EFFECTS ON REGIONAL EMPLOYMENT FROM NIH AND VENTURE CAPITAL FUNDING: EVIDENCE FROM THE MEDICAL DEVICE INDUSTRY†

[1]HYUNSUNG D. KANG, [2]DAVID N. KU, [3]ELAZER R. EDELMAN

Berry College, Georgia Institute of Technology, Massachusetts Institute of Technology
E-mail: hkang@berry.edu , david.ku@me.gatech.edu, eedelman@mit.edu

Abstract- Funding for scientific advancement comes from two dominant sources: public funds used to generate knowledge, and private sector funds in the pursuit of commercial products. It is not clear how to compare the outputs of these two financial mechanisms because both sectors are motivated by common goods but are also governed by divergent forces. Employment within a geographic region may be a metric of mutual value that can be applied equally to assess the societal impacts of two financing sources. We focused on a single industry, medical devices, which is a robust sector of growth for the United States economy. The US NIH and venture capital community are representatives of public and private capital, respectively. Using information from the Institute for Strategy and Competitiveness at Harvard University, we find that NIH funding creates as many as three times the number of jobs per million dollars compared with VC funding within 5 years of endowments. We also find that a major reason for the higher employment levels from governmental funding is due to an indirect effect from generated intellectual property seen in years 4 and 5, surpassing that of VC funding. These findings imply that policy decisions regarding enhancing regional employment should consider the typology of financial capital and its differential effects effectively.

Index Terms- venture capital, NIH, innovation, Medical device industry, jobs

I. INTRODUCTION

The life sciences drive a vibrant economy. In 2002, expenditures on medical devices totaled $220 billion, and on pharmaceuticals and biotechnology products another $176 billion.[1] Growth in the medical device and diagnostics sector has averaged 8%-9% over the past four years and should expand at 7.2% annually over the next four years.[2] This is a sector where manufacturing remains in the United States.

Similar to other high-technology industries, medical device firms often experience a "valley of death" transitional phase where developing technology is deemed promising yet without validated commercial potential and, therefore, fails to attract capital necessary for continued development.[3] Medical device firms generally do not make significant investments in basic science, deepening their dependence on basic scientific research conducted at universities and leading laboratories. Private financing is emerging as a force in support of academic research, especially in biomedical and life sciences. Whereas public financing, for example, from the National Institutes of Health (NIH) was responsible for 95% of academic funding in 1985 that number has now dropped to 50%.[4] Amongst concerns raised by this transition are loss of independence and intellectual freedom, directed translation surpassing basic scientific focus, perversion of career choice for emerging scientists, and limitations on impact for public good.[5] Though possible legitimate, there has not been sufficient valid data to enable reasonable debate.

This knowledge gap exists, in part, because there was not a consensus metric of impact. Private of corporate funding is seemingly not motivated by the same forces as public financing, and not subject to the same scrutiny, stakeholders, forces, and governing bodies. NIH funding is filtered through scientific peer-review where merit is often based on publications. Utilitarian products are not the goal. In contrast, venture capital (VC) fund companies must make commercial products and services. Patents gain competitive advantage, while publications are not encouraged as they might disclose trade secrets. Profits and return on investment may supersede other concerns. Thus, comparison of output between these funding sources is likely to be skewed should one choose endpoints such as publications, impact factor, profit, or patents. As an alternative, we propose to compare employment growth within a geographic region as a surrogate endpoint common to both sources. For NIH, the scientific achievement might spur the creation of a critical mass of scientists in a research field. For VCs, the formation of a company would bring together teams of people creating commercial products. The comparison of employment within a geographic region is reasonable as face-to-face proximity is useful for collegial collaboration and efficient development and production. In addition, the creation and preservation of local economies is one of the key concerns for entrepreneurial managers and guardians of public good alike.

We hypothesize that NIH and VC funds generate employment in the medical device field. We posit that jobs creation is a mutual metric of impact that can assess the relative merits of each mode of support. We further test two sub-hypotheses: that funding has a direct effect by immediate hiring, and

an indirect of delayed hiring due to intellectual capital advancements; and that employment levels can be shown to be causative by assessing temporal changes over multiple years.

II. METHODS

A. Data

We focused on the medical device industry. We obtained medical device cluster performance data between 1990 and 2001 from the Cluster Mapping Project at the Institute of Strategy and Competitiveness (ISC) at the Harvard Business School. By focusing solely on the medical device industry, we naturally control for tax burdens,[6] public infrastructure,[7] and industry structure.[8] We included all Metropolitan Statistical Areas (MSA) with nonzero medical device employment over the study period yielding medical device firms located in 247 MSAs. Medical device firms tend to stay in their places of origin because these firms typically have regulatory entry barriers, strong intellectual property protection, and high profit margins.[9]

B. Model

Our basic model is the widely used Cobb-Douglas production function to describe the relationship between multiple inputs and the economic output.[10] This formulation is written as:

$$Y_i = \alpha V_i^{\beta_1} N_i^{\beta_2} L_i^{\beta_3} R_i(V_i, N_i)^{\beta_4} E_i^{\beta_5} e^{\varepsilon_i} \quad , \quad (1),$$

where Y_i is the level of employment in a specific region i, V_i is VC funding, N_i is NIH funding, L_i is labor capital, R_i is intellectual capital, E_i is entrepreneurial capital, and e is an error term. α, β, and ε are the output elasticities produced by fitting the inputs to the model. Note that the intellectual capital $R_i(V_i, N_i)$ is a function of V_i and N_i.

Employment serves as the common economic output production for both VC and NIH funding inputs. We investigate the period of five years after VC and NIH funding is endowed in the regions. We control for the level of employment in the previous year (t-1) of the endowments of VC and NIH funding (t) and MSA and year-fixed effects, resulting in our empirical specification being a first-order autoregressive model (AR(1)), with fixed effects. The autoregressive model is a common approach to describe time-varying processes and specifies that the output variable depends linearly on its own previous values.[11] Specifically, we used the following econometrics model to predict the level of employment (Y_{it}) as:

$$Y_{it} = a + b_1 Y_{it-1} + b_2 V_{it} + b_3 N_{it} + b_4 Z_{it} + \mu_{it}, \quad (2)$$

where V_{it} is VC funding, N_{it} is NIH funding, Z_{it} are control variables, μ_{it} is an error term. t denotes the year in which VC and NIH funding is endowed in region i. a and b are parameters.

We estimate the direct effects of VC and NIH funding on the level of employment by including the VC and NIH funding variables and the intellectual capital variable along with control variables in the model. We then estimate the total effects of VC and NIH funding by excluding the intellectual capital from the model. The indirect effects are then calculated as the difference between the total effects and the direct effects.[12]

We evaluate causality among variables using two-stage least squares analysis.[13] More specifically, this analysis examines causality between VC and NIH funding and the level of employment. VC and NIH funding are each instrumented by funding invested in other regions, which is calculated as the sums of VC and NIH funding invested in all regions at t, subtracted by VC and NIH funding invested in the region i and t, respectively.

C. Variables

Our dependent variable is the level of employment in the medical device industry. We used the log of the number of employees in the region i at t rather than actual values to reduce concerns about heteroscedasticity. VC funding is the log of the amount of VC invested in the region i at t. It was collected from the SDC Platinum VentureXpert database published by Thomson Reuters and converted into 2001 constant US dollars. NIH funding was given by the log of the amount of NIH research grants awarded annually from the Office of Extramural Research at the NIH. Both financial variables are collected within the medical device industry.

We proxy an MSA's intellectual capital using the number of medical device patents assigned to each cluster by the USA Patent Trademark Office. The number of science Ph.D.s who graduated from research universities gave an MSA's human capital endowment. The annual data on Ph.D.s were obtained from the National Science Foundation (NSF). Entrepreneurial capital was estimated using the average size of the medical device firms, which is the ratio of the number of employees to the number of firms.[14] We included two types of types of fixed effects: dummy variables that correspond to specific MSAs and years.

III. RESULTS

A. Descriptive Statistics

Descriptive statistics report 2,573 annual records of 247 distinct MSAs in the US medical device industry between 1990 and 2001 (Table 1). The level of employment and employment growth are greater with high VC funding and high NIH funding. Similarly, intellectual capital and human capital are greater with high VC and NIH funding over the entire data set.

B. Direct and Indirect Effects

Table 2 reports our model that predicts the level of employment from the time period in which financial capital were invested and for five years thereafter. Consistent with our predictions, the level of employment prior to funding indicates positive and significant coefficients across models. VC and NIH funding also have positive coefficients across models at 1% level, supporting our hypothesis that VC and NIH funding stimulate employment within a region. Intellectual capital also indicates positive and significant coefficients across models at 1% level. These coefficients are supportive of our predictions that financial capital may directly impact the level of employment and indirectly impact it through enhancing intellectual capital. Human capital shows positive coefficients but significance is not shown. Entrepreneurial capital indicates positive and significant coefficients across all models.

By calculating the total effects in a way shown in the model section, we report the direct, indirect, and total effects of VC and NIH funding on the level of employment. Specifically, Table 3-A reports these effects from VC funding while Table 3-B reports these effects from NIH funding. The direct effects of both financial sources are large and positive. The indirect effects are also significant for both financial sources, indicating the role of generation of intellectual capital. As an unreported and corollary analysis, the statistical Wald test indicates that the coefficients of VC and NIH funding are significantly different.

The regression model can be interpreted quantitatively as the change in employment produced by an incremental change from VC and NIH funding. Our results indicate that a 1% change in VC and NIH funding led to 0.0759% and 0.1322% changes in the level of employment for five years after the endowment of VC and NIH funding and, on average, 0.0126% and 0.0220% changes annually, respectively. Alternatively, the percentages can be converted to actual funding amounts by converting the logarithmic values into natural numbers of the level of employment and the dollar values of VC and NIH funding. The results indicate that 1 million dollars of VC funding creates 12.39 jobs for five years after funding is endowed in the region and 2.06 new jobs annually. In contrast, 1 million dollars of NIH funding creates 35.32 jobs for five years and 5.89 jobs annually after this funding is endowed.

Our results are shown graphically to compare the relative size of total, direct, and indirect effects of two financial sources (Fig. 1). The total (line 3) and direct (line 5) effects of VC funding tends to create a stock of jobs immediately, but this effect gradually decreases. In contrast, the total (line 1) and direct (line 2) effects of NIH funding has a more level pattern as NIH funding is typically evenly allocated over 5 years. Lines 4 and 6 highlight the differences between the indirect effects of NIH and VC funding. NIH funding creates large indirect effects in years 4 and 5 that contribute significantly to continued employment. This increase in indirect effects by enhancing intellectual capital created by NIH funds in later years can be understood such that it requires a substantial amount of time (e.g., here 3 years) because a time lag between scientific research (Research) and applied research (Development) exists. In sum, the graph supports the concept that while the indirect effects of NIH funding are small for the first three years, the intellectual advancements generated by NIH funding becomes important in year 4 and 5, reflected in significantly more regional employment compared with VC funding.

C. Causality

We examine the causality between the both financial sources and the level of employment using two-stage least squires specification. VC funding (or NIH funding) in a certain region is instrumented by VC funding (or NIH funding) endowed in other regions. This analysis does not include year fixed effects that may lead to biased results by interacting with the instrumental variables. The first stage regression in Model 1 predicts the level of employment from VC funding. Likewise, the first stage regression in Model 2 predicts the level of employment from NIH funding. We find that the VC (or NIH) funding in other regions produces negative and significant effects on VC (or NIH) funding within a region. Second stage regressions show that VC (or NIH) funding indicates positive and significant coefficient on the level of employment. Thus, these results support the causality of financial sources to enhance the level of employment.

DISCUSSION

This study provides several implications for those responsible for job creation and economic sustainability. VC and NIH funding both impact employment through immediate hiring, but also by a delayed, indirect effect from increased intellectual capital. NIH funding, however, creates almost threefold more employment growth over an equal infusion of VC funding over a 5-year timeframe. The common metric of employment between public investment in science and private investment in companies shows higher productivity from a long-term investment in generating intellectual capital. This finding is consistent with the justification for the public support of research universities and research centers even in regions that may not enjoy vigorous entrepreneurial activities.[15] Such regions would still provide knowledge advancements and achieve high employment by endowing public funds. Our finding that public capital takes longer to realize its indirect effect on employment calls into question the increasing trend of limiting NIH funding to fewer years. Policy makers may utilize an augmented

perspective about the role of the federal government in the allocation of research support to develop long-term strategic employment initiatives.

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Table 1. Descriptive Statistics.

	(1)				(2)		(3)		(4)		(5)	
	All sample				High VC funding		Low VC funding		High NIH funding		Low NIH funding	
	Mean	S.D.	Min	Max	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
1. Level of employment	5.81	1.84	0.69	10.28	7.64	1.38	5.33	1.63	7.27	1.60	5.31	1.64
2. Employment growth	0.38	0.48	0.00	1.00	0.47	0.50	0.35	0.48	0.46	0.50	0.35	0.48
3. VC funding	3.55	6.95	0.00	21.11	16.97	1.69	0.00	0.00	8.67	8.69	1.82	5.21
4. NIH funding	3.77	6.56	0.00	19.35	9.43	7.75	2.27	5.27	14.87	2.13	0.00	0.00
5. Intellectual capital	10.35	22.17	0.00	243.00	32.59	37.62	4.46	9.03	26.31	32.16	4.93	13.85
6. Human capital	21.47	44.57	0.00	362.00	57.36	68.94	11.96	28.71	53.07	64.52	10.74	28.21
7. Entrepreneurial capital	63.72	87.56	0.67	962.50	68.80	41.59	62.38	96.09	64.69	44.84	63.40	97.92
Number of observations	2573				539		2034		652		1921	

Table 2. Direct Effects of VC and NIH Funding.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable year	Level of employment (t)	Level of employment (t+1)	Level of employment (t+2)	Level of employment (t+3)	Level of employment (t+4)	Level of employment (t+5)
Level of employment (t-1)	0.7249***	0.7722***	0.6860***	0.7566***	0.7357***	0.5195***
	(0.0284)	(0.0247)	(0.0321)	(0.0277)	(0.0286)	(0.0409)
VC funding	**0.0144***	**0.0116***	**0.0108***	**0.0098***	**0.0082**	**0.0065**
	(0.0028)	(0.0025)	(0.0026)	(0.0027)	(0.0034)	(0.0033)
NIH funding	**0.0225***	**0.0173***	**0.0205***	**0.0171***	**0.0161***	**0.0183***
	(0.0040)	(0.0037)	(0.0048)	(0.0041)	(0.0043)	(0.0066)
Intellectual capital	0.0065***	0.0051***	0.0069***	0.0067***	0.0123***	0.0242***
	(0.0018)	(0.0017)	(0.0022)	(0.0022)	(0.0035)	(0.0056)
Human capital	0.0004	0.0004	0.0011	0.0005	0.0000	0.0017
	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0011)
Entrepreneurial capital	0.0034***	0.0023***	0.0022***	0.0014***	0.0012***	0.0013***
	(0.0009)	(0.0006)	(0.0005)	(0.0003)	(0.0003)	(0.0005)
Constant	0.8997***	0.6707***	0.8187***	0.5176***	0.5843***	1.0536***
	(0.0930)	(0.0714)	(0.0879)	(0.0766)	(0.0824)	(0.1095)
MSA and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2573	2349	2128	1913	1697	1489
Number of groups	247	247	243	242	241	239
Overall R^2	0.88	0.88	0.88	0.89	0.88	0.86

Notes. Robust standard errors are presented in parentheses throughout all tables. ***, **, and * denote significance at 1%, 5%, and 10%.

Table 3. Direct, Indirect, and Total Effects of VC and NIH Funding.

3-A. Effects of VC Funding

YEAR	t	t+1	t+2	t+3	t+4	t+5	Total
Direct effect	0.0144	0.0116	0.0108	0.0098	0.0082	0.0065	0.0613
Indirect effect	0.0028	0.0021	0.0020	0.0021	0.0029	0.0027	0.0146
Total effect	0.0172	0.0137	0.0128	0.0119	0.0111	0.0092	0.0759

3-B. Effects of NIH Funding

	t	t+1	t+2	t+3	t+4	t+5	Total
Direct effect	0.0225	0.0173	0.0205	0.0171	0.0161	0.0183	0.1118
Indirect effect	0.0013	0.0019	0.0022	0.0027	0.0052	0.0071	0.0204
Total effect	0.0238	0.0192	0.0227	0.0198	0.0213	0.0254	0.1322

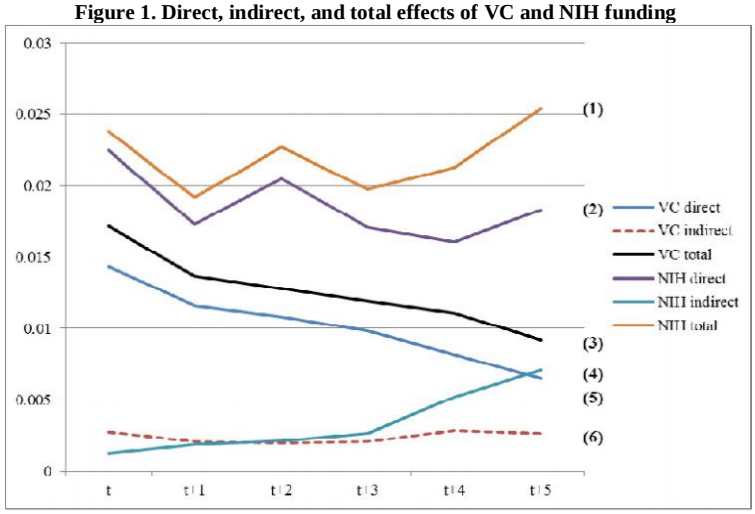
Notes. Indirect effects=total effects-direct effects. All coefficients for direct and total effects are significant at 1% level.

Table 4. Causality between VC and NIH Funding and Employment:

Model	(1)		(2)	
Stage	1st	2nd	1st	2nd
Dependent variable	VC funding (t)	Level of employment (t)	NIH funding (t)	Level of employment (t)
Level of employment (t-1)		0.6947*** (0.0191)		0.7194*** (0.0120)
VC funding (t)		**0.0491*** (0.0176)**	0.0747*** (0.0112)	0.0139*** (0.0027)
NIH funding (t)	0.1768*** (0.0202)	0.0186*** (0.0036)		**0.0271*** (0.0040)**
Intellectual capital	0.1184*** (0.0082)	0.0033 (0.0021)	0.0214*** (0.0051)	0.0064*** (0.0012)
Human capital	0.0340*** (0.0034)	-0.0007 (0.0008)	0.0199*** (0.0021)	0.0002 (0.0005)
Entrepreneurial capital	0.0012 (0.0012)	0.0036*** (0.0002)	-0.0002 (0.0007)	0.0035*** (0.0002)
VC funding in other regions	**-22.3050*** (2.7777)**			
NIH funding in other regions			**-5.6e+02*** (9.0207)**	
Constant	148.4744*** (18.5383)	0.5724*** (0.2100)	3.9e+03*** (62.1157)	0.5010** (0.1996)
MSA fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Number of observations	2868	2573	2868	2573
Prob>χ^2	0.0000	0.0000	0.0000	0.0000
Overall R^2	0.5238	0.8732	0.8066	0.8810

Notes. Robust standard errors are presented in parentheses throughout all tables. ***, **, and * denote significance at 1%, 5%, and 10%.

Figure 1. Direct, indirect, and total effects of VC and NIH funding



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