Employment growth from public support of innovation in small firms.

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Abstract:

Herein, we investigate the impacts of the US publicly funded Small Business Innovation Research (SBIR) program's funding on the overall employment growth of SBIR award-recipient firms. This paper is motivated by the US Congress' continued emphasis on employment growth during its deliberations on the reauthorization of the SBIR program. We set forth a model of employment growth; the model offers a framework through which we can compare a firm's actual level of employment after receipt of an SBIR award and completion of the research project to the level of employment predicted by the firm's characteristics prior to the award. Using data collected by the National Research Council within the National Academies, we estimate our model, and we conclude that, on average, the overall employment effects associated with the SBIR program are large absolutely and relative to dollars of funding, but these effects are, in general, not statistically significant.

Keywords: employment growth | entrepreneurship | innovation | technology | small businesses | economics

Article:

Introduction

The Small Business Innovation Research (SBIR) program was established by the US Congress through the Small Business Innovation Development Act of 1982 (Public Law 97–219). The Act required that all government departments and agencies with external research programs of greater than $100 million establish their own SBIR program and set aside funds equal to, at that time, 0.20% of the external research budget. Today, the set-aside percentage is 2.5%.1

The objectives of the program were then as they are now:

(1) to stimulate technological innovation,

(2) to use small business to meet federal research and development needs,

(3) to foster and encourage participation by minority and disadvantaged persons in technological innovation, and

(4) to increase private-sector commercialization of innovations derived from federal research and development.

These objectives are met through competitive research awards defined by three phases (National Research Council 2004). Phase I awards are small, generally less than $100,000 for the six-month award period. The purpose of Phase I awards is to assist businesses as they assess the feasibility of an idea's scientific and commercial potential in response to the funding agency's objectives.2 Phase II awards are capped at $750,000 and generally last for two years. These awards are for the business to develop its proposed research further, ideally leading to a commercializable product, process, or service.3 Further work on the projects launched through the SBIR program occurs in what is called Phase III, which does not involve SBIR funds.4 At this stage, firms needing additional financing – to ensure that the product, process, or service can move into the marketplace – are expected to obtain it from sources other than the SBIR program.

In 1986, the 1982 Act was extended through 1992 (Public Law 99-443). In 1992, the SBIR program was reauthorized again until 2000 through the Small Business Research and Development Enactment Act (Public Law 102-564). Under the 1982 Act, the set-aside had increased to 1.25%; the 1992 reauthorization raised that amount over time to its current level of 2.50% and re-emphasized the commercialization intent of SBIR-funded technologies (see point (4) of the 1982 Act given above).5 The Small Business Reauthorization Act of 2000 (Public Law 106-554) extended the SBIR program until 30 September 2008. The Congress did not reauthorize the SBIR program by the legislated date of 30 September 2008; rather, the Congress continued to temporarily pass extensions. At the time of this writing, the program has been temporarily reauthorized to 16 December 2011 (H.R. 2121).

Although job growth is not an explicit objective of the SBIR program, current policy discussions about the reauthorization of the program are focusing on that dimension. In fact, the most recent Congressional version of a reauthorization is part of the proposed ‘The Creating Jobs Through Small Business Innovation Act of 2011’.6 , 7

From a broader perspective, economic policies in the USA have been promulgated on the following arguments: (1) public-sector and private-sector investments in R&D support the innovation process (Link and Siegel (2003)); (2) innovation is closely tied to entrepreneurial activity, and new and existing small firms are more entrepreneurial than large firms; and (3) entrepreneurship and innovation are the drivers of competitiveness, new jobs, productivity growth, and overall economic well-being.8

The purpose of this paper is to investigate systematically the direct impact of the public-sector support of R&D on economic well-being, employment growth, in particular. The US policy relevance of this study aside, there has been a conspicuous absence of systematic empirical analyses related to public-sector R&D investments in technology-based entrepreneurial enterprises. The primary reason for this has been the lack of entrepreneurial firm-specific or project-specific data that can uniquely, though empirical models, be related to any particular R&D policies. The excellent empirical studies to date have been constrained to focus on the relationship between R&D and/or innovative policy activity and employment growth at the aggregate level (Pianta 2004; Vivarelli 2007).9 There is a rich related literature about the introduction of technology or innovation and employment growth at the industry and firm levels without regard to the policy that brought about the technology or innovation (Doms, Dunne, and Roberts 1995; Blanchflower and Burgess 1998; Mastrostefano and Pianta 2009). However, this paper takes such investigations a step further by associating employment growth to the promulgation of a specific innovation policy rather than to an economic unit's adoption of others' technology. In the second section, we motivate the paper through an overview of the policy emphasis on innovation in small firms.10 In the third section, we set forth a model of employment growth. The model offers a framework through which we can compare a firm's actual level of employment after receipt of an SBIR award and completion of the research project to the level of employment predicted by the firm's characteristics prior to the award. In the fourth section, we describe the data set used to estimate our model. It contains information on funded Phase II projects over the award years 1992 through 2001 collected in 2005 by the National Research Council (NRC) within the National Academies. Our empirical findings, which we view as the first empirical findings about the public policy support of R&D and consequential employment growth at a firm/project level, are presented in the fifth section, and we offer concluding remarks in the final section.11

Evolution of a policy emphasis on innovation in small firms

Productivity growth in the USA fell during the early 1970s and then again during the late 1970s and early 1980s, as it did in many industrialized nations. The evidence shows that total factor productivity growth during the late 1960s and early 1970s was less than one-half of that during previous decades.12 While there have been many ex post explanations for the slowdown, such as the Organization of the Petroleum Exporting Countries (OPEC) oil crisis in 1973 and industry's slow adjustment to it, there seems to have been a general agreement at that time and shortly thereafter that public policy aimed at stimulating innovation would be effective for stimulating economic growth. As a result, the Bayh–Dole Act was passed in 1980,13 and the R&E tax credit was passed in 1981.14

In addition to the broad-based emphasis on innovation (i.e. the diffusion of patented technologies and the increase in R&D investments from these two legislative initiatives, respectively), a research report from the Massachusetts Institute of Technology's Neighborhood and Regional Change program was independently and coincidently published in 1979. Birch (1979, 1981) concluded in that report that three-fifths of the net new jobs between 1969 and 1976 were created by small firms with 20 or fewer employees. According to Birch (1979, 29), 'On the average about 60 percent of all jobs in the U.S. are generated by firms with 20 or fewer employees, about

50 percent of all jobs are created by independent, small entrepreneurs. Large firms (those with over 500 employees) generate less than 15 percent of all net new jobs'. Also, Birch (1979) reported that approximately 80% of net new jobs were created by firms with 100 or fewer employees.15 Birch's writings became the genesis for a new research field related to the economics of small businesses.16

Reflecting more broadly than on the productivity slowdown in the 1970s – a period of economic disequilibrium – Schultz (1980, 443) noted that

[D]isequilibria are inevitable in [a] dynamic economy. These disequilibria cannot be eliminated by law, by public policy, and surely not by rhetoric. A modern dynamic economy would fall apart if not for the entrepreneurial actions of a wide array of human agents who reallocate their resources [to form new combinations] and thereby bring their part of the economy back into equilibrium.

It could be argued that this constant readjustment toward equilibrium by enterprises stimulates economic growth.17

One might think of the productivity recovery that began in the early 1980s in terms of entrepreneurial responses to disequilibria.18 Or, using the terms of Audretsch and Thurik (2001, 2004), the recovery from the productivity slowdown reflects the end of the era of the Managed Economy (with predictable outputs coming from an established manufacturing sector) and the emergence of the Entrepreneurial Economy.

In the Entrepreneurial Economy, characterized by the emergence of economic agents embodied with entrepreneurial capital, smaller firms have a greater ability to be innovative, or to adopt and adapt others' new technologies and ideas, and thus quickly and efficiently appropriate investments in new knowledge that are made externally.19 Entrepreneurial capital engenders growth in new enterprises, and enterprise growth augments economic growth. Entrepreneurial capital also provides diversity among firms.20 According to Audretsch and Thurik (2004, 144), with an emphasis on small firms within the Entrepreneurial Economy, 'entrepreneurship has emerged [during the late 1970s] as the engine of economic and social development throughout the world'. As a result, it is perhaps not surprising that policy-makers toward the end of the 1970s embraced small firms as engines of future economic growth.

Carlsson (1992) offered two explanations for this shift in policy emphasis toward small, entrepreneurial firms. First, there had been a fundamental change in the world economy beginning in the mid-1970s.21 Global competition was increasing, markets were becoming less fragmented, and the determinants of future economic growth were uncertain. Thus, entrepreneurial leadership adjusted to this disequilibrium. Second, and related, flexible automation was being introduced throughout the manufacturing sector, thus reducing economies of scale as a barrier for entry into many markets and thereby opening the door for smaller, entrepreneurial firms to enter and succeed.

It is not surprising, then, that the policy environment in the late 1970s and early 1980s was receptive to the establishment of the SBIR program.

Model of employment growth

Consider a general continuous-time growth model; apart from random error, the firm grows continuously.22 A firm's employees, y, at time, t, are

$$y(t) = ae^{gt}e^{\varepsilon},$$

where y(t) is the number of employees t years after the firm was founded; a, an estimated parameter of the model, is the start-up number of employees; g is the annual rate of growth of employees; and ϵ is a random error term. The growth rate of employment is a function of various explanatory variables, x 1–x k , given as follows:

$$\frac{(\partial y(t)/\partial t)}{y(t)} = g = b_0 + b_1 x_1 + \cdots + b_k x_k.$$

We refer to Equation (2) as our growth model. Below, we hypothesize particular explanatory variables to be included in the model.

From Equation (1), it follows that

$$\ln y(t) = \ln a + gt + \varepsilon.$$

Substitution of Equation (2) for g into Equation (3) yields

$$\ln y(t) = lna + b_0 t + b_1 x_1 t + \ldots + b_k x_k t + \varepsilon.$$

Equation (4), which we refer to as our employment growth model, is estimated using a cross-section of pre-SBIR award firm information, and then ln y(t) is predicted for 2005 (with pre-award firm characteristics and allowing the firm to grow from its founding until 2005) and that prediction is compared with the survey data on actual post-award employees in 2005.23 The year 2005 is the terminal year of data. Stated differently, the prediction of firm employment in 2005 is a prediction that is based on information about the past before the Phase II project began, and thus it is a prediction not using any information about the funded project.24

Specifically, we determine if having the Phase II award (i.e. receiving SBIR funding) changed the trajectory for the firm that is predicted by the pre-award history using only firm information that does not reflect any knowledge about the Phase II project. Thus, the numerical difference between the firm's actual employment in 2005 with the SBIR award and the firm's predicted level of employment based on pre-award information (used in the estimation of Equation (4)) is the employment impact of SBIR funding on the firm. As stated in the first section, the estimation of this model represents an important step forward in the empirical technology-employment literature because it allows for the estimation of the impact of a specific innovation policy on subsequent employment growth rather than simply the impact associated with the presence of a technology or innovation, from some source, on employment growth.

The NRC database

The Small Business Reauthorization Act of 2000 mandated that, among other things, the NRC conduct ‘an evaluation of the economic benefits achieved by the SBIR program’ and make recommendations to the Congress for ‘improvements to the SBIR program’. The NRC conducted an extensive and balanced survey in 2005 based on a population of 11,214 projects completed from the Phase II awards made between 1992 and 2001 by five agencies: Department of Defense (DoD), National Institutes of Health (NIH), National Aeronautics and Space Administration (NASA), Department of Energy (DOE), and National Science Foundation (NSF). These are the five largest SBIR agency programs, as shown in Table 1, accounting for nearly 97% of the program's expenditures in the survey year.

Table 1. SBIR awards and dollars, fiscal year 2005.

Agency	**Phase I awards**	**Phase I dollars**	**Phase II awards**	**Phase II dollars**	**Total awards**	**Total dollars**
DoD	2344	$213,482,152	998	$729,285,508	3342	$942,767,660
HHS [a]	732	$149,584,038	369	$412,504.975	1101	$562,089,013
DOE	259	$25,757,637	101	$77,852,565	360	$103,610,202
NASA	290	$20,183,648	139	$83,014,853	429	$103,198,501
NSF	152	$15,054,750	132	$64,101,179	284	$79,155,929
USDA	91	$7,195,211	40	$11,738,536	131	$18,933,747
DHS	62	$6,158,240	13	$10,241,202	75	$16,399,442

Table 1. SBIR awards and dollars, fiscal year 2005.

Agency	Phase I awards	Phase I dollars	Phase II awards	Phase II dollars	Total awards	Total dollars
ED	22	$1,646,603	14	$6,749,980	36	$8,396,583
DoC	34	$2,373,433	19	$5,469,846	53	$7,843,279
EPA	38	$2,652,216	14	$3,540,251	52	$6,192,467
DoT	7	$679,154	3	$1,765,468	10	$2,444,622
Total	4031	$444,767,082	1842	$1,406,264,363	5873	$1,851,031,445

Source: U.S. Small Business Administration (2006).

a The NIH is under the Department of Health and Human Services (HHS).

Notes: USDA, US Department of Agriculture; DHS, Department of Homeland Security; ED, Department of Education; DoC, Department of Commerce; EPA, Environmental Protection Agency; DoT, Department of Transportation.

Table 2 shows the distribution of the population of 11,214 projects by funding agency and the percentage of those projects taken by each agency's Phase II projects. The total number of projects surveyed from the 11,214 population of projects was 6408. The number and percentage of respondents from these 6408 surveyed projects are given in Table 3.25 The total number of responding projects was 1916, and the average response rate across all five agencies was 30%. Also, the total number of projects in the final random sample of completed Phase II projects, by agency, is given in Table 3.26 , 27

Table 2. Population of SBIR Phase II projects, 1992–2001.

	Completed Phase II	
Agency	**projects**	**Percentage**
DoD	5650	50.38
NIH	2497	22.27
NASA	1488	13.27
DOE	808	7.21
NSF	771	6.88
Total	11,214	100.00

Table 3. Descriptive statistics on the NRC survey of Phase II awards.

	Phase II		Response rate	Random
Agency	sample size	Respondents	(%)	sample
DoD	3055	920	30	891
NIH	1678	496	30	495
NASA	779	181	23	177
DOE	439	157	36	154
NSF	457	162	35	161
Total	6408	1916		1878

The definitions of the key variables used in our estimation of Equation (4) are given in Table 4. Descriptive statistics on these variables are given in Table 5.

Table 4 is omitted from this formatted document.

Table 5. Descriptive statistics for the variables.

Variable category	DoD (n=755)	NIH (n=391)	NASA (n=155)	DOE (n=140)	NSF (n=141)
Firm characteristics					
firmage	11.61	9.32	12.81	11.74	10.67
	(10.74)	(9.13)	(10.83)	(11.25)	(12.84)
	{0–98}	{0–100}	{1–50}	{0–97}	{0–94}
empt	35.46	20.50	45.66	33.14	23.54
	(61.51)	(38.98)	(78.47)	(60.11)	(37.03)
	{1–326}	{1–301}	{1–376}	{1–451}	{1–201}
empt	59.93	60.41	62.54	55.71	40.99
	(100.51)	(293.38)	(94.83)	(118.51)	(85.43)
	{1–1001}	{1–4001}	{1–521}	{1–851}	{1–751}
diff	0.1359	0.1201	0.02067	−0.1098	−0.3915
	(1.172)	(1.338)	(1.089)	(1.218)	(1.261)
	{−5.940 to 4.244}	{−4.158 to 4.942}	{−3.723 to 4.509}	{−4.008–3.193}	{−3.935 to 1.938}
tsa	7.464	7.233	8.084	7.836	6.894
	(2.810)	(2.586)	(2.923)	(2.732)	(2.466)

	{4–13}	{4–13}	{4–13}	{4–13}	{4–13}
Sbirfnd	0.2159	0.2583	0.2065	0.2500	0.2057
	(0.4117)	(0.4383)	(0.4061)	(0.4346)	(0.4056)
	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}
otherstarts	1.301	1.194	1.787	1.443	1.631
	(2.322)	(1.930)	(3.062)	(1.957)	(2.579)
	{0–18}	{0–18}	{0–18}	{0–11}	{0–18}
busfndrs	0.6927	0.6624	0.6839	0.6357	0.7305
	(1.015)	(1.460)	(1.018)	(0.9760)	(0.9326)
	{0–8}	{0–18}	{0–6}	{0–5}	{0–5}
acadfndrs	1.078	1.325	1.181	1.121	1.142
	(1.280)	(1.064)	(1.360)	(1.226)	(1.205)
	{0–8}	{0–7}	{0–6}	{0–5}	{0–7}
numsvyd	4.106	2.194	5.258	3.379	2.965
	(6.046)	(2.583)	(7.645)	(4.708)	(3.932)
	{1–31}	{1–27}	{1–31}	{1–27}	{1–27}
phIItsvy	13.96	4.798	19.86	10.68	9.156
	(27.46)	(10.51)	(35.14)	(21.68)	(18.77)

	{1–127}	{1–120}	{1–127}	{1–120}	{1–120}
SBIR research variables					
awardamt	718,999.6	653,972.2	567,243.1	682,761.3	375,938.1
	(359,360.4)	(211,411.5)	(73,385.9)	(104,086.4)	(74,389.2)
	{69,673–6,190,970}	{14,834–1,644,022}	{350,000–1,125,000}	{347,681–900,000}	{213,271–500,001}
prjage	7.464	7.233	8.084	7.836	6.894
	(2.810)	(2.586)	(2.923)	(2.732)	(2.466)
	{4–13}	{4–13}	{4–13}	{4–13}	{4–13}
prevphII	8.551	2.120	13.75	7.107	4.355
	(26.69)	(7.241)	(36.56)	(18.49)	(12.57)
	{0–193}	{0–79}	{0–222}	{0–116}	{0–90}
Market variables					
lateeval	0.1444	0.0486	0.09032	0.1286	0.1064
	(0.3517)	(0.2153)	(0.2876)	(0.3359)	(0.3094)
	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}
Geographic variables					
northeast	0.3099	0.3223	0.2903	0.2786	0.3404
	(0.4628)	(0.4679)	(0.4554)	(0.4499)	(0.4755)

	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}
south	0.2490	0.2558	0.2323	0.1643	0.1560
	(0.4327)	(0.4368)	(0.4236)	(0.3719)	(0.3642)
	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}
midwest	0.1250	0.1841	0.09677	0.1429	0.1560
	(0.3258)	(0.3881)	(0.2966)	(0.3512)	(0.3642)
	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}
West	0.3205	0.2379	0.3806	0.4143	0.3475
	(0.4670)	(0.4263)	(0.4871)	(0.4944)	(0.4779)
	{0/1}	{0/1}	{0/1}	{0/1}	{0/1}

Note: The values given are mean, (standard deviation), {range}.

Empirical analysis

Given the limitation that the NRC database contains data on firm employment at only two points in time (when the Phase II award was made t years after the firm was founded and in 2005), the credibility of our empirical approach, of course, depends on the accuracy of the prediction from Equation (4). Furthermore, the accuracy of the prediction from Equation (4), of course, depends on the accuracy of the specification of the growth model, g, in Equation (2).

To increase the robustness of our model, and thus to provide a degree of confidence about the general predictive power of Equation (4), we allow for predictions that not only vary across firms but also vary through time by age for each firm.[28]

Two hypotheses guide our choice of variables to be included in Equation (2), and we tie each variable to economic theory and/or to the extant academic literature.[29] However, these variables are limited in number, and their choice is driven by the availability of data related to the publicly funded project.

Hypothesis 1. The growth rate of employment, g, will eventually decrease with firm age, all else remaining constant.

This hypothesis follows from the general concepts of diminishing returns and learning-by-doing (Arrow 1962) and from the empirical research of Evans (1987). Following Arrow, the economic returns that the firm can earn over time from its resources will eventually decline. The firm, or more specifically the firm's entrepreneur, will learn over time to optimize, but unless the physical capital or the entrepreneurial capital of the firm changes, the impact of this learning-by-doing will diminish. As shown in Table 5, the average age of a funded firm, across agencies, is between 9 and 13 years, and it is likely that in some of the earlier years, the firm's revenues were $0.

Hypothesis 1 could also be viewed as an extension of the empirical work of Evans, who demonstrated that among larger and older manufacturing firms, the growth rate of employment decreased with firm age.

Hypothesis 2. As a complement, and perhaps an alternative to Hypothesis 1 relating growth rate of employment to the age of the firm, research-oriented firms, especially, may benefit from prior market and research experience and avoid any downturn in the growth rate of employment, all else remaining constant.

The more experienced the firm with research, such as, for example, any SBIR research prior to the SBIR award being studied for the firm in our particular sample, the greater the likelihood that the firm will avoid a decline in its employment growth. Of course, research experience can be controlled, and then given that control, the nonlinear effect of the firm's age might still be expected. In that sense, Hypothesis 2 is a complement to Hypothesis 1. But it can also be considered as a potential alternative hypothesis here because age itself will measure experience for the firm that may allow it to avoid any decline in the growth rate of its employment.

Hypothesis 2 follows from the argument that with prior experience, and with the learning-by-doing that has occurred, the entrepreneur has an increased base of tacit and codified knowledge to draw upon to meet the inherent vagaries of research and the inevitable pressures of competition, all else remaining constant.

Following Jovanovic (1982, 649), ‘Firms learn about their efficiency as they operate in the industry. The efficient grow and survive; the inefficient decline and fail’. Thus, each firm in an industry has a level of efficiency and that efficiency, assumed here to be correlated with experience, helps to ensure that it survives and grows (and for the estimation of Equation (4), which follows from Equation (2), we are observing firms that have survived for t years).

Econometric results

In the growth model in Equation (2), we quantify the x’s with the following variables.30 Firm age (firmage), its square, and its cube are included in the growth model to allow for an unconstrained estimation of the effect of age on the growth rate of employment.31 Therefore, in Equation (4), there are the variables t, along with the firm age variable multiplied by t, firm age squared multiplied by t, and firm age cubed multiplied by t. In effect, Equation (4) has as regressors t, t 2, t 3, and t 4.

From Hypothesis 1, the growth rate of employment is, eventually, a decreasing function of the age of the firm. Importantly, when we use our estimated employment growth model in Equation (4) to project the firm's level of employment in 2005 in the counterfactual case that the firm had not received the SBIR award, the predicted rate of employment growth for the firm not only differs across firms but also changes for each firm as the firm ages.

Regarding the firm's previous market and research experience, the following variables are considered: a qualitative variable denoting if the firm was founded at least in part as a result of the SBIR program (sbirfnd), the number of other firms started by the firm's founder(s) (otherstarts), and the number of previous Phase II awards (prevphII).32 From Hypothesis 2, such experience is positively related to the growth rate of employment.

Also included in Equation (2) are controls for the firm's innate innovative capabilities. Specifically, we control for the business (busfndrs) and academic (acadfndrs) backgrounds of the firm's founder(s). In our many interviews (Link and Scott 2000) of the principals (owner/manager/founder/entrepreneur) of SBIR firms, we have found that the experience represented by business backgrounds and academic backgrounds shapes the innovative capabilities of the entrepreneurial firms, and our empirical work (Link and Scott 2009, 2010, 2011) has found these variables to be important for understanding innovative success of the entrepreneurial firms. We also control for how well the firm has evaluated the commercial potential of its SBIR projects during and/or after the completion of the Phase II research (lateeval). Appropriate evaluation of commercial potential is a crucial aspect of an entrepreneurial firm's innovative capability – no matter how sophisticated an invention is, its commercial potential is a key to successful innovation.

Our argument about the importance of the origins of the firm is based on several strands of literature. Sociologists contend that individuals imprint their beliefs and values on situations in which they have control.33 The founding history or background of the firm's founders establishes blueprints or organizational forms that direct, to varying degrees over time, the observed behavior of the organization that they influence.34 From an economic perspective, if the firm's capabilities are influenced, if not determined, by the founder's background, then that background should influence how the firm achieves its comparative advantage.35 And, from a management perspective, the resource-based view of the firm posits that firms are bundles of heterogeneous resources and capabilities, and these resources and capabilities influence the firms' competitive strategy. To the extent, then, that these bundles of heterogeneous resources and capabilities have been influenced by the entrepreneur's blueprint for the firm and attendant skills within the firm, aspects of the firm's and/or founder's background are related to the firm's performance.36 Related to the firm's evaluation of the commercial potential of its SBIR projects, comparative advantage and chosen competitive strategy characterize the firm's 'dynamic capabilities' in the sense of Augier and Teece (2007). We conjecture that employment growth is a manifestation of the firm's dynamic capabilities.37

Finally, variables are included for the geographic region in which the firm operates (northeast, south, midwest, with the effect for west left in the intercept) to control for regional differences in labor markets, competitive environment, and in the availability of venture capital and other sources of external financing to assist the firm's commercialization efforts (National Association of Seed and Venture Funds (2010)).

Equation (4) is estimated with control for response to the project survey; that is, it is estimated as a maximum-likelihood model with selection. Thus, Equation (4) is estimated simultaneously with a model of the probability of response to the project survey. The response model ideally captures the underlying, ultimate explanations for non-response by firms for which awards were sampled. These ultimate explanations include not only behavioral stories about decisions to respond or not, but also structural factors that are correlated with a lack of response to the NRC survey because a firm no longer has valid postal or email addresses.

One project-specific control included in the probability of response model is the amount of the Phase II award (awardamt). A priori, we hypothesize that the amount of the Phase II award will have a positive effect on the probability of response because firms receiving larger awards might be more inclined to respond as a quid pro quo for the greater SBIR support. Moreover, the larger awards may be associated with firms that have stable information about how to contact them.

The firm's number of Phase II awards that were among the population of 1992–2001 projects for sampling in the NRC survey (phIItsvy) is also held constant in the response model.38 This variable is one measure of firm size; a priori, firms that are larger in this dimension are hypothesized to be more likely to respond to the survey because they have the resources available to do so and, perhaps as well, as a quid pro quo for greater SBIR support. Again, the variable may also be associated with stable contact information increasing the likelihood of successfully getting a response for sampled projects.

Also included as a regressor is the number of a firm's Phase II projects that were surveyed by the NRC (numsvyd). On the one hand, this variable might have a negative effect on the probability of response if a larger reporting burden lowers the probability of response. On the other hand, firms with larger numbers of surveyed projects are those that have received more SBIR projects, so they might be inclined to respond because of this fact. Furthermore, such firms might have the resources at hand to respond more readily to the survey than the firms with fewer awards, and, again, the variable is likely to be correlated with the type of institutional stability that avoids a failure of the survey to find its recipient.

Finally, we hypothesize that firms would be less likely to respond to a specific project survey the older the project is because institutional memory about the project may have faded with time or the older set of facts simply may have been more difficult, and hence costly, to assemble and report. Thus, we expect that the project's age (prjage) will be negatively related to the probability of response. Also, other things being the same, such projects could be correlated with a loss of contact information needed to successfully reach the recipient of the survey.

Equation (4) is estimated with robust standard errors to allow heteroscedasticity in the errors in the equation, but also the standard errors are clustered by firm to control for correlation of the errors in the equation for the observations of those firms with more than one Phase II project in the sample.39 The estimation uses probability weights, also called sampling weights.40 The estimated results from Equation (4), with control for response to the survey, are given in Table 6. They show cross-agency differences in the coefficients' sizes, signs, and levels of significance for the variables in our employment growth model – Equation (4).41

Table 6. The results from the firm employment growth model, Equation (4), with control for response.[a]

Variable	**DoD**	**NIH**	**NASA**	**DOE**	**NSF**
Regression model for ln(empt)					
t	0.02896	0.18547	0.15927	0.14967	0.10812
	(0.0404)	(0.0558)*****	(0.0740)***	(0.0509)****	(0.0385)****
$\text{firmage} \times t$	0.00351	−0.00853	−0.00447	−0.00408	−0.00138
	(0.0026)	(0.0053)*	(0.0042)	(0.0024)* *	(0.0018)
$\text{firmage} \times t^2$	−0.00013	0.00018	0.00004	0.00002	4.20×10^{-6}
	(0.00006)***	(0.0001)	(0.00006)	(0.00002)	(0.00002)
$\text{firmage} \times t^3$	8.99×10^{-7}	-1.14×10^{-6}	–	–	–
	(3.46×10^{-7})****	(9.99×10^{-7})			

Table 6. The results from the firm employment growth model, Equation (4), with control for response.[a]

Variable	**DoD**	**NIH**	**NASA**	**DOE**	**NSF**
sbirfnd $\times t$	0.00405	−0.0672	−0.06520	0.01489	−0.05108
	(0.0174)	(0.0166)*****	(0.0338)* *	(0.0240)	(0.0263)* *
otherstarts $\times t$	−0.00152	0.00085	−0.00023	−0.00016	0.01237
	(0.0015)	(0.0048)	(0.0016)	(0.0040)	(0.0042)****
prevphII $\times t$	0.00013	0.00091	−0.00011	0.00063	−0.00056
	(0.00008)*	(0.0006)*	(0.0002)	(0.0004)*	(0.0005)
busfndrs $\times t$	0.00937	−0.00360	0.00180	−0.00287	0.02846
	(0.0024)*****	(0.0055)	(0.0049)	(0.0118)	(0.0193)*
acadfndrs $\times t$	0.00530	0.01595	0.01058	0.01346	0.03217
	(0.0026)***	(0.0057)****	(0.0055)* *	(0.0090)*	(0.0086)*****
lateeval $\times t$	0.01871	−0.01982	−0.04907	−0.00136	0.01771
	(0.0122)*	(0.0384)	(0.0213)***	(0.0227)	(0.0194)

Table 6. The results from the firm employment growth model, Equation (4), with control for response.[a]

Variable	**DoD**	**NIH**	**NASA**	**DOE**	**NSF**
$\mathrm{northeast} \times t$	0.00889	−0.01398	0.01176	−0.01109	−0.02783
	(0.0010)	(0.0246)	(0.0163)	(0.0180)	(0.0153)* *
$\mathrm{south} \times t$	0.03410	−0.03447	0.08332	−0.02988	−0.05539
	(0.0103)*****	(0.0245)	(0.0295)****	(0.0399)	(0.0332)* *
$\mathrm{midwest} \times t$	0.02223	−0.02065	0.03441	0.05006	−0.00853
	(0.0137)*	(0.0268)	(0.0398)	(0.0326)*	(0.0293)
Constant	3.228	2.5344	3.09273	2.1893	3.1811
	(0.2143)*****	(0.3680)*****	(0.4408)*****	(0.3761)*****	(0.3433)*****
Probit model for Response to the survey					
ln(awardamt)	−0.01558	0.13469	0.20504	0.66435	0.83227
	(0.0670)	(0.0839)*	(0.2222)	(0.4057)*	(0.5015)* *
ln(phIItsvy)	0.13862	0.24769	0.04407	0.09363	0.18444

Table 6. The results from the firm employment growth model, Equation (4), with control for response.[a]

Variable	DoD	NIH	NASA	DOE	NSF
	(0.0482)****	(0.0886)****	(0.0638)	(0.1122)	(0.0497)*****
numsvyd	0.03768	−0.00254	0.06455	0.01059	0.01142
	(0.0142)****	(0.0369)	(0.0181)*****	(0.0391)	(0.0139)
prjage	−0.04888	−0.03562	−0.03182	0.00253	0.00367
	(0.0100)*****	(0.0132)****	(0.0194)* *	(0.0310)	(0.0359)
Constant	−0.33888	−2.4513	−3.52892	−9.4935	−11.38831
	(0.9180)	(1.0990)***	(2.97564)	(5.5423)* *	(6.6563)* *
ρ	−0.85080	−0.72823	−0.88485	−0.68498	−0.97940
	(0.0343)*****	(0.1005)*****	(0.0518)*****	(0.1766)***	(0.0218)*****
σ	1.5095	1.2730	1.6128	1.18964	1.90361
	(0.1059)*****	(0.1629)* *	(0.2330)*****	(0.1832)	(0.2436)*****
n	2994	1644	771	430	446

Table 6. The results from the firm employment growth model, Equation (4), with control for response.[a]

Variable	**DoD**	**NIH**	**NASA**	**DOE**	**NSF**
Censored	2239	1253	616	290	305
Uncensored	755	391	155	140	141
Wald chi-squared(df)	313.23 (13)*****	149.61 (13)*****	123.24 (12)*****	280.55 (12)*****	341.60 (12)*****
Log pseudo-likelihood	−5481.05	−2237.56	−1213.99	−904.88	−811.24
Wald chi-squared (1) test of independent equations (ρ=0)	102.51*****	18.69*****	34.33*****	6.35***	18.16*****

Notes: The values given are coefficient (robust standard error).

The NASA, DOE, and NSF samples have too few uncensored observations on different ages to sensibly fit the firmage ×t 3 term.

aExplanation of the total number of observations and the number of uncensored observations is given in Link and Scott (2011). Estimation is done with probability weights (also called sampling weights) and standard errors adjusted for clusters by firm, respectively. The significance levels for ρ and σ are the significance levels for the estimated ancillary parameters from which ρ and σ were derived.

*Significance levels (two-tailed excepting chi-squared): 0.15.

* *Significance levels (two-tailed excepting chi-squared): 0.10.

***Significance levels (two-tailed excepting chi-squared): 0.05.

****Significance levels (two-tailed excepting chi-squared): 0.01.

*****Significance levels (two-tailed excepting chi-squared): 0.001.

Interpretation of the findings

We interpret our econometric results given in Table 6 as support for Hypothesis 1. The DoD example is the most striking, with an increase in the growth rate of employment to approximately t=20 followed by the hypothesized eventual decline to approximately t=65. The decline in the growth rate of employment begins immediately for the other four agencies. We interpret this support for Hypothesis 1 as empirical evidence for the credibility of our growth model in Equation (2) and thus of our employment model in Equation (4).

Empirical support for Hypothesis 2 is mixed across agencies. Among the DoD, NIH, DOE, and NSF firms, at least one measure of previous market and research experience is positive and significant (sbirfnd, otherstarts, prevphII). But one of the three experience variables has a negative and significant estimated coefficient among the NIH, NASA, and NSF firms, contrary to our hypothesis. Only among the NSF firms is there empirical evidence that the number of other firms started by the firm's founder(s) is positively related to employment growth.

Finally, considering the remaining control variables, across all agencies, a dimension of the founders' background – the imprint of their beliefs and values – is positively related to employment growth (busfndrs, acadfndrs).

The survey information about actual firm employment at the time of the sampled award and actual firm employment in 2005 can be used to calculate the actual annual growth rate of employees after the firm receives its Phase II award as42

$$g_{\text{post}} = \frac{(\ln(\text{empt}_{05}^{A}) - \ln(\text{empt}))}{\text{tsa}},$$

where g post is the post-award growth rate, $\text{empt}_{05}^{\text{A}}$ is the actual level of employment in 2005, empt is the number of employees at the time of the award (previously defined), and tsa is the amount of time since the Phase II award (tsa = 2005 – year of the Phase II award; it is, therefore, equivalent to prjage).

Table 7 shows the mean growth rate of firms, by agency. Across all agencies, the mean annual growth rate of post-award employees was over 8%, and by agency, the range of mean growth rates was 5.9–9.2%; over 75% of the firms had a positive growth rate, by agency, with nearly 40% of the firms enjoying growth greater than the agency mean; and, by agency, for about 10% of the firms, employment growth after receipt of the SBIR award was exceptional (growth rates greater than 1 standard deviation above the mean) and those firms averaged nearly a 40% growth in employment (with a range from 31% for the DOE firms to nearly 45% for the NASA firms).

Table 7 is omitted from this formatted document.

Table 8 shows the mean level of actual (i.e. reported in the survey) employment in 2005 and the mean level of firm employment predicted (when t is redefined so that the firm has existed right up to 2005) from the estimated results given in Table 6, by agency. The predictions are the predictions of employment conditional on the response to the survey, because, of course, we have the actual employment outcomes only for those firms that responded to the survey and completed the questionnaires.43

Table 8. Mean actual and predicted employment in 2005 for Phase II SBIR award recipients, by agency.

Agency	n	Actual	Predicted
DoD	755	59.93	31.38
NIH	391	60.41	19.10
NASA	155	62.54	48.71
DOE	140	55.71	34.11
NSF	141	40.99	79.16
	1582		

The information given in Table 8 suggests that among the firms in four agencies – DoD, NIH, NASA, and DOE – there was, on average, positive employment growth that is attributable to the SBIR award. Although SBIR-induced employment growth is, on average, substantial, few of these average gains are statistically significant. As shown in Table 9, the difference between the natural logarithms of actual (A) employment in 2005 and predicted (P) employment – $\mathbf{diff} = (\ln(\mathrm{empt}_{05}^{A}) - \ln(\mathrm{empt}_{05}^{P}))$ – is, at the level of the individual projects' effects on their sponsoring firms' employment, on the whole, not statistically different from zero in any of these four agencies. For NSF, where the average induced growth was negative, none of the individual firm cases for overall firm employment growth induced by the SBIR award are significantly different from zero. However, there are many individual cases for the DoD (10 cases) and NIH (16 cases) samples for which the positive employment growth attributable to the SBIR award is statistically significant at the 5% level for a two-tailed test.

Table 9. Ratio of the logarithmic metric, diff, for SBIR-induced employment growth to the standard error of the forecast.

Range for ratio	**DoD**	**NIH**	**NASA**	**DOE**	**NSF**
≥2	10	16	1	1	0
≥1.5 and <2	25	12	0	3	0
≥1 and <1.5	42	29	5	11	0
≥0 and <1	349	139	79	46	61
≥ −1 and <0	272	153	61	58	64
≥ −1.5 and < −1	39	28	8	18	10
≥ −2 and < −1.5	17	9	0	1	6
< −2	1	5	1	2	0
Total	755	391	155	140	141

Notes: Alternatively, using the usual z-value of 2 to leave a probability of approximately 0.025 in each tail of the distribution, calculating the 95% confidence interval around each observation's predicted employment as the antilogs of the predicted ln(employment in 2005) plus or minus the antilogs of two standard errors of the forecast, we would, of course, have the number of cases for which the actual 2005 employment fell outside of the confidence interval as shown in the first and last rows of the table: 11 cases for DoD, 21 cases for NIH, 2 cases for NASA, 3 cases for DOE, and 0 cases for NSF. Stated differently, although there are in absolute numbers several cases for DoD and NIH for which actual employment is significantly greater than the employment predicted by the counterfactual model, on the whole, the performance of the companies after winning the sampled Phase II award is not typically significantly different from what would have been predicted without the award. There is, nonetheless, quite a range of differences between the actual and the predicted employment, and we have explored the determinants of these differences in Link and Scott (2011). Furthermore, as can be seen in Tables

8 and 10, the average difference between the actual and the predicted employment is positive for DoD, NIH, NASA, and DOE, although these average differences are not statistically significant.

Although, on the whole, the economic effects, as seen in the overall growth in firm employment attributed to the SBIR awards, are not statistically significant, the effects are fairly large absolutely and in terms of the employment effects per million dollars of funding. Table 10 compares, by agency, employment gains per sampled project to the level of funding, and Table 11 shows the total employment gain to all the sampled SBIR award recipients in each agency. As shown in Table 10, for the two agencies where the average employment gains are largest, the average firm employment gain per million dollars of funding estimated with each sampled Phase II project is 45.5 for DoD and 65.0 for NIH.

Table 10. Mean SBIR-induced ‘employment gain’ by agency.[a]

Agency	***n***	**Mean ‘employment gain’ (standard deviation)**	**Mean ‘employment gain’ per million dollars awarded[b] (standard deviation)**
DoD	755	28.54 (89.78)	45.53 (163.61)
NIH	391	41.31 (291.33)	65.00 (378.47)
NASA	155	13.83 (67.80)	24.40 (118.45)
DOE	140	21.60 (114.91)	32.51 (182.07)
NSF	141	na	na

a‘Mean employment gain’ is the average difference between the actual and the predicted employment in 2005 for Phase II SBIR award recipients (rather than the difference in the actual and predicted natural logarithms as given by diff). The firms with more than one Phase II award sampled provide multiple experiments from which to estimate the impact of an award on overall firm growth. However, these experiments produce forecasts of predicted employment in 2005 that are not independently distributed (recall that the errors in the equation in the growth model were assumed to be correlated for sampled awards won by the same firm). To evaluate the significance of the average employment gains reported in the table, we need the standard error for the average forecast. It is the square root of the estimated variance of the average forecast. The average forecast is the weighted sum (with each weight being 1/n) of the n individual forecasts. The variance of the average forecast is then a double sum over the weighted (with each weight being 1/n 2) covariances of the forecasts. Because not all the n forecasts are independently distributed, the standard error of the average forecast is not simply the square root of (1/n 2) (sum of the estimated variances for the n awards). Accounting for the covariances (when there are multiple projects from the same firm) yields a standard error for each of the average gains that is somewhat larger than the average gain itself; hence, the average gains are not statistically different from zero.

b‘Employment gain’ per million dollars awarded is defined for each sampled award as the ‘employment gain’ for the firm winning the award divided by the amount of the Phase II award in millions of dollars.

Table 11. SBIR-induced ‘employment gain’ by agency: using just a single sampled award for each firm.[a]

Agency	***n***	**Mean ‘employment gain’ (standard deviation)**	**Total ‘employment gain’ for responding firms**
DoD	487	22.92 (90.60)	$487 \times 22.92 = 11,162$
NIH	290	32.40 (243.67)	$290 \times 32.40 = 9396$
NASA	123	12.62 (70.75)	$123 \times 12.62 = 1552$
DOE	110	19.10 (99.26)	$110 \times 19.10 = 2101$
NSF	na	na	na

aFor the responding firms with multiple awards, just the first (i.e. oldest) sampled award is used in the table, capturing for all firms the extent to which the initial SBIR award changed each firm's trajectory of employment growth.

Conclusions

The goals of the SBIR program, set out by the Congress in the Small Business Innovation Development Act of 1982, did not include the growth of employment, yet employment growth has become a focal performance variable of the program. In this exploratory paper, we used an original empirical framework with a rich and unique set of data collected by the NRC to investigate whether public support of innovation has in fact stimulated employment growth for the firms that have received SBIR awards.

For four of the five agencies' samples of projects, there are substantial average employment gains attributable to the SBIR award. However, the large average gains, despite being substantial in absolute amount, are not statistically significant. Nonetheless, there are a number of individual cases where the actual employment for the firm exceeds the predicted employment by a statistically significant amount.44

Although SBIR projects are commercially successful, roughly half of the time (Link and Scott 2010), in many cases, the employment growth that would accompany the sales from successful projects may not be observed in the firms performing these projects, but instead will occur elsewhere in the economy. Conceivably, the employment growth to support sales from technologies developed with SBIR funds will be realized in other firms that purchase or license the technology or have manufacturing agreements with the firm that performed the SBIR program research. The NRC data do not allow us to document the employment growth at firms other than the award recipients, but we are able to determine if employment growth for the award recipients is less when the recipients have made commercial agreements allowing other firms to use the technologies created by the SBIR award. In fact, this is the case, as we have shown in Link and Scott (2011), supporting the hypothesis that the SBIR awards may have significant employment effects for firms other than the award recipients.

Our model establishes a novel framework for future empirical analyses that are aimed at assessing the employment growth impact associated with a specific innovation policy.

Applying the model in our analysis of the SBIR program, in this paper, the positive employment growth that we found during exploratory analysis of the employment effects of SBIR awards is not, on the whole, statistically significant. Therefore, our research implies that the claims of employment growth resulting from public support of innovation through the SBIR program should be made cautiously.

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Notes

For a legislative history of the program, including a chronicle of increases in this set-aside percentage, see Link and Scott (2009, 2010, 2011).

'The objective of Phase I is to establish the technical merit and feasibility and potential for commercialization of the proposed R/R&D efforts and to determine the quality of performance of the small business awardee organization prior to providing further Federal support in Phase II'. See: http://grants.nih.gov/grants/funding/sbirsttr_programs.htm.

'The objective of Phase II is to continue the R/R&D efforts initiated in Phase I. Funding is based on the results achieved in Phase I and the scientific and technical merit and commercial potential of the project proposed in Phase II'. See http://grants.nih.gov/grants/funding/sbirsttr_programs.htm. It is not uncommon for Phase II awards to exceed the $750,000 threshold; this is done at the discretion of the Director of an agency's SBIR program.

'The objective of Phase III, where appropriate, is for the small business concern to pursue with non-SBIR funds the commercialization objectives resulting from the outcomes of the research or R&D funded in Phases I and II'. See http://grants.nih.gov/grants/funding/SBIRContract/PHS2008-1.pdf, p. 1.

The percentage increased to 1.50 in 1993 and 1994, 2.00 in 1995, and 2.50 in 1997. Also, the 1992 reauthorization broadened objective (3) to focus also on women: 'to provide for enhanced outreach efforts to increase the participation of … small businesses that are 51 percent owned and controlled by women'.

See the Congressional testimony of Audretsch (2011) and Link (2011).

This emphasis on job growth is not unexpected. In 2009, the National Economic Council (2009, 4) stated that 'Innovation is essential for creating new jobs in both high-tech and traditional sectors. … A more innovative economy is a more productive and faster growing economy, with higher returns to workers and increases in living standards. … Innovation is the key to global competitiveness, new and better jobs [emphasis added], a resilient economy, and the attainment of essential national goals'. This theme was also re-emphasized in National Economic Council (2011).

The premise that technology leads to productivity growth can be traced historically to Adam Smith's The Wealth of Nations. A careful reading of his argument leads one to conclude that improvements in technology result from the division of labor, and a greater division of labor stimulates productivity growth, which in turn leads to overall economic growth.

There is also a rich literature of comparative and cross-sectional studies related to innovation, firm size, and employment. Jewkes, Sawers, and Stillerman (1958) were among the first scholars to shed light on industrial R&D as a source of industrial progress. Of the 61 important inventions they named that were made in the USA and Great Britain during the first half of the twentieth century, more than half could be attributed to entrepreneurs working on their own (i.e. as small firms). More recent research has focused on per period differences in small- versus large-firm behavior. Acs and Audretsch (1990) showed that the average number of innovations per 1000 employees by small firms in the US manufacturing sector was nearly 50% greater for small firms than for large firms.

We thank an anonymous referee for emphasizing that our analysis could also have been motivated based on the rich extant literature related to innovation and employment growth. We fully agree, but we have chosen to motivate it from a policy perspective for at least two reasons. The first reason is that many, if not most, of the empirical studies to date have focused on the aggregate relationship between R&D and/or innovative activity and employment and/or economic growth. See the excellent surveys of this literature by Pianta (2004) and Vivarelli (2007). The second reason is that while the more micro innovation–employment relationship has largely been ignored by scholars, within the current economic environment in most industrialized nations, job growth is one issue that is raised in connection with nearly every public-sector expenditure, and in the USA, a focal public-sector initiative is the SBIR program.

The remainder of this paper is based on Link and Scott (2011), with permission of the W.E. Upjohn Institute for Employment Research.

Kendrick and Grossman (1980) reported annual total factor productivity growth in the private business sector from 1948 to 1966 to have been 2.9%, but only 1.4% from 1966 to 1976. See Link (1987) and Link and Siegel (2003) for an overview of the productivity slowdown literature.

The University and Small Business Patent Procedures Act of 1980, also known as the Bayh–Dole Act, reformed federal patent policy by providing incentives for the diffusion of federally funded innovation results. Universities, in particular, were permitted to obtain titles to innovations developed with government funds. See Stevens (2004) for a historical account of the passage of the Bayh–Dole Act.

The Economic Recovery and Tax Act of 1981 included a tax credit for qualified R&E expenditures in excess of the average amount spent in previous years. See Atkinson (2007) and Tassey (2007) for an overview of the past effectiveness and current state of the R&E tax credit.

In subsequent research, Birch (1987) found that small businesses with less than 20 employees accounted for 88% of all net new jobs over the 1981–1985 time period. Also, according to Birch (1981, 7), ‘Smaller businesses more than offset their higher failure rates with their capacity to start up and expand rapidly’.

Some disagree with Birch's analyses and the findings of others who reached similar conclusions from analyses of firm and aggregated data. See, in particular, Davis, Haltiwanger, and Schuh (1996).

According to Klein (1979), the slowdown in productivity growth in the 1970s can be viewed in terms of a decline in businessmen's ability, or perhaps their desire, to deal with disequilibria.

Innovation and entrepreneurship are closely related concepts. For Schumpeter (1934), the entrepreneur was the persona causa of economic development. The process of ‘creative destruction’ is the essence of economic development and growth, he wrote (Schumpeter 1950); it is a process defined by the carrying out new combinations in production. An underlying hypothesis in the examination of employment growth is that the Schumpeterian process of creative destruction is instigated in substantial part by small, entrepreneurial firms. The impact of the SBIR program on the process is explored in this paper.

Relatedly, the NSF and the U.S. Small Business Administration released the Gellman Report in 1976. It showed that small firms, over the 1953–1973 period, were more innovative per employee than larger firms. This finding complements the more systematic research of Acs and Audretsch (1990).

‘[I]t is the exchange of complementary knowledge across diverse firms and economic agents that yields an important return on new economic knowledge’ (Thurik 2009, 10).

See Link and Tassey (1987) for documentation of this shift.

This model is based on Link and Scott (2006, 2011).

The dependent variable is the natural logarithm of the number of employees (empt) adding 1 for the owner/manager/founder/entrepreneur at the time of the Phase II award, t years after the firm was founded. We have added 1 to the number of employees to include the owner/manager or the founder; especially for the younger firms, the addition is of substantive importance. Obviously someone was employed at the firm and filling out the survey forms in those firms reporting zero employees. We have interviewed the owner/manager/founder/entrepreneur of SBIR firms where that one individual was the firm's president and CEO as well as the chief researcher; he/she ‘wore all the hats’. See Link and Scott (2000) for the case-study examples.

One alternative methodology to evaluate the employment effects attributable to SBIR is random assignment of the awards to those that would have been awarded the award. Another approach could be to find firms that were equally worthy of the awards, except that for limited resources, funds were only available for a subset and the agency randomly decided which firms would receive them. Alternatively, firms could be ranked according to their qualifications for the award and compared with those below the cutoff point. Unfortunately, these valid possibilities are moot because of data limitations.

We thank Dr Charles Wessner of the NRC for making these data available to us for this project.

The NRC surveyed a number of non-randomly selected projects because they were projects that had realized significant commercialization, and the NRC wanted to be able to describe such interesting success stories. These non-randomly selected projects are not considered herein. A detailed description of the data reduction process is given in Link and Scott (2011) or it is available from the authors upon request.

The NRC database does not contain information on projects that were not funded by SBIR, and it does not contain information on projects for which a firm applied for SBIR support but was declined or on comparable projects in firms that did not seek SBIR support. This lack of the so-called matched pairs has been viewed by some (e.g. Wallsten 2000) as a long-standing shortcoming of SBIR data collected either by the NRC as part of its 2000 Congressional mandate or by others. \\ Firms that receive SBIR awards are small and unique in their research and organizational structure. Although Lerner (1999) has compared a large sample of SBIR awardees and matching firms, finding that the SBIR award recipients have higher employment growth, Lerner and Kegler (2000, 321) explained that it is difficult with the matched pair analysis ‘to disentangle whether the superior performance of the awardees is due to the selection of better firms or the positive impact of the awards’. \\ Our structural model in the third section provides a solution to the customary complaint about working with SBIR project data, namely the need for a control group. Our model provides a counterfactual control by its prediction of employment, based on pre-award information only, to be compared with actual employment.

Even if Equation (4) has been specified completely in the cross-sectional context our data allow, if we had a time series of pre-award annual employment for each firm, an employment model using the time series could be specified and our predictions would likely be more accurate. However, on the positive side, given employment data for only two points in time, our approach is novel in that it allows us to overcome the data constraint and estimate a growth model. Certainly, future work related to public policy initiatives to stimulate innovation and employment growth will overcome this data deficiency. With an annual time series for pre-award employment, a growth model would be expected to have smaller standard errors of the forecast, and perhaps the SBIR employment effects that are absolutely large would, for the most part, also be statistically significant.

To our knowledge, our analysis is the first to use a counterfactual model to quantify the relationship between investments in innovation through public support of R&D and employment growth in firms of any size. As such, our empirical analysis is exploratory in nature.

Firm size is not a variable in the model of growth because we estimate it with observations at two times – the beginning when all firms are of the same size and then using size at the time of the award. There is a rich literature related to testing Gibrat's law (see Sutton (1997) for a critique of this literature). Empirically, models that test Gibrat's law that firm growth is proportional to firm size include in the regression model base firm size, S_t , as a regressor. In our model, all firms’ base size, where size is measured in terms of employment, is the parameter a in Equation (1). Thus, with the NRC data, a comparable test of Gibrat's law is not possible.

In the growth model estimated on pre-award information, the age of the firm (firmage) at the time of the Phase II award is measured in years (t). When the estimated employment model is used to predict the counterfactual employment for the firm in 2005, the variables firm age and time are, of course, growing and the predicted annual growth rate for the firm is changing as the firm ages.

The number of previous Phase II awards might be associated with types of firms that are especially likely to grow rapidly given previous SBIR support. Yet, alternatively, such experience could be associated with ‘SBIR mills’ that may have more interest in receiving multiple awards than in pursuing the commercial applications of these awards (Siegel and Wessner, forthcoming; Wessner 2000).

For example, Stinchcombe (1965) is often credited with the general observation that the founding history of an organization (e.g. a firm) directly influences the present structure of the organization. Baron, Hannan, and Burton's (1999, 529) interpretation of Stinchcombe's theory is that ‘… founding conditions become imprinted on organizations and mold their subsequent development’.

Link and Scott (2009, 269) observed that ‘On the one hand, experience in business is expected to be positively associated with commercialization. Yet, on the other hand, the SBIR program could be seen as looking for business entrepreneurs who have innovative ideas yet would not (because of market failures that could include the financial market's failure to support some entrepreneurs lacking business experience yet having socially desirable projects) receive sufficient R&D funding from the private sector alone. Given the SBIR support, such award recipients, vigorously pursuing and championing perhaps their first foray into business, may actually have greater success in commercializing than award winners with business backgrounds’.

Richardson (1972, 888) argued that ‘The capabilities of an organisation may depend upon command of some material technology … [and] organisations will tend to specialize in activities for which their capabilities offer some comparative advantage …’.

The unique characteristics of firms and hence their unique behaviors and performances, even after controlling for the characteristics of the industries in which they operate, were first demonstrated convincingly for large samples of lines of business for manufacturing firms in Scott (1984) and Scott and Pascoe (1986).

Augier and Teece (2007, 179) observed that ‘Dynamic capabilities refer to the (inimitable) capacity firms have to shape, reshape, configure and reconfigure the firm's asset base so as to respond to changing technologies and markets. Dynamic capabilities relate to the firm's ability to proactively adapt in order to generate and exploit internal and external firm specific competencies, and to address the firm's changing environment’.

This variable is the firm's number of Phase II awards in the sampling pool.

The model is estimated using StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP.

Detailed information about the sampling weights is given in Link and Scott (2011), or it is available on request from the authors.

An estimate (ρ) of the correlation between the error in the model of employment and the error in the model of selection and an estimate (σ) of the standard deviation of the error in the employment model are provided and subsequently used with the probability density and probability of selection, as well as the estimates from the employment model, to provide predictions of employment conditional on response to the NRC survey.

$$\mathrm{empt}_{05}^{\mathrm{A}} = (\mathrm{empt})\mathrm{e}^{g_{\mathrm{post}}(\mathrm{tsa})}.$$

The formula for the expected value of the dependent variable conditional on response to the survey is developed and given by Greene (2003, 784). Briefly, the conditional expectation is the inner product of the values for the explanatory variables and the estimated parameters for the employment model plus the product of three factors: the correlation (ρ) of the error in the employment model and the error in the selection model, the estimate (σ) of the standard deviation of error in the employment model, and the ratio of the probability density of response to the probability of response. Thus, we use the ‘ycond’ option with the post-estimation command ‘predict’ for the maximum-likelihood Heckman selection model in StataCorp. 2007. *Stata Statistical Software: Release 10*. College Station, TX: StataCorp LP. Thus, ‘ycond’ calculates the expected value of the dependent variable conditional on the dependent variable being observed (i.e. selected).

Just as Lerner (2010) found that some public programs to stimulate high-potential business ventures have failed while others have succeeded, within the SBIR program that we studied by looking at many of its awards, we found a range of outcomes, from unsuccessful to successful, for the program's effects on employment.

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