the UN Comtrade Database (comtrade.un.org).

FDI: Data on Foreign Direct Investments (FDI) to/from the US was obtained from the US BEA (www.bea.gov/international/di1fdibal).

Migrant stocks: International Migrant Stocks of all US-country pairs was obtained from the UN Population Division (www.un.org/development/desa/pd/content/international-migrant-stock).

C State Match Policies

C.1 Isolating the Windfall Funding

The variation in funding across technology groups is due to the variation in funding across FOAs. The total amount I invested into each FOA k in a year t is the sum of federal awards I_{kt}^{fed} and any matching funds awarded by states I_{kt}^{match}. We are concerned that the federal investments are endogenous, in that they may be correlated with unobservable productivity or demand shocks. Thus, we cannot assume that the variation due to state matches (which are a function of federal investments) is exogenous. Thus, we isolate the variation in state match investments across FOAs that arises only due to the distribution of SBIR grant winners across states with and without matching policies.

We first write match investments I_{kt}^{match} as a function of federal investments I_{kt}^{fed}:

$$I_{kt}^{\text{match}} = \alpha + I_{kt}^{\text{fed}}\gamma_t + W_{kt} \;\text{ if }\; I_{kt}^{\text{fed}} > 0, \tag{C.1}$$

where α is a constant and the parameter γ_t captures the fact that all (year-specific) matching programs are a linear transformation of federal awards (i.e., if all have states a 50% matching rate and received the same level of federal investments, then $\gamma = 0.5$).[6] If we estimate Eq. C.1 via OLS, our estimate of γ_t reflects the average of match rates across the country in year t, weighted by the amount of I_{kt}^{fed} invested in each state. The residual W_{kt} – which we term the state match windfall – arises because firms working on different technologies are differentially concentrated in states with or without matching programs. Therefore, our key identification assumption is that the distributions of firms and state policies are not related to any unobservable productivity or demand shocks. In other words, it cannot be the case that more (less) productive firms working on technologies with larger (smaller) unobservable productivity shocks are concentrated in states with larger (smaller) matching rates.

We know the true grant-level match rates for each state, which is how we construct I_{kt}^{match}. But we must estimate the effective "FOA-level" match rates, the γ_t parameters, from the data. To ensure that each observation's windfall estimate is not driven by that observation's role in determining our estimate of these γ_t parameters, we take a jackknife approach in the spirit of Angrist et al. (1999) and construct our windfall estimates as:

$$W_{kt} = I_{kt}^{\text{match}} - \widehat{\alpha^{-k}} - I_{kt}^{\text{fed}}\widehat{\gamma_t^{-k}}, \tag{C.2}$$

[6] In practice, many states' programs operate as lump sum matches. But because the size of Phase I and Phase II awards is largely standardized, this is effectively equivalent to the states setting a match rate.

where $\widehat{\alpha^{-k}}$ and $\widehat{\gamma_t^{-k}}$ are our estimates of those parameters from estimating Eq. C.1 while excluding FOA k from the regression.

C.2 Comparison of States with SBIR Match Policies

In this subsection, we test two hypotheses: (1) state-years with SBIR match programs do not systematically differ in the amount of federal funding awarded to the firms located in that state-year, and (2) small firms are not more or less likely to relocate into or out of state-years that have enacted an SBIR matching program.

To test the first hypothesis, we estimate the following regression model at the state-year st level:

$$\text{SBIR Funding}_{st} = \text{Match Status}_{st}\beta + \tau_t + \epsilon_{st} \ , \tag{C.3}$$

where a significant estimate of the β would reject our hypothesis of the null. We explore three measures of a stat-years' match status: (1) whether there is any match, and then whether the match rate is (2) above the median or (3) below the median.

As shown in Table C.1, which uses two different measures of SBIR funding (total funding in cols. 1–4 and funding per capita in cols. 5–8), state-years with match policies generally appear to receive less federal SBIR funding, but in no specification do we estimate a statistically significant value for β. The point estimates generally suggest that state-years with any match have about 30-50% less federal funding, but these estimates have large standard errors such that we cannot reject a null of no difference. Furthermore, in the linear models we obtain very small R^2 values, suggesting these policies are likely not directly responsible for (or indirectly correlated with) larger shifts within states surrounding the SBIR program. This gives us confidence that there are not significant differences in the SBIR-involved firms residing in states with or without the match programs, as our identification strategy assumes.

To test the second hypothesis – that small firms are not moving into or out of states with matching programs – we use data from the National Establishment Time Series spanning 2000 to 2015 and covering 13,325 small firms to estimate the following model of firms' location:

$$\mathbf{1}\{\text{Location}_{ist}\} = \text{Match Status}_{st}\beta_{DoE(i)} + \alpha_i + \sigma_s + \tau_t + \epsilon_{st} \tag{C.4}$$

where firm-state-year observations are indexed by ist, $\mathbf{1}\{\text{Location}_{ist}\}$ is a dummy variable indicating that firm i resides in state s in year t, Match Status$_{st}$ is again a dummy variable indicating whether state s has a matching program in place in year t, and α_i, σ_s, τ_t are firm, state, and year fixed effects sometimes included in the models.

All firms in the sample win an SBIR award at some time from the DoE or any of the other major federal agencies. We can observe firms' locations from the time they first appear in

Table C.1: Federal DoE SBIR Flows by State Match Status

	SBIR $M				SBIR $ per M capita			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any match	–0.366	–0.589			–0.719	–0.357		
	(0.280)	(0.402)			(1.131)	(0.305)		
High match			–0.375	–0.573			0.0913	–0.311
			(0.372)	(0.568)			(1.102)	(0.369)
Low match			–0.396	–0.633			–1.591	–0.393
			(0.358)	(0.473)			(1.491)	(0.453)
N	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
R^2	0.038		0.039		0.031		0.034	
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Model	OLS, ihs	PPML	OLS, ihs	PPML	OLS, ihs	PPML	OLS, ihs	PPML

Notes: Reports various estimates of β from Eq. C.3 using either state-wide annual SBIR funding in $-millions (cols. 1–4; mean=3.8, s.d.=6.9), or state-wide annual SBIR funding in $-per-million-people (cols. 5–8; mean=631,000, s.d.=973,000). Standard errors clustered at the state level. "OLS, ihs" indicates model is estimated using OLS with an inverse hyperbolic sine transformation of the dependent variable. "PPML" indicates model is estimated as a Poisson pseudolikelihood regression.

the National Establishment Time Series data onwards, and can match about 80% of ever-SBIR-winners. We allow firms' response to vary as a function of whether they ever receive a DoE award or not, as indicated by the $\beta_{DoE(i)}$ parameter.

Table C.2 reports the results of these regressions, which are economically insignificant. Regardless of how much we saturate the model (or not) with fixed effects, there is no meaningful association between the movement of these award winners and the state matching policies. In all cases, we cannot reject a null that this set of firms are neither more nor less likely to locate in states when a match policy is in place. This suggests that the firms winning awards in states with matching policies likely did not relocate their firm to the state because of the matching policies or any of the underlying economic or political forces that motivated the enactment of those policies.

Table C.2: Small Firm Locations per State Match Status

	(1)	(2)	(3)
Never DoE SBIR	–0.00964	–0.000216	–0.000201
× State Match	(0.00575)	(0.000441)	(0.000443)
Ever DoE SBIR	–0.0104	–0.000936	–0.00107
× State Match	(0.00561)	(0.00117)	(0.00126)
N	7,006,300	7,006,300	7,006,300
R^2	0.001	0.046	0.046
Year FE	Y	Y	Y
State FE		Y	Y
Firm FE			Y

Notes: Reports various estimates of the β parameters from Eq. C.4 using varying degrees of year, state, and firm fixed effects. The mean of the dependent variable is $1/50$ since the dependent variable is whether or not a given firm resides in a given state in a given year. Standard errors clustered at the state level.

D Technological Spillover Boundary Search

This section outlines our approach to arriving at an assumption about the boundary of technological spillovers. This assumption is of the sort motivated by Manski (1993), which is required to achieve identification of peer effects. For reference, our focal production function is as follows:

$$\mathbb{E}[Y_{jt}^{d} \,|\, W_{jtb}] = \exp\Big(\sum_{b \in \mathcal{B}} \frac{W_{jtb}}{\overline{W}} \theta_b^d + \tau_t^d\Big) \,. \tag{D.1}$$

In the context of this model, the question is what should be chosen for the maximum technological distance bin b in $\mathcal{B}$. In other words, what is the threshold of the textual similarity score between an FOA topic and a CPC group beyond which we can safely assume there is not effect of investment in that FOA topic on the patent flows in that CPC group?

Clarke (2017) tackles this exact question, framing it as a bandwidth selection problem (similar to the challenge of determining the optimal bandwidth for regression discontinuity designs). To illustrate the approach, let us instead consider a simple Poisson model:

$$\mathbb{E}[y_i \,|\, x_i] = \exp(\alpha + x_i \beta) \,.$$

Letting $\widehat{\alpha^{-i}}$ and $\widehat{\beta^{-i}}$ indicate the parameter estimates from a regression where i is excluded, we construct two predicted values of the outcome to use in the cross validation procedure:

$$\begin{aligned} \widehat{y}_i &= \exp(\widehat{\alpha^{-i}} + x_i \widehat{\beta^{-i}}), \\ \widetilde{y}_i &= \widehat{\alpha^{-i}} + x_i \widehat{\beta^{-i}}. \end{aligned}$$

But instead of obtaining parameter estimates for every i, we simplify the number of computations by following Clarke (2017) and use a "k-fold" approach, setting k to ten as is commonplace. This approach randomly splits the sample of N observations into ten equal-size groups and estimates a series of ten regressions, where each group is excluded from estimation and the resulting parameter estimates are used to form the expected values for that excluded group.

We test three different measures that are commonly used in practice for assessing the cross validation fit of Poisson models:

$$\text{Mean Squared Error (MSE): } \frac{1}{N}\sum_i (y_i - \widehat{y}_i)^2 \ ,$$

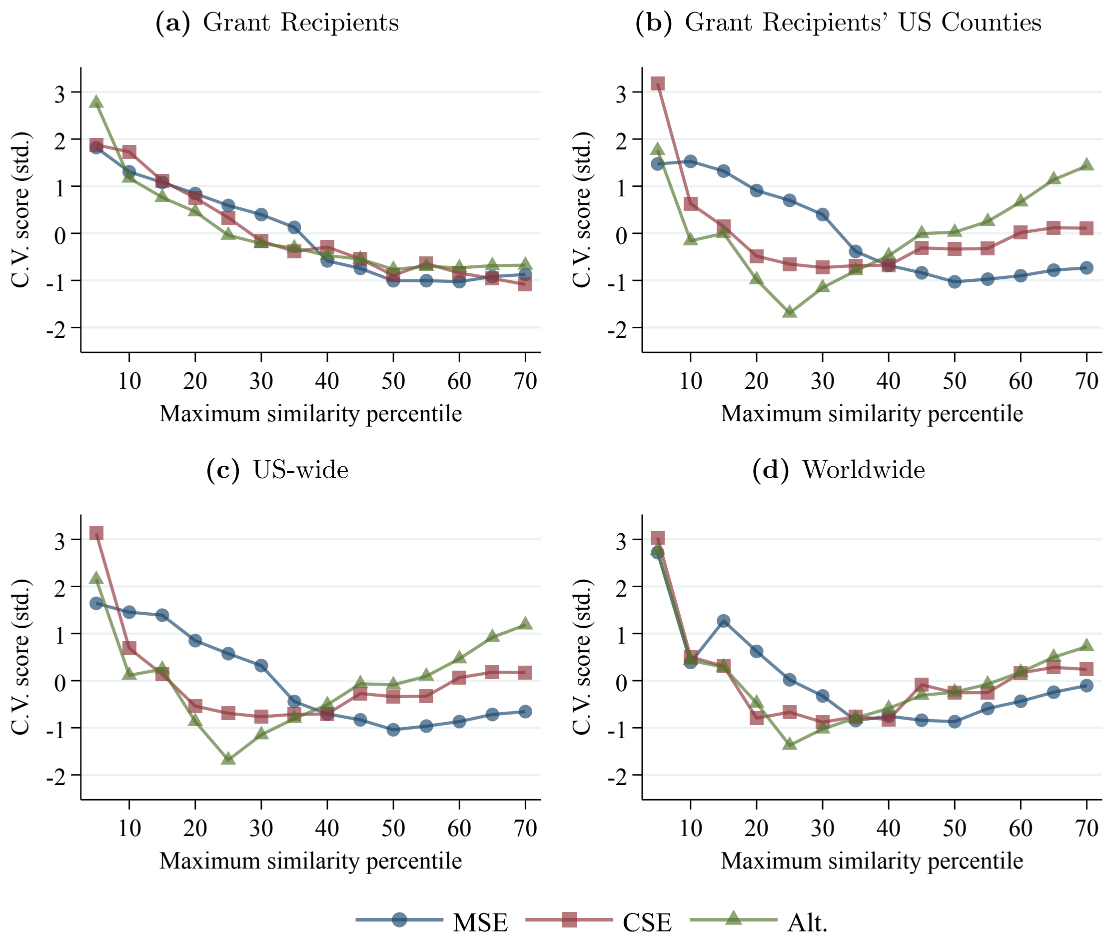
$$\text{Mean Chi-Squared Error (CSE): } \frac{1}{N}\sum_i \Big((y_i - \widehat{y}_i)^2/\widehat{y}_i\Big) \ ,$$

$$\text{Mean Alternative Error (Alt.): } \frac{1}{N}\sum_i (-y_i\widetilde{y}_i + \widehat{y}_i) \ ,$$

where the "Alternative" function is the same function employed in the Stata© `lasso poisson` command.

Figure D.1 plots the results of the bandwidth searches. For the grant recipients, we observe a convergence to a minimum at approximately the 60$^{\text{th}}$ percentile, and for the rest of the sets of patents we observe minimums at approximately the 40$^{\text{th}}$ percentiles. Thus, we use these values for the threshold in our main specifications. Clearly, these minimums are not extremely sharp, and so we also report robustness tests that vary these thresholds but plus/minus 10 percentiles, but we obtain similar results in all cases.

Figure D.1: Cross Validation Technological Spillover Boundary Search



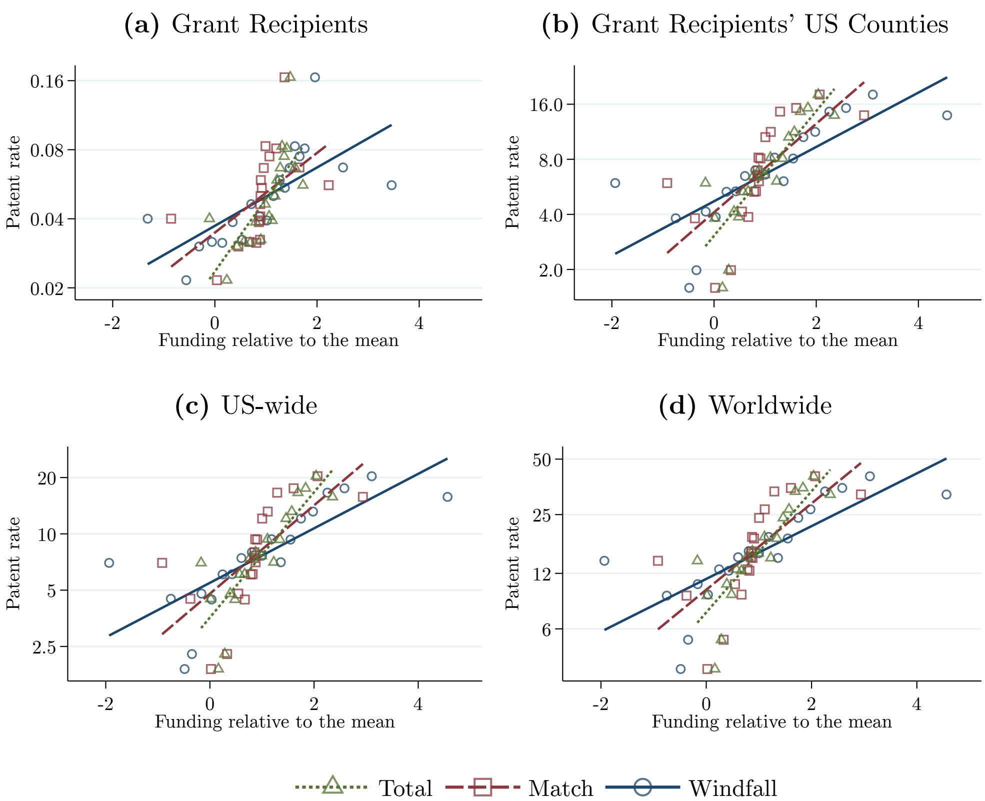
Notes: Plots the standardized cross validation scores from varying the maximum similarity percentile that determines the boundary of technological spillovers using three different penalty functions (MSE, CSE, Alternative). Each panel corresponds to a different set of patents used as the dependent variable.

E Additional Results, Specifications, & Robustness Tests

E.1 Binned Scatterplots

Figure E.1 contains binned scatter plots of the variation underlying Table 2 in the main text. The axes are scaled so that the linear fits mimic the constant elasticity assumption used throughout the paper. Except for outliers at the funding extremes, this constant elasticity assumption appears very reasonable. The downward shift in the slope of the fitted lines graphically depicts the pattern seen in Table 2 columns 1–3. We estimate smaller elasticities as we shift from using all of the funding variation (federal and state), to focusing on the state match variation, to finally focusing only on the windfall subset of the match-based variation.

Figure E.1: Patenting and Funding Conditional on Aggregate Time Trends



Notes: Plots the annual flow of patents within a CPC group (y-axis; log scale) as a function of the stock of SBIR funding in that CPC group (x-axis; scaled relative to the sample mean to approximate a log transformation) after conditioning out year fixed effects. The funding variation is always the same, but the set of firms and inventors whose patents are included in the dependent variable is different in each panel.

E.2 Alignment with Howell (2017)

When we focus only on the patents produced by grant recipients, our estimates suggest an average marginal cost of approximately \$1.3 million per patent, with 95% confidence intervals spanning \$1 million to \$1.6 million. The estimates from Howell (2017) indicate that Phase I and Phase II grants lead to anywhere from 30%–80% more citation-weighted patents. Taking the lower bound of these estimates, and assuming that these magnitudes are similar for raw patent counts (which Howell 2017 does not report), which has a mean of 2.0 in that sample, would imply conservative average marginal costs per patent of \$250,000 ($= 1/((2.0 \times 0.3)/\$150,000)$) for Phase I grants and \$1.7 million ($= 1/((2.0 \times 0.3)/\$1,000,000)$) for Phase II grants. And since roughly one-third of total DoE SBIR dollars in that sample are awarded via Phase I grants, this suggests an average marginal cost of \$1.2 million on a per-dollar basis. Using the less conservative estimates from Howell (2017) can yield a per-dollar cost closer to \$750,000.

This close overlap supports our empirical approach. We are comfortable focusing on the most conservative estimates from Howell (2017) because (1) Howell (2017) focuses on just two of the more "applied" funding offices of the DoE (and we look at all offices, which may incorporate funding less likely to lead to patents), and (2) our estimate is an intent-to-treat, since we cannot observe the actual match-based funding awarded.

E.3 Robustness to Technology-specific Time Trends

Perhaps the largest threat to our identification strategy is that there are unobservable shocks correlated with both (1) which CPC groups receive windfall funding because of the state match policies, and (2) the supply of or demand for patents in those same CPC groups. This could arise if firms in states with match policies are more productive or tend to pursue technologies more in-demand, or vice versa in each case. Our findings in Appendix C.2 suggest this is likely not the case.

To further explore this possibility, we estimate a series of models of the form:

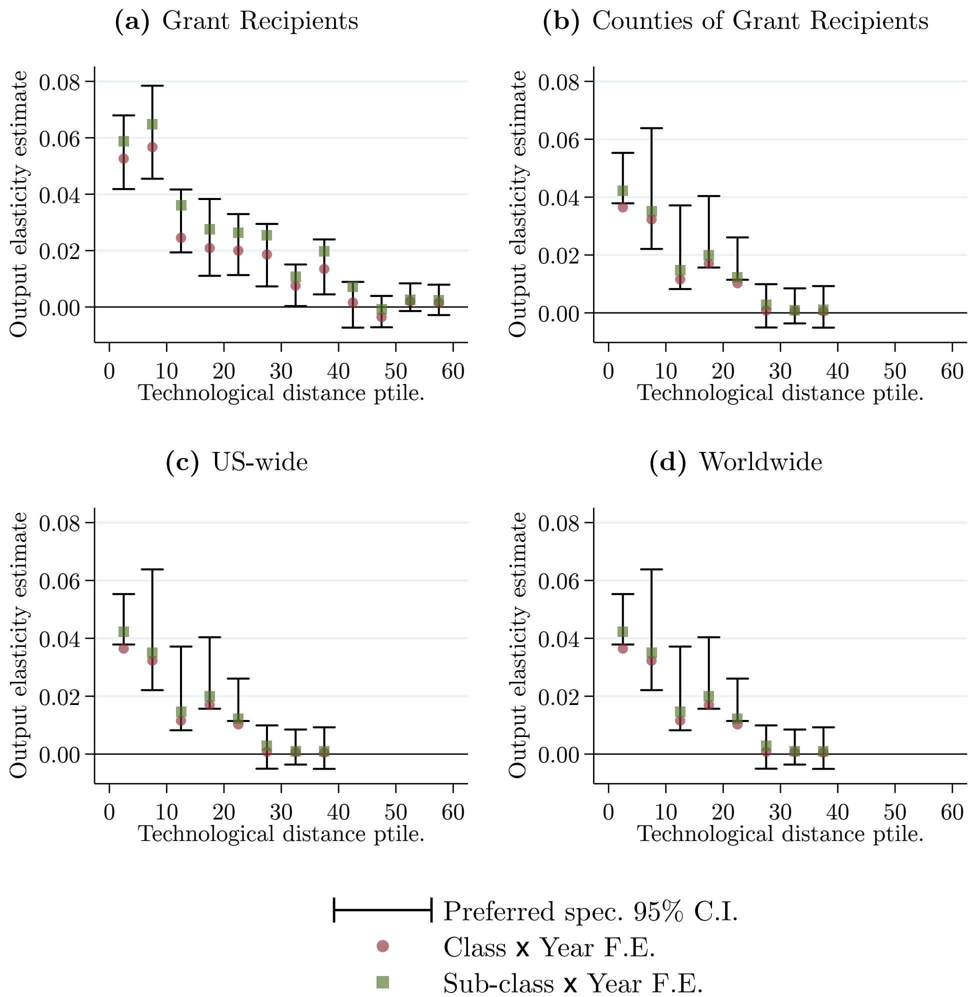
$$\mathbb{E}[Y_{jt}^d \,|\, W_{jtb}] = \exp\Bigg(\sum_{b\in\mathcal{B}} \frac{W_{jtb}}{\overline{W}}\theta_b^d + \tau_{g(j)t}^d\Bigg) \,, \tag{E.1}$$

which are identical to our main regression specification (Eq. 4), except now we allot the year fixed effects to be specific to different sets g of CPC groups (which are indexed by j). To construct these sets, we leverage the hierarchical nature of the CPC scheme and estimate two versions of equation E.1 aggregating the j-level CPC codes we use ("Main Groups") up either one level (to the level 3 "Sub-class") or two levels (to the "Class") in the hierarchy.

Removing this variation from the data with these fixed effects decreases the likelihood that our estimates are driven by any worrisome aggregate shocks that are unique to different sets of technologies. However, it also introduces the possibility of exacerbating measurement error in our independent variable and biasing our coefficients towards zero (Griliches and Mairesse 1995).

Figure E.2 plots the results of these regressions (along with the 95% confidence intervals from our preferred specification). We do tend to estimate coefficients closer to zero in many cases. But overall, the estimates from these models saturated with more fixed effects are broadly consistent with our main results. And given the large amount of variation in the data that these fixed effects remove, these results suggest that our identification strategy is not merely reflecting some unobservable trends that are covarying with patenting rates and the SBIR match policies

Figure E.2: Patent Output Elasticity Estimates with Technology-specific Time Trends



Notes: Plots the point estimates of $\theta^{d,b}$ from Eq. E.1 when using either group-time or sub-class-time fixed effects. The error bars plot the 95% confidence interval from our preferred specification (Eq. 4) based on standard errors clustered at the CPC group level.

E.4 Alternative Data Construction and Regression Specifications

Alternative Specifications

Figure E.3 reports estimates from a range of specifications that use alternative choices at the data construction, sample inclusion, or estimation stages. We present the results here only for our two geographic edge cases for brevity (only grant recipients in Figure E.3a and then all firms and inventors in Figure E.3b), though we find very similar patterns when focusing on other sets of firms and inventors. In all cases, we obtain point estimates and patterns in coefficients that are very similar to our preferred specification which gives us confidence that no single choice we make is driving our results in particular.

"FOA FE in sim calc." includes FOA fixed effects in the text similarity analyses, which removes variation across FOAs that may be erroneous (e.g., due to different writing styles of DoE program managers). However, it also imposes an assumption that the latent patentability of all FOAs is the same, which is an assumption we would rather not make. This is why our preferred specification estimates the percentiles of technological distances using the full distribution of raw similarity scores. Regardless, the estimates are very similar.

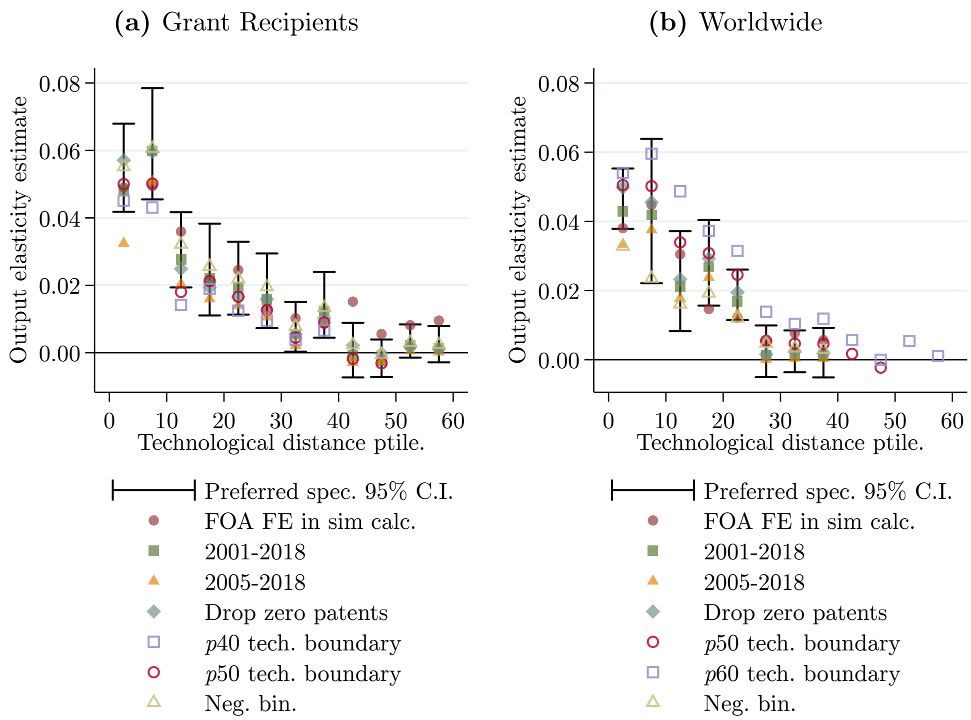
The results are very similar when we constrain the sample to exclude early years, which suggests that it is not important that the state matches were much rarer in the early years, or that we use some of these early years of data to construct the patent-FOA text similarity. Likewise, dropping observations with zero patent flows, making minor adjustments to the boundary of technological spillovers, or estimating the regression as a negative binomial model all yield very similar results.

Alternative Investment Discounting

The stock-flow knowledge production function model assumes that current investments have some (possibly discounted) ability to generate output in all future periods. We are limited in our ability to understand the specific lag structure of production, but we explore this timing issue partly by altering our assumption about the discount value of the R&D stock.

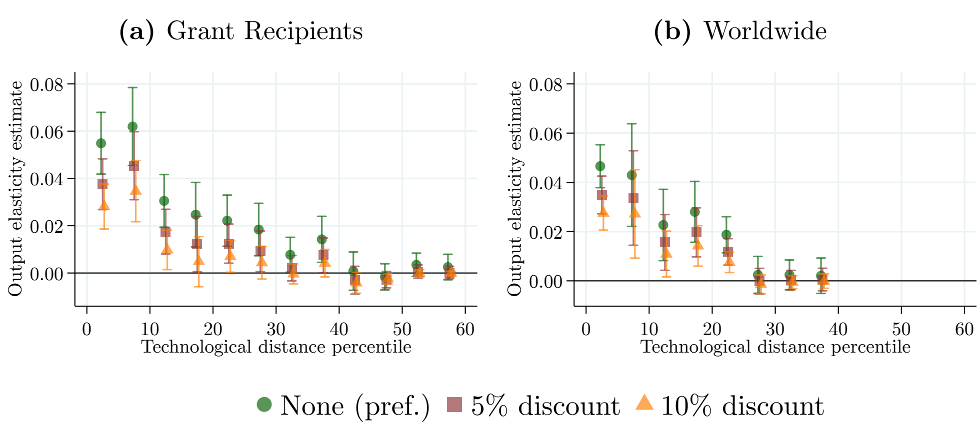
Figure E.4 plots the estimated coefficients from two regressions where we use a non-zero discount rate on the stock of R&D investments in our production function: 5% and 10%. If production is relatively short-term, this discounting should not alter our estimates since the meaningful variation in R&D stocks will not be compressed by the discounting. But we do see the estimates from these models tend to move closer to zero by a reasonable amount – roughly 30–50% for some point estimates. With discount rates of 5–10%, it would take roughly five to seven years to reduce this much variation in a stock, which we take as

Figure E.3: Patent Output Elasticity Estimates, Alternative Specifications



Notes: See text for descriptions of alternative specifications.

Figure E.4: Alternative Investment Discounting, Coefficients



Notes: Plots the point estimates and standard errors (clustered at the CPC group level) under alternative assumptions for the discount rate of the funding stock.

suggestive evidence that the most common production lags – the time from DoE investment to the appearance of new patents – are on this scale.

Alternative CPC Group Division

Our preferred approach to accounting for the fact that patents receive multiple CPC codes is to divide each code proportionally based on how many times it appears on the patent (e.g., if a patent has codes C01P2004/61, C01P2004/80, and C10L1/16, then we would assign 2/3 to CPC group C01P2004 and 1/3 to C10L1). This approach ensures that when we sum up these fractions over CPC groups, the resulting number (which serves as our dependent variable) corresponds to a count of "patent's worth" of CPC codes.

An alternative approach would be to give all CPC groups that appear on each patent a value of one (e.g., if a patent has codes C01P2004/61, C01P2004/80, and C10L1/16, then we could assign 1 to CPC group C01P2004 and 1 to C10L1). While simple, this approach yields a number that is much more difficult to interpret and benchmark. However, for the purposes of estimating spillovers, we cannot hypothesize why it would not be the case that both approaches yield similar magnitudes of spillovers.

Table E.1 reports the results from this alternative approach of assigning a value of one for all CPC groups listed on each patent (Panel b) compared to our preferred approach (Panel a). It is difficult to compare the elasticities across these two approaches within the same set of patents (i.e., within columns in the Table), because of the differences in the dependent variables. But most importantly, the magnitude of spillovers (here across geographic distances) is very similar in both cases. For example, grant recipients appear to account for roughly 18% (=0.54/2.97) of the net marginal product per our preferred approach, and in the alternative approach they account for roughly 21% (=2.06/9.63). Thus, it does not appear that the spillover magnitudes we are estimating are driven by our approach to handling CPC group assignment.

Table E.1: Alternative CPC Group Approach

	Grant recipients (1)	Recipients' counties (2)	US-wide (3)	Worldwide (4)
Panel (a): CPC Group Share Division				
Windfall \$	0.134	0.125	0.123	0.130
	(0.021)	(0.016)	(0.015)	(0.014)
$\frac{\partial \text{ patent}}{\partial \text{ \$1M}}$	0.54	1.40	1.73	2.97
	[0.5,0.6]	[1.2,1.6]	[1.5,1.9]	[2.5,3.3]
Panel (b): Any CPC Group Flag = 1				
Windfall \$	0.063	0.080	0.077	0.081
	(0.016)	(0.011)	(0.011)	(0.010)
$\frac{\partial \text{ CPC flag}}{\partial \text{ \$1M}}$	2.06	5.12	6.10	9.63
	[1.9,2.3]	[4.4,6.0]	[5.2,7.2]	[8.0,11.4]
N obs.	235,406	235,384	235,384	235,384
Tech. boundary	$p60$	$p40$	$p40$	$p40$
Year F.E.	Y	Y	Y	Y

Notes: Reports the output elasticity estimates from regressions using the "simple" model that aggregates all technological spillovers into a single bin per either the preferred approach of dividing patents amongst CPC groups equally (Panel a, which replicates Table 2 in the main text) versus assigning a count of one for all CPC groups listed on each patent (Panel b). Standard errors clustered at the CPC group level are reported in parentheses.

E.5 Additional Results: Paper Trails and Conduits

Comparison to Citation-based Approaches

The vast majority of empirical economic research on R&D spillovers, much of which stems from early influential papers such as Jaffe et al. (1993), has used front-page patent-to-patent citations as a proxy or evidence of a spillover. As noted in the main text, while this data has proven useful in many regards, it is not without serious limitations as noted by, at least, Alcácer et al. (2009), Arora et al. (2018) and Bryan et al. (2020).

Our empirical approach does not rely on these citations to identify spillovers. But we can impose this assumption to explore the extent to which the R&D spillovers we identify may be reflected in the paper trail. We do this by estimating another regression using our main specification (Eq. 4), but only include patents in the dependent variable that are connected to patents from DoE SBIR grant recipients through a direct citation (which we term the "1°" approach) or through any possibly combination of citation links (which we term the "All°" approach).

Figure E.5a plots the coefficients from these regressions, which behave very similarly to what we estimate when we use the universe of USPTO patents as the dependent variable. But as seen in Figure E.5b, relying on the 1^o or even the All^o approach captures at most only about 50% of the net output we observe from using the universe of USPTO patents. In other words, it appears that roughly half of the spillovers we identify are not reflected in citation linkages. Importantly, we cannot test what share of citation linkages reflect spillovers. Still, these results suggest that our approach to capturing R&D spillovers in the patent record could continue to prove useful as it may be much more flexible.

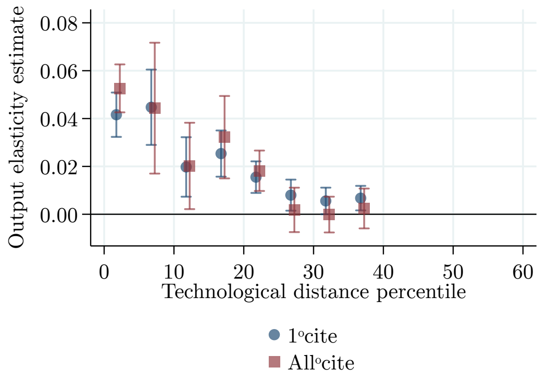
Individuals versus Firms as Conduits of R&D Spillovers

In our preferred specifications, we assign the geographic location of a patent to be equally representative of the locations of the individual inventors and firm assignees on the patent – if a patent has one inventor in one location and one firm assignee in another location, each receives one half of a patent in terms of the dependent variable. At the boundary cases of grant recipients or the entire universe of USPTO patents, this distinction is irrelevant. But for all interior cases, this choice of how to divide patents across locations may be relevant for understanding how R&D spillovers permeate geographic space.

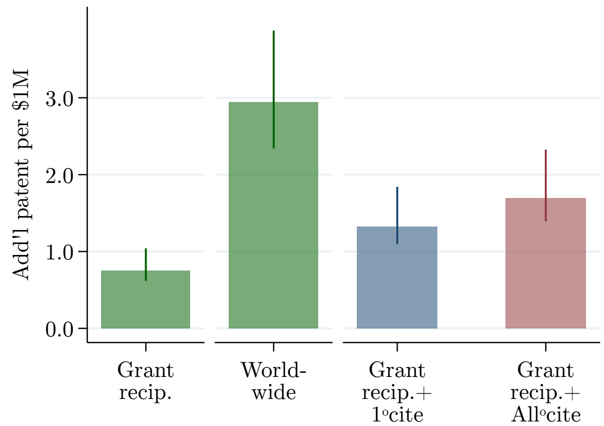
To explore this further, we estimated the main regression specification again, assigning the geographic location to be entirely based on either the inventors' locations or the firm assignees' locations. Figure E.6 plots the resulting distribution of marginal products across

Figure E.5: Comparison to Citation Linkages

(a) Patent Output Elasticity Estimates



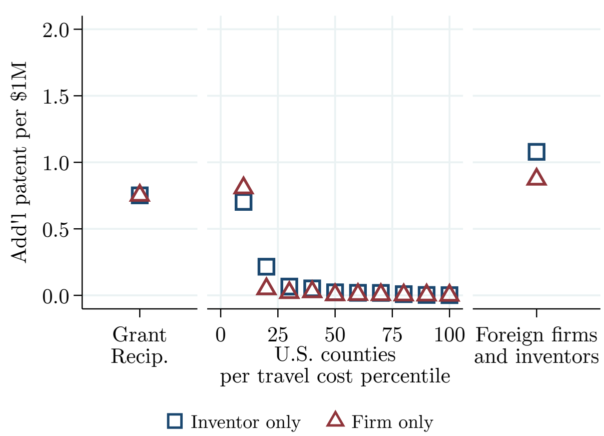
(b) Marginal Products



Notes: Plots the coefficient estimates from using the two alternative citation-based approaches to capture spillovers (Panel E.5a) and the implied marginal products from our preferred approaches (shown for grant recipients and the worldwide inventor sets in green) compared to these citation-based approaches (Panel E.5b).

geographic space (incorporating all technological spillovers) and shows that the specifics of how we assign geographic location does not make a large difference in our results.

Figure E.6: Alternative Inventor/Firm Attributions



Notes: Plots the average marginal product when attributing patents' geographic location entirely to either inventors or firm-assignees (where the preferred specification makes an equal attribution).

This consistency is likely driven in part by the fact that geographic locations of firms and inventors are relatively correlated: 83% of all inventor-assignee pairs are from the same country, and amongst pairs where one is located in the US, 50% are located in the same state and 31% are located in the same county. But it may also reflect the fact that both firms and inventors are equally important conduits of R&D spillovers across geographic space. There are some minor differences in the shapes of the within-US spillovers and the level of international spillovers. It appears that firms may be slightly more important in facilitating spillovers over very short geographic distances and individuals may be slightly more important for facilitating international spillovers.

F The Explore-Exploit Index and other Regional Correlates of R&D Spillovers

Studies have explored the role of forces such as trade patterns and market sizes (Eaton and Kortum 2002), foreign direct investment (Branstetter 2006), and multinationals (Griffith et al. 2006) in facilitating R&D spillovers. Still, inference in these settings is often either indirect or based on aggregate patterns. Here, we report the results of a purely descriptive search for the correlates of R&D spillovers. We cannot make any causal statements, but our setting and data provide a unique opportunity to (1) estimate how specific regions (e.g., US counties, foreign countries) are more or less likely to benefit from spillovers, and then (2) regress these estimates on features of each region to explore what is more or less correlated with the level of spillovers into that region.

In addition to features motivated by prior work, we focus on the degree to which a region appears to *exploit* knowledge produced by SBIR firms and focus on technologically similar inventions versus using that knowledge to *explore* technological space and focus on technologically distant inventions. We term this feature simply the "exploit-explore index" of a region. The notions of exploitation and exploration are pervasive in innovation economics and typically posed as a tradeoff (e.g., Manso 2011). But the importance of these alternative strategies, and whether such a tradeoff exists, has not received much attention in the context of R&D spillovers.

There are good reasons that exploit-oriented regions may be responsible for a large fraction of spillovers: the R&D performed by SBIR firms may de-risk ideas surrounding only the particular technologies they pursue (Howell 2017); the new patents obtained by SBIR firms may be signals that draw investors attention to those particular technologies (Conti et al. 2013); the nature of absorptive capacity (Cohen and Levinthal 1990) may lead only firms who focus on the particular technologies funded by the DoE to benefit from these advances (Aghion and Jaravel 2015); and the large adjustment costs of modern science (Myers 2020) might constrain inventors from taking these new ideas and applying them to more distant technologies.

Conversely, there are also good reasons why explore-oriented regions may be more likely to generate the spillovers we observe. First, the theoretical motivation for these subsidies should steer the DoE to target technologies where appropriating value – obtaining a patent – is difficult. So, perhaps once the SBIR firms are successful in these technological areas, they can be used in other areas where patenting incentives are relatively higher. Furthermore, recent work by Acemoglu et al. (2020) provides evidence that when firms are more "creative" or "open to disruption" they are more likely to pursue new lines of research and develop more radical patents. This could suggest that when regions are more willing to take an idea developed by an SBIR firm and use it in a novel way, they will ultimately be more productive and produce more patents.

Region-specific Spillover Levels

First, to obtain region-specific estimates of the relative spillovers into that region, we estimate a series of regressions that use our preferred specification:

$$\mathbb{E}[Y_{jt}^r \mid W_{jtb}] = \exp\Big(\sum_{b \in \mathcal{B}} \frac{W_{jtb}}{\overline{W}} \theta_b^r + \tau_t^r\Big) \ , \tag{F.1}$$

which we estimate for each region r – either BEA-defined economic areas or foreign countries – which yields many estimates of the $\theta^{b,r}$ parameters. When focusing on domestic spillovers, Y_{jt}^r is based on the flow of patents from only firms or inventors in economic area r except for any patents from DoE SBIR grant recipients who might also be located in r. When focusing on international spillovers, Y_{jt}^r is based on the flow of patents from only firms or inventors in foreign country r, which by construction excludes patents from DoE SBIR grant recipients.

For each of these regressions, we then calculate the relative amount of spillovers into that region by simply summing up the $\theta^{b,r}$ estimates – larger elasticities means larger spillovers, and for this purely vertical metric, we are not concerned whether these spillovers are at low or high technological distances. To account for the uncertainty in these estimates (since we use these numbers as the outcome variable in the prediction exercise), we use the popular empirical Bayes procedure to shrink our estimates. Thus, our final estimate of the relative level of spillovers into each region r is:

$$\text{Relative Spillover Level}_r \equiv \underbrace{\sum_b \widetilde{\theta^{b,r}}}_{\substack{\text{sum of post-} \\ \text{shrinkage estimates}}} \ ,$$

where $\widetilde{\theta^{b,r}}$ is the post-shrinkage estimate of the parameter. We focus on the elasticities (and not the absolute levels of patent spillovers) because we do not want to introduce a mechanical connection between the baseline patenting levels in each region and the degree to which we think that region is benefitting from spillovers.

The "Exploit-Explore" Index

As motivated in the main text, one of the features we think might be important for influencing spillover levels is each region's propensity to use the knowledge created by SBIR firms to either exploit or explore technology space. An exploitation tendency involves the development of patents that tend to be more similar to the R&D performed by SBIR firms, and vice versa for regions with an exploration tendency. In other words, we can proxy for a regions' stance on this exploit-explore index by measuring the share of patents produced by spillovers in that region that are more similar (low tech. distance) or less similar (high tech. distance) from the DoE's objectives.

Figure F.1a illustrates how we use our $\theta^{b,r}$ estimates to calculate this proxy. We fit a separate line through each of the r-specific set of $\theta^{b,r}$ estimates (using the post-shrinkage estimates), the slope of which describes how the relative flow of patents changes with each increase in the technology distance percentile:

$$\text{Exploit-Explore}_r \equiv \underbrace{\frac{\partial \widetilde{\theta^{b,r}}}{\partial b}}_{\substack{\text{slope of linear fit of} \\ \text{post-shrinkage estimates}}},$$

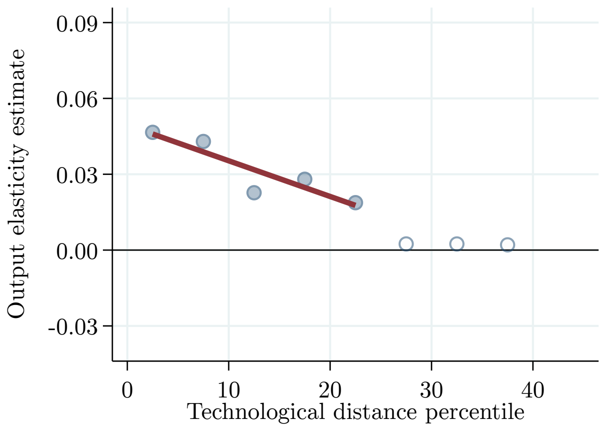
where more positive values indicate a more explorative orientation.

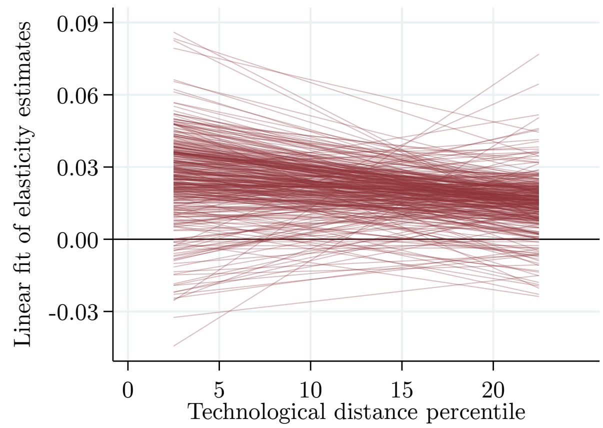
To see how this captures the notion of exploitation versus exploration, consider a region where we estimate equal $\theta^{b,r}$ parameters for all b – the slope of the fitted line is zero. This implies that the spillovers into that region led to an increase in patents evenly across all feasible areas of technology space. This is likely to happen only if the firms and inventors in that region are willing and able to explore technology space. Conversely, consider a region where we estimate a non-zero $\theta^{b,r}$ at the closest technological distance – the slope of the fitted line is very negative. This implies that the spillovers into that region led to an increase in patents only in the same areas that the DoE targeted grants towards. This is likely to happen only if the firms and inventors in that region avoid (or are ineffective at) exploring technology space and instead prefer to exploit.

It was apparent that, in virtually all cases, we estimate very small elasticities for distances beyond the 25th percentile of technological distance. Thus, we use only the estimates from within this technological distance boundary for all of the analyses in this section. This helps minimize a purely mechanical relationship that would arise between our measure of relative spillovers and the exploit-explore proxy.[7]

[7] We also tested other versions of this measure based on the share of patent spillovers that are within the

Figure F.1: Estimates of Region-specific Spillovers and the Explore-Exploit Index





Notes: Figure F.1a plots an example set of output elasticity (θ^b) estimates, one for each of the eight values of b (here, recreating Figure 2d) along with a linear fit of these point estimates. Figure F.1b plots the actual distribution of these linear fit aligns based on the region-specific estimates using within-US economic areas (domestic spillovers) and non-US countries (international spillovers).

Figure F.1b plots the distribution of the fitted lines across all regions, the slope of which is our Exploit-Explore index. There is clearly variation across regions in terms of their tendency to produce more exploitative or more explorative patents via spillovers.

Other Regional Features

For the set of possible correlates in addition to the exploit-explore index, we collect a large amount of data on regions from various sources (see Appendix B.5 for more). We focus on features that have been suggested to be relevant by prior work (e.g., firm sizes, trade volumes and compositions, venture capital levels, foreign direct investment, proximity to universities and federal labs, etc.).

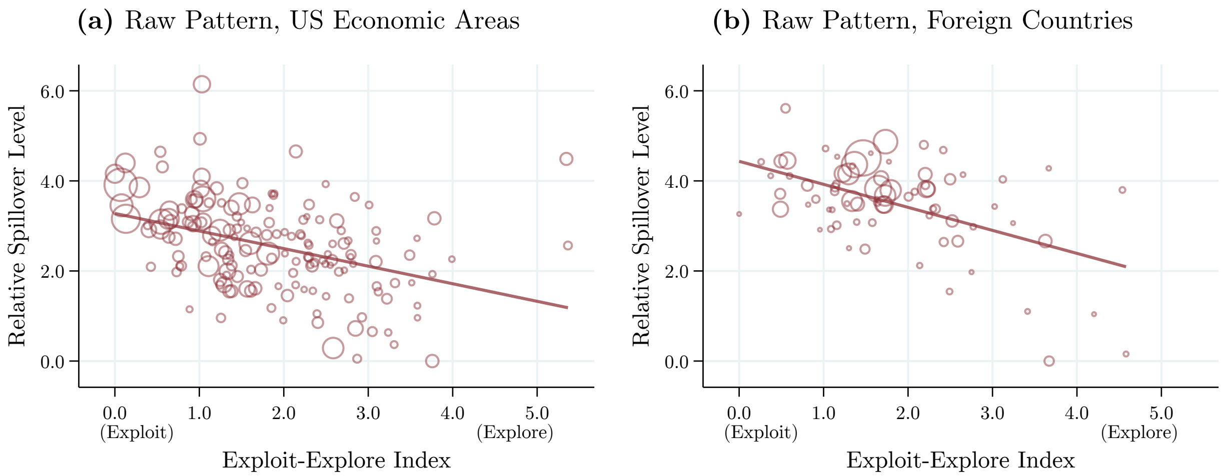
F.1 The Exploit-Explore Index is Unique and Important

To begin, Figure F.2 plots regions' exploit-explore index (x-axis) and how it covaries with the relative spillover levels in that region (y-axis). For comparability, the spillover levels and exploit-explore metrics are normalized within either set of regions so that their minimum is zero and a one unit change equals one standard deviation. Our focus is on relative differences, not absolute values. In both cases of within-US (Fig. F.2a) and international (Fig. F.2b)

5th or 10th percentile of technological distances – more discrete approaches to estimating the slope of the coefficients – and obtained very similar results.

spillovers, there is a clear correlation – regions with more of an exploit orientation tend to have relatively larger amounts of spillovers. At both domestic and international levels, regions that are one standard deviation closer to the exploit end of the spectrum have relative spillover levels that are roughly one half of a standard deviation larger on average.

Figure F.2: Regions that Tend to Exploit also Tend to Produce More Spillovers



Notes: Panels F.2a–F.2b are scatterplots and linear fits of the total amount of spillovers a region is responsible for as a function of their exploit-explore index (defined in text), with the markers weighted by the annual average total USPTO patent output of the region. Excludes regions with extremely small patent output. Both metrics are normalized within either set of regions (US economic areas or foreign countries) so that the minimum is zero and a one unit change equals one standard deviation.

Next, we explore other correlates of R&D spillovers and test whether the tendency for more exploitative regions to produce relatively more spillovers is a unique pattern or simply reflects other underlying correlations. We use the stability selection procedure proposed by Meinshausen and Bühlmann (2010). This amounts to performing a series of bootstrap sampling (we use 100 iterations), where a random half of the sample data is retained and a Lasso is performed on the subsample. The "Importance" score is then the share of subsamples in which a variable is selected as relevant by the Lasso. We supplement this process by also calculating the partial R^2 of each variable selected within an iteration (via OLS) and then calculate what we term the "effective" partial R^2 by taking the average of the partial R^2 values for each variable across all iterations, where the partial R^2 is zero if the variable is not selected by the Lasso.

The left-hand columns of Tables F.1 and F.2 report the results from this exercise. In short, we find many of the features related to the supply of and demand for energy technologies to be relevant, but few features consistently explain more variation in a region's ability to capitalize on spillovers than their exploit-explore index. Even after conditioning on large vectors of other relevant controls, regions that appear more willing to focus on the same technologies that the SBIR firms pursued are more likely to create more patents. In the case of domestic spillovers, the index is the fourth most important feature (out of 50 possible), with only industry clusters in IT, production technologies, and oil and gas appearing more important. At the international level, the index is found to be the most important feature.[8]

It does not appear to be the case that this exploration orientation is simply a proxy for other economic fundamentals of these regions. First, the variable itself is selected as important by the stability selection routine, which includes the large vector of features that should provide direct or proxy measures of many fundamentals. Second, we also perform a series of stability selection routines where we treat the exploit-explore index as the outcome, and we find that it is more difficult to predict this feature (using all other features) than it is to predict relative spillover levels. The right-hand columns of Tables F.1 and F.2 report the results from the same stability selection exercise, this time treating the index as the outcome to predict. In both domestic and international cases, it appears more difficult to predict this index than it is to predict the relative spillover levels. We take this as evidence that this index is not simply reflecting other fundamentals and may in fact capture a unique way in which firms and inventors differ across regions.

We emphasize again that the results here need not reflect causal effects – some features highly correlated with spillovers may simply reflect other unobservable differences across regions. Still, the apparently large importance a region's exploitation orientation highlights something that, to our knowledge, has received little attention to date.[9]

This finding is very much in line with Aghion and Jaravel (2015), who discuss the implications of absorptive capacity – the exploitation of knowledge created by others (Cohen and Levinthal 1990) – for growth models and other dimensions related to R&D spillovers. In the context of absorptive capacity, the term "exploit" has often been used generally to refer to the process of extracting value from other's advances. And the complementarities between firms' R&D investments are often considered only in the sense of the rate of R&D. Our results in this section indicate that this exploitation may also involve an important notion of

[8]Other important correlates of domestic spillovers include the number of workers with advanced scientific degrees, distance from SBIR grantees, and GDP per capita. Other important correlates of international spillovers include features related to natural resource rents, pollution, and clean energy, which all suggest that the supply of and demand for specific types of energy in different countries might be playing an important role in incentivizing foreign inventors to make use of this DoE-funded R&D.

[9]Our results are not at odds with Acemoglu et al. (2020), who focus more on the probability of observing radical patents (whereas we focus on total patent counts) and whose results might reflect factors important in de novo R&D (whereas our focus on spillovers likely ties us to R&D that is more cumulative or sequential in nature).

the direction of R&D, since we find regions more likely to stay focused on the technologies where initial advances are made (exploiters) tend to create more new patents than those who appear to use those advances elsewhere in technology space (explorers). Altogether, our results suggest a need continued work on why different groups of innovators are more likely to exploit or explore technology space, especially after they observe others generating new knowledge, and how this influences the rate and direction of invention writ large.

Table F.1: Predicting Spillovers & Exploration Orientation across 174 US Economic Areas

Panel (a): Full Sample Selection					
Net Spillovers			Exploration Orientation		
N Features Selected	26 / 50		N Features Selected	13 / 49	
R^2	0.52		R^2	0.41	

Panel (b): Stability Selection					
Net Spillovers			Exploration Orientation		
Feature	Importance $[0,1]$	Effective partial R^2	Feature	Importance $[0,1]$	Effective partial R^2
Cluster: IT	1.00	0.19	Cluster: Oil & Gas	0.98	0.09
Cluster: Prod. Tech.	0.94	0.07	Cluster: IT	0.98	0.06
Cluster: Oil & Gas	0.80	0.03	Wages	0.91	0.02
Exploit-Explore index	0.77	0.05	Travel cost	0.88	0.02
Scientific workforce	0.71	0.03	Research Nuc. Reactor	0.86	0.02
Dist. from SBIR grantees	0.70	0.01	Cluster: Prod. Tech.	0.84	0.02
GDP per capita	0.64	0.05	Internat. migration	0.77	0.02
Cluster: Construction	0.60	0.02	FFRDC, any	0.72	0.02
Cluster: Metal mining	0.58	0.04	Power Nuc. Reactor	0.65	0.02
Cluster: Coal mining	0.50	0.02	Cluster: Lighting	0.64	0.03
Cluster: Auto.	0.47	0.01	Cluster: Enviro.	0.58	0.02
Firm sizes	0.39	0.01	University count	0.54	0.01
Cluster: eComm. & Distr.	0.34	0.01	Young adult share	0.47	0.00
Labor force productivity	0.33	0.01	Labor mobilization	0.46	0.01
Exports	0.29	0.01	Cluster: Elec. power	0.45	0.01

Notes: Panel (a) reports the number of features selected and the R^2 of the resulting regression when the Lasso is applied to the full sample. Panel (b) reports the importance of each feature as the share of 100 bootstrap samples where the feature is selected by the Lasso, as well as the effective partial R^2 which is the the average partial R^2 across all bootstrap subsamples, by construction set to zero when the feature is not selected. All results based on 174 observations of US economic areas.

Table F.2: Predicting Spillovers & Exploration Orientation across 207 Foreign Countries

Panel (**a**): Full Sample Selection

Net Spillovers		Exploration Orientation	
N Features Selected	27 / 83	N Features Selected	3 / 82
R^2	0.97	R^2	0.27

Panel (**b**): Stability Selection

Net Spillovers			Exploration Orientation		
Feature	Importance $[0, 1]$	Effective partial R^2	Feature	Importance $[0, 1]$	Effective partial R^2
Exploit-Explore index	0.52	0.26	Nat. reso. rents, %GDP	0.48	0.24
Nat. reso. rents, %GDP	0.43	0.27	Renew. elec. output	0.38	0.09
Labor force partic.	0.37	0.20	Export to US: Nuclear	0.34	0.14
NO2 emiss., energy	0.27	0.12	GDP per capita, growth	0.33	0.09
Renew. elec. output	0.24	0.07	Internet use rate	0.32	0.10
Renew. energy consump.	0.23	0.06	Pop. density	0.27	0.12
Methane emiss., energy	0.14	0.06	Internet serv. per capita	0.25	0.09
English speaking	0.14	0.05	GDP growth	0.20	0.04
GDP per capita	0.11	0.03	English speaking	0.18	0.04
In-US migrant stock	0.10	0.02	NO2 emiss., energy	0.16	0.08
Inflation rate	0.09	0.02	Pop. growth	0.16	0.04
Pop. growth	0.09	0.02	Unemployment rate	0.14	0.04
Unemployment rate	0.08	0.03	Export to US: Biotech.	0.13	0.05
Export to US: Biotech.	0.07	0.03	Labor force partic.	0.13	0.04
Avg. USPTO patent rate	0.07	0.02	FDI: Chemical Sector	0.12	0.03

Notes: Panel (a) reports the number of features selected and the R^2 of the resulting regression when the Lasso is applied to the full sample. Panel (b) reports the importance of each feature as the share of 100 bootstrap samples where the feature is selected by the Lasso, as well as the effective partial R^2 which is the the average partial R^2 across all bootstrap subsamples, by construction set to zero when the feature is not selected. Imports and exports are based on bilateral trade with the US.

G Quality Effects and Patent Value Capture

G.1 Isolating Quality-margin Effects

The following analyses and findings center on determining (1) whether SBIR funding effect patent quality, and then (2) whether we can make any reasonable inference about the share of patent-based value that accrues to different sets of firms and inventors. Answering the first question is necessary to answer the second, and the answer to the second can start to shed light on the size of any gap between the private and social returns to R&D. We use forward citations as our focal proxy for patent quality because of its clear association with the private value of patents (Kogan et al. 2017).

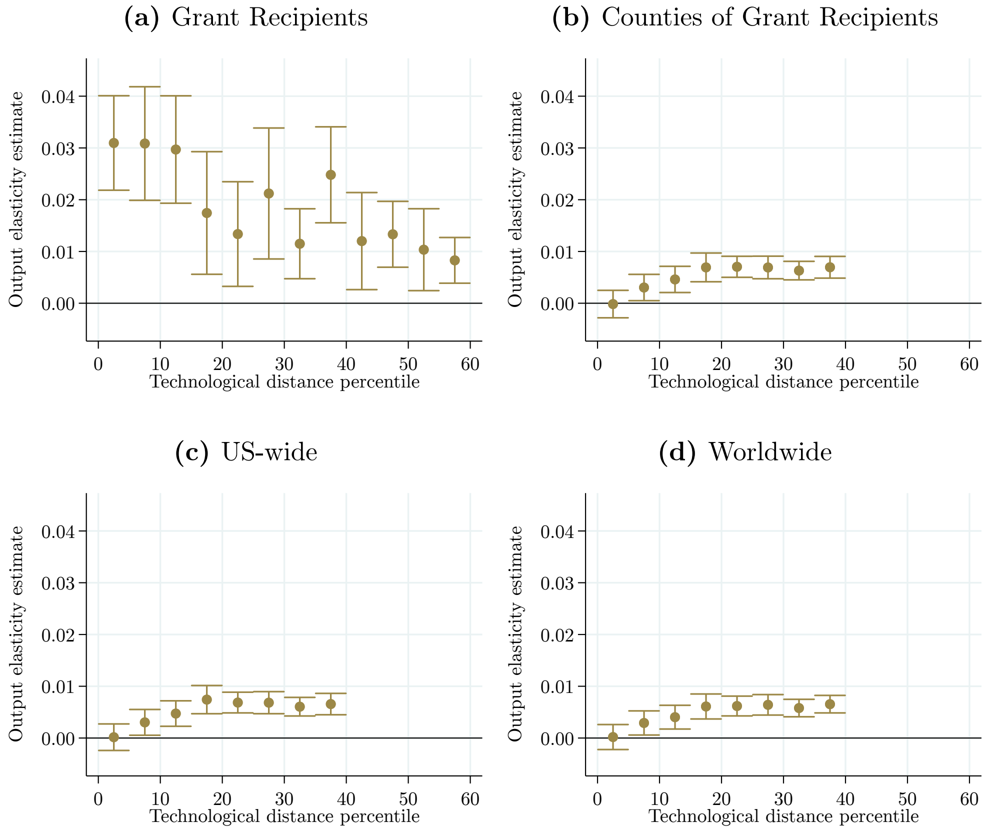
First, we estimate our main regressions again, but replace the dependent variable to be the number of citations-per-patent (instead of raw patent counts) within each CPC level observation. Figure G.1 plots the point estimates from these regressions, which clearly indicate that SBIR funding increases the citations per patent, but only in a meaningful way when we focus only on the patents of grant recipients.

Next, we want to approximate what share of the total patent-based value generated by the SBIR grants is captured by (patents obtained by) the grant recipients. The results reported in the main text indicate that grant recipients are responsible for only about 25% of the net patent output they stimulate. Thus, if we ignore any potential differences in the quality of these new patents and make the most generous assumptions possible about other important dimensions, this can imply that, as a lower bound, grant recipients also capture only about 25% of the net patent value the create following the SBIR grant.[10] This order of magnitude is in line with the few firm-level (Bloom et al. 2013) and macroeconomic studies (Jones and Williams 1998) that estimate this fraction to be on the scale of 25–50%.

However, that we observe increases on the quality margin only for grant recipients suggests that this estimate may be too low. Depending on the private value associated with forward citations, it may be the case that the private value of the grant recipients' patents is larger than the spillover-based patents that other firms and inventors obtain. As shown in Figure G.2, these quality effects are markedly different, so it may be that grant recipients capture much more than 25% of the net patent value. In the main text, we show how incorporating these quality effects alters the implied share of patent value captured by different sets of

[10] This lower bound is also based on the following assumptions: (1) spillovers are entirely driven by pure productivity shocks such that non-SBIR firms are *not* increasing private investments (which would reduce the true social returns); (2) product market rivalry spillovers after the patenting stage are negligible; and (3) none of the spillovers are due to market transactions where grant recipients are compensated (e.g., via patent licenses).

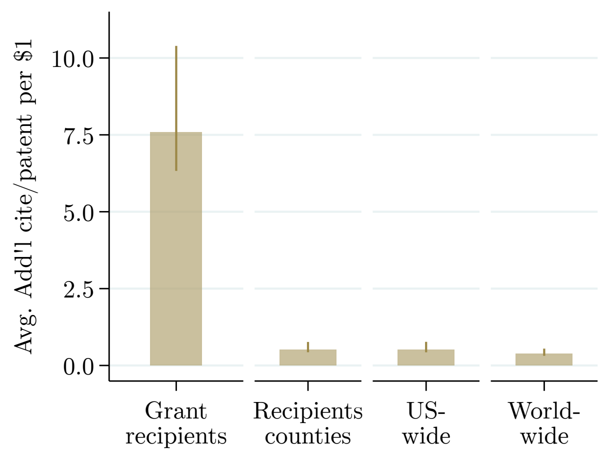
Figure G.1: Cite-per-Patent Output Elasticity Estimates



Notes: Plots the point estimates and 95% C.I. (standard errors clustered at the CPC group level) from estimating the main regression using forward citations-per-patent as the dependent variable.

firms and inventors.

Figure G.2: Average Level Changes in Cite-per-Patent



Notes: Plots the average marginal increase in patent quality associated with $1 million when examining four different aggregations of patents, with error bars indicating the 5th-95th percentiles across FOA topics.

G.2 Combined Quality-and-quantity-margin Effects

In the preceding analyses, we isolated effects on the quality of patents (as proxied with forward citations). Another popular approach in similar studies is to jointly estimate the effect of R&D investments on both the quality and quantity margins by using citation-weighted patent counts. Typically, a patent is weighted by the count of forward citations it has received to date, also possibly adding a value of one to that count. The former approach implies that the marginal citations (holding patent counts fixed) are associated with infinitely more value compared to marginal patents (holding citation counts fixed), while the latter implies that marginal patents and citations are associated with equal value. Recall, the empirical evidence to date suggests that marginal patents are associated with anywhere from three to twenty times as much value (to the recipient firm) than marginal citations.

While we prefer our approach of independently investigating the quality margin (by focusing on the change in the citations-per-patent), we also investigated the implied magnitude of spillovers using these other popular approaches of citation weighting.

Table G.1 reports the results from estimating our "simple" model that focuses only on geographic spillovers and uses a single bin of investments that spans the entire boundary of technological spillovers. Panel (a) recreates the four rightmost columns of Table 2 in the main text for comparison.

Overall, and in line with our results in the previous sub-section, we find that spillovers are smaller if we put a larger implicit weight on citations. Panel (b), which only values citations, indicates that grant recipients are responsible for about 75% (=6.77/8.97) of net citation output from these investments. Panel (c), which values citations and patents equally, indicates that grant recipients are responsible for about 38% (=3.78/10.05) of net patent-plus-citation output from these investments. These magnitudes largely overlap with the range of magnitudes we report in Figure 4 in the main text. To summarize, it appears that unless one places an extremely large value on citations relative to patents, the spillovers from these R&D grants are economically meaningful.

Table G.1: Alternative Approaches to Citations

	Grant recipients (1)	Recipients' counties (2)	US-wide (3)	Worldwide (4)
		Panel (a): No citation weights		
Windfall $	0.134	0.125	0.123	0.130
	(0.021)	(0.016)	(0.015)	(0.014)
$\frac{\partial \text{ patent}}{\partial \text{ \$1M}}$	0.54	1.40	1.73	2.97
	[0.5,0.6]	[1.2,1.6]	[1.5,1.9]	[2.5,3.3]
		Panel (b): Citation weight = forward citations		
Windfall $	0.552	0.320	0.316	0.322
	(0.049)	(0.027)	(0.026)	(0.023)
$\frac{\partial \text{ citation}}{\partial \text{ \$1M}}$	6.77	5.60	6.78	8.97
	[6.6,7.2]	[4.9,6.4]	[5.9,7.6]	[7.8,10.1]
		Panel (c): Citation weight = 1 + forward citations		
Windfall $	0.469	0.284	0.280	0.274
	(0.041)	(0.023)	(0.022)	(0.018)
$\frac{\partial \text{ patent+citation}}{\partial \text{ \$1M}}$	3.78	5.58	6.83	10.05
	[3.7,4.1]	[4.8,6.3]	[5.8,7.7]	[8.5,11.4]
N obs.	235,406	235,384	235,384	235,384
Tech. boundary	$p60$	$p40$	$p40$	$p40$
Year F.E.	Y	Y	Y	Y

Notes: Reports the output elasticity estimates from regressions using the "simple" model that aggregates all technological spillovers into a single bin. Standard errors clustered at the CPC group level are reported in parentheses.

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