

## A public sector knowledge production function

By: [Albert N. Link](#) and [Martijn van Hasselt](#)

Link, A. N. & Van Hasselt, M. (2019). A Public Sector Knowledge Production Function. *Economics Letters*, 175, 64-66. DOI: 10.1016/j.econlet.2018.12.025

Made available courtesy of Elsevier: <https://doi.org/10.1016/j.econlet.2018.12.025>



This work is licensed under a [Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License](#).

### Abstract:

There are no studies of the R&D-to-patenting relationship at the federal agency level. We estimate a public sector knowledge production function using federal agency patent application data over the years 2003 through 2014. We find that the patent application elasticity with respect to per capita R&D spending is about 1.06. This measure might be interpreted as one dimension of the social returns to public sector R&D generated through newly created knowledge.

**Keywords:** Patents | R&D | Knowledge production function | Technology transfer

### Article:

#### 1. Introduction

The literature is replete with studies of the private sector's R&D-to-patenting relationship, as recently reviewed by, for example, Hall and Harhoff (2012). A portion of that literature represents itself as an empirical test of a knowledge production function (Griliches, 1979) by arguing that patents are a proxy for the generation of new knowledge. Absent from this literature are studies that examine the relationship between public sector patenting activity and publicly funded R&D. Here, we present estimates of a public sector's R&D-to-patenting relationship.

Little is known about the economic impact of publicly funded R&D on public sector patents. The absence of such information is one factor that motivated the National Institute of Standards and Technology (NIST) and the White House Office of Science and Technology Policy (OSTP) to sponsor recently the Unleashing American Innovation initiative.<sup>1</sup> As stated in the Administration's President's Management Agenda (undated, p. 48)<sup>2</sup> : The Federal Government invests approximately \$150 billion annually in research and development (R&D) conducted at Federal laboratories ... it is essential to optimize technology transfer and support programs to increase the return on investment (ROI) from federally funded R&D.

In Section 2, we present an overview of the public sector's responsibility toward technology transfer. In Section 3, we focus on patent activity in federal agencies because it represents the generation of new knowledge and because other scholars have emphasized patent applications within the knowledge production function literature. We conclude in Section 4 with

a statement that our measure of the patent elasticity with respect to per capita R&D might represent a dimension of the social returns to public sector investments in R&D generated through newly patented knowledge, and we suggest the need for future research on this policy-centric topic.

Table 1  
Definitions of variables

Variable	Definition
<i>PatApp</i>	Number of federal laboratory patent applications, by agency and by year
<i>RD</i>	Federal R&D expenditures, by agency and by year (millions of 2016 constant dollars)
<i>L</i>	Number of STEM (science, technology, engineering, and mathematics) employees, by agency and by year (1000s)

Sources:

*PatApp*: <https://www.nist.gov/tpo/federal-laboratory-interagency-technology-transfer-summary-reports>. Accessed July 9, 2018.

*RD*: <https://www.aaas.org/page/historical-trends-federal-rd#Agency>. Accessed July 9, 2018.

*L*: <https://www.fedscope.opm.gov/>. Accessed July 9, 2018.

Table 2  
Descriptive statistics, total sample (n = 126) and by agency.

Variable	Mean	Standard deviation	Range
<i>PatApp</i>	201.22	299.26	0–1144
<i>RD</i>	14 174.24	24 727.46	512.0–91 744.0
<i>L</i>	11.40	5.64	4.50–26.10

  

Agency	Variable	Mean	Standard deviation	Range
USDA	<i>PatApp</i>	108.92	26.17	60.0–157.0
	<i>RD</i>	2687.91	238.44	22 16.0–3027.30
	<i>L</i>	24.99	0.99	22.90–26.10
DOC	<i>PatApp</i>	16.0	7.40	5.0–26.0
	<i>RD</i>	1400.58	117.94	1237.0–1598.0
	<i>L</i>	12.68	0.45	12.10–13.40
DOD	<i>PatApp</i>	700.0	209.29	354.0–1013.0
	<i>RD</i>	83 446.67	8478.88	68 473.0–91 744.0
	<i>L</i>	10.0	1.35	8.60–12.0
DOE	<i>PatApp</i>	844.83	134.63	661.0–1144.0
	<i>RD</i>	11 183.92	643.00	10 165.0–12 349.0
	<i>L</i>	4.70	0.15	4.50–4.90
HHS	<i>PatApp</i>	236.83	42.70	164.0–291.0
	<i>RD</i>	34 063.50	1556.55	31 208.0–35 966.0
	<i>L</i>	12.66	0.94	11.60–14.0
DHS	<i>PatApp</i>	5.83	4.22	2.0–12.0
	<i>RD</i>	870.33	231.61	512.0–1124.0
	<i>L</i>	7.18	0.73	6.0–7.80
DOI	<i>PatApp</i>	5.25	2.38	2.0–8.0
	<i>RD</i>	806.58	44.66	746.0–873.0
	<i>L</i>	17.29	0.52	16.20–18.0
DOT	<i>PatApp</i>	2.17	1.59	0–5.0
	<i>RD</i>	946.58	106.57	821.0–1188.0
	<i>L</i>	6.74	0.79	5.40–7.40
VA	<i>PatApp</i>	28.92	11.18	13.0–54.0
	<i>RD</i>	1079.67	123.12	907.0–1258.0
	<i>L</i>	7.97	0.99	6.50–9.20
EPA	<i>PatApp</i>	10.17	5.59	3.0–23.0
	<i>RD</i>	665.08	88.44	554.0–835.0
	<i>L</i>	7.69	0.30	7.0–8.10
NASA	<i>PatApp</i>	156.83	36.90	122.0–231.0
	<i>RD</i>	12 113.83	1460.08	98 11.0–13 803.0
	<i>L</i>	11.43	0.26	11.0–11.80

Notes:

USDA: Department of Agriculture; DOC: Department of Commerce; DOD: Department of Defense; DOE: Department of Energy; HHS: Department of Health and Human Services; DHS:

Department of Homeland Security; DOI: Department of Interior; DOT: Department of Transportation; VA: Department of Veteran’s Affairs; EPA: Environmental Protection Agency; NASA: National Aeronautics and Space Administration Patent application data for DHS are available beginning in 2009.

Table 3.  
OLS, Poisson, and negative binominal estimates (n = 126)

Variable	(1) OLS results log(PatApp)	(2) Poisson results PatApp	(3) Negative binominal results PatApp
log(L)	0.881 (0.878)	-0.910 (0.506)	0.781 (0.623)
log(RD/L)	1.058*** (0.145)	0.701*** (0.124)	1.067*** (0.237)
PatentDummy	-4.674*** (0.586)	-	-
Intercept	-4.456 (2.258)	2.409* (1.062)	-3.804 (2.415)
R-squared	0.78	-	-
Log Pseudo-Likelihood	-	-4868.77	-664.66

Notes:

Standard errors clustered at the agency level and reported in parentheses below coefficient estimates.

The intercept term in column (1) is based on replacing PatApp = 0.1 for two observations where patent applications are zero. If those two observations are deleted instead, the coefficient estimates remain unchanged.

A binary control variable, PatentDummy, for no reported patent applications was included in the linear specification of column (1).

\* p <0.05, \*\* p <0.01, \*\*\* p <0.001

## 2. Public sector patenting activity

U.S. President Jimmy Carter emphasized, in his 1979 Domestic Policy Review, the importance of the transfer of technical knowledge from federal agencies.<sup>3</sup> His focus was, in part, motivation for the passage of the Stevenson-Wydler Technology Innovation Act of 1980. This legislation is considered to be the first public policy to address the transfer of technology developed in federal agencies to the private sector.

To enhance the public sector’s technology transfer mission, Congress amended the Stevenson-Wydler Act with the passage of the Federal Technology Transfer Act of 1986. This act encouraged technology transfer from federal agencies through cooperative research and development agreements (CRADAs). Then, in 1987, as required through President Ronald Reagan’s Executive Order 1259, the Office of Technology Policy within the Technology Administration of the Department of Commerce began submitting biannual reports to Congress on technology transfer activities from federal agencies. We constructed a panel of new patent application data from these reports for fiscal years 2003 through 2014 across 11 federal agencies.

## 3. Theory, data, and econometric results

### 3.1. Conceptual framework

Knowledge production is generally represented in terms of new patent applications (PatApp), R&D investments (RD), and labor (L):

$$PatApp = A RD^\alpha L^\beta \quad (1)$$

where A is a constant, and  $\alpha$  and  $\beta$  measure the contribution of each input to the production of patent applications. Eq. (1) can be rewritten as:

$$PatApp = \exp(\log(A) + (\alpha + \beta)\log(L) + \alpha \log(RD/L)), \quad (2)$$

which suggests that  $(\alpha + \beta)$  and  $\alpha$  can be estimated by a Poisson regression (Hall and Ziedonis, 2001; Czarnitzki et al., 2009) or a negative binominal regression of PatApp on  $\log(L)$  and  $\log(RD/L)$ . Alternatively, when the number of patent applications is non-zero:

$$\log(PatApp) = \log(A) + (\alpha + \beta)\log(L) + \alpha \log(RD/L). \quad (3)$$

### 3.2. Data and econometric results

The annual variables used to estimate Eqs. (2) and (3) are defined in Table 1; descriptive statistics are reported in Table 2.

Estimates of  $\alpha$  from a Poisson regression of Eq. (2) can be interpreted as the patent application elasticity with respect to per capita R&D (Cameron and Trivedi, 1998). The same interpretation applies to  $\alpha$  from Eq. (3). Estimates from the linear model for  $\log(PatApp)$  and the Poisson and negative binominal models for PatApp are shown in Table 3. Estimates from the linear model in column (1) show that a 10 percent increase in agency per capita R&D is associated with a 10.58 percent increase in patent applications. According to the Poisson estimates in column (2), a 10 percent increase in per capita R&D is associated with a 7.01 percent increase in the number of patent applications. Finally, the negative binominal estimates in column (3), show that a 10 percent increase in per capita R&D is associated with a 10.67 percent increase in the number of patent applications. Based on the (pseudo-) log likelihood, the negative binomial regression provides a better fit than the Poisson model. Moreover, the negative binomial and OLS estimates of the elasticity are very close.

In additional regressions not reported here, we accounted for agency and year fixed effects. The year fixed effects were mostly insignificant and including them had a negligible effect on the elasticity estimates. Including agency effects led to a poorly identified model due to the limited variation in the regressors over time within each agency.<sup>4</sup>

## 4. Concluding remarks

Motivating this study is the absence of empirical analyses of a public sector knowledge production function as well as the Administration's emphasis on a ROI estimate of R&D expenditures in federal agencies. Our measure of the patent application elasticity with respect to agency per capita R&D of around 1.06 might be interpreted as a dimension of the social returns to public sector investments in R&D generated through newly patented knowledge. While not a traditional ROI measure as called for in the President's Management Agenda, our findings do

motivate the need for further study of the social impact of publicly funded R&D outputs from federal agencies.

For context, our elasticity estimate is about two times of that presented by Czarnitzki et al. (2009, p. 142), using a model similar to that in Eq. (2) for a sample of private sector Flemish firms. New and potentially patented knowledge in private sector firms might be fully appropriable by the firms, at least for a limited period of time, whereas new and potentially patented knowledge in federal agencies will likely spill over to other federal research establishments as well as to private sector licensees. Thus, the social return to such knowledge generated from federal R&D will likely be greater by more than a factor of two compared to private sector firms because of spillover effects.

### **Declarations of interest**

None.

### **Notes**

☆ This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

\* Corresponding author.

E-mail addresses: [anlink@uncg.edu](mailto:anlink@uncg.edu) (A.N. Link), [mnvanhas@uncg.edu](mailto:mnvanhas@uncg.edu) (M. van Hasselt).

1 See, <https://www.nist.gov/tpo/return-investment-roi-initiative/unleashingamerican-innovation-symposium>. Accessed July 16, 2018.

2 See, <https://www.whitehouse.gov/omb/management/pma/>. Accessed July 16, 2018.

3 See: <http://www.presidency.ucsb.edu/ws/index.php?pid=31628>. Accessed July 19, 2018.

4 These results are available from the authors on request.

### **References**

Cameron, A.C., Trivedi, P.K., 1998. *Regression Analysis of Count Data*. Cambridge University Press, Cambridge.

Czarnitzki, D., Kraft, K., Thorwarth, S., 2009. The knowledge production of 'r' and 'd'. *Econom. Lett.* 105, 141-143.

Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. *Bell J. econ.* 10, 92-116.

Hall, B.H., Harhoff, D., 2012. Recent research on the economics of patents. *Annu. Rev. Econ.* 4, 541-565.

Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979-1995. *Rand J. Econ.* 32, 101-128.