Federal Funding and the Rate and Direction of Inventive Activity

Rafael A. Corredoira, Brent Goldfarb & Yuan Shi*

April, 2017

Draft version: 2.6

Abstract

Leveraging a new measure of patent citation trees (Corredoira & Banerjee, 2015), we demonstrate that research funded by the federal government is likely to spark more active technological trajectories. Our findings tie government funding to the generation of breakthrough inventions. The differences are only evident at the upper percentiles of the distribution of long term patent influence and stem primarily from research conducted at universities and academic medical centers that is sponsored by the DOD, HHS and NSF. Additional analyses indicate that federal programs invest in many technological areas that private corporations eschew. In this sense, the government affects both the rate and direction of inventive activity.

* This research was supported by NSF Award #1565555 and the Schulze Foundation. We thank Christian Catalini and seminar participants at the University of Maryland, as well as conference participants at REER, DRUID, the Wharton Technology Conference, and the LEI-Brick Workshop 2016 for helpful comments. All remaining errors are ours.

"Generally speaking, the scientific agencies of Government are not so concerned with immediate practical objectives as are the laboratories of industry nor, on the other hand, are they as free to explore any natural phenomena without regard to possible economic applications as are the educational and private research institutions." - Vannevar Bush, Science the Endless Frontier*"*, 1945.

1. Introduction

The Federal government funds 30% of US research and development (R&D).[2] However, since 2010, US government spending on research and development has remained flat and funding in real terms, R&D has actually declined (Sargeant, 2015). Vannevar Bush's 1945 Report to the President first articulated the basic logical argument for government funded R&D.[3] Nelson (1959) and Arrow (1962) explored the welfare reasons to support Bush's policy recommendations. Nelson suggested and Arrow formalized the idea that the government might play a role in sponsoring R&D because the private sector is likely to underinvest in R&D due to difficulties in appropriating returns to particular projects. The appropriability problem is exacerbated by the technological riskiness of innovative projects that reduce expected private value. Ideally, government investments should focus less on the near-term private return and more on the long-term public welfare. In this sense, government's support for difficult-to-appropriate technologies whose direct and indirect influence may unfold over a long period of time would not have been superseded by private investors that lack the incentive to do so. A lengthy literature has explored this fundamental proposition and measures the returns to R&D spending, the indirect effects of government research spending on private sector research spending, the nature of spillovers and the diffusion of knowledge through citation patterns. In general, most methods and assumptions show a strong positive private return to R&D spending, and some evidence of spillovers from the public to the private sector (Hall, Mairesse, and Mohnen, 2009).[4]

If the federal government is indeed financing projects whose value is more difficult to appropriate in the short term than that funded by private enterprise, we would expect to see the value of federal funded projects to emerge over time. This proposition has been tested by comparing

---

[2] The statistic refers to the latest available year, 2011. National Science Foundation, Science and Technology Indicators (2014). Chapter 4. http://www.nsf.gov/statistics/seind14/index.cfm/chapter-4/c4h.htm

[3] Bush writes, "Industry will fully rise to the challenge of applying new knowledge to new products. The commercial incentive can be relied upon for that. But basic research is essentially noncommercial in nature. It will not receive the attention it requires if left to industry.", Ch. 3. This logic still appears in government policy documents (Sargeant, 2015).

[4] Stokes (1997) describes knowledge in a two-dimensional space: Quest for fundamental understanding, and consideration of use. Stokes partitions the knowledge space into 4 quadrants. Exclusively basic knowledge (Bohr's quadrant), knowledge that is simultaneously basic and applied (Pasteur's quadrant), knowledge that is applied but not basic (Edison's quadrant) and he leaves the final quadrant, knowledge that is neither basic nor applied unnamed. There is also a small literature that investigates the returns to R&D funding in terms of publications and scientific collaborations – though this literature does not distinguish between Pasteur's and Bohr's quadrants (Arora and Gambardella, 1996; Carter., Winkler and Biddle-Zehnder, 1987; Jacob and Lefgren, 2011). In this paper, our concern is with Pasteur's and Edison's quadrants.

patents, which is the central measurable inventive output that both for-profit and non-for-profit organizations produce. However, Henderson, Jaffe and Trajtenberg (1998) found that university patents, largely funded by the Federal government, were, on average, declining in importance throughout the 1980s and early 1990s, as measured by first generation patent citations. Mowery and Ziedonis (2002) found no decline among patents of two leading universities before and after the 1981 Bayh-Dole Act while Mowery, Sampat and Ziedonis (2002) found evidence that part of the measured decline in citations to university patents in the 1980s was reversed.

We revisit this question and address several limitations in the literature in the current study. First, instead of simply testing the baseline differences, we explore a wide range of second-order questions concerning the contingencies of the federal funding of innovation. For example, do funding mechanisms matter? Do different funding agencies perform the same way? Unpacking these second-order differences is critical as agencies are treated differently in science policies.

Second, we adopt a more inclusive measure of long-term value of patented inventions. The measure, *influence,* takes into account both the number of patents in the multi-generational forward citation tree as well as the intraconnectedness of the tree's structure over a defined time period.[5] *Influence* is particularly appropriate for patents because unlike authors of academic papers, inventors and their agents are only required to cite the immediate precedents of inventions and have no incentive to cite anything more than necessary (Corredoira and Banerjee, 2015; Nagaoka, Motohashi and Goto, 2010). While first generation citations, which we label *impact*, and *influence* are correlated to some extent ($r < 0.2$), a significant share of highly influential patents do not enjoy high levels of first generation impact.[6,7] This indicates that direct forward citations alone do not capture the full picture of how a particular invention affects technological trajectory over the long term. In addition to offering the proper setting for the measurement, patents also offer a more conservative estimate of the value of federally funded research, if one were to believe that the majority of the products of

---

[5] Patents build on prior technological solutions. However, any given patent may rely on alternative prior inventions – there is more than one way to skin a cat. Influence that is driven by tree intraconnectedness reflects knowledge with fewer technological solutions outside the tree. It's difficult to find alternative methods to skin the cat! In this sense, the citation trees of more influential patents reflect greater downstream inventive activity that is magnified by the opening of new streams of inventive activity. These new streams would have been difficult to discover absent the influential patent. In this sense patents with high *influence* are breakthroughs.

[6] *Impact* is equivalent to how the HJT measure of *importance* has been implemented, though not to how it was originally conceptualized. Henderson, Jaffe and Trajtenberg (1998) anticipate this problem as their measure of importance aspires to measure citations across two generations. However, their data did not allow them to follow citations more than a single generation. Corredoira and Banerjee's measure can and does accommodate any number of generations in any analysis timeframe.

[5] The correlations of the measures are low. However, the correlations of the natural logs of citations and influence are much higher, 0.93 in the first 95% of the distribution. The top of the distribution - the top 5% is only correlated at 0.22. The importance of the right tail highlights the skewed nature of the distribution of returns to innovation, and indeed foreshadows the empirical strategy in this paper.

federal R&D are in the form of research papers in basic science and that private sector are more incentivized to patent efficiently.[8]

Third, our analysis of 4,311 federally funded patents across multiple agencies relies on a flexible and precise matching scheme. The results of the bootstrapping scheme are not subject to the loss of information of arbitrary choice of one of multiple potential matches. This allows us to avoid spurious results based on a random set of match choices.

Our results indicate that Federal funding affects the *rate* of innovation: applied research funded by the US federal government is more likely to spark active technological trajectories in both the near and long terms. As compared to corporate funded patents, the most seminal federally funded patents spur approximately 51% more *influence*. The higher *impact* and *influence* of government sponsored patents is largely driven by a subset of government agencies that fund research conducted externally at universities and other non-profit entities. Patents sponsored through the mechanism of intramural funding tend to be less influential than their counterparts and the pattern does not appear to vary across major agencies. Our second central finding is that federal funding affects the *direction* of technological change. Federal funds appear to be more likely to support R&D in less commercially active and vibrant areas. Neither does the choice of funding a technological area seem to be attracted by past corporate patenting, nor does it crowd out future corporate patenting. Moreover, growing areas that receive federal funding are more likely to sustain and accelerate growth in the future. Through these findings, we demonstrate the direct link between government funding and the generation of breakthrough inventions in technological domains that likely would have been neglected by the public sector. While the evidence is largely consistent with the premise that the government sponsors research in areas that we expect the private sector to underinvest due to appropriability problem, the results are not universal across federal programs. It is plausible that less influential federal programs are funded because they produce knowledge only or primarily useful to the government.

2. **Funding Sources and Inventive Activity**

While the theoretical justification for government sponsorship of academic research is well understood, the political nature of government may stymie efforts to fund riskier, and more basic long term research. The literature questioning the efficacy of government spending has pointed out that government decision-making mechanisms are prone to error and political considerations. For example, Cohen & Noll (1991) argue that legislators will direct technology development dollars towards their (voting) constituents. Supportive of the rich descriptive and basic statistical narrative found in the chapters of Cohen & Noll's book, Hegde & Mowery (2008) find that between 3% and 7% of federal spending on biomedical research is politically motivated, and these funds are most

---

[8] Sampat (2006) found that university patents tend to cite more scientific articles than do private sector patents. Under a certain set of assumptions about the patenting decision and process, this suggests that university patents are embodiments of more basic knowledge.

likely directed at the least productive researchers. However, even in the absence of congressional representatives directing money to their districts, politically savvy government decision makers may wish to avoid risk in their choice of research projects. Less risky projects are more likely to succeed and lead to demonstrable, short-term metrics of efficacy. Indeed, Wallsten (2000) finds that innovation grants to small business administered through the SBIR program crowd out private sector investments. However, newly available data of the Department of Energy SBIR program that allows better identification techniques indicates the Wallsten result is confined to later stage investments. SBIR administrators at the (DOE) seem to be fulfilling the Arrow-Nelson social mission more faithfully with their early stage investments (Howell, 2015).

On the other hand, as Bush observed in 1945, the private sector suffers its own set of biases vis-a-vis the social optimum (Nelson, 1959; Arrow, 1962). Perhaps the best arguments that illuminate why actors may have trouble appropriating returns has come from the work of Nathan Rosenberg. In 1996, Rosenberg, in *Uncertainty & Technological Change,* culminates a series of his own papers regarding the difficulty in foreseeing the value of current inventions[9]. New technologies are built upon the recombination of existing technology, but generally the two recombined technologies are not discovered simultaneously. For example, Internet communication relies on, among other things, lasers, fiber optic cables and transistors. When in 1949 Thomas Watson Sr., President of IBM, foresaw a market for only five computers, he was referring to machines that filled large rooms and used vacuum tubes and mechanical relays. Watson was very wrong – at least one of the authors owns more than five computers himself. But Watson was not a fool, only human. He could not imagine the application and miniaturization of transistors, advances in glass technology that allowed fiber optic cables, and of course, the laser that is used to send signals through these cables. Nor was he able to anticipate the myriad of advances in signal technology that has increased the capacity of cables by several orders of magnitude. Even if he had imagined the development of each of these technologies, only a prophet could have correctly anticipated how the combination and integration of these technologies would have opened up the host of new uses such as personal computing as well as the variety of business models and economic systems that have been created to profit from them. We could amuse ourselves with many additional examples of the limits of human imagination, and Rosenberg provides several more. But it is should not be particularly surprising that it is difficult for private sector managers to imagine which projects are most likely to have long term impact to such broad streams of innovation and, of course, appropriate returns from them. Instead, they will prefer more short term activities from which they are able to predict and appropriate returns. To quote a personal conversation one of the authors had with Nathan Rosenberg, "Obviously, the future is not obvious".

Of course, the practical uses of research output are also a concern for the US Federal Government, which directs the vast majority of its research spending through mission oriented

[9] For example, despite various modeling efforts, it is still very difficult to predict first-generation citations of scientific papers over the long term (Wang, Song & Barabasi, 2013).

agencies (Goldfarb, 2008). To the extent that the government is interested in developing technologies for its own narrow needs, we might expect some programs and perhaps entire agencies to not generate long-term trajectories. Nevertheless, a significant share of government sponsored research is directed to the exploration of fundamental knowledge. And, of course, a great deal of fundamental discoveries was made in the pursuit of applied goals.[10] Even if the technological risk between the public and private sector projects were the same, the private sector is concerned with a project's commercial viability, whereas the public sector is not. Indeed, it is difficult to find leadership positions in high technology industries that emerged without the support of governments (c.f., Mowery & Nelson, 1999). These facts have led some to argue for a strong government role in guiding the rate and direction of technological change (Mazzucato, 2015).

Our results suggest that the government is producing high quality patents that colonize technological areas that likely would not have been explored as deeply if not for government activity. We cannot evaluate whether the government is acting as the "Entrepreneurial State" as Mazzucato advocates, but our results are most consistent with the idea that the government is effectively nurturing certain technological areas. To see this, we next consider our central tool of measurement, patent citations, and then describe our data, empirical analyses and results.

3. Patent Citations as Embodiment of Invention

Patent citations are a legal mechanism to document precedence and delineate intellectual property rights. Thus, a citation may not indicate that there was a transfer of knowledge, it could instead indicate that there were multiple teams working on similar problems, and one team was able to establish precedence. Indeed, many patent citations are not added by the inventors, but by patent examiners (Alcacer & Gittelman, 2006) and at times, firms strategically do not include any citations in their patents, and turnover of examiners might affect the inclusion of citations (Alcacer, Gittleman & Sampat, 2009). Nevertheless, in the Handbook of Economics of Innovation, Nagaoka, Matohashi and Goto (2011) write "a large number of forward citations means that the patent serves as a giant shoulder for many other subsequent innovations" (p. 1112). In this paper, we interpret citations as being correlated with knowledge flows, despite these imperfections. We do this with a caveat that a multi-generational measure may not indicate direct knowledge transfers in the traditional sense because early inventions become embedded in subsequent technology in such a way that downstream inventors may not even be aware of the source of upstream inventions embedded in their technology.

An additional challenge is that even when citations unambiguously pick up knowledge flows, they are likely to only capture a fraction of the knowledge that is flowing. This is true for several reasons. Roach and Cohen (2013) suggest that tracking patent citations to academic articles is

[10] The field of Bacteriology emerged as a consequence of a pursuit for better wine. Radio Astronomy can be traced to the nuisance of radio static, and as noted by Kenneth Arrow, the discovery of the New World was motivated by the pursuit of better tasting food (Rosenberg 1996).

a better measure than patent citations to academic patents for understanding the linkages between academia and industry. (see also Narin, Hamilton & Olivastro, 1997). Indeed, Li, Azoulay & Sampat (2017) find that only 1 in 10 NIH grants directly generate a patent, but almost 1 in 3 generate an article that is eventually cited by a patent. Our paper complements this work by asking whether directly funded patents are more important in generating future technological trajectories across multiple technological domains and agencies.

If public research is fulfilling the Arrow-Nelson ideal, then patents that rely heavily on science will also likely seed and be critical linchpins of fertile technological trajectories. Examining whether patents that rely more heavily on academic research is beyond the scope of this study. An astute critique of patent measures would also note that any patent measure only captures the informational contribution to technology embedded in the patent. It cannot capture, for example, the basic science contribution to instruments utilized to develop a patent, or to inventor's training because that is not reflected in citations (Corredoira and Banerjee, 2015, Pavitt, 1991).

Our focus on differences in the influence of federally funded and privately funded patents implies that we restrict our analyses to outputs of research that are firmly in Pasteur's or Edison's quadrants. Since much Federal sponsorship of research activity may support research that is unlikely to be immediately useful and patentable, we view our work as providing a lower bound of the contribution of science to technology.[11] Furthermore, in addition to the influence measure, and to address the issues raised by Thompson & Fox-Keane (2005), we designed a comprehensive matching scheme which matches a federally funded patent with a control patent as close as possible in terms of technology subclass and granting time. The matching scheme also allows for the possibility of no match as well as randomness in multiple matches. The empirical strategy bears immediate fruit as it allows us to examine whether patented technological inventions funded by federal government agencies are more influential than their private counterparts. We are also able to examine whether differences are due to funding mechanisms, the type of recipient or the funding agency. Based on analysis of a unique sample of federally funded US patents in the period of 2001-2004, our results indicate that government funded projects are more likely to lead to "home-run" inventions that make long-lasting and large contributions to technological trajectories. However, the median government sponsored and privately sponsored patents are different in neither impact nor influence.

4. Data and Sample

To examine the possible effect of federal funding on applied research, we first need to observe a population of applied research projects and whether those are funded by the federal

[11] Given the centrality of publications in the scientific enterprise, it is not surprising that patenting itself is not the most important mechanism of knowledge transfer from the public to private sectors (Agrawal & Henderson, 2002). Further, scientific research tends to be under-cited by patents (Meyer, 2000; Nagaoka and Yamauchi, 2015). In future projects we hope to better understand whether federally funded patents draw more or less on the scientific literature.

government. We began by collecting data on granted patents and patent applications from USPTO. We limited our sample to those patents whose granting year and application year fall between 2001-2004 because bulk data files for US patent applications became available electronically in 2001. By limiting the grant year to 2004 we were able to measure influence of the sampled patents in the following ten years, which allows us to compare at least medium-term influence of the sample patents.

We then identified federally funded patents from this time period. We used three approaches to identify federally funded patents in the sample. First, we utilized a data field that is rarely used by prior research, "Federal Research Statement" from patent applications[12]. We identified all patents that report information in this data field, and then dropped all cases of false positives by manually examining all indicated patents. Second, we located all patents assigned to federal government agencies from the assignment information reported in the NBER 2006 patent data. We were aware that the assignee type information reported in the NBER data is noisy so we went through all assignee names in all the government types, generated a list of US federal government assignees and extracted all patents associated with them. Third, we also included additional patents reported in the NIH and DOE's public patent database.[13] The process generated 4,311 federally funded patents in total, which is about 1.6% of all patents granted during the period.

More than 90% of the patents in our sample are funded by the Departments of Defense (DOD, 1,753 patents including 925 attributed to the Navy, 416 to the Army and 308 to the Airforce, the rest distributed among other units, such as DARPA), the Health and Human Services (HHS, 925), Energy (DOE, 416), the National Aeronautics and Space Administration (NASA, 283) and the National Science Foundation (NSF, 263).[14] Most HHS funding reported in patents comes directly from National Institutes of Health. We also examined the distribution of federally funded patents among six HJT categories (Hall et al., 2001). While Category 4 (Electric) has the most patents (26.83%) and Category 6 (Others) has the least (7.1%), the portions of federally funded patents in other HJT categories range from 11.95% (Category 5: Mechanic) to 21.51% (Category 3: Drugs & Medicine). Given the fair representation of these major technological categories in the sample, it is unlikely that our findings would only apply to one or two technological categories where federal R&D funding is concentrated.

5. Method

[12] The data filed is equivalent to the "Government Interest Statement" in granted patents. However, the latter is a less reliable source for the funding information.

[13] We also contacted other major federal government agencies and requested data of their funded patents by email but could not obtain any additional data.

[14] Some patents are developed from multiple agencies. In addition, there are 87 USDA patents, 20 associated with the Department of Interior, 18 with the Environmental Protection Agency and 17 with the National Security Administration.

5.1 Matching Techniques

There are two central ways in which federal funding might lead to different levels of influence. The first is that federally funded projects may be different along the ways described in the introduction. That is, federally funded projects might be more oriented towards uncovering fundamental principles and more oriented to long term ideas. This would then lead to a greater degree of measurable influence. It is also possible that given identical research outputs, federally funded inventions may receive greater influence due to the greater likelihood that a federally funded invention is assigned to a public sector or university assignee. Such actors may be more likely to emphasize diffusion of an invention over appropriation of returns. In this case, differences in influence would be caused not by differential motives of funders playing out in the choice of project types, but rather in differential motives leading to different institutional mechanisms that affect diffusion.

An ideal test would distinguish between these two mechanisms. For example, such a test might compare the influence of two identical inventions, one federally funded invention and the second funded by the private sector. Once identifying this post-invention institutional effect, we could then compare closely related patents to determine if the underlying potential for influence differs across projects of differing funding types. As such counterfactuals are not observable in reality, our strategy is to identify similar inventions. We match each government funded (sample) patent with a privately funded (control) patent that is introduced around the same period. These control patents represent a reference group of inventions that are similar in nature but do not receive federal support. While this approach cannot precisely distinguish between a pre-invention quality or selection effect and a post-invention institutional or treatment effect, we will compare the funded patents assigned to for-profit organizations and non-profit organizations to test the difference in post-invention diffusion.

In order to identify the matched control groups, we primarily rely on the information of the primary subclass and granting date of the patent. Matching on the subclass, the most fine-grained patent classification, minimizes the possibility of spurious effects of unobserved differences within the aggregated 3-digit class and ensures that the matched patent embodies technology similar to that of the sample patent (Thompson & Fox-Kean, 2005). We first defined the universe of patents for matching as all US patents filed and granted in 2001-2004 in accordance with the sampling window of federally funded patents. We then located all the patents in the same primary subclass and the same grant year and then viewed all patents issued on the closest granting date as potential matched.

We adopted two approaches to tackle critical problems encountered in the matching process. First, in the case of no match in the same subclass, we continue to search the "parent" of the focal subclass in the hierarchical structure of USPTO classification system until one match can be identified or randomly picked. Second, we repeated the matching process for thirty times to exhaust potential multiple matches for any given sample patent. All but three sample patents receive fewer than 30 matches after the last round of matching, suggesting that the vast majority of the possible matching options have been exhausted. This approach, along with the bootstrapping which will be explained later, alleviates the concern that our estimation may be driven by the "luck" stemming from arbitrary choice from multiple matches. A more detailed discussion on the matching scheme can be found in Appendix I.

Following bootstrap techniques, we randomly sample 4,311 treated patent with replacement and then randomly sample a corresponding match for each bootstrapped sample patent independently. We repeated this process and constructed 2,000 bootstrapping samples for regression analysis.[15] Therefore, we have 8,622 patents in each bootstrapping sample.[16] The approach allows us to maintain the balance between treated and control groups while exploiting the variant number of matches for the treated group. Balance in the bootstrapping sample is crucial because it helps to reduce model dependence and potential bias (Ho et al., 2007). We also refer the readers to Fox (2015), chapter 21 for a primer on bootstrapping techniques.[17] Intuitively, we explore the robustness and variance of the estimate across the universe of potential matches. This allows us to rule out the possibility that our results are an artifact of certain matches.

An immediate concern is whether the actual universe of patents would allow us to gain significant variance in matches and thus increase substantial statistical power over one-time matching. To verify the effectiveness of our matching scheme, we randomly picked results from three out of thirty rounds of matching. It is found that 1,020, or 23.66% of the sample patents have more than one match, of which 229 patents are matched to a different patent in each round. Additionally, sample patents with extremely high influence score are critical to our findings in quantile regressions. Hence we restricted our comparison to top 5% of the sample patents, and found that 22.32% of these patents have two or three matches in three control groups. Taken together, the matching scheme does expand the sample size and increase the variance.

Another major concern with our matching scheme is that whatever the results we found is driven by the different matching processes for cases where a match is found in the same subclass. To address this concern, we constructed a dummy representing whether a sample patent is matched within its own subclass and added it as a moderator of the main independent variable in the main

[15] Bootstrapped standard errors commonly are done by holding the regressors fixed and calculating residuals based on bootstrapped samples. The distribution of bootstrapped residuals is then used to calculate the standard errors of the coefficients. Alternatively, the regressors themselves are bootstrapped. The former method requires assumptions that the errors are i.i.d. and that the functional form is correct. One concern with the former is that the error terms may not be estimated consistently when using propensity score matching estimators (Abadie & Ibbens, 2006). However, as pointed out by Caliendo & Kopeinig, (2008) this may be less of a concern because we can match exactly for most of our sample and because the variance estimator will be asymptotically efficient if the number of potential matches increases more rapidly than the increase in the treated - a condition that is satisfied in our sample.

[16] Because the number of unique matches for each sample patent is different, pooling all matches together would cause the data structure to be unbalanced. Duplicates in sample patents and matches are possible because the random draw is with replacement.

[17] http://www.sagepub.com/sites/default/files/upm-binaries/21122_Chapter_21.pdf

analysis. We found no significant moderating effect, which suggests that the main results are not sensitive to the matching process.

As our matches will be imperfect, so we control for patent scope using the number of claims, a measure that has also been used to proxy for economic value. We also include the HJT measure for originality.[18] All regressions include patent class and granting year fixed effects.

5.2 Measure of Influence

We followed Corredoira and Banerjee and measured the patent influence by an iterated sum capturing the size and the interconnections of the citation tree that followed the patent. To directly compare the influence of a single sample patent and its match, we constructed a forward citation tree which is composed of all the direct and indirect citing patents in the 10-year window. We then calculated the *influence* for the focal patent in this network as:

$$Influence = \sum_{k=0}^{K} A^{Tk} \quad (Eq. 1)$$

Where k is the citation generation, and A^T is the transpose of the adjacency matrix defined by patent citations.[19]

Additionally, for each sample and control patent, we also counted the number of forward citations in the 10-year window as the conventional measure of *impact*. Corredoira and Banerjee (2015) offer a comprehensive discussion on the patent influence measure and why it is different from direct impact. The construction of independent variables will be detailed in the next section as we walk through the findings.

5.3 Summary Statistics

The correlation between Impact and Influence is 0.13 for 2001-2004 population of patents, though only 0.02 for the patents in the sample. Due to the high skewness of the data, we used the logged value from Eq.1 as influence and we also log impact. We compare the logged count of direct citations (impact), and the logged "influence" of the focal patent for the federally funded patents and their multiple matches. The correlation of logged influence and logged impact is .93 for the bottom 95 influence percentiles of the sample and matches in this study but only .21 for the top 5 percentiles. This suggests statistical distinctiveness, especially at the (most interesting) right tail. Table 1 provides an overview of the descriptive statistics of our sample of federally funded patents,

---

[18] Inclusion of other measures such as generality do not affect the results and are not measurably related to impact or influence.

[19] The full measure is $Influence = (\sum_{k=0} a^k A^{Tk})e$ (Eq. 1), which allows weighting of individual patents by relative contribution, measured perhaps as the number of claims, as well as altering the attenuation factor α. In this paper we assume these values to be one, which weights each patent equally and gives equal weight to all generations.

their matches, and the rest of the patents in the same sampling frame. We also compare the mean of the key variables across the first three groups of patents. T-tests reveal that federally funded patents ("Sample") are more original and have more claims than the matching patents and the general population. Both logged influence and impact are not significantly different between the sample and the population, while an economically small but statistically significant difference on the mean is found between the sample and the matches. Moreover, we compare the median and 95% percentile of the impact and influence of these three groups of patents and the differences are minor between the sample and the match. While the median impact of the patent population is larger, the 95% percentile of the impact of the funded patents is also slightly greater. The last section of the table reports the same summary statistics from the 2000 bootstrapping samples, which demonstrate a distribution similar to the sample and match group.

5.4 Econometric Model

We used Quantile Regression to estimate the effect of federal funding on patent influence and impact. Quantile regression models are chosen for two reasons. First, our dependent variables are highly skewed, and outliers were found to overwhelm any meaningful average effects yielded by traditional OLS models. Quantile regressions are known for their superior capability to embrace outliers because they analyze the relative distribution rather than the absolute mean of variables. Second, empirically we are interested in those outliers at the top, namely those extremely influential inventions that may be "homeruns" or what is commonly known as "breakthroughs", and fundamentally different from other inventions.

For each sample and control patent, we control for the number of claims and fixed effects of granting years and the major 3-digit USPTO classes with 75 patents or more. Due to the complexity of the optimization process, especially in the analysis of top quantiles, further including USPTO classes would result in frequent convergence failures. However, it should not be a major concern because the control patent is in the same or closest subclass available in a given class and the treatment and control groups are balanced in size. The technologies embodied in the sample and control patent are as similar as it gets in reality. Moreover, while it is possible that various other unobserved characteristics of the patent may be related to patent influence, the estimates would be unbiased if these characteristics are distributed randomly across sample and control groups, which we hope to approximate by randomness from repeated matching. Moreover, the dependence on specific models that include or omit certain additional variables is minimized by a balanced sample structure.

Following standard bootstrapping estimation procedure, we ran each regression in all 2,000 bootstrapping samples and obtain the distributions of the coefficients of interest across different samples. For a given coefficient, the bootstrapping estimate is the mean of the individual coefficient estimates from each of the 2,000 bootstrapping samples. The 95% normal-theory confidence interval is then calculated based on the distribution of the same population of coefficient estimates.[20]

6. Findings

6.1 Baseline analysis: are federally funded inventions more influential?

We compared 99%, 95%, 90%, 75%, 50% percentiles of the influence of the sample patents with that of the whole population of patents in the same period and found very similar values. The only noticeable difference is that sample patents have fewer zero values at the bottom.

Given that the technological niche and time of introduction are matched as closely as possible between the sample group of federally funded patents and the control group of matches, we expect to see no difference in the impact/influence between two groups if federal funding has a null effect on the invention. In other words, if the inventions funded by the government are more influential than those funded by other sources in the same period and technological niche at conventional significance level, then we may infer that federal funding is unique in supporting certain types of R&D projects and may not be interchangeable with private funding or other types of public funding.

We first compare the impact score and influence score between federally funded patents and their matches to set the baseline for our further analyses. To identify the effect of federal funding, we create an independent variable, Federal Funding, which equals one if the focal patent is a federally funded patent and zero if it is a match. With this variable, we attempt to test whether on average inventions funded by the federal government outperform or underperform the imperfectly constructed counterfactuals.

Bootstrapping estimates and confidence interval at the 75%, 90%, 95% and 98% quantiles for each outcome variable from 2000 iterations are reported in Table 2. First, federally funded patents have more direct impact than their matches at 95% quantile. Second, top federally funded patents are much more influential than their privately funded matches at 98% quantile. In both cases, most federally funded patents, in particular, those below the 95% quantile are neither more impactful nor influential than their matches. We use 95% confidence intervals to frame our discussion of the economic magnitude of the effects. Other conditions being equal, the 95% percentile of the impact of federally funded patents is 0 and 26% higher than that of the control patents, but certainly not lower. We bound the 95th percentile of influence between -10% to +55%. The 98% quantile or federally funded patents is estimated to between 0 and 127% more influential than privately funded patents. We note that these confidence intervals that range from +/-100% of the point estimate are typical of coefficients that are considered just statistically significant at the 5% levels in a 2-sided test.

[20] To justify the choice of normal-theory confidence interval, we tested the normality of the coefficient distribution and found no evidence that the normality assumption is violated. Compared to percentile intervals, normal-theory intervals are more reliable and produce less coverage error (Carpenter & Bithell, 2000).

As mentioned in Section 5.4, several alternative determinants of patent influence are accounted for in the regression model. We find that, not surprisingly, claims shift the distributions of both impact and influence to the right. The distribution of impact of patents shifts about 1-1.5% to the right with each additional claim. Influence shifts 1.5%-3%. To summarize the main findings, we detect a baseline difference between the group of federally funded patents and the matched control group. Specifically, the federally funded patents are more influential and impactful than their matches, but only at the very top. Moreover, the difference is much larger when the whole forward citation network of the focal patents is taken into consideration.

6.2 Analysis of mechanisms of federal funding: are inventions funded internally more (or less) influential than those funded externally?

Is the difference between government and private sponsorship driven by distinctive funding mechanisms, namely intramural and extramural funding? Intramural research is performed by R&D personnel of a federal agency and funded internally. Extramural research is performed by researchers affiliated with external institutions and funded through contracts, grants and cooperative agreements (National Institute of Allergy and Infectious Diseases, 2015; National Science Foundation, 1995).

For there to be a difference between the two, one or more mechanisms might be at play: First, the projects done intramurally and extramurally might be different in kind. Second, the quality of researchers in the two settings might differ. Finally, the post-invention institutional settings might lead to different diffusion and citation patterns.

Federally funded patents were identified through both the government mandated disclosure on patent applications as well as the patent assignment information of federal government agencies, based on which we are able to empirically observe inventions supported by both intramural and extramural federal funding.[21] Extramural Federal Funding is defined as one if the relevant funding support information is reported in federal research statement of the patent replication and zero otherwise. Intramural Federal Funding is defined as one if the no information on federal support is disclosed in the patent application and the patent is assigned to the federal government, and zero

[21] The Bayh-Dole Act and Executive Order 12591 requires that "in applying for a patent, the organization (who is the contractor or grantee) must add a government interest statement that discloses the government's rights to the invention" (page 4, United States General Accounting Office, 1999). Meanwhile, intramural research not funded through external grants and contracts do not seem to be subject to the mandated disclosure, since 82.88% of all the patents assigned to the federal government do not report sponsorship information in the federal research statement. Accordingly, we distinguish extramural funding from intramural funding based on whether the patent application discloses funding information in the federal research statement. Among the 4311 federally funded patents in the sample, 3023 patents disclose funding support information in the application files, and 1554 patents are assigned to the federal government, which largely correspond to extramural and intramural funding mechanisms. For 266 patents that are assigned to the federal government and yet discloses federal support information, we classify them as recipient of extramural funding because we assume these patents are developed by intramural researchers (assignment to the federal government) with support from other federal agencies (disclosure of federal government support as a grantee/contractor). The classification may not be entirely accurate, but the noise in the measurement would bias the estimation downward and thus make the estimation more conservative.

otherwise. These two dummies would replace the dummy Federal Funding which lumps both funding mechanisms together in the estimation.

Table 3 reports the bootstrapped estimates of the effect of extramural funding on patent impact (Panel 3-a) and influence (Panel 3-b). The data do not allow us to conclusively say that one value is larger than the other in the tradition of a null hypothesis test at the 75th and 90th percentiles. However, by examining the range of the 95% confidence intervals of the estimates, we can rule out the possibility that privately funded patents are more influential than publicly funded patents in any meaningful economic sense. This implies that either the influence of government and privately sponsored patents is economically similar, or government sponsored patents are meaningfully more influential. To see this, the *impact* of extramural patents is between 0% and 22% larger than privately funded patents at the 75th percentile. Similarly, compared to privately funded patents, the *influence* of extramural patents is between 5% smaller to 32% larger at the 75th percentile. The difference in the 90th percentile of *influence* ranges between -5% to +62%. At the higher percentiles, the precision of our measurement increases. The *impact* of extramurally funded patents at the 90th, 95th and 98th percentiles range is between 8% to 42% higher than their privately funded matches. The 95th percentile of *influence* is between 2% to 112% higher and the 98th percentile of *influence* is between 22% to 200% higher.

In contrast, the distribution of intramural patents appears *to the left* of the corporate funded matches. In particular, the 75th, 90th, 95th and 98th percentiles of impact of intramurally funded patents may be close to 0, but also may be up to 29% lower than their corporate funded matches. The distribution of *influence* is also shifted to the left, though the range of uncertainty is large at the 98th percentile. Based on Table 3, we may infer that the estimates in Table 2 were masked by the contrasting differences between intramural and extramural patents and their privately funded matches.

6.3 Analysis of funding agencies: do some federal agencies fund more influential inventions?

The baseline analysis performed in Section 6.1 also lumps together the potential effects of different funding agencies, which we separately measure in this section. Our empirical approach matches patents in the same or similar technological fields together and thus allows us to make reasonable comparisons between different agencies. We will focus on the "Big Five" federal agencies because each agency accounts for more than 5% of all patents in the sample and together they fund about 90% of the sample patents. Given the dominant presence of Department of Defense (DOD) funding in the sample (1753 or 40.66% patents funded), we are able to further unpack the differences among its three major sub-agencies, US Army (ARMY), US Navy (NAVY), US Air

Force (USAF) from other agencies. Other "Big Five" federal agencies include Department of Human Health Services (HHS), Department of Energy (DOE), National Aeronautics and Space Administration (NASA) and National Science Foundation (NSF). An agency dummy, labeled by the abbreviation of the agency, is defined as 1 if agency information is either identified from the federal research statement or the assignee name. We will further disentangle effects of different funding mechanisms by major agencies in Section 6.4. Additionally, we create a dummy, Other Agencies, to represent funding support from other agencies or records where agency information is not identifiable. For the analysis on DOD sub-agencies, we also create a dummy, DOD - Other, to capture the effect of funding from other independent DOD sub-agencies (e.g., DARPA).

Table 4 reports our findings on the relationship between funding agency, patent impact (Panel 4-a) and patent influence (Panel 4-b). We first replace the dummy Federal Funding with six agency dummies and find that only three agencies fund more highly influential patents compared to the control groups. We then further replace the dummy for DOD with four dummies representing DOD sub-agencies.

The distribution of patents backed by DOD funding is between -6% to 40% of the distribution of privately funded matches. A closer look at sub-agencies at DOD reveals that the positive aggregate effect of the agency may stem in part from Army-backed patents. However, the strongest effect is from research agencies outside the Army, Navy or Air Force, such as DARPA.

The funding effects of HHS and NSF showcase the virtue of the influence measure in capturing indirect, long-term patent value. We can rule out strong negative differences in *impact* between HHS and the comparative sample, leaving the possibilities that they are economically close to zero or somewhat positive. The *influence of HHS* patents is between 28% and 385% higher at the 98th percentile. At the top, the HHS funds highly influential, seminal patents. The DoD also moves fields. The *influence* of DoD-other patents is higher than the private sector patents assuredly at the 75th, 90th and 95th percentiles though precision is lost at the 98th percentile. Funding from research agencies outside the three traditional DoD branches, such as DARPA appears particularly important for technological trajectories. Interestingly, while we can say that distribution of *influence* of NSF patents may be up to double that of corporate patents, we cannot rule out that it may also be smaller –only slightly at the 75th, 90th and 95th percentiles, but perhaps up to 84% so at the 98th percentile. This contrasts with a relatively constant and robust shift of the distribution of NSF funded patents across the higher percentiles of *impact*.

To sum up, DOD sub-agencies such as DARPA appear to have funded some inventions high in both direct and indirect impact (at 90% and 95% quantile). HHS-backed patents do not receive more direct citations but outperforms the matches when citations of second and more distant generations are accounted for. Furthermore, patents that receive NSF funding have more direct impact on 90% and 95% quantiles but may not be more influential. Meanwhile, we do not find any evidence that sample patents funded by DOE, NASA and other federal agencies perform differently from their matches in the similar technological spaces.

Note that these findings are also suggestive that the government has had a disproportionate influence in the biological sciences and high-risk enterprises characterized by DARPA funding. To the degree that these efforts would not have been replicated by the private sector, the government is not only influencing the rate of inventive activity, but also the direction.

6.4 Analysis of funding agencies by funding mechanisms: do effects of funding mechanisms vary by agency?

The question that follows naturally from the findings on funding mechanisms in 4.2 and funding agencies in 4.3 is whether the effectiveness of extramural and intramural funding vary across different agencies. In light of the previous findings, we are curious to know (i) whether the null findings on DOD are due to the opposite effects of extramural funding and intramural funding, and (ii) whether the positive effects of HHS is primarily driven by research conducted internally or externally. The NSF does not conduct any intramural research, and the other agencies are too small to distinguish between intra and extra mural patents.

We split each agency dummy into two dummies representing extramural and intramural funding of the focal agency. Take DOD as an example, "DOD: Extramural" is coded as one if the federal research statement of the patent application acknowledges the support from DOD and zero otherwise. "DOD: Intramural" is coded as one if the federal research statement does not report any information related to DOD, and the patent is assigned to DOD. Other variables in the regression model remain the same. Table 5 reports the findings on the effect of DOD and HHS split by funding mechanisms. We find strong evidence that extramural funding of DOD and HHS is effective in sponsoring highly impactful and influential inventions. In contrast, inventions developed in-house by either agency do not have more impact or influence, and if anything, they may be less impactful and influential on different quantiles in the case of DOD. Our results further suggest that highly influential patents (at 98% quantile) sponsored by extramural funding from HHS may not have more direct impact.

In sum, our results suggest that extramural funding is consistently associated with inventions that have higher impact and influence in the case of DOD and HHS. We do not find evidence that intramural funding has the same effect. In contrast, we discover evidence that intramural funding might be less effective in supporting highly influential patents at least in DOD. This is by and large consistent with the aggregate findings in Section 6.2.

6.5 Analysis of funding recipients: do some types of funding recipients produce more influential inventions?

In this section, we ask whether the locus of innovation is associated with differences in *influence*. We proxy for the location of activity with the patent assignees. To this end, we interact the federal funding dummy with the US corporation assignee dummy, the only for-profit assignee category in the sample. The baseline comparison group consists of patents assigned to all the other assignees in the public sector, including universities, hospitals and research institutes. This analysis is restricted to the smaller subsample of 3,023 extramural patents.

We report the findings in Table 6. As a whole, the findings demonstrate that the main difference on impact and influence among all extramurally funded patents are on the mean level. The main funding effect is marginally significant, possibly due to the restricted sample size and limited statistical power. However, we do not have sufficient statistical power in this smaller sample to make strong statements about differences in the distributions of *influence* or *impact* of corporate and public sector extramural patents.

6.6 Does the Federal government fund different classes than the private sector?

We first establish that the Federal government funds different types of subclasses as compared to the private sector. To this end, we run a bi-variate Probit model using characteristics of the 34,578 primary subclasses in which patents were classified between 1998-2000 to predict the presence of government and corporate funded patents in our sample 2001-2004 period. For brevity, this analysis is reported in Table A1 in Appendix III. The regression clearly indicates that the government and private sectors emphasize different technological areas. First, a large predictor of current activity is past activity. Corporations are more active in areas in which they were active in the past, and the same is true for universities. However, the presence of corporate patents in one period is not associated with the presence of university patents in the next, and vice versa. So, there is no reduced form evidence that would indicate either complementarities or crowding out. There is some evidence that the government is more active in riskier subclasses of lower commercial value. In particular, the government is active in subclasses where the lag between application and grant is longer - which arguably indicates higher risk. The measured effect is between 0 and 20% of the baseline, based on the prediction of a subclass that has solely federal patents and no corporate patents. The confidence interval is between -0.005% and 0.1%., whereas the baseline is 0.54%. Lower commercial value is indicated by the fact that corporations are more likely to be active in subclasses in which patents are more likely to be renewed after 12 years - though this is not a predictor of government activity.

Conditional on the presence of government funding in a subclass, we can ask how different types of subclasses are shared between government sponsored and privately funded patents. If federally funded patents were distributed randomly, then we should expect that, on average, 6.53% of patents in any given subclass would be federally funded and 3,667 subclasses would be funded.[22] However, there are only 2,899 subclasses with federally funded inventions between 2001 and 2004, indicating that the government specializes in certain areas. We present the share of patents in government active subclasses across mechanisms of funding in Table 7. Panel 7-a. For example, intramurally funded patents represent 11% of patents in their represented subclasses (or 1.44 times the baseline 6.53%). In subclasses with patents coming from government sponsored extra-mural research, almost 1 in 5 (19%) are federally funded - almost 3 times the baseline. Government funded

[22] The baseline rate is 6.53%, an average calculated from 50 simulations of assigning federally funded patents randomly to all available subclasses at the time. Note that the median in any subclass would be 0, as there are over 50,000 subclasses in the data.

corporate patents represent only 7.6% of patents in their respective subclasses or 1.16 the baseline. In all government-active subclasses, corporations produce 58% of the patents. We now consider how and whether these differences vary by agency sponsor. Not surprisingly, in the first column we see that each agency is only active in a subset of all federally active subclasses. The DoD is active in the broadest range of subclasses (1,373), while NASA is active in a more limited number (243). Across most agencies, federally funded extramural patents, which largely emerge from universities, make up about a fifth of all patents in their subclasses, and about a quarter in HHS, NSF and DOE-sponsored areas. However, both NASA and the DOE tend to make up a smaller share of the areas they are active in. In general, intramural patents do not dominate the subclasses in which they are active.

In order to further understand the nature of the technological areas supported by the federal government, we ask whether the government has funded a greater share of patents in newer or faster growing technological areas. To this end, we grouped the funded subclasses along two dimensions, age and growth. We used the earliest application year in which a subclass can be found as a proxy for age. In Panel 7-b, we see that roughly 65% patents granted between 1976 and 2004 belong to the 1,869 subclasses that can be traced back to subclasses with below median age, that is those from 1976 or earlier.[23] The subclass quantiles are determined by the entire patent database - thus the fact that 65% of government active subclasses date back prior to 1976 indicates that the government is particularly active in older areas. Only 43 government active subclasses, or 1.5% of all government active subclasses are from 1993 or later, though 5% of all subclasses are of this vintage. However, in these 43 subclasses, extra-mural patents make up 42% of all patents, where as corporate patents drop to 27%. The government does, at times, seed new areas. The pattern is similar as we move back the age quantiles. The government tends not to be in newer areas, but when it is, it has a disproportionate impact. This appears to happen through government sponsored extramural research, which largely occurs at universities.

Finally, in Panel 7-c we examine the share of government sponsored patents conditional on age of subclass and whether the subclass is growing. Growing subclasses are those with positive average growth rates and the others are classified as non-growing.[24] Since our analysis examines patents applied or granted between 2001-2004, we lag the characteristics of the subclasses vis-a-vis the patents we analyze. As noted in Panel 7-b, the government is more active in older subclasses. However, conditional on activity in a new subclass - in this case a subclass that is less than 20 years old, the government has a relatively large share of activity in non-growing classes, and a smaller

---

[23] We have pre-1976 classes because the year is on application dates. While we do not have data on patents granted before 1976, many applications for patents granted in1976 or later were filed before 1976.

[24] A challenge in calculating year-to-year growth on the fine-grained level of subclasses is that many subclasses have zero patent granted in one year or more. To simplify the calculation, we assume a 100% year-to-year growth rate if the patent output is zero in the previous year and positive in the current year, and -100% vice versa. We also assume a 0% year-to-year growth rate if patent output is zero in both previous and current year. The year-to-year growth rate is then averaged over the 3-year time window. For example, if a subclass has zero patent in 1998, one patent in 1999, and zero patent in 2000. The 3-year average growth rate is [100% + (-100%)]/2 = 0%.

share in growing subclasses - this is true in older subclasses as well, though the government's presence in the younger, non-growing subclasses is somewhat larger. Corporate shares in non-growing subclasses in which the government is active is smaller. For example, in post-1980 subclasses, corporations make up, on average, 46% of patents and government-funded university and other non-profit patents make up 14% of patents. Government sponsored corporate patents make up a similar share (12%). In growth subclasses, we see a different pattern. Government-funded university and other non-profit patents make up 11% and government sponsored corporate patents drop to 7%. At the same time, privately funded corporate patents increase to 64%. We see a similar presence in non-growing areas in older, pre-1980 subclasses. Clearly, the government is toiling in different sectors than the private sector and tends to decrease activity in a relative sense in areas that are seeing an increase in patenting activities.

To test more rigorously whether the government is seeding new growth areas, we take a cross section of all subclasses from the 2001-2004 sampling window and track their growth over the next three years. Specifically, we calculate the average growth rate of the number of patents whose application year is 2005 or later and granting year falls in 2005-2007 in those subclasses. We follow similar approach as described in Footnote 17 to impute value of growth rate in subclasses that are inactive in one or more years.

Our dependent variable is a dummy that equals one if a subclass experiences growth in 2005-2007. We include several explanatory variables in the model. "Subclass size" is measured as the number of patents granted in the 2001-2004 sampling period. "Recent Subclass" is a dummy that equals one if the application year of the oldest patent in the subclass is 1993 or later. As noted in Section 6.6, only 5% of all patents granted in 1976-2006 are in those subclasses. We then use the percentage of patents assigned to US corporations and universities and other non-profits to account for the effect of alternative funding sources. To capture the life cycle stage of the subclass, we control for the expiration rate and 4th year renewal rate in the subclass with the expectation that high expiration rate and low renewal rate would indicate the declining phrase of the area. Finally, we account for the growth state of the subclass during 2002-2004 with a dummy for subclasses that experience growth in the previous period as we expect past growth to be a strong predictor of future growth.

Model 1 and Model 2 in Table 8 reveal that funding mechanisms matter to whether federal support may activate growth in an area or not. While we do not find any evidence that areas supported through intramural funding have higher chance of growth, extramural funding is associated with subsequent growth of the subclass. The marginal effect on the mean reveals that extramural funding may increase the chance of future growth by between .3% to 3.6%, while the actual probability of a subclass being in the growth state during 2005-2007 is 16.80%.

Does government funding activate dormant areas or sustain and accelerate growing areas? Recall that federally funded inventions seem to gear towards non-growing areas in our funded subclass analysis, but this presence may spark future growth. To tease out the two explanations, we split the sample by the previous growth state of the subclass in Model 3 and Model 4. On one hand, if the R&D spending of federal government ignites growth in once inactive or declining areas, we expect the funding effect to show up in Model 3. On the other hand, if the federal agencies sustain and accelerate emergent areas with high growth potential, we would capture the effect in Model 4. Results suggest that the second explanation prevails. Above and beyond the baseline difference in chance of growth between non-growing and growing areas, federal funding plays a more recognizable role in helping growing areas to sustain their trend. In supplemental analysis, we also find that extramural funding also help to accelerate growth in growing areas. These results are robust to inclusion of all controls that appear in Table A1 as well as a logit specification.

7. Limitations

We should be careful in drawing broad conclusions from our research. For example, we are constrained by the limited timeframe of our analysis. We examine only patents from 2001 through 2004, and this in turn limits the time window with which we can measure influence. Although this still allows us to track patent trees across several generations, patterns in some slower moving fields may be obscured. It should also be noted that some of our tests in the quantile regressions rely on a small population of home run inventions. While the quantile regression methodology is not sensitive to the precise magnitudes of outliers, perhaps small shifts in the influence of a few inventions may affect our results in many of the more fine-grained sub-agency analyses. Replication using other samples of government funded patents will be necessary to draw stronger conclusions.

Although we are able to associate greater influence with university-assigned patents funded by particular government agencies, we cannot identify the mechanism by which these differing citation patterns occur. There are well-known institutional differences in the propensity to patent across these organizational types as well as the strategic nature of technological choices post patenting. For example, David and Hall (2000) point out that positive spillovers (or more negative crowding out) of private sector R&D efforts by publicly sponsored R&D may operate across many mechanisms. Federally funded research may generate spillovers through selection and treatment effects. The marginal productivity of privately funded research may increase because it relies on a larger knowledge base. Private enterprise may be more likely to choose to be active in technological spaces with government funding to take advantage of a larger technological foundation. We leave it to future researchers to attempt to further disentangle these mechanisms.

In addition, due to data constraints, we cannot offer further insight on the implications of project characteristics. While the federal research statements in some patent applications further report information on the specific grants or contracts sponsored by the agency, such information is noisy and proves to be difficult to be matched to the data on federal grants and contracts reliably. Moreover, even if the information on the amount of project funding is available for all federally funded patents, it is challenging to draw implications on how much money is allocated to the specific invention as compared to other inventions and scientific papers from the same project. As a result, with our current data we cannot evaluate the efficiency of federal and non-federal R&D dollars in spurring future technological development. Future researchers who can overcome these data challenges may be able to address these important questions.

By definition the influence of a patent application yet to be granted is not possible to measure. For this reason, our analyses are conditioned on the success of a given patent application. Nevertheless, by focusing on granted patents, we may overlook the pre-selection process of USPTO. The working assumption for our main analyses is that patent applications are examined based on merit only, and should not be subject to different treatment based on the source of funding support. Thoughtful readers may argue that patent examiners may interpret the information of federal government sponsorship as a certification or signal of quality and act differently towards those federally funded applications. Future research may explore the possibility of learning about the ex ante assumption held by the patent examiners and estimating how much of the difference in granted patents can be attributed to the application process. Nevertheless, such a bias would likely work against our findings, as it would lead to the lowering of at least the average quality of federally funded inventions.

8. Discussion & Conclusions

Our results indicate that federally funded inventions are more influential in the sense that they are associated with more *influence,* i.e., larger and more interconnected citation trees. Controlling for technological class and patenting year, the most productive technological trajectories are likely to build on government funded inventions. However, the median government funded and privately funded patents are no different in terms of long term citations. The government has a different technological emphasis than the private sector and takes the lead in the areas they choose. These technological areas have attributes likely associated with diminished commercial value - they are riskier, not growing in terms of raw patents, and they tend not to have greater renewals.

In general, we are not concerned that the mean and median federally funded patent is as ordinary as its commercial counterpart. Technological advance is a small tail phenomenon in which influential inventions are rare. However, it is disconcerting that seminality appears confined to a few agencies and is mostly present with government funding of academic research. Further consideration of when patent influence is a reasonable way to measure the long-term effects of federally funded research conducted by for-profit firms as well as federal labs is needed to draw sharp policy recommendations. Many government agencies fulfill specific missions and so government agencies may support research that are necessary to fulfill these missions but is not seminal. That is, not all research and development dollars are designed to fulfill Vannevar Bush's policy ideal – nor should they be.

The results are intriguing because they do not map perfectly with the emphasized type of research (applied vs. basic) of the agencies. On the one hand, the National Science Foundation is the sole agency whose mission is to support basic research. However, while we find that the agency sponsors patents of greater *impact* than the private sector, our findings of longer term *influence* are less conclusive – though suggestive of potentially very large effects. The Department of Energy and National Aeronautics and Space Administration whose emphasis is more applied, are neither more nor less likely to produce path-breaking technologies than the private sector. However, it is entirely plausible that these agencies' activities are correctly directed at fulfilling their missions. One of NASA's primary objectives is facilitating space flight - which until quite recently was of limited commercial interest.

Our finding that intramurally funded patents tend to be less influential is also intriguing. It does not follow, necessarily, that intramural programs are wasteful. Some intramural programs focus on translational research which works to translate seminal results to the private sector. Some programs may promote mission-oriented goals with limited widespread commercial application. Some intramural-extramural collaborations, facilitate the translation of basic research results to practical solutions embodied in patents. Future research will be necessary to see if this is indeed the case.

Of course, due to their sheer size, the bulk of influential patents come from research funded by the Department of Defense and the National Institutes of Health. It is these agencies that drive our main results. In particular, it appears that DoD programs such as DARPA, which are not classified as Army, Navy or Air Force generate seminal patents.[25] Similarly, NIH funded patents produces breakthrough inventions. A more in-depth program level analysis will be necessary to understand further the sources of these differences.

The results are consistent with Vannevar Bush's assertion: *"Generally speaking, the scientific agencies of Government are not so concerned with immediate practical objectives as are the laboratories of industry nor, on the other hand, are they as free to explore any natural phenomena without regard to possible economic applications as are the educational and private research institutions."* Research results are hard to predict, and the long-term implications of results or even entire fields of research are exceptionally difficult to foresee. If science policy is fulfilling its role, we should expect to see this particularly in the long term. Our results suggest that for all its imperfections, US science policy remains successful in supporting the long-term productivity of inventive activity. Our results are also consistent with the notion that the government nurses particular areas, sometimes over long periods of time. Our results are in line with the notion that federally sponsored research leads to an increased rate of inventive activity and also the support of areas of research that would otherwise be orphaned or neglected by the private sector. In this sense, federally funded research affects both the rate and direction of inventive activity.

[25] We must also consider that the influence of the DOD might be underestimated if the most advanced technologies under development are classified.

References

Abadie, A., & Imbens, G. W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica*, 76(6), 1537-1557.

Aghion, P., & Tirole, J. (1994). The management of innovation. *The Quarterly Journal of Economics*, 109(4),1185-1209.

Agrawal, A., & Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. *Management Science*, 48(1), 44-60.

Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics,* 88(4), 774-779.

Alcacer, J., Gittelman, M., & Sampat, B. (2009). Applicant and examiner citations in US patents: An overview and analysis. *Research Policy*, 38(2), 415-427.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The rate and direction of inventive activity: Economic and social factors*, 609-626. Princeton University Press.

Caliendo, M. and Kopeinig, S. (2008), Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22, 31–72.

Carpenter, J., & Bithell, J. (2000). Bootstrap confidence intervals: when, which, what? A practical guide for medical statisticians. *Statistics in Medicine*, 19(9), 1141-1164.

Cohen, L., & Noll, R. (1991). *The Technology Pork Barrel.* Washington, D.C.: The Brookings Institution.

Corredoira, R. A., & Banerjee, P. M. (2015). Measuring patent's influence on technological evolution: A study of knowledge spanning and subsequent inventive activity. *Research Policy*, 44(2), 508-521.

David, P. A., & Hall, B. H. (2000). Heart of darkness: modeling public–private funding interactions inside the R&D black box. *Research Policy*, 29(9), 1165-1183.

Fox, John. (2015) *Applied regression analysis and generalized linear models*. Sage Publications.

Goldfarb, B., (2008). The effect of government contracting on academic research: Does the source of funding affect scientific output?, *Research Policy*, 37(1), 41-58.

Goldfarb, B. (2008). The effect of government contracting on academic research: Does the source of funding affect scientific output?. *Research Policy*, 37(1), 41-58.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools*. NBER working paper 8498.

Hall, B., Mairess, J and Mohnen, P. (2009), Measuring the Returns to R&D. NBER working paper 15622.

Hegde, D., & Mowery, D. C. (2008). Politics and funding in the US public biomedical R&D system. *Science*, *322*(5909), 1797-1798.

Henderson, R., Jaffe, A. B., & Trajtenberg, M. (1998). Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. *Review of Economics and statistics*, 80(1), 119-127.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, 15(3), 199-236.

Howell, Sabrina. (2015). "Financing constraints as barriers to innovation: evidence from R&D grants to energy startups" Working paper, Harvard University.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108(3), 577-598.

Li, D., Azoulay, P., & Sampat, B. N. (2017). The applied value of public investments in biomedical research. *Science*, Forthcoming.

Lichtenberg, F. R. (1987). The effect of government funding on private industrial research and development: a reassessment. *The Journal of Industrial Economics*, 36(1),97-104.

Mazzucato, M. (2015). *The entrepreneurial state: Debunking public vs. private sector myths*. Public Affairs.

Meyer, M. (2000). Does science push technology? Patents citing scientific literature. *Research Policy*, *29*(3), 409-434.

Mowery, D. C., & Nelson, R. R. (Eds.) (1999). *Sources of Industrial Leadership, Studies of Seven Industries*. Cambridge University Press.

Mowery, D. C., Sampat, B. N., & Ziedonis, A. A. (2002). Learning to patent: Institutional experience, learning, and the characteristics of US university patents after the Bayh-Dole Act, 1981-1992. *Management Science*, 48(1), 73-89.

Mowery, D. C., & Ziedonis, A. A. (2002). Academic patent quality and quantity before and after the Bayh-Dole act in the United States. *Research Policy*, 31(3), 399-418.

Nagaoka, S., Motohashi, K., & Goto, A. (2010). Patent statistics as an innovation indicator. *Handbook of the Economics of Innovation*, 2, 1083-1127.

Narin, F., Hamilton, K. S., & Olivastro, D. (1997). The increasing linkage between US technology and public science. *Research Policy*, 26(3), 317-330.

National Institute of Allergy and Infectious Diseases. (2015). Extramural and Intramural Research Questions and Answers. http://www.niaid.nih.gov/researchfunding/qa/pages/extraintra.aspx. Accessed on Aug. 30, 2015.

National Science Foundation. (1995). Federal Funds Glossary. http://www.nsf.gov/statistics/fedfunds/glossary/def.htm. Accessed on Aug. 30, 2015.

Nelson, R. R. (1959). The simple economics of basic scientific research. *Journal of political economy*, *67*(3), 297-306.

Pavitt, K. (1991). What makes basic research economically useful? *Research policy*, 20(2), 109-119.

Roach, M., & Cohen, W. M. (2013). Lens or prism? Patent citations as a measure of knowledge flows from public research. *Management Science*, *59*(2), 504-525.

Sampat, B. N. (2006). Patenting and US academic research in the 20th century: The world before and after Bayh-Dole. *Research Policy*, 35(6), 772-789.

Sampat, B. (2010). When do applicants search for prior art? *Journal of Law and Economics* 53(2), 399-416.

Sargent, John F. (2015). Federal Research and Development Funding: FY2015. Congressional Research Service Report, R43580, 7-5700.

Thompson, P., & Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers:

A reassessment. *American Economic Review*, 95(1), 450-460.

United States General Accounting Office. (1999). Reporting Requirements for Federally Sponsored Inventions Need Revision, GAO/RCED-99-242, 1-35.

Wallsten, S. J. (2000). The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *The RAND Journal of Economics*, 82-100.

Wang, D., Song, C., & Barabasi, A. L. (2013). Quantifying long-term scientific impact. *Science*, 342(6154), 127-132.

Table 1. Summary statistics of the sample patents, matching patents and the population.[1]

Variable	Sample (Obs. = 4311)				
	Mean	Std. Dev.	Median	95% Percentile	
ln(Impact)	1.075	1.181	0.693	3.296	
ln(Influence)	1.948	2.305	1.386	6.306	
No. of Claims	20.733	17.681	17.000	51.000	
Corrected Originality	0.692	0.499	0.745	1.500	
	Match (Obs. = 6857)				
	Mean	Std. Dev.	Median	95% Percentile	p-value of t-test vs. Sample
ln(Impact)	1.069	1.163	0.693	3.219	0.056
ln(Influence)	1.974	2.310	1.386	6.518	**0.000**
No. of Claims	18.830	16.482	15.000	48.000	**0.000**
Corrected Originality	0.633	0.522	0.667	1.500	**0.000**
	Population excluding Sample and Match (Obs. = 263525)				
	Mean	Std. Dev.	Median	95% Percentile	p-value of t-test vs. Sample
ln(Impact)	1.111	1.161	1.099	3.219	0.770
ln(Influence)	2.109	2.402	1.609	6.658	0.560
No. of Claims	17.255	14.213	15.000	41.000	**0.000**
Corrected Originality	0.605	0.495	0.656	1.500	**0.000**
	All Bootstrapping Samples (Obs. = 17244000)				
	Mean	Std. Dev.	Median	95% Percentile	
ln(Impact)	1.055	1.167	0.693	3.219	
ln(Influence)	1.918	2.286	1.386	6.301	
No. of Claims	19.866	17.156	16.000	50.000	
Corrected Originality	0.671	0.511	0.720	1.500	

Table 2. Regression analysis of baseline funding effects on patent impact and influence[1 2 3 4]

Panel 2-a	DV: ln(Impact)				
Model	OLS (Mean)	75%	90%	95%	98%
Federal Funding	0.027	0.019	0.070	**0.118**	0.107
	(-0.009, 0.062)	(-0.045, 0.083)	(-0.026, 0.165)	**(0.002, 0.233)**	(-0.040, 0.254)
No. of Claims	**0.008**	**0.014**	**0.016**	**0.015**	**0.015**
	(0.006, 0.01)	**(0.010, 0.018)**	**(0.012, 0.02)**	**(0.011, 0.020)**	**(0.010, 0.019)**
Corrected Originality	0.012	0.030	0.075	0.055	0.032
	(-0.028, 0.053)	(-0.045, 0.105)	(-0.041, 0.191)	(-0.079, 0.189)	(-0.143, 0.206)
Panel 2-b	DV: ln(Influence)				
Model	OLS (Mean)	75%	90%	95%	98%
Federal Funding	0.035	0.011	0.026	0.164	**0.412**
	(-0.036, 0.105)	(-0.072, 0.093)	(-0.181, 0.234)	(-0.112, 0.439)	**(0.002, 0.822)**
No. of Claims	**0.014**	**0.023**	**0.031**	**0.029**	**0.024**
	(0.011, 0.018)	**(0.015, 0.03)**	**(0.023, 0.039)**	**(0.02, 0.038)**	**(0.007, 0.04)**
Corrected Originality	0.021	0.035	0.054	0.111	0.244
	(-0.060, 0.102)	(-0.058, 0.128)	(-0.182, 0.289)	(-0.202, 0.424)	(-0.181, 0.670)

[1] Sample: 4311 federally funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class and granting year.

Table 3. Quantile regression of funding mechanism on patent impact and influence[1 2 3 4]

Panel 3-a	DV: ln(Impact)			
Model	75%	90%	95%	98%
Federal Funding: Extramural	0.103	**0.183**	**0.237**	**0.202**
	(-0.001, 0.208)	**(0.074, 0.293)**	**(0.103, 0.370)**	**(0.051, 0.353)**
Federal Funding: Intramural	**-0.109**	**-0.187**	**-0.173**	-0.184
	(-0.216, -0.002)	**(-0.320, -0.053)**	**(-0.339, -0.007)**	(-0.391, 0.023)
No. of Claims	**0.014**	**0.015**	**0.015**	**0.014**
	(0.010, 0.018)	**(0.011, 0.019)**	**(0.011, 0.019)**	**(0.009, 0.018)**
Corrected Originality	0.031	0.061	0.052	0.039
	(-0.05, 0.113)	(-0.055, 0.177)	(-0.076, 0.179)	(-0.139, 0.217)
Panel 3-b	DV: ln(Influence)			
Model	75%	90%	95%	98%
Federal Funding: Extramural	0.115	0.218	**0.385**	**0.649**
	(-0.052, 0.282)	(-0.046, 0.481)	**(0.021, 0.750)**	**(0.200, 1.098)**
Federal Funding: Intramural	**-0.152**	**-0.385**	-0.300	-0.362
	(-0.302, -0.002)	**(-0.692, -0.078)**	(-0.698, 0.098)	(-1.000, 0.275)
No. of Claims	**0.023**	**0.031**	**0.028**	**0.023**
	(0.015, 0.030)	**(0.023, 0.039)**	**(0.019, 0.038)**	**(0.007, 0.039)**
Corrected Originality	0.034	0.034	0.135	0.258
	(-0.076, 0.144)	(-0.223, 0.292)	(-0.172, 0.443)	(-0.181, 0.698)

[1] Sample: 4311 federally funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class and granting year.

Table 4. Quantile regression of funding mechanism on patent impact and influence[1 2 3 4]

Panel 4-a	DV: ln(Impact)							
Model	75%		90%		95%		98%	
DOD	0.054		0.091		0.122		0.153	
	(-0.062, 0.169)		(-0.043, 0.226)		(-0.027, 0.27)		(-0.035, 0.341)	
Army		0.137		0.224		0.246		0.251
		(-0.078, 0.352)		(-0.052, 0.501)		(-0.038, 0.529)		(-0.124, 0.627)
Navy		-0.071		-0.047		0.022		0.043
		(-0.207, 0.065)		(-0.203, 0.109)		(-0.170, 0.213)		(-0.197, 0.282)
USAF		0.183		0.152		0.100		0.074
		(-0.036, 0.402)		(-0.127, 0.431)		(-0.175, 0.376)		(-0.449, 0.598)
DOD - Other		**0.691**		**0.500**		**0.518**		0.455
		(0.096, 1.287)		**(0.142, 0.859)**		**(0.115, 0.922)**		(-0.002, 0.911)
HHS	0.047	0.046	0.125	0.140	0.205	0.193	0.133	0.124
	(-0.083, 0.178)	(-0.081, 0.172)	(-0.089, 0.339)	(-0.072, 0.352)	(-0.044, 0.453)	(-0.052, 0.438)	(-0.107, 0.373)	(-0.12, 0.367)
NSF	0.317	0.310	**0.434**	**0.414**	**0.455**	**0.453**	0.413	0.407
	(-0.010, 0.643)	(-0.003, 0.624)	**(0.065, 0.802)**	**(0.033, 0.794)**	**(0.058, 0.852)**	**(0.070, 0.835)**	(-0.028, 0.854)	(-0.066, 0.879)
DOE	0.068	0.073	0.110	0.117	0.118	0.120	0.049	0.047
	(-0.102, 0.238)	(-0.097, 0.244)	(-0.085, 0.305)	(-0.070, 0.304)	(-0.075, 0.311)	(-0.073, 0.313)	(-0.194, 0.292)	(-0.200, 0.295)
NASA	0.044	0.031	0.062	0.053	0.171	0.178	0.374	0.385
	(-0.233, 0.322)	(-0.248, 0.311)	(-0.217, 0.341)	(-0.214, 0.320)	(-0.314, 0.657)	(-0.324, 0.680)	(-0.068, 0.817)	(-0.056, 0.825)
Other Agencies	-0.040	-0.039	-0.028	-0.031	0.134	0.134	0.102	0.108
	(-0.259, 0.179)	(-0.258, 0.181)	(-0.260, 0.204)	(-0.252, 0.189)	(-0.184, 0.453)	(-0.191, 0.459)	(-0.143, 0.347)	(-0.145, 0.361)
No. of Claims	**0.014**	**0.014**	**0.016**	**0.015**	**0.016**	**0.015**	**0.014**	**0.014**
	(0.010, 0.018)	**(0.010, 0.018)**	**(0.012, 0.020)**	**(0.011, 0.020)**	**(0.011, 0.020)**	**(0.011, 0.020)**	**(0.009, 0.019)**	**(0.009, 0.019)**
Corrected Originality	0.029	0.024	0.074	0.061	0.040	0.036	0.017	0.006
	(-0.049, 0.106)	(-0.052, 0.099)	(-0.042, 0.189)	(-0.049, 0.17)	(-0.085, 0.165)	(-0.086, 0.159)	(-0.162, 0.197)	(-0.185, 0.198)

[1] Sample: 4311 federally funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class and granting year.

Panel 4-b	DV: ln(Influence)							
Model	75%		90%		95%		98%	
DOD	0.178		0.056		0.184		0.315	
	(-0.072, 0.427)		(-0.223, 0.334)		(-0.170, 0.537)		(-0.179, 0.810)	
Army		0.310		0.002		-0.106		-0.063
		(-0.124, 0.744)		(-0.463, 0.467)		(-0.794, 0.581)		(-1.146, 1.019)
Navy		-0.060		-0.113		0.069		0.134
		(-0.349, 0.229)		(-0.485, 0.260)		(-0.385, 0.523)		(-0.524, 0.793)
USAF		0.330		0.458		0.517		1.315
		(-0.120, 0.78)		(-0.317, 1.233)		(-0.339, 1.372)		(-1.048, 3.677)
DOD - Other		**1.283**		**1.157**		**1.433**		1.083
		(0.334, 2.232)		**(0.054, 2.260)**		**(0.150, 2.717)**		(-1.440, 3.606)
HHS	0.009	0.015	0.156	0.165	0.565	0.617	**0.874**	**0.913**
	(-0.105, 0.124)	(-0.098, 0.128)	(-0.298, 0.610)	(-0.289, 0.619)	(-0.214, 1.344)	(-0.136, 1.371)	**(0.254, 1.495)**	**(0.248, 1.579)**
NSF	0.567	0.544	0.896	0.859	0.821	0.829	0.557	0.645
	(-0.125, 1.259)	(-0.131, 1.22)	(-0.038, 1.829)	(-0.026, 1.744)	(-0.277, 1.919)	(-0.363, 2.021)	(-0.611, 1.725)	(-0.469, 1.759)
DOE	-0.016	-0.009	-0.043	-0.031	0.142	0.157	0.251	0.297
	(-0.268, 0.236)	(-0.261, 0.242)	(-0.436, 0.35)	(-0.428, 0.365)	(-0.459, 0.743)	(-0.446, 0.759)	(-0.552, 1.053)	(-0.538, 1.132)
NASA	-0.013	0.001	0.256	0.246	0.631	0.590	0.394	0.440
	(-0.545, 0.519)	(-0.531, 0.534)	(-0.636, 1.147)	(-0.639, 1.132)	(-0.366, 1.628)	(-0.477, 1.657)	(-0.369, 1.157)	(-0.3, 1.181)
Other Agencies	-0.086	-0.081	0.102	0.109	0.053	0.075	-0.017	0.057
	(-0.329, 0.156)	(-0.327, 0.165)	(-0.528, 0.731)	(-0.510, 0.728)	(-0.466, 0.573)	(-0.447, 0.597)	(-0.973, 0.939)	(-0.899, 1.013)
No. of Claims	**0.022**	**0.022**	**0.032**	**0.032**	**0.028**	**0.028**	**0.025**	**0.026**
	(0.015, 0.030)	**(0.014, 0.030)**	**(0.024, 0.040)**	**(0.024, 0.040)**	**(0.019, 0.038)**	**(0.019, 0.038)**	**(0.009, 0.041)**	**(0.009, 0.042)**
Corrected Originality	0.035	0.034	0.047	0.042	0.080	0.083	0.207	0.150
	(-0.060, 0.129)	(-0.058, 0.127)	(-0.190, 0.283)	(-0.203, 0.287)	(-0.242, 0.402)	(-0.242, 0.408)	(-0.245, 0.658)	(-0.316, 0.616)

[1] Sample: 4311 federally funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class and granting year.

Table 5. Quantile regression of funding agency on patent impact and influence by funding mechanism[1 2 3 4]

Panel 5-a	DV: ln(Impact)			
	75%	90%	95%	98%
DOD: Extramural	**0.471**	**0.517**	**0.523**	**0.414**
	(0.266, 0.677)	**(0.326, 0.708)**	**(0.304, 0.741)**	**(0.158, 0.67)**
DOD: Intramural	**-0.147**	**-0.257**	**-0.284**	**-0.478**
	(-0.27, -0.024)	**(-0.411, -0.103)**	**(-0.472, -0.096)**	**(-0.713, -0.243)**
HHS: Extramural	0.084	**0.201**	**0.221**	0.097
	(-0.061, 0.229)	**(0.010, 0.393)**	**(0.016, 0.425)**	(-0.168, 0.362)
HHS: Intramural	0.019	0.344	0.491	0.325
	(-0.330, 0.368)	(-0.487, 1.175)	(-0.039, 1.022)	(-0.489, 1.139)
No. of Claims	**0.015**	**0.016**	**0.016**	**0.014**
	(0.010, 0.02)	**(0.010, 0.022)**	**(0.012, 0.021)**	**(0.009, 0.019)**
Corrected Originality	0.032	0.076	0.076	0.075
	(-0.051, 0.115)	(-0.064, 0.216)	(-0.079, 0.23)	(-0.110, 0.259)
Panel 5-b	DV: ln(Influence)			
	75%	90%	95%	98%
DOD: Extramural	**0.844**	**0.962**	**0.996**	0.637
	(0.523, 1.164)	**(0.475, 1.448)**	**(0.377, 1.616)**	(-0.047, 1.321)
DOD: Intramural	**-0.262**	**-0.418**	**-0.501**	-0.539
	(-0.502, -0.022)	**(-0.736, -0.101)**	**(-0.976, -0.027)**	(-1.406, 0.329)
HHS: Extramural	0.051	0.287	0.577	**0.957**
	(-0.093, 0.195)	(-0.133, 0.706)	(-0.214, 1.367)	**(0.266, 1.647)**
HHS: Intramural	4.451E-4	0.599	0.849	-0.062
	(-0.340, 0.341)	(-1.188, 2.387)	(-0.439, 2.136)	(-1.333, 1.209)
No. of Claims	**0.023**	**0.036**	**0.033**	**0.038**
	(0.014, 0.032)	**(0.026, 0.046)**	**(0.019, 0.048)**	**(0.01, 0.067)**
Corrected Originality	0.026	0.180	0.353	0.455
	(-0.075, 0.128)	(-0.113, 0.472)	(-0.031, 0.736)	(-0.113, 1.022)

[1] Sample: 2751 DOD and HHS funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class and granting year.

Table 6. Regression analysis of funding recipient type on patent impact and influence[1 2 3 4 5]

Panel 6-a	DV: ln(Impact)				
Model	OLS (Mean)	75%	90%	95%	98%
Federal Funding	0.109	0.145	0.254	**0.316**	0.297
	(-0.002, 0.219)	(-0.074, 0.364)	(-0.010, 0.517)	**(0.001, 0.631)**	(-0.044, 0.637)
Federal Funding × US Corp. Assignee	**-0.161**	-0.206	-0.311	-0.285	-0.262
	(-0.299, -0.023)	(-0.521, 0.109)	(-0.640, 0.017)	(-0.672, 0.103)	(-0.705, 0.182)
No. of Claims	**0.006**	**0.010**	**0.011**	**0.012**	**0.011**
	(0.004, 0.008)	**(0.006, 0.014)**	**(0.007, 0.016)**	**(0.007, 0.016)**	**(0.005, 0.017)**
Corrected Originality	0.026	0.035	0.039	0.045	0.038
	(-0.025, 0.076)	(-0.056, 0.126)	(-0.098, 0.175)	(-0.108, 0.199)	(-0.131, 0.207)
Panel 6-b	DV: ln(Influence)				
Model	OLS (Mean)	75%	90%	95%	98%
Federal Funding	0.178	0.171	0.413	**0.625**	0.926
	(-0.026, 0.382)	(-0.144, 0.485)	(-0.151, 0.977)	**(0.038, 1.211)**	(-0.067, 1.919)
Federal Funding × US Corp. Assignee	**-0.266**	-0.340	-0.625	-0.562	-0.581
	(-0.526, -0.005)	(-0.791, 0.111)	(-1.312, 0.063)	(-1.448, 0.325)	(-1.871, 0.709)
No. of Claims	**0.011**	**0.017**	**0.024**	**0.023**	0.023
	(0.007, 0.015)	**(0.008, 0.025)**	**(0.016, 0.033)**	**(0.011, 0.034)**	(-0.001, 0.047)
Corrected Originality	0.036	0.018	-0.007	0.051	0.237
	(-0.067, 0.14)	(-0.096, 0.132)	(-0.332, 0.319)	(-0.302, 0.404)	(-0.346, 0.821)

[1] Sample: 3023 extramurally funded patents and their matches, based on bootstrapping with 2000 iterations.
[2] Normal theory bootstrap confidence intervals reported in parentheses.
[3] Significance at 95% level marked in bold.
[4] All regressions include fixed effects for patent class, granting year and assignee type.
[5] The omitted category includes patents assigned to non-profit entities including universities, hospitals and institutes.

Table 7. Concentration of alternative funding sources in subclasses.

Panel 7-a: By Agency							
Agency	# Subclasses	% Fed Intra	% Fed Extra	% Corp Funded	% Corp Not Funded	% NPO Funded	% NPO Not Funded
Total	2899	0.11	0.19	0.08	0.58	0.09	0.05
DOD	1373	0.16	0.14	0.06	0.58	0.04	0.04
HHS	659	0.03	0.24	0.05	0.58	0.18	0.10
NSF	253	0.01	0.26	0.05	0.61	0.18	0.07
DOE	664	0.04	0.25	0.11	0.61	0.12	0.06
NASA	243	0.12	0.14	0.05	0.63	0.05	0.05
Panel 7-b: Old vs. Young Subclasses							
Age Quantile	# Subclasses	% Fed Intra	% Fed Extra	% Corp Funded	% Corp Not Funded	% NPO Funded	% NPO Not Funded
Below Median (-1976)	1869	0.11	0.17	0.06	0.60	0.08	0.05
Median - 75% Quantile (1977-1981)	542	0.13	0.22	0.09	0.53	0.11	0.06
75% -90% Quantile (1982-1989)	331	0.09	0.25	0.11	0.54	0.12	0.08
90% - 95% Quantile (1990-1993)	114	0.11	0.20	0.08	0.62	0.10	0.04
Above 95% Quantile (1993-2004)	43	0.21	0.42	0.14	0.27	0.19	0.04
Total	2899	0.11	0.19	0.08	0.58	0.09	0.05
Panel 7-c: Growing vs. Non Growing Subclasses							
	Post-1980 Subclasses						
Growth	# Subclasses	Corp.: Funded	Corp.: Not funded	NPO: Funded	NPO: Not Funded	Fed Intra	Other Gov.
No	310	0.12	0.46	0.14	0.07	0.14	0.03
Yes	247	0.07	0.64	0.11	0.06	0.06	0.01
Total	557	0.10	0.54	0.12	0.07	0.11	0.02
	Pre-1980 Subclasses						
Growth	# Subclasses	Corp.: Funded	Corp.: Not funded	NPO: Funded	NPO: Not Funded	Fed Intra	Other Gov.
No	1129	0.09	0.51	0.11	0.05	0.16	0.03
Yes	1213	0.05	0.66	0.07	0.05	0.07	0.02
Total	2342	0.07	0.58	0.09	0.05	0.11	0.02

Table 8. Probit models predicting future growth state in subclass and marginal effects.[1]

	Model 1	Model 2	Model 3	Model 4
	Coefficient			
	Baseline	By Mechanism	Non-growing areas in 2002-2004	Growing areas in 2002-2004
Prob.(Growth > 0 during 2005-2007)	16.80%	16.80%	11.30%	30.11%
Funded by Federal Government	0.045			
	(-0.013, 0.104)			
Funded through Extramural Funding		**0.081**	0.049	**0.124**
		(0.012, 0.149)	(-0.042, 0.140)	**(0.017, 0.232)**
Funded through Intramural Funding		-0.038	-0.007	-0.085
		(-0.134, 0.058)	(-0.131, 0.116)	(-0.235, 0.066)
Subclass Class Size	9.2E-5	4.2E-5	-2.1E-4	-2.2E-4
	(-0.001, 0.001)	(-0.001, 0.001)	(-0.002, 0.001)	(-0.001, 0.002)
Recent Subclass	-0.052	-0.052	**-0.077**	-0.017
	(-0.110, 0.006)	(-0.110, 0.006)	**(-0.152, -0.001)**	(-0.110, 0.075)
Growth > 0 during 2002-2004	**0.689**	**0.689**		
	(0.663, 0.714)	**(0.663, 0.714)**		
% Patents assigned to US Corp.	**0.063**	**0.061**	0.037	**0.098**
	(0.030, 0.096)	**(0.028, 0.094)**	(-0.006, 0.080)	**(0.045, 0.151)**
% Patents assigned to US Non-Profit Org.	**0.256**	**0.240**	0.145	**0.366**
	(0.139, 0.372)	**(0.122, 0.358)**	(-0.014, 0.305)	**(0.181, 0.551)**
% Expired	0.015	0.016	0.023	0.002
	(-0.020, 0.050)	(-0.019, 0.051)	(-0.022, 0.068)	(-0.054, 0.058)
	Marginal effect			
	Model 1	Model 2	Model 3	Model 4
Funded by Federal Government	0.011			
	(-0.003, 0.025)			
Funded through Extramural Funding		**0.019**	0.009	**0.044**
		(0.003, 0.036)	(-0.008, 0.027)	**(0.007, 0.081)**
Funded through Intramural Funding		-0.009	-0.001	-0.030
		(-0.032, 0.014)	(-0.025, 0.022)	(-0.082, 0.023)
Subclass Class Size	2.2E-5	9.6E-6	-3.9E-5	7.3E-5

	(-2.6E-4, 3.1E-4)	(-2.8E-4, 3.0E-4)	(-3.6E-4, 2.8E-4)	(-5.1E-4, 6.6E-4)
Recent Subclass	-0.012	-0.012	**-0.015**	-0.006
	(-0.026, 0.001)	(-0.026, 0.001)	**(-0.029, -2.7E-4)**	(-0.038, 0.026)
Growth rate > 0 during 2002-2004	**0.165**	**0.165**		
	(0.159, 0.171)	**(0.159, 0.171)**		
% Patents assigned to US Corp.	**0.015**	**0.015**	0.007	**0.034**
	(0.007, 0.023)	**(0.007, 0.023)**	(-0.001, 0.015)	**(0.016, 0.053)**
% Patents assigned to US Non-Profit Org.	**0.061**	**0.057**	0.029	**0.125**
	(0.033, 0.089)	**(0.029, 0.086)**	(-0.002, 0.060)	**(0.060, 0.190)**
% Expired	0.004	0.004	0.004	8.1E-4
	(-0.005, 0.012)	(-0.005, 0.012)	(-0.004, 0.013)	(-0.019, 0.020)
% Renewed upon the 4th year	-0.011	-0.010	0.030	-0.159
	(-0.126, 0.104)	(-0.126, 0.105)	(-0.076, 0.135)	(-0.438, 0.120)
No. of Obs.	56675	56675	40122	16553

Appendix I. Description of repeated matching scheme based on patent subclass.

In a perfect universe, we would find a unique match for each sample patent. However, two problems emerge in the actual matching process. First, multiple patents may be matched to a sample patent. While this seems to be a good problem to have, and one solution is to randomly pick one match from all the candidates, potentially meaningful variance is lost when we drop all the equally good alternatives. The result based on such single matching scheme may be an artifact of a particular match. Second, inventive activities are very sparse in many subclasses, resulting in scarcity of the available matches. In our data, we find no matches in the same subclass and granting year for around 30% of the sample patents.

It is also worth noting that there are two scenarios in which no match is found for a sample patent. One is that all patents in the subclass are funded by the federal government. In this case a match does not exist. Another more complicated scenario is that there are not enough candidates of matches for all sample patents in the subclass. For instance, patents X and Y are potential matches for federally funded patents A, B, C and D in a given subclass, so patent X and Y may be matched to only two of A, B, C and D. Consequently, there will always be two sample patents with no matches and the choice of these two sample patents is arbitrary.

Traditional remedies of matching pose a dilemma in this setting. While matching on more observable characteristics of the patent would alleviate the first problem of multiple matches, it would worsen the second problem of no admissible match because the universe of patents is further reduced by the additional criteria imposed. Meanwhile, relaxing certain criteria for the matching process would alleviate the second problem of no match while aggravating the situation of multiple matches.

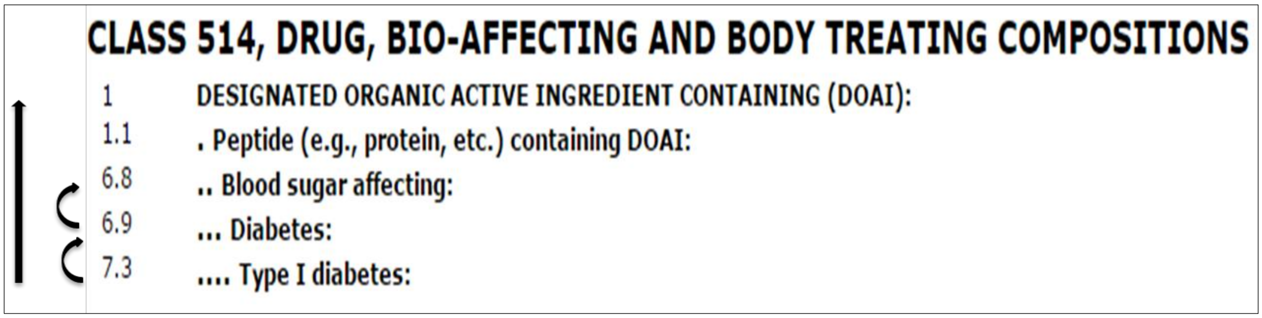
We took advantage of the hierarchical structure of the classification scheme of USPTO to tackle the problem of no match.[26] Under the classification scheme, subclasses under a given 3-digit class are nested within one another, creating a multilevel structure where lower levels are aggregated to higher levels. For a patent without a "perfect" match in the same subclass, we searched through the hierarchical structure of the subclass to locate its parent subclass (the one which can be identified as the immediate next aggregated level of the subclass) and then repeat the search within the parent subclass. If no admissible result is found, the search is repeated in a subclass on the more aggregated level, until the universe of patents is reached. Once "imperfect" matches are found in the closest subclass available, we randomly pick one on the closest granting date in the same year.

As illustrated in Figure A-1, in Class 514 "Drug, Bio-affecting and Body Treating Compositions", Subclass 514/7.3 "Type I Diabetes" is a level 4 subclass nested within Subclass 514/6.9 "Diabetes" (level 3), which is further nested in Subclass 514/6.8 "Blood sugar affecting" (level 2). In a similar fashion, level 2 Subclass 514/6.8 can be aggregated to level 1 Subclass 514/1.1 "Peptide (e.g., protein, etc.) containing DOAI", which is a branch of the level 0 Subclass 514/1

[26] We use subclass information in master classification file (MCF) released in 2014 to identify matches, and the subclass hierarchy file is based on classification scheme of 2006.

"Designated organic active ingredient containing (DOAI)", the most aggregated subclass under Class 514. Following the direction of the arrow in Figure A1, if no match is found in 514/7.3, a search will be conducted in the most immediate parent subclass, in this case, 514/6.9. If no match turns up in 514/6.9, the search will then be further expanded to the parent subclass of 514/6.9, i.e. 514/6.8. The process will be repeated to broader neighboring subclasses until one or more matches are identified.

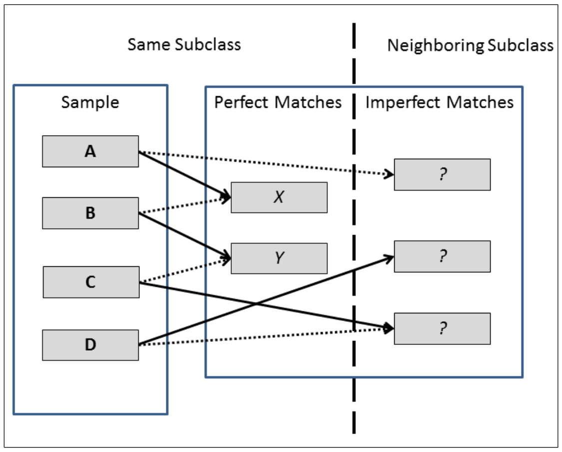
Figure A1. Hierarchy of USPTO Subclass 514/7.3 "Type I diabetes".



To account for the second issue of multiple matches, we also bake randomness of selecting matches into the multiple rounds of matching. First, every time multiple matches are identified for a sample patent, one of the matches will be randomly selected. Second, when a control patent is identified as a match for multiple sample patents, one sample-control pair will be randomly created and the rest of the sample patents will be rematched to the universe of patents again. Note that the whole landscape of matching is reshuffled in each round of matching due to the simultaneous presence of the two aforementioned problems.

In the earlier example of four sample patents (A, B, C, D) and two possible matches (X, Y) in the same subclass, in one round of matching we may randomly choose two sample-control pairs A-X and B-Y, in which X and Y are perfect matches, as shown in the solid arrows in Figure A2. Then patent C and D have to go through the process of "imperfect matching" in the neighboring parent subclass, as illustrated in the solid arrows originating from C and D. More than two imperfect matches are likely to be found for C and D, which further increases the possible combinations of sample-match pairs. The matching links represented by the dotted arrows in Figure A2 represent a different scenario for the same sample patents, in which B and C are randomly selected to match X and Y within the same subclass and A and D will be paired with patents in other subclasses following the hierarchical structure like the one illustrated in Figure A1.

Figure A2. Scenarios of Repeated Matching Scheme.



Appendix II. ***Auxiliary analysis of funded subclass: what kind of technological niches are selected by extramural federal funding?***

Our main findings are conditioned on the specific technological subclasses being selected by federal funding, and consequently most subclasses with no federal presence are not within the scope of the analysis. Hence, we have not been able to address the question of how these subclasses, or "niches" in the technological space supported by the federal government may be different. This is an important question as it directly relates to how we can explain the main findings from the selection side.

We examine how various characteristics of the subclass may influence the chance of extramural funding presence in the class in the subsequent year and compare it to that of the presence of corporate funding. We will focus on the presence of extramural federal funding in patent applications in a given technological niche (among all niches in the patent universe defined in Section 2) in the sampling frame, and examine how various characteristics of the subclass may predict the presence of government and corporate funding in the subclass.

First, we use the number of patents granted over the last three years (1998-2000) (Patent Count) as well as the average growth rate in the number of patents ("Avg. Growth: Patent Count") to capture the size and trend in the area. We further decompose the body of patents in a given subclass by calculating the proportion belonging to various types of assignees (US Corporation, US Federal Government, US State Government, US University, and US Institute/Hospital). Given the scarcity of activities in many subclasses, we also create a dummy that equals one if no patent is assigned to a certain type of assignee to capture lack of activities (“ No US Corp. Patent ”, for example) and zero otherwise.

Second, we capture the potential of a subclass through the average growth rate of the 10-year citation count over the past 3 years (“Avg. Growth: Patent Impact”). Third, we account for uncertainty in the granting process by including the mean (“Avg. Time btw. App. & Granting”) and normalized standard deviation (“Variance in Time btw. App. & Granting”) of the time lapse between application and granting. Last but not least, we measure the commercial value of a subclass by the proportion of the patents that expired later (“ % Expired ”), as well as the proportion of patents whose maintenance fees were paid at the 12th year (“ % Renewed 12th Year”). Meanwhile, “% Small Entity Status” captures the proportion of patents assigned to individuals, small businesses and non-profit organizations, which may be a proxy for the entrepreneurial value. To identify nascent or inactive subclasses, we calculate the number of years where at least one patent was granted during 1998-2000 (“Active Years”) and create a dummy for subclasses that have no record of renewal events (“No Renewal Event Reported”) during the same time.

We use seemingly unrelated bivariate Probit model with robust errors to jointly estimate the effect of the aforementioned factors on the presence of federal and private funding in a subclass, as we are interested in understanding the commonality and differences in two types of funding choices. Regression results are displayed in Table A1. “Extramural” is coded as 1 if at least one patent is funded through extramural federal funding in 2001-2004. “US Corp.” is coded as 1 if at least one patent is assigned to a US corporation during the same period.

Overall, our tentative analysis reveals interesting patterns of selection by the federal agencies vis-à-vis the private sector. First, federal funding does not seem to be sensitive to the proportion of corporation-backed inventions and vice versa. This suggests that the notion that federal government crowding out the private investments may not be true. Second, while federal funding appears to be drawn to areas of increasing impact, corporate funding seems to be more likely to be present in area with increase output, which indicates difference in goals of their R&D investments. Third, while corporate presence are likely to be in areas with high commercial value and avoids areas where prospect of commercialization is obsolete, federal funding does not seem to be sensitive to the commercial aspect of the area.

Some commonalities exist as well. First, both federal and private funding are likely to be present in subclasses where past patenting activities are present, though this is a decreasing marginal relationship. Second, lack of past inventions from most entities, including the federal government per se, appears correlated with lack of future funding from both government and corporations. Third, they are both less likely to be present in area with high entrepreneurial activities.

To further unpack the unique characteristics of the technological areas funded by either source, we estimate the marginal effects on subclasses funded by only one of two sources at the mean and report the results in the second and fourth column of Table A1. While most findings are consistent with the regression results, it is noteworthy that the largest effect come from the university patents in the past. Lack of inventions assigned to universities in the past will decrease the chance of subclass funded by extramural funding by 0.47%.

Table A1. Seemingly unrelated bivariate Probit model predicting federal and corporate funding in subclass

	Model 1	Marginal Effects	Model 2	Marginal Effects
DV	Extramural = 1	Predict: Fed Extramural = 1, US Corp = 0, 187 cases (0.54%)	US Corp. = 1	Predict: Fed Extramural = 0, US Corp = 1, 22369 cases (64.65%)
Active Years	**0.059**	1.4E-4	**0.07**	0.019
	(0.026, 0.093)	(-2.5E-4, 5.3E-4)	**(0.048, 0.092)**	**(0.011, 0.026)**
Patent Output	**0.005**	**-1.3E-4**	**0.026**	**0.008**
	(0.004, 0.006)	**(-1.6E-4, -1.1E-4)**	**(0.023, 0.029)**	**(0.007, 0.009)**
Patent Output Sq.	**0.000**	**4.6E-8**	**0.000**	**-2.7E-6**
	(-0.000, -0.000)	**(3.7E-8, 5.5E-8)**	**(-0.000, -0.000)**	**(-3.0E-6, -2.4E-6)**
Avg. Growth: Patent Count	0.038	-6.9E-5	**0.067**	0.019
	(-0.002, 0.077)	(-5.3E-4, 3.9E-4)	**(0.042, 0.091)**	**(0.011, 0.027)**
Avg. Growth: Patent Impact	**0.010**	7.4E-5	0.004	6.9E-4
	(0.002, 0.017)	(-2.0E-5, 1.7E-4)	(-0.002, 0.010)	(-0.001, 0.003)
Avg. Time btw. App. & Granting	0.035	4.7E-4	-0.013	-0.006
	(-0.008, 0.078)	(-4.8E-5, 9.8E-4)	(-0.042, 0.016)	(-0.016, 0.003)
Variance in Time btw. App. & Granting	0.075	8.2E-4	-0.002	-0.006
	(-0.085, 0.235)	(-9.8E-4, 0.003)	(-0.088, 0.083)	(-0.034, 0.023)

% US Corp.	0.005	**-0.006**	**0.82**	**0.263**
	(-0.116, 0.127)	**(-0.007, -0.004)**	**(0.745, 0.896)**	**(0.238, 0.288)**
% US Gov.	**0.847**	**0.009**	0.066	-0.034
	(0.224, 1.470)	**(8.2E-4, 0.017)**	(-0.464, 0.595)	(-0.209, 0.142)
% US Univ.	**1.239**	**-0.037**	-0.076	0.838
	(0.858, 1.621)	**(-0.087, 0.013)**	(-0.461, 0.310)	(-0.272, 1.948)
% State Gov.	-1.97	0.014	2.214	-0.105
	(-6.015, 2.075)	(0.009, 0.019)	(-1.141, 5.569)	(-0.229, 0.019)
% Research Institute/Hospital	0.400	0.009	-0.620	-0.225
	(-0.309, 1.110)	(-7.2E-4, 0.018)	(-1.377, 0.137)	(-0.472, 0.023)
No US Corp = 1	**-0.294**	**-0.003**	**-0.086**	-0.008
	(-0.427, -0.162)	**(-0.004, -0.001)**	**(-0.144, -0.028)**	(-0.029, 0.012)
No US Gov. = 1	**-0.462**	**-0.004**	**-0.158**	-0.021
	(-0.557, -0.367)	**(-0.005, -0.003)**	**(-0.262, -0.053)**	(-0.054, 0.013)
No US Univ. = 1	**-0.51**	**-0.005**	**-0.117**	-0.005
	(-0.587, -0.434)	**(-0.006, -0.004)**	**(-0.197, -0.037)**	(-0.030, 0.021)
No State Gov. = 1	**-0.435**	-0.005	-0.016	0.023
	(-0.737, -0.132)	(-0.009, 2.2E-4)	(-0.491, 0.458)	(-0.131, 0.177)
No Research Institute/Hospital = 1	**-0.41**	**-0.003**	**-0.138**	-0.018
	(-0.514, -0.307)	**(-0.005, -0.002)**	**(-0.267, -0.009)**	(-0.059, 0.024)
% Small Entity Status	**-0.341**	**-0.003**	**-0.096**	-0.009
	(-0.437, -0.245)	**(-0.004, -0.002)**	**(-0.144, -0.048)**	(-0.025, 0.008)
% Expired	-0.138	-6.1E-4	**-0.123**	-0.030
	(-0.337, 0.060)	(-0.003, 0.002)	**(-0.216, -0.030)**	(-0.062, 0.001)
No Renewal Event Reported = 1	**-0.386**	-0.003	-0.105	-0.009
	(-0.730, -0.042)	(-0.007, 3.7E-4)	(-0.229, 0.018)	(-0.053, 0.035)
% Renewed - 4th Year	-0.667	-0.012	0.702	0.269
	(-2.742, 1.409)	(-0.035, 0.011)	(-0.273, 1.678)	(-0.066, 0.603)
% Renewed - 8th Year	1.04	0.014	-0.431	-0.206
	(-1.024, 3.104)	(-0.012, 0.040)	(-1.639, 0.776)	(-0.646, 0.234)
% Renewed - 12th Year	-0.009	-0.001	**0.169**	**0.055**
	(-0.127, 0.110)	(-0.003, 4.8E-5)	**(0.102, 0.236)**	**(0.032, 0.077)**
Constant	-0.429		-0.013	
	(-0.819, -0.039)		(-0.521, 0.496)	
N	34598		34598	
[1] Significance at 95% level marked in bold.				