[The use of intellectual property protection mechanisms by publicly supported firms]

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Abstract:

Technology-based firms use intellectual property protection mechanisms (IPPMs) to appropriate the returns to their research investments. The empirical literature has generally focused on the use of IPPMs by private sector firms to appropriate the returns to their *privately financed* R&D-based technologies. To date, studies have not considered the use of IPPMs by private sector firms whose research is *publicly financed*. We identify empirically a number of significant covariates with the use of a portfolio of formal IPPMs consisting of patents, copyrights, and trademarks. However, our multivariate empirical analyses show that caution is needed in generalizing about such covariates when discussing any one particular formal IPPM.

Keywords: patents | copyrights | trademarks| intellectual property | SBIR program | program evaluation | technology

Article:

> Nature is all that a man brings with himself into the world; nurture is every influence from without that affects him after his birth.[1] — Francis Galton

1. Introduction

Firms, especially technology-based firms, use intellectual property protection mechanisms (IPPMs) to appropriate the returns to their research investments. The academic and policy literatures are rich in studies that examine the effectiveness of this use of IPPMs; however, less researched in these literatures are the economic factors associated with a firm's choice of which IPPMs to adopt.

The attendant empirical literature has generally focused on the use of IPPMs by private sector firms to appropriate the returns to their in-house research investments. These are the returns to

[1] *English Men of Science: Their Nature and Nurture* (1895, 9).

the firms' *privately financed* R&D-based technologies. As discussed in Amoroso and Link (2019), this literature has considered firm and sectoral characteristics associated with the choice among IPPMs (e.g. Veugelers and Schneider 2017); the complementarity among formal (e.g. patents) and informal (e.g. trade secrets) IPPMs (e.g. Gallié and Legros 2012); and the situations in which informal IPPMs may be more appropriate to use than formal IPPMs (e.g. Hall et al. 2014). To date, to the best of our knowledge, no studies have considered the use of IPPMs by private sector firms whose research is *publicly financed*. This is an important void to begin to fill as more and more economic growth policies, especially those that are targeted to small firms, are focused on public sector financial support of innovative activity.

In this paper, we build on the existing literature by exploring the use of IPPMs by firms to appropriate the returns to their *publicly financed* R&D-based technologies. In other words, the research question that we address in this paper is, Which, if any, IPPMs are used by private sector firms to protect the technologies developed with the support of public sector money, and what are the characteristics of owners and principal investigators (PIs) relevant to the IPPMs that are used?[2] A secondary research question that we consider is, What is the appropriate framework for identifying empirically the relevant characteristics associated with the use of IPPMs?

The former is an important question to consider for at least two reasons. At an academic level, the answer to this question contributes to the existing literature on the appropriability-related use of IPPMs; at a policy level, the answer provides information to public-sector funding agencies on possible advice or guidance to offer to funded firms, especially nascent and small firms, to protect their publicly funded technologies.[3] And, protection of publicly funded technologies is a step forward to ensuring that the public's investment dollars are effective in meeting the public's intended funding objective.[4] The latter is also an important question to consider because it relates to the accuracy of answers to the former question.

In Section II, we discuss the data that we use to explore the relationship between the use of IPPMs and the characteristics of involved individuals. We divide the characteristics of interest into those that reflect nature (i.e. demographic) characteristics of the funded firm's owner and the principal investigator (PI) involved in the research, versus the nurture (i.e. experiential) characteristics of the funded firm and its founders.[5,6,7] In Section III, we present our empirical model of the use of alternative IPPMs, followed by our empirical findings in Section IV. We offer concluding remarks in Section V.

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[2] An ideal experiment would be to study matched pairs of private sector firms, one-half that fund their technologies with their own R&D and one-half that fund their technologies with publicly funded R&D.
[3] See Santamaría, Barge-Gil, and Modrego (2010) and Antonelli (2020) on factors that influence a firm's likelihood of receiving public-sector funds, and see Busom (2000) on the benefits of such funds.
[4] We elaborate on this final point below in our discussion of the mission of the SBIR program; the data that we examine related to SBIR funded projects.
[5] Conley (1984) argues that the origin of the nature versus nurture controversy traces to William Shakespeare's *The Tempest* (1610): 'A devil, a born devil, on whose nature nurture can never stick … '.
[6] See Audretsch and Link (2018) and Link (2020) for a discussion of John Locke's view of experiences (i.e. nurture) over nature, and the role of experiences in crafting public sector and private sector entrepreneurial behavior.
[7] We are not the first researchers to address nature versus nurture aspects of the innovation process. See, for example, Aghion et al. (2017); Bell et al. (2019); and Nicolaou et al. (2008).

2. Description of the data

The data that we study in this paper relate to Phase II research projects funded by the U.S. Small Business Innovation Research (SBIR) program.[8] The SBIR program was initiated through the Small Business Innovation Development Act of 1982 (Public Law 97–219). This legislation was not only a response to the success of the prototype SBIR program that began at the National Science Foundation in 1977, but also it was a response to the pervasive productivity slowdown in the United States that began in the early-to-mid 1970s and continued into the early 1980s.

In response to the productivity slowdown, U.S. President Jimmy Carter initiated in 1979 a Domestic Policy Review, and among his eight corrective policy initiatives was one to foster the development of small, innovative firms (Carter 1979, 65).

As legislative background, the mission of the SBIR program created through the Act of 1982 is:[9]

> … to support scientific excellence and technological innovation through the investment of Federal research funds in critical American priorities to build a strong national economy. The program's goals are four-fold:
>
> - Stimulate technological innovation.
> - Meet Federal research and development needs.
> - Foster and encourage participation in innovation and entrepreneurship by women and socially or economically disadvantaged persons.
> - Increase private-sector commercialization of innovations derived from Federal research and development funding.

Eleven agencies currently participate in the SBIR program. These programs fund Phase I and Phase II projects. The objective of a Phase I project is to establish proof of concept of the research as well as the technical merit and commercial potential of the proposed R&D effort. These six-month projects are legislatively funded at no more than $150,000. The objective of a Phase II project is to continue the R&D efforts from Phase I. Only Phase I awardees can apply for a competitive Phase II award. It is anticipated that by the end of the two-year Phase II projects, which are legislatively funded at no more than $1 million, the awardees will have commercialized the newly developed technologies.[10,11]

As part of the SBIR program reauthorization in 2000, the U.S. Congress authorized the National Research Council (NRC) of the National Academies[12] to conduct a survey of Phase II projects that were previously funded by the Department of Defense (DOD), the National Institutes of

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[8] We have written about the institutional and policy history of the SBIR program many times, so duplication of text and quoted materials from the enabling legislation is inevitable. See Link and Scott (2012); the collection of papers in Link (2013); Hayter, Link, and Scott (2018); and most recently Audretsch, Link, and van Hasselt (2019).

[9] See, https://www.sbir.gov/about/about-sbir (accessed September 13, 2020).

[10] To the extent that the small firm that receives SBIR Phase II funding is able to protect the intellectual property of its newly developed technology, the greater the commercialization success of the technology and thus the greater the extent to which the purpose of the Phase II funding is achieved.

[11] There are agency-specific exceptions to the upper limits of a Phase I and Phase II award.

[12] See, https://www.nationalacademies.org/ (accessed September 13, 2020).

Health (NIH), the National Aeronautics and Space Administration (NASA), the Department of Energy (DOE), and the National Science Foundation (NSF). Based on the success of that survey and the NRC reports that followed, Congress reauthorized a second assessment survey. Phase II projects funded by the DOD and NASA were surveyed in 2011,[13] and Phase II projects funded by the NIH and DOE were surveyed in 2014. We have unique access to the data from the second survey of the DOD, NASA, NIH, and DOE funded projects; and these project data frame the empirical analyses in this paper.

Our sampling population of Phase II projects is described in Table 1, by funding agency. To arrive at the final sample of projects, we deleted projects that were not completed at the time of the NRC survey and projects that were discontinued prior to realizing any sales up to the time of the survey. The projects that were discontinued without sales have been referred to in the literature as *failed projects* (Link and Wright 2015; Andersen, Bray, and Link 2017). We also note in Table 1 the number of projects that were deleted due to nonresponses to key survey questions (i.e. we deleted projects with missing data).

Table 1. Data Reduction Process.

	DOD	**NIH**	**NASA**	**DOE**	**All Agencies**
Random sample of Ph II projects from NRC surveys	1155	572	298	244	2269
Sample after removal of incomplete and failed projects	803	456	213	175	1647
Number of projects with missing data	554	266	160	89	1069
Final Sample	249 (43.08%)	190 (32.87%)	53 (9.17%)	86 (14.88%)	578

The academic literature on IPPMs defines patents, copyrights, and trademarks as formal IPPMs.[14] The formal IPPM variables of emphasis in the analyses that follow are based on the NRC Phase II survey question:[15]

> Please give the number of patents, copyrights, trademarks received … for the technology developed as a result of this funded Phase II project.

Figures 1 and 2 overview the responses to this survey question for those Phase II projects that were completed and did not fail ($n = 1{,}647$; see Table 1). Figure 1 shows the percentage of Phase II projects using each of the three IPPMs considered in the NRC survey question. Patents are the most frequently used IPPM by the Phase II project firms, and copyrights are the least frequently used.[16] Figure 2 shows the percentage of Phase II projects that use no IPPMs or only one IPPM. More than 60 percent of the 1,647 Phase II projects in our sampling population use no IPPMs,

[13] Phase II projects funded by NSF were also surveyed, but the data at our access on those projects is limited.
[14] See, Amoroso and Link 2019, and the papers summarized and referenced therein.
[15] Our study is limited to these three IPPMs. Amoroso and Link (2019) study a broader set of IPPMs, but none of the firms in their sample are protecting publicly funded technologies. Patents have been studied extensively in the economics and policy literatures. To the best of our knowledge, the only economics study of copyrights is by Rooksby and Hayter (2017), and we know of no studies related to trademarks individually as an IPPM.
[16] We thank Silvio Vismara for pointing out that little is known about the timing of the adoption of different IPPMs. Are such mechanisms adopted contemporaneously or over time as a technology matures?

while just over 20 percent use only patents.[17] About 2 percent of the sampling population uses only copyrights or only trademarks.

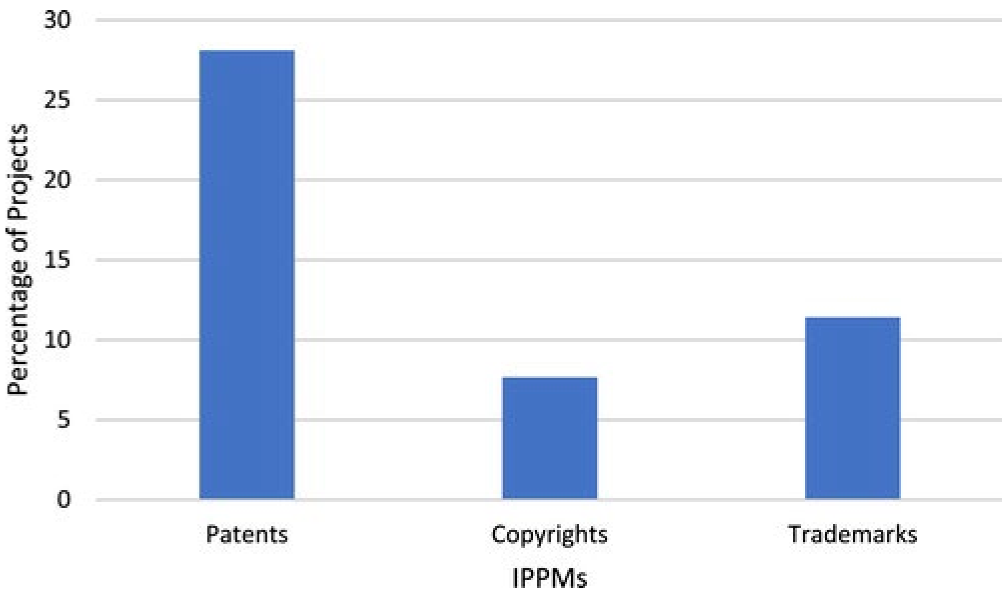

Figure 1. Percentage of Phase II SBIR Projects Using Alternative IPPMs (*n* = 1647). Note: A firm can use more than 1 IPPM to protect its Phase II intellectual property.

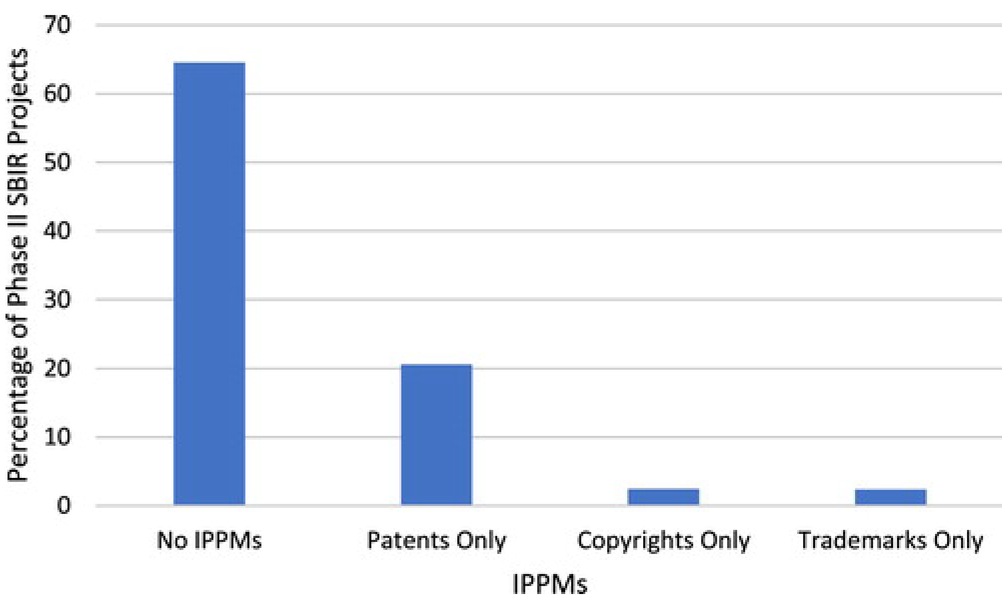

Figure 2. Percentage of Phase II SBIR Projects Using No or Only One IPPM (*n* = 1647)

Table 2 defines the IPPM, nature (i.e. demographic), and nurture (i.e. experiential) variables used in this paper.

[17] Potekhina and Blind (2020) provide empirical evidence that technology as well as human motivation (e.g. reward recognition) influence the decision to patent.

Descriptive statistics for all the variables listed in Table 2 are in Table 3, by funding agency as well as for the full sample.

Table 2. Definition of Variables.

Variable	Definition
IPPM	
AnyFormalIPPMDmy	Equals 1 if the firm received any patents, copyrights, or trademarks for the technology developed during the Phase II project, 0 otherwise
PatentsDmy	Equals 1 if the firm received any patents for the technology developed during the Phase II project, 0 otherwise
CopyrightsDmy	Equals 1 if the firm received any copyrights for the technology developed during the Phase II project, 0 otherwise
TrademarksDmy	Equals 1 if the firm received any trademarks for the technology developed during the Phase II project, 0 otherwise
Nature	
WomanOwned	Equals 1 if the firm is owned by a woman, 0 otherwise
WomanPI	Equals 1 if the PI is a woman, 0 otherwise
HomophWoman	Equals 1 if the firm is owned by a woman and the PI is a woman, 0 otherwise
PIAge	The midpoint of the PI's age bracket (measured in 5-year intervals)
Nurture	
ProjectYears	Year of the NRC Phase II survey minus the year the Phase II funding was awarded
NumFounders	Number of founders of the firm
EmpAtAward	Number of employees at the time of the current Phase II award
AddlDevelFunding	Equals 1 if the firm received additional development funding for the technology developed during the Phase II project, 0 otherwise
NumPrevPhII	Number of prior Phase II awards received related to the technology supported by the current Phase II award

Note: *PIAge* could also be considered a nurture variable to the extent it reflects accumulated experience that comes with age.

Table 3. Descriptive Statistics ($n = 578$).

Variable	DOD	DOE	NASA	NIH	Full Sample
IMMP					
AnyFormalIPPMDmy	0.23	0.38	0.30	0.63	0.39
	(0.42)	(0.49)	(0.46)	(0.49)	(0.49)
PatentsDmy	0.16	0.33	0.19	0.46	0.29
	(0.36)	(0.47)	(0.39)	(0.50)	(0.45)
CopyrightsDmy	0.07	0.03	0.15	0.24	0.13
	(0.25)	(0.18)	(0.36)	(0.43)	(0.33)
TrademarksDmy	0.10	0.09	0.11	0.33	0.17
	(0.30)	(0.29)	(0.32)	(0.47)	(0.38)
Nature					
WomanOwned	0.13	0.09	0.15	0.15	0.13
	(0.34)	(0.29)	(0.36)	(0.36)	(0.34)
WomanPI	0.05	0.08	0.08	0.15	0.09
	(0.22)	(0.28)	(0.27)	(0.36)	(0.29)
HomophWoman	0.02	0.03	0.08	0.10	0.05
	(0.14)	(0.18)	(0.27)	(0.30)	(0.23)
PIAge	45.78	48.28	45.11	48.66	47.03
	(9.73)	(9.71)	(9.05)	(10.08)	(9.87)
	[22, 67]	[32, 67]	[27, 62]	[27, 67]	[22, 67]

Variable	DOD	DOE	NASA	NIH	Full Sample
Nurture					
ProjectYears	6.03	6.49	7.03	7.52	6.68
	(1.97)	(2.45)	(2.95)	(2.79)	(2.51)
	[4, 13]	[4, 13]	[4, 13]	[4, 13]	[4, 13]
NumFounders	2.40	2.29	2.17	2.37	2.35
	(2.76)	1.84	(1.66)	(1.46)	(2.18)
	[1, 30]	[1, 12]	[1, 12]	[1, 10]	[1, 30]
EmpAtAward	41.48	26.51	31.91	16.92	30.30
	(63.10)	30.22	(59.12)	(32.98)	(51.30)
	[1, 480]	[1, 150]	[1, 400]	[1, 300]	[1, 480]
AddlDevelFunding	0.73	0.92	0.77	0.91	0.82
	(0.44)	(0.27)	(0.42)	(0.29)	(0.38)
NumPrevPhII	1.49	1.24	1.57	1.44	1.44
	(1.81)	(1.64)	(2.11)	(1.75)	(1.79)
	[0, 10]	[0, 10]	[0, 10]	[0, 11]	[0, 11]

Note: The table contains sample means and, in parentheses, standard deviations. Numbers in square brackets, where reported, indicate the minimum and maximum values.

3. The empirical model

Our first empirical model explores covariates with the use of any IPPM from a completed and successful Phase II project. It takes the general functional form:

1. Pr(*AnyFormalIPPMDmy* = 1) = f (**Nature**, **Nurture**, **Funding Agency Controls**),

where Pr(·) denotes probability, the specific variables in the vectors **Nature** and **Nurture** vector are defined in Table 2, and the funding agency controls are a set of indicator variables to account for differences in the propensity to use IPPMs by funding agency.

We do not offer hypotheses about the directional effect of the nature variables on the probability that the firm will use a formal IPPM to protect its Phase II technology; these variables in this context are relatively new to the literature (Link and Morrison 2019).[18] We do note, however, that homophilic firms (e.g. woman owned and woman PI) have been shown empirically to commercialize more often than other owner/PI combinations (Bednar, Gicheva, and Link 2019). To the extent that firms that are successful in commercialization are also firms that seek to protect the IP of their commercialized technology, *HomophWoman* should have a positive sign.

Regarding the nurture variables, we hypothesize that *ProjectYears* will be positively related to the likelihood of using a formal IPPM. One might logically expect that the more time a firm has from the time it began its Phase II project until it was surveyed about its use of IPPMs, the greater the likelihood that an IPPM could be used if for no other reason but to ensure that the firm was able to navigate around any related institutional barriers (e.g. the time to apply and time to receive a patent).[19]

[18] See also Swanson (2016).
[19] Perhaps more subtle reason for a positive relationship relates to SBIR-funded firms being in a state of liminality in which they are attempting to define their identity as a technology-based organization and adopt attendant strategies. See, for example, Beech (2011) and the references therein.

We offer no hypothesis about the human capital endowment with the funded firm as measured by the variable *NumFounders*. On the one hand, the more founders of a firm, the greater the collective experience base of the firm and the more likely the firm would have the human capital resources to construct meaningful IPPMs. On the other hand, with more such experience, the firm might be in the position to know if and when IPPMs are important. Thus, the relationship of this variable to the likelihood of using a formal IPPM could be positive or negative.

The extent to which the variable *EmpAtAward* proxies firm size, its relationship to the likelihood of using formal IPPMs is also ambiguous. One the one hand, firm size might reflect relevant internal resources requisite for successfully adopting a relevant IPPM; but on the other hand, firms with more internal resources might not require IP protection to the same extent as a smaller firm.

We hypothesize that the variable *AddlDevelPhII* is positively related to the likelihood of using formal IPPMs. The presence of additional development funding often implies the presence of additional investors in the Phase II project itself, or at least in the subsequent development of the Phase II technology. It is not unreasonable to expect such investors to encourage the use of IPPMs to protect their investments.

We hypothesize that the variable *NumPrevPhII* is positively related to the likelihood of using formal IPPMs. To the extent that a greater focused knowledge base implies that the firm is wedded to or dependent on the particular technology developed thought the Phase II award, the more important it might be for the firm to adopt an IP protection strategy to protect such a strategic and thus critical technology.

The choice model in equation (1) focuses on the use of *any* IPPM versus *none*. In our second empirical specification, we consider firms' choices for the three specific types of IPPM, namely patents, copyrights, and trademarks. Specifically, we use a multivariate Probit model (e.g. Wooldridge 2010) to model the distribution of the trivariate binary vector (*PatentsDmy, CopyrightsDmy, TrademarksDmy*). The control variables in this model are the same as in equation (1). The advantage of the multivariate Probit model in this context is twofold. First, we can learn about the relation between various nature and nurture characteristics and the propensity to use different IPPMs. Second, the model allows for the possibility that these choices are correlated, even after controlling for observed characteristics.

4. Empirical findings

The Probit results from the estimation of three specification of equation (1) are presented in Table 4. The differences among the three specifications are related to the inclusion/exclusion of the variable *HomophWoman*.[20]

The Probit results in Table 4 confirm the directional effects hypothesized above, including those for which directional ambiguity is reflected in a statistically insignificant Probit coefficient.

[20] Variance inflation factor (VIF) tests show no multicollinearity in any of these specifications. These results are available from the authors on request.

Table 4. Estimates from the Probit Model for the Use of Any IPPM ($n = 578$).

Variable	**(1)**	**(2)**	**(3)**
WomanOwned	0.3316*	–	0.2403
	(0.1783)		(0.2058)
WomanPI	−0.0820	–	−0.2727
	(0.2147)		(0.3100)
HomophWoman	–	0.3666	0.4030
		(0.2409)	(0.4348)
PIAge	0.0048	0.0047	0.0045
	(0.0058)	(0.0058)	(0.0058)
ProjectYears	0.0561**	0.0547**	0.0550**
	(0.0226)	(0.0225)	(0.0226)
NumFounders	0.0099	0.0140	0.0110
	(0.0290)	(0.0282)	(0.0288)
EmpAtAward	−0.0016	−0.0017	−0.0016
	(0.0014)	(0.0013)	(0.0013)
AddlDevelFunding	0.4242***	0.4234***	0.4267***
	(0.1633)	(0.1634)	(0.1634)
NumPrevPhII	0.0831**	0.0786**	0.0816**
	(0.0327)	(0.0327)	(0.0329)
Agency funded controls	yes	yes	yes
Wald chi-square statistic	93.24	93.26	94.32
(*p*-value)	(<0.00)	(<0.00)	(<0.00)
Log-likelihood	−335.53	−336.24	−335.11

Notes: Robust standard errors in parentheses.
*** significant at the .01-level, ** significant at the .05-level, * significant at the .10-level.

We referenced a number of studies in the Introduction to this paper that explored covariates with the use of formal, as well as informal, IPPMs. However, greater insight into covariates with the use of a particular IPPM might provide new evidence to inform the extant literature. Thus, we use a multivariate Probit specification to model the three dependent variables *PatentsDmy*, *CopyrightsDmy,* and *TrademarksDmy* jointly. The independent variables in each of these three models are the same as discussed with reference to Table 4. As mentioned in Section III, the advantage of the multivariate model is that it allows for the possibility that the unobservables affecting the choices for the types of IPPMs are correlated across the three equations.

The multivariate probit model was estimated using the **mvprobit** package in Stata 15.1 (Cappellari and Jenkins 2003). Estimation is performed by simulated maximum likelihood, which requires the user to specify a seed number for the random number generator, as well as the number of random draws used to simulate the likelihood function. We set the number of random draws equal to 100, which substantially exceeds the empirical rule-of-thumb of the square root of the sample size.[21] We also experimented with different seed numbers and found our estimates to be robust.[22]

The multivariate Probit results are in Table 5. The first observation from these results is that the significant covariates differ across IPPMs.[23] For example, the only significant covariate with the variable *PatentsDmy* is *AddlDevelFund*, and this relationship is positive as we hypothesized. That same independent variable is significant and positive in the *TrademarksDmy* equation but not in the *CopyrightsDmy* equation.

Table 5. Estimates from the Multivariate Probit Model for Patents, Copyrights, and Trademarks ($n = 578$).

Variable	**(1)**	**(2)**	**(3)**
PatentsDmy			
WomanOwned	0.0559	–	0.1310
	(0.1935)		(0.2216)
WomanPI	−0.2913	–	−0.1593
	(0.2292)		(0.3088)
HomophWoman	–	−0.3209	−0.2920
		(0.2605)	(0.4524)
PIAge	0.0004	0.0007	0.0006
	(0.0061)	(0.0061)	(0.0061)
ProjectYears	0.0336	0.0345	0.0346
	(0.0236)	(0.0236)	(0.0237)
NumFounders	0.0411	0.0420	0.0401
	(0.0260)	(0.0260)	(0.0260)
EmpAtAward	−0.0014	−0.0014	−0.0014
	(0.0013)	(0.0013)	(0.0013)
AddlDevelFunding	0.7017***	0.6976***	0.7005***
	(0.1973)	(0.1971)	(0.1974)
NumPrevPhII	0.0300	0.0303	0.0317
	(0.0318)	(0.0319)	(0.0320)
CopyrightsDmy			
WomanOwned	0.4781**	–	0.4757*
	(0.2129)		(0.2453)
WomanPI	0.1288	–	0.0680
	(0.2541)		(0.3828)
HomophWoman	–	0.5923**	0.0893
		(0.2506)	(0.5055)
PIAge	0.0061	0.0053	0.0060

[21] The rule of thumb suggests using at least sqrt(578) or 24 random draws. Using a higher number increases estimation accuracy but also computing time. We experimented with 25, 50, 75 and 100 random draws. The estimates were robust in the sense that the coefficient signs remained the same and, at the 1% and 5% significance levels, no coefficients switched from being statistically significant to insignificant, or vice versa. The results reported here correspond to 100 random draws.
[22] Robustness refers to the sign and significance of the estimated coefficients (see footnote 17). Estimates from the robustness checks are available from the authors on request.
[23] We are using the term *significant* in the following description of the multivariate Probit results to refer to estimated coefficients that are significant at the .10-level or better in at least one of the specifications considered.

Variable	(1)	(2)	(3)
	(0.0074)	(0.0074)	(0.0074)
ProjectYears	0.0086	0.0051	0.0083
	(0.0283)	(0.0282)	(0.0283)
NumFounders	−0.1333**	−0.1293**	−0.1349**
	(0.0617)	(0.0607)	(0.0620)
EmpAtAward	−0.0034*	−0.0036*	−0.0034*
	(0.0020)	(0.0021)	(0.0020)
AddlDevelFunding	−0.1247	−0.1300	−0.1257
	(0.1983)	(0.1982)	(0.1983)
NumPrevPhII	0.1158***	0.1083***	0.1157***
	(0.0355)	(0.0354)	(0.0355)
TrademarksDmy			
WomanOwned	0.3364	–	0.1407
	(0.2083)		(0.2447)
WomanPI	−0.3985	–	−1.0415**
	(0.2582)		(0.4796)
HomophWoman	–	0.1464	1.0103*
		(0.2542)	(0.5847)
PIAge	0.0018	0.0023	0.0016
	(0.0068)	(0.0067)	(0.0068)
ProjectYears	0.0461*	0.0432*	0.0440*
	(0.0257)	(0.0256)	(0.0258)
NumFounders	−0.0253	−0.0157	−0.0205
	(0.0433)	(0.0413)	(0.0426)
EmpAtAward	−0.0026*	−0.0027*	−0.0027*
	(0.0015)	(0.0016)	(0.0015)
AddlDevelFunding	0.5374**	0.5462**	0.5570**
	(0.2190)	(0.2201)	(0.2199)
NumPrevPhII	0.0624*	0.0552*	0.0573*
	(0.0325)	(0.0325)	(0.0325)
Wald chi-square statistic	144.87	139.47	147.99
(*p*-value)	(<0.00)	(<0.00)	(<0.00)
Log-likelihood	−672.68	−676.31	−670.16

Notes: Standard errors in parentheses. The sample size is $n = 578$. The coefficients are estimated using simulated maximum likelihood. The number of random draws to simulate the likelihood function is $M = 100$.
*** significant at the .01-level, ** significant at the .05-level, * significant at the .10-level

In the *CopyrightsDmy* equation, both nurture and nature independent variables are significant, as they are in the *TrademarksDmy* equation. Woman-owned firms are associated with a greater likelihood of using copyrights to protect their Phase II project's technology, but projects with a woman PI have a lesser likelihood (in the specification in column (3)) of using trademarks for the same purpose. If the owner-PI relationship is female homophilic (i.e. woman owned and woman PI), there is a positive association with the use of both copyrights and trademarks as IPPMs.

Firm size, as measured in terms of the variable *EmpAtAward*, is negatively associated with the use of both copyrights and trademarks as IPPMs. The coefficients for this variable are also negative in the *PatentsDmy* equation, but not significant.

Other relationships showing a greater or lesser likelihood for the use of either copyrights or trademarks as IPPMs are observable in Table 5. As a final note, we did not report the correlations between the errors in the three equations of the multivariate Probit model.[24] These correlations were all positive and statistically significant. The error correlation between copyrights and trademarks was particularly high, ranging between 0.78 and 0.80 across the three model specifications. Thus, after controlling for nature, nurture and agency effects, firms that use copyrights as an IPPM are more likely to also use trademarks, and vice versa.

5. Concluding remarks

In the Introduction we raised the two questions that would be addressed in this paper. First, Which, if any, IPPMs are used by private sector firms to protect the technologies developed through their use of public sector money, and what are the characteristics of owners and principal investigators (PIs) relevant to the IPPMs that are used? And second, What is the appropriate framework for identifying empirically the relevant characteristics associated with the use of IPPMs?

Focusing on technologies developed through publicly financed R&D, we identified empirically a number of significant covariates with the use of a portfolio of formal IPPMs consisting of patents, copyrights, and trademarks. However, our multivariate empirical analyses show that caution is needed in generalizing about such covariates when discussing any one particular formal IPPM. We did not identify a covariate that was simultaneously statistically related to the use of patents, the use of copyrights, as well as the use of trademarks.

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[24] These statistics are available from the authors on request.

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