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Measuring the Technology Transition Performance by Data Envelopment Analysis

Dr. Toshiyuki Sueyoshi—is a Full Professor at New Mexico Tech and is an internationally well-known scholar in the field of data envelopment analysis. He has published more than 300 articles in top-tier journals such as *European Journal of Operational Research, Decision Support Systems, Energy Policy, Energy Economics*, and *Applied Energy*. Before joining New Mexico Tech, he was a Full Professor at Tokyo Institute of Technology and an Assistant and Associate Professor at the Ohio State University.

Dr. Youngbok Ryu—is a visiting Assistant Professor at New Mexico Tech. Before joining New Mexico Tech, he worked with research institutes in the United States and South Korea. His research appeared in journals such as *STI Policy Review, Journal of Conservation Planning*, and *RAND Health Quarterly*, as well as in the research reports published by RAND Corporation and the National Academies of Sciences, Engineering, and Medicine.

Abstract

This study aims to examine the technology transition efficiency of the U.S. Department of Defense (DoD) Small Business Innovation Research (SBIR) program. To attain it, this study decomposes the process of technology transition into three sub-processes: research and development (R&D), network building, and commercialization. By employing data envelopment analysis (DEA), this study examines the efficiency of each sub-process at firm and agency levels. Subsequently, Tobit regression analyses explore what factors influence the efficiency measures. Based upon the results of DEA and Tobit analyses applied to federal procurement contracts, SBIR awards, and patent data of 252 technology-based small businesses, this study finds that firm-level efficiency ranges from 30% to 60%, while agency-level ones are between 70% and 90%. Commercialization efficiency is relatively higher at the firm level, whereas network building efficiency is relatively higher than others at the agency level. Efficiency-related significant factors include the number of employees, degree of technology distance relative to DoD and prime contractors, location, industrial focus, and primary affiliation with DoD agencies.

Introduction

This study is interested in the technology transition performance of the U.S. Department of Defense (DoD) Small Business Innovation Research (SBIR) program. One of the primary SBIR objectives is to use small businesses to meet federal research and development (R&D) needs. We pay attention to the DoD because technology-based small businesses (TBSBs) can provide the DoD with suggestions to technical problems that are critical in the national security. This is a rationale on why the DoD implements the SBIR on a contract basis when compared to the grant-based SBIR agencies such as the National Institutes of Health (NIH) and the National Science Foundation (NSF). When the SBIR projects conducted by selected TBSBs are successfully completed, the DoD expects the procurement of the project outcomes to acquire cutting-edge technologies and meet warfighters' various needs.

In the same vein, technology transition is broadly defined as knowledge flow from private sectors (e.g., TBSBs) to public sectors (e.g., DoD).[1] More specifically, TBSBs are involved in transitioning their abstract ideas to concrete products or services that can be used by warfighters by identifying technical feasibility, conducting R&D, and commercializing R&D outcomes.[2] While dual-use technologies have a potential to be commercialized in private markets, the target technologies in this study are the primary objects of federal procurement contracts. To facilitate the transition of SBIR technologies, the DoD (including its components such as Air Force, Army, and Navy, and their research labs) implements various programs such as Mentor–Protégé Program (MPP) and Commercialization Readiness Program (CRP), where SBIR awardees can build networks and develop their R&D and marketing capacities. In this sense, the technology transition is the results of orchestrated efforts made by public–private partnerships.

Performance may have various meanings, often combined with the term "measurement." It is socially constructed and as a result, it has various implications to different people, particularly when considering numerous stakeholders. This study looks at performance from economic and operational perspectives, where performance is measured through efficiency (productivity or the ratio of output to input). By measuring the performance, this study seeks to determine the efficiency of technology transition performed by DoD components and their SBIR awardees.

The remaining sections of this research discuss research background; describe data, conceptual framework, and methodology with a focus on the DEA approach; show our empirical results obtained in this study; and conclude with summary and policy implications.

Background

The SBIR program started in mid-1980s as a public venture to capitalize on the technical capacity of TBSBs in the attempt to regain the U.S. technological and economic leadership. Evidenced by a series of successful reauthorizations, the SBIR program has contributed to the national competitiveness by achieving its four major goals: 1) stimulating technological innovation; 2) using small businesses to meet federal R&D needs; 3) fostering and encouraging participation by minority and disadvantaged people in technological innovation; and 4) increasing private-sector commercialization of innovations derived from federal R&D (Small Business Administration, 2014). In particular, as the private sector's capacity surpasses the public sector in some technical areas (e.g., information and communication technology and biotechnology), the SBIR program functions as a conduit for the DoD to take advantage of the technical superiority of TBSBs.

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[1] Technology transition may be viewed as an opposite concept of technology transfer where knowledge flows from the public sector (e.g., national labs and universities) to private sector (e.g., large and small businesses).

[2] For instance, Dobbins (2004, p. 14) defines technology transition as "the process by which technology deemed to be of significant use to the operational military community is transitioned from the science and technology environment to a military operational field unit for evaluation and then incorporated into an existing acquisition program or identified as the subject matter for a new acquisition program."

With the passage of multiple reauthorization acts, the SBIR program has been extended in terms of size and coverage. Both the number of SBIR-participating agencies and the amount of their set-aside budgets have increased over time.[3] Currently, all federal agencies with a considerable R&D function (specifically, those who have more than $100 million extramural R&D budget) are taking part in the SBIR program, whose annual total budget is greater than $2 billion. Of them, the DoD is responsible for about half of the total budget (approximately $1 billion), followed by National Institutes of Health, Department of Energy, National Science Foundation, and National Aeronautics and Space Administration. Within the DoD, Air Force, Navy, and Army represent 32%, 23%, and 18%, respectively, while all other components such as Defense Advanced Research Projects Agency (DARPA), Missile Defense Agency (MDA), and Chemical and Biological Defense (CBD) account for 27%.

Although the overall program is harmonized by the Small Business Administration (SBA), the program is independently operated by each participating agency (National Research Council, 2008). As such, each agency seeks to achieve its own objectives in addition to the aforementioned four main goals. In particular, the DoD makes contracts with TBSBs to procure technologies generated through the SBIR program while other federal agencies provide grants to SBIR awardees. In addition, DoD components and their research labs take extensive measures to generate SBIR topics, encourage TBSBs to apply for their programs, assist selected firms in developing their new ideas and building entrepreneurial networks, and provide additional funds to address the “valley of death” issue.

Drawing on the significant program budget and its contribution to the national competitiveness, the SBIR program has been assessed occasionally by chartered organizations such as the National Academies of Sciences, Engineering, and Medicine and the RAND Corporation and has been studied by many scholars. While those assessment reports and academic papers measure and analyze the economic impacts of the SBIR program in a systematic and empirically robust manner, their approaches tend to rely on surveys and econometrics-based methods. Particularly, assessment reports are based on extensive surveys of SBIR awardees, interviews with program officers, and case studies of selected companies. Most SBIR-related papers are published by economists using various parametric techniques.

This research attempts to narrow down the SBIR-related scope to technology transition by considering federal procurement contracts alone and excluding sales in the private market. This study also seeks to delve into multiple data sources (e.g., SBIR awards, patents, and federal procurement contracts) and combine parametric with non-parametric techniques. Particularly, this study endeavors to measure the performance of DoD

[3] SBIR participating agencies include the Department of Agriculture, Department of Commerce–National Institute of Standards and Technology and National Oceanic and Atmospheric Administration, Department of Defense, Department of Education, Department of Energy, Department of Health and Human Services–National Institutes of Health, Department of Homeland Security, Department of Transportation, Environmental Protection Agency, National Aeronautics and Space Administration, and National Science Foundation. They are required to set aside 3.2% of their R&D budget for the SBIR program as of Fiscal Year 2017. Refer to https://www.sbir.gov/about/about-sbir

components and their SBIR awardees by employing data envelopment analysis (DEA) and explore what factors influence the performance.

Research Assumptions

To shed light on how efficiently the DoD SBIR outcomes are transitioned from R&D and network building stages to commercialization stage (procurement contracts) and what factors affect the efficiency, we address the following research questions in this study:

1. What are the efficiency measures of technology transition at firm and agency levels across R&D, network building, and commercialization stages?
2. What factors influence the efficiency level?

Originality of this study: To better understand the technology transition process, this research stratifies the process into three sub-processes: (a) R&D, (b) network building, and (c) commercialization. Specifically, existing studies related to innovation productivity tend to identify the process as a single black box or two linear stages consisting of R&D and commercialization sub-processes. Their inputs also tend to focus upon only human and financial capitals. As the importance of social capital emerges (particularly to small businesses that wish to obtain necessary resources through social networks), this study incorporates the network building sub-process into the model. To do that, this study attempts to use technological distance as an input and the number of connections to funding agencies as an output.

By employing DEA, we identify firms (and agencies as an aggregation of those firms) as decision-making units (DMUs) that can create entrepreneurial opportunities on their own.[4] By investing human, financial, and social capitals in R&D and network building, firms can generate useful knowledge and networks, both of which are essential for commercialization. While public- and private-sector investments tend to be evaluated via financial indicators such as benefit/cost ratio and return on investment (ROI), this study measures relative efficiency scores by comparing DMUs on the efficiency frontier with those not on the frontier in terms of technology transition.

This research also explores if "serial innovators" are equivalent to "serial entrepreneurs." To do that, this study looks into the relationship between R&D and commercialization sub-processes by comparing their efficiency scores and also shedding light on the role of network building sub-process in the overall entrepreneurial process.

Approach

Data

This study keeps track of 252 elite DoD SBIR awardees. The firms have been awarded SBIR Phase II funding (as a follow-up of Phase I) from the DoD over the period of 2001 to 2010. Out of 2,889 firms that have won the DoD SBIR awards during the same period, 252 firms have filed more than 15 patents that meet the criteria of "serial innovators" (Hicks & Hegde, 2005). Given that half of all SBIR awardees have filed no patent application

[4] There are arguments over how to look at entrepreneurial opportunities: exogenous vs. endogenous (Audretsch, 2008). In the regard, this study follows the *Endogenous Entrepreneurship Hypothesis*.

at all and most of them have filed one single patent application, the 252 firms can be regarded as “elite TBSBs” or “serial innovators.”

To measure the technology transition performance of those small firms, this study collected various secondary data related to

- DoD SBIR awards from the SBA’s SBIR database (www.sbir.gov)
- Federal procurement contracts from the Federal Procurement Data System—Next Generation (www.fpds.gov)
- SBIR awardees’ demographics from the System for Award Management (www.sam.gov)
- Patent data from the Korea Intellectual Property Rights Information Service (www.kipris.or.kr) based on the U.S. Patent and Trademark Office’s original source.

Table 1. Descriptive Statistics

Variable	Definition	Obs.	Mean	Min	Max
FPC	Action obligation of federal procurement contract ($million)	252	98.14	0.19	2,433.14
PAT	Number of patent applications	252	49.61	15	1,251
SEC	Eigenvector centrality in the SBIR funding network	252	.024	0.001	0.045
ASA	Amount of SBIR awards ($million)	252	5.78	0.29	103.27
EMP	Number of employees	252	86.17	2	480
TDD	Technological distance from DoD’s patent portfolio	252	0.3845	0.0002	0.8805
TDP	Technological distance from prime contractors’ patent portfolio	252	0.4650	0.0005	0.9733
AGE	Age of firms	252	22.17	2	122
MFG	Dummy (0 or 1) whether manufacturer of goods or not	234	0.509	0	1
LOC	Dummy (0 or 1) whether locating in leading states or not	252	0.718	0	1
HTC	Dummy (0 or 1) whether belonging to high-tech industries or not	252	0.861	0	1
SEQ	Dummy (0 or 1) whether belonging to core or periphery in the SBIR funding network	252	0.302	0	1
HUB	Dummy (0 or 1) whether located in HUBZone or not	252	0.012	0	1
RUR	Dummy (0 or 1) whether located in rural areas or not	252	0.385	0	1
MOW	Dummy (0 or 1) whether owned by minority	252	0.040	0	1
WOW	Dummy (0 or 1) whether owned by women	252	0.044	0	1
VOW	Dummy (0 or 1) whether owned by veteran	234	0.034	0	1

In terms of data collection, it is worth noting that there is a time lag between input-related data and output-related data to avoid simultaneity. While the former is based on the year 2010, the latter was collected at the end of 2015. Generally, it takes considerable time to transition technologies from SBIR Phase II (R&D stage) to Phase III (commercialization stage). The time lag varies by firms' internal capacity (e.g., marketing expertise) and external environment (e.g., industry), but it has been identified as five to seven years.[5]

Conceptual Framework

To reply to research question 1), this study dissects the process of technology transition into three sub-processes: a) R&D, b) network building, and c) commercialization. Most existing literature that applies DEA to the innovation research tends to use the single-stage model. In other words, they view the innovation process as a big black box—an innovation production function with multiple inputs (e.g., R&D expenditure and the number of scientists/engineers) and outputs (e.g., the number of patents/publications and sales). For instance, Kuah and Wong (2011) examined university-level research efficiency using research grants and the numbers of research staff and students as inputs and the numbers of publications, awards, and intellectual properties as outputs. Sueyoshi and Goto (2013) explored the firm-level efficiency linking R&D expenditure to the corporate value (represented by Tobin's q). There are also some studies looking into the regional- and national-level innovation efficiency by employing a single-stage DEA model.

Recently there have been a few attempts to shed light on the black box by dividing the whole innovation process into two sub-processes (considering R&D and commercialization sub-processes only), which may not fully cover the complex innovation process and assumes that those two sub-processes are completely linear (see Carayannis et al., 2016; Chen et al., 2018; Wang et al., 2016).

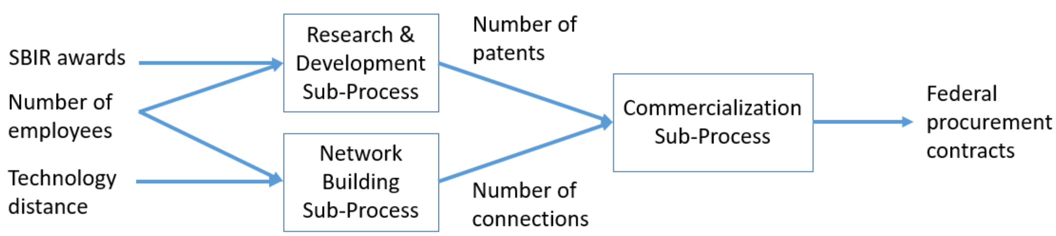

Figure 1. Technology Transition Process

While those studies may work well with well-established large companies, their approach may not apply to relatively nascent small firms that have limited financial and human resources and lack social capital. In the start-ups, for instance, workers should have multitasking capacity (e.g., working for R&D and network building tasks simultaneously) (Appelbaum & Kamal, 2000). In terms of financing, they tend to have minimal funding from family, friends, and other acquaintances and look for public support (e.g., SBIR) before receiving private funding from angel investors, venture capital, and crowdfunding sources

[5] For instance, Xue & Klein (2010) put a five-year time lag between predictors and dependent variables to examine the effect of regional determinants on entrepreneurial activities. Maine & Seegopaul (2016) indicate development/commercialization times, faced by ventures, for software and advanced materials are 0 to 2 and 5 to 15 years, respectively. National Research Council (2009) presents a table regarding time elapsed between an SBIR award and sales (p. 239). Of 378 SBIR projects, 349 (92.33%) and 372 (98.41%) projects led to sales in five- and seven-year elapsed times, respectively.

(Cooper, 2003). Some studies confirm that the receipt of SBIR funding provides a positive signal (in terms of technical excellence and market potential) to private-sector funders (Meuleman & De Maeseneire, 2012).

One missing component of the existing literature is the role of social capital. Although many studies have underlined the importance of entrepreneurial social networks for the better performance of TBSBs, there is little literature that incorporates the network building component into the innovation process in the realm of DEA. As shown in Figure 1, specifically, this study seeks to add "Network Building Sub-Process" into the overall technology transition process by placing the sub-process in parallel with "R&D Sub-Process."

SBIR awards. The amount of SBIR awards is positively associated with the number of patent applications (Ryu, 2017). As a public venture capital, the SBIR program provides a substantial amount of money to TBSBs. Generally, the program offers $150,000 for Phase I awardees to explore technical feasibility and $1 million for Phase II awardees to conduct R&D. Additionally, the DoD SBIR program provides Phase II+ funding to facilitate the technology commercialization. These financial resources are critical for TBSBs to secure funding for developing their new ideas and overcome the valley of death.

Number of employees. Human resources with not only technical/commercial knowledge but also interpersonal skills are essential for R&D as well as network building (Man, Lau, & Chan, 2002). Particularly, because valuable scientists or engineers contribute to firms' specialized knowledge stocks, human resources play a pivotal role in the long-run competitiveness of TBSBs (Hsu, 2008). In addition, high-quality human resources can develop firms' social capital by building and broadening their entrepreneurial networks that may be a conduit for financial resources, information, and other resources (Sorenson, 2017).

Technological distance. Technology-based collaborations (e.g., strategic alliances and joint ventures) tend to take place to fill the gap by supplementing complementary assets (Gilsing et al., 2008). This may apply to the DoD to satisfy warfighters' demands that cannot be addressed with in-house capacity but can be solved externally. TBSBs with that capacity can be a solution to the DoD and be placed in the advantageous position in building networks with the DoD. In this regard, technological distance means how dissimilar technologies TBSBs have relative to the DoD. Following Choi and Yeniyurt's (2015) approach, this study calculates the technological distance (TD) using the following formula: $TD_{ij} = 1 - F_i F_j' / [(F_i F_i')(F_j F_j')]^{1/2}$ where TD_{ij} = technological distance; F_i = vector of firm i's patent portfolio (i.e., distribution of patent applications across patent classes); and F_j = vector of DoD's patent portfolio.

Number of patents. Results of industrial R&D usually lead to the filing of patents because organizations want to protect their novel and non-obvious ideas with industrial utility and to recoup their R&D investment through either enjoying the appropriability of their technologies (via a legal system, particularly intellectual property rights) or licensing their technologies to other entities. Thus, the number of patents (granted patents or patent applications) is widely used as an indicator for technological innovations.[6] Specifically, this is true for TBSBs that look for external funding, because filing more patents enables them to boast their technological strength and attract investors (Conti, Thursby, & Thursby, 2013).

Number of connections. Firms' social capital may be manifested in the number of ties they have generated (Casson & Giusta, 2007). In the military technology market, particularly, connections with the DoD are critical in that the market is characterized by monopsony (i.e., the DoD is a single buyer in the market). However, all DoD components do not have equal capabilities to procure private-sector technologies. They may vary with the size of DoD components. For instance, Air Force, Army, and Navy may have stronger purchasing power than other relatively small components (e.g., MDA and CBD). In this vein, this study uses the eigenvector centrality in the SBIR funding network rather than just the degree centrality (Powell, Koput, Smith-Doerr, & Owen-Smith, 1999). Since the funding network is bipartite (i.e., connections between a group of TBSBs and a list of federal agencies without connections between TBSBs and between federal agencies), TBSBs with many links to more influential agencies (e.g., three services) have higher scores than those with links to less influential agencies.

Federal procurement contracts. The final output of technology transition is represented by the federal procurement contracts (Edison, 2010). TBSBs may be able to increase the amount of contracts by developing more attractive technologies (represented by the number of patents) and/or by building wider and stronger networks with large DoD components (represented by the number of connections).

Method

To answer the first research question, this study employs DEA. As a non-parametric technique, DEA does not make assumptions about the form of the production function. Since Sueyoshi and Goto (2018) provide a detailed description on DEA, this article drops the description.

To measure the technology transition performance, this study particularly employs a modified two-stage DEA. At the first stage, R&D and network building sub-processes take place in tandem. At the second stage, the commercialization sub-process follows. To understand better this whole process as a starting point, this study intentionally uses parsimonious DEA models with two inputs and one output across stages. For the R&D sub-process, specifically, a simplified knowledge production function with SBIR awards (as a financial capital input, particularly R&D expenditure), the number of employees (as a human resources input), and the number of patent applications (as an intermediate R&D output) is used. For the network building sub-process, a novel network production function with technology distance (as a competitive network asset input), the number of employees (as a shared human resources input), and the number of connections (as an intermediate network building output) is developed. In other words, SBIR awards and technology distance play as

[6] There is some argument about the validity of patents as a proxy for technological innovations. Main arguments include that all inventions do not necessarily result in the patent filing and the propensity to file patents varies by industry. In this study, all sample firms are aware of the importance of patents given that they have filed more than 15 patents despite their small size and limited resources. A majority of sample firms also focuses on high-tech industry, where patenting activity is very common.

a dedicated input that is devoted to a specific sub-process while the number of employees functions as a shared input that is used for both sub-processes. In the commercialization sub-process, a function for integrative market production has two intermediate outputs (the numbers of patents and connections) as inputs and federal procurement contracts (i.e., the ultimate goal of technology transition) as a final output.

To address research question 2, this study employs tobit models because the efficiency scores are non-negative and censored to the right (Ji & Lee, 2010). The maximum value of the efficiency scores is 1. $y_i = y_i^* \; if \; y_i^* < 1$ & $1 \; if \; y_i^* \geq 1$ where y_i^* Is a latent variable: $y_i^* = \beta x_i + u_i$, $u_i \sim N(0, \sigma^2)$.

Results and Discussion

Firm-Level DEA Analysis

Drawing on DEA analyses, this study identified three different types of efficiencies—R&D, network building, and commercialization—of 252 TBSBs who have won the DoD SBIR funding. In terms of R&D performance, they are “serial innovators” by meeting the criterion of more than 15 patent applications. However, it may be questionable if they are also “serial entrepreneurs” based on Joseph Schumpeter’s conceptualization of entrepreneurs as “efficiency-inducing change agents” (Hsu, 2008). Particularly, given that entrepreneurs require not only R&D capacity but also network building and commercialization capacities, they need to be more than just inventors or inefficient innovators. They need to optimize the efficiency of knowledge, network, and market productions by managing financial, human, and social capitals better.

Relative to the most efficient performers on the frontier, a majority of firms show relatively low efficiency scores in R&D and network building (on average 32.65% and 29.81%, respectively) while demonstrating relatively high efficiency scores in commercialization (on average 57.01%).[7] Although it is not directly comparable, the commercialization efficiency of this study is placed in the range of other studies’ efficiency scores. For instance, Průša (2009) looked into the efficiency of small businesses in Czech Republic over the period of 2002 to 2005, and the average efficiency score was 39.60%. Alvarez & Crespi (2003) explored the efficiency of Chilean manufacturing firms (micro, small, and medium-sized), and the average efficiency score was 65%. Grilo & Santos (2015) examined the efficiency of Portuguese TBSBs in the business incubators from 2009 to 2011, and the average efficiency score was 75.15%.

Overall, there is some room for improvement among the DoD SBIR awardees (67.35%, 70.19%, and 42.99% for R&D, network building, and commercialization sub-processes, respectively). One obvious way to address this issue would be to benchmark the efficient firms on the frontier.

[7] To determine if those three efficiency scores are statistically different, this study employs the Wilcoxon signed-rank test rather than paired t-test because the assumption on the normal distribution is not needed. According to the Wilcoxon test, all three types of efficiency scores are different from each other.

Table 2. Statistics of Firm-Level Efficiency Scores

Efficiency	Obs	Mean	Min	Max
R&D	252	0.3265	0.0154	1
Network building	252	0.2981	0.0132	1
Commercialization	252	0.5701	0.0618	1
Average	252	0.3982	0.1009	0.9608

Examining Figure 2, R&D and network building efficiency scores show a positive skew, while commercialization and average efficiency scores indicate a somewhat negative skew and symmetrical distribution, respectively.

Table 3 summarizes the scale efficiency scores in the sub-processes of R&D, network building, and commercialization. A majority of R&D and commercialization inefficiencies stem from increasing returns to scale (IRS) while approximately equal portion of network building inefficiencies arise from both IRS and decreasing returns to scale (DRS).

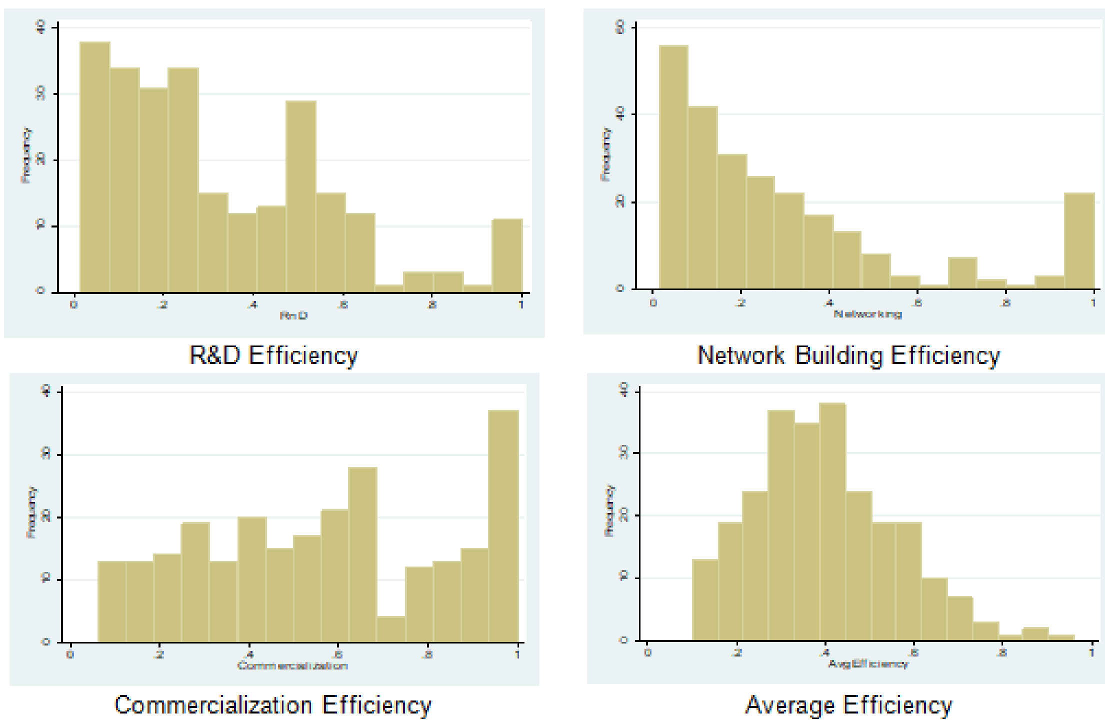

Figure 2. Histograms of Efficiency Scores
Note: Average efficiency is computed based on the arithmetic mean

Table 3. Scale Efficiency Scores

Efficiency	Obs	RTS			SE		
		IRS	CRS	DRS	Mean	Min	Max
R&D	252	224	4	24	0.4819	0.0298	1
Network building	252	118	3	131	0.5909	0.0304	1
Commercialization	252	251	1	0	0.0724	0.0002	1

Note: RTS = returns to scale; IRS = increasing returns to scale; CRS = constant returns to scale; DRS = decreasing returns to scale; and SE = scale efficiency

Figure 3 shows the location of each firm depending on their three types of efficiency scores. Firms in the first quadrant (e.g., Hansen Engine Corp. and Benedict Engineering Co.) demonstrate better performance in both R&D and network building. Those in the second quadrant (e.g., Polaronyx and TPL) show better performance in network building but there is room for improvement in R&D. Those in the fourth quadrant (e.g., Rapid Pathogen Screening and T Networks) have to maintain their R&D efficiency but need to focus on optimizing their network building. Those in the third quadrant have to improve their performance in R&D as well as network building.

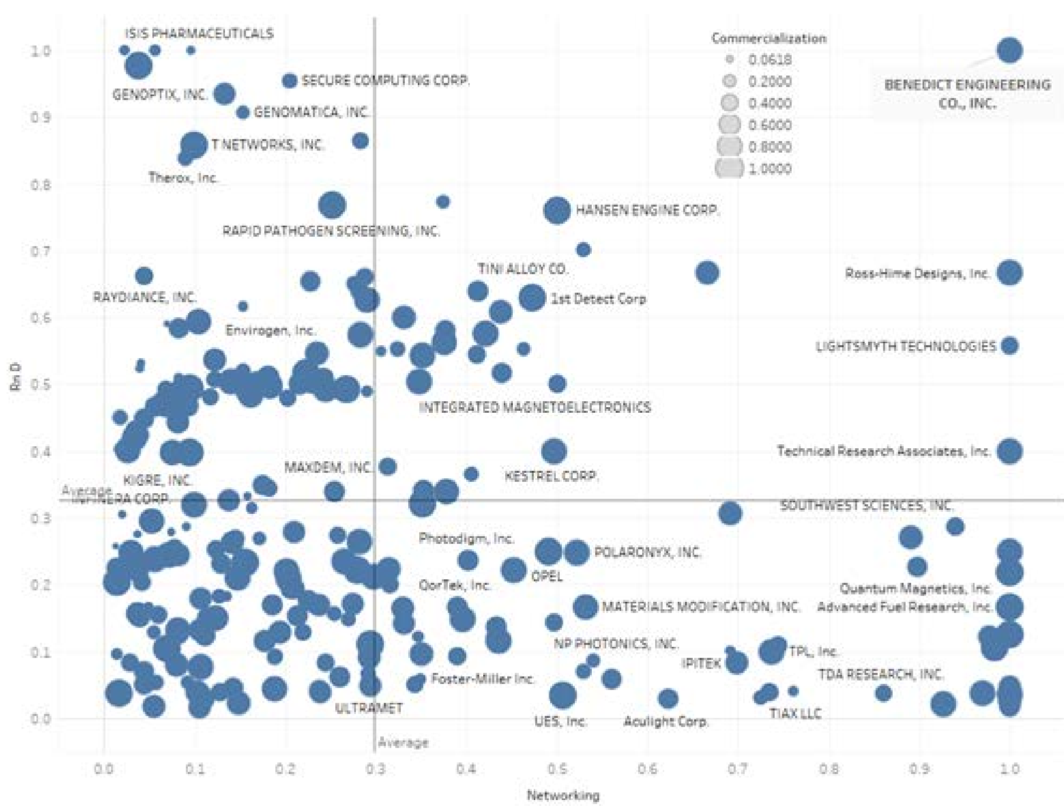

Figure 3. Firm-Level Efficiency Scores in the Four Quadrants

Note: x-axis = network building efficiency; y-axis = R&D efficiency; and bubble size = commercialization efficiency

Agency-Level DEA Analysis

To determine agency-level efficiency scores, this study aggregated 252 firms into eight agencies depending on their primary affiliation.[8] On average, agency-level R&D, network building, and commercialization efficiency scores are 71.07%, 90.13%, and 79.46%, respectively (see Table 4). It means that

1. Two inputs (SBIR awards and the number of employees) for the R&D sub-process could be reduced by 28.93%;
2. Technology distance and the number of employees for the network building sub-process could be reduced by 8.87%; and
3. The number of patents and the number of connections could be reduced by 20.54%.

Table 4. Statistics of Agency-Level Efficiency Scores

Efficiency	Obs	Mean	Min	Max
R&D	7	0.7107	0.3601	1
Network building	7	0.9013	0.5086	1
Commercialization	7	0.7946	0.3989	1
Average	7	0.8022	0.5265	1

Overall, CBD leads in all three types of efficiency scores. It has the highest efficiency score (1.00), followed by DARPA (0.88), Army (0.84), Air Force (0.80), MDA (0.80), and Navy (0.76). As shown in Table 5 and Figure 4, DARPA and MDA perform better in both R&D and network building than commercialization, while Air Force and Navy demonstrate better performance in network building and commercialization than R&D. Army shows balanced efficiency scores in the three types.

Table 5. Efficiency Scores by Agency

Efficiency	Air Force	Army	CBD	DARPA	MDA	Navy	OSD
R&D	0.43	0.82	**1.00**	**1.00**	**1.00**	0.36	0.37
Network building	0.99	0.81	**1.00**	**1.00**	**1.00**	**1.00**	0.51
Commercialization	**1.00**	0.88	**1.00**	0.65	0.40	0.93	0.70
Average	0.80	0.84	**1.00**	0.88	0.80	0.76	0.53

Table 6 describes agency-level DEA results (particularly, SE) by sub-process. In the R&D sub-process, there are a minimal level of scale inefficiencies in Air Force and Navy stemming from IRS, while there are some scale inefficiencies in Army, MDA, and Office of the Secretary of Defense (OSD) arising from DRS, implying that these three agencies are

[8] For instance, 1st Detect Corp. has won the SBIR awards only from the Office for Chemical and Biological Defense, so this company is aggregated to CBD. In the case of Cascade Designs, it has won the SBIR awards from both Army ($1.23 million) and Navy ($0.77 million), but it is aggregated to Army since it has received much more funding from Army than Navy. So, Cascade Designs' primary affiliation is determined Army.

larger than optimal scale. In the network building sub-process, all scale inefficiencies result from IRS, particularly in CBD and OSD, meaning that CBD and OSD operate at sub-optimal scale. In the commercialization sub-process, there is some scale inefficiency in Army stemming from DRS, meaning that Army is larger than optimal scale. Considerable scale inefficiencies, on the other hand, result from IRS among CBD, DARPA, MDA, Navy, and OSD, meaning that they operate at sub-optimal scale. Overall, Air Force tends to operate at optimal scale whereas Army is larger and Navy is smaller than optimal scale. It suggests that Army needs to reduce its scale (particularly, in R&D and commercialization sub-processes), but Navy needs to increase its scale (particularly, in network building and commercialization sub-processes). CBD and DARPA tend to be sub-optimal while MDA and OSD have unbalanced scale between R&D and commercialization sub-processes. It suggests that CBD and DARPA need to beef up scale (particularly in commercialization sub-process), and MDA and OSD need to scale down R&D but scale up commercialization.

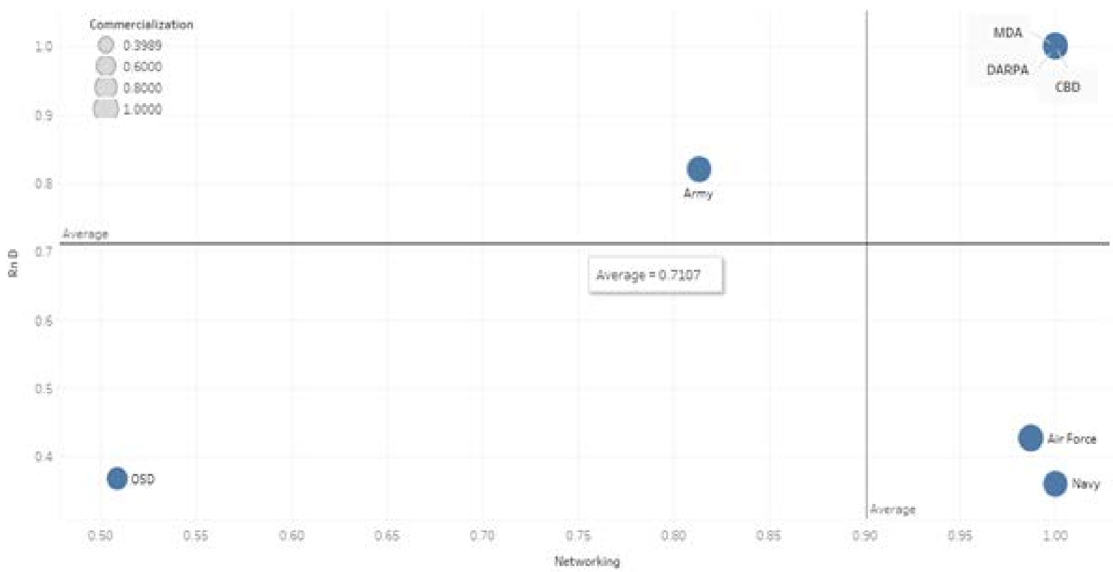

Figure 4. Agency-Level Efficiency Scores in the Four Quadrants

Note: x-axis = network building efficiency; y-axis = R&D efficiency; and bubble size = commercialization efficiency

Table 6. Agency-Level DEA Results by Sub-Process

Agency	R&D Sub-Process				Network Building Sub-Process				Commercialization Sub-Process			
	TE_{CRS}	TE_{VRS}	SE	RTS	TE_{CRS}	TE_{VRS}	SE	RTS	TE_{CRS}	TE_{VRS}	SE	RTS
Air Force	0.42	0.43	0.99	IRS	0.95	0.99	0.96	IRS	1	1	1	CRS
Army	0.72	0.82	0.87	DRS	0.76	0.81	0.93	IRS	0.78	0.88	0.89	DRS
CBD	1	1	1	CRS	0.51	1	0.51	IRS	0.39	1	0.39	IRS
DARPA	1	1	1	CRS	1	1	1	CRS	0.13	0.65	0.20	IRS
MDA	0.82	1	0.82	DRS	1	1	1	CRS	0.27	0.40	0.67	IRS
Navy	0.35	0.36	0.98	IRS	0.88	1	0.88	IRS	0.61	0.93	0.66	IRS
OSD	0.22	0.37	0.61	DRS	0.05	0.51	0.11	IRS	0.20	0.70	0.28	IRS

Note: TE = technical efficiency; TECRS = TE under CRS model; TEVRS = TE under VRS model; SE = scale efficiency (TECRS/TEVRS); RTS = returns to scale; IRS = increasing returns to scale; DRS = decreasing returns to scale; and CRS = constant returns to scale.

Firm-Level Tobit Analysis

To identify which factors influence the three types of efficiency scores, this study employed Tobit regression analyses. Since Tobit models also follow the ordinary least squares (OLS) linear regression assumptions, non-normality and heteroscedasticity can generate biased coefficients (McDonald, 2009). Given that the distributions of all three types of efficiency scores are skewed, this study uses the normally distributed average efficiency scores (see Figure 3).[9] To address the heteroscedasticity issue, this study also employed Tobit Multiplicative Heteroscedasticity Regression (Shehata, 2011). For the Tobit regression analysis, various firm-level variables were used, including demographics (e.g., *AGE* and *MOW*), location (e.g., *RUR* and *HUB*), industry (e.g., *IPC*), and government affiliation (e.g., *DOD*). Depending on a list of independent variables, Models I, II, III, and IV were constructed and tested.

Drawing on the results of analyses (see Table 7):

1. *Number of employees (EMP).* EMP is negatively associated with the technology transition performance of TBSBs. It implies that EMP is one of the critical sources for inefficiencies.
2. *Technological distance relative to DoD (TDD).* TDD is negatively associated with the average efficiency. It implies that homophily is more dominant than heterophily in the technology transition process, particularly in building the network between the DoD and TBSBs. In other words, the DoD (and its research labs) may generate the SBIR topics with which they are familiar, and seek TBSBs that have similar patent portfolios to them. With similar technological background, the DoD and TBSBs tend to build and develop their networks more efficiently. It may be because the DoD calls for

[9] We also checked the normality of the average efficiency scores using *qnorm* Stata command.

incremental/evolutionary innovations or component technologies (that are on the technological trajectories of the DoD) from small businesses while relying on large companies for disruptive/revolutionary innovations and architectural technologies (that are not on the DoD's technological path).

3. *Women ownership (WOW).* WOW has a positive coefficient but the 95% confidence interval ranges positive and negative numbers, implying WOW's inconclusive (positive or negative) association with the average efficiency. One aspect on the positive side is that government agencies have encouraged acquisitions from women-owned TBSBs. Many policy and grant programs implemented by the SBA (including women's business centers), DoD, and Girlboss Foundation, for instance, tend to place women-owned businesses in the advantageous position in funding and procuring technological products and services. For instance, the DoD has made over $230 billion of federal procurement contracts with women- and minority-owned businesses over the period of 2010 to 2016 (GAO, 2017).[10] Given that one of the SBIR objectives is fostering and encouraging participation by minority and disadvantaged people in technological innovation, women-owned TBSBs may capitalize on their status to transition their technologies better.
4. *Industry (IPC and HTC).*[11] *IPC_A* (human necessities)[12] and *B* (performing operations and transporting)[13] are positively associated with the average efficiency while *IPC_G* (physics)[14] and *H* (electricity)[15] are negatively related. TBSBs working in IT industry (i.e., IPC G and H) tend to file more patents than those in other industries, but they also tend to use patents as a defensive means (Ziedonis, 2008). As a consequence, IT companies are less likely to use their patents for the commercialization purpose. In other words, they may generate too many patents when compared to the amount of federal contracts they made. On the contrary, TBSBs in medical and mechanical industries (i.e., IPC A and B) tend to file less patents but use them better than IT industries (Schankerman, 1998). In addition, *HTC*[16] is positively associated with the efficiency, indicating high-tech areas create more technology transition opportunities to TBSBs.

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[10] In Fiscal Year 2010, $8.1 billion of federal procurement contracts were obligated to women-owned businesses. In addition, $5.8 billion was obligated to both minority- and women-owned businesses.
[11] Out of 252 firms, 32 (13%) specialize in H01L industry. The next most popular technical area is G02B (17 firms, 7%) – optical elements, systems, or apparatus.
[12] Patent Class A includes wearing apparel, footwear, medical device, life-saving, etc.
[13] Patent Class B includes mechanical metal working, machine tools, ship, aircraft, nanotechnology, etc.
[14] Patent Class G includes measuring, testing, computing, signaling, information storage, nuclear engineering, etc.
[15] Patent Class H includes electric power, electronic circuitry, electric communication, etc.
[16] While *IPC* represent high-level technical areas (as a one-digit patent classification code), *HTC* indicate a set of more specific technical areas across multiple industries (as a four-digit code).

5. *Location (LOC, RUR,* and *STE).* Location-related factors are negatively associated with the efficiency. Overall it means that TBSBs located in leading states (e.g., NY, MI, OH, and TX) or rural areas (communities with less than 50,000 population) are more likely to be inefficient. On the other hand, it implies that TBSBs situated in lagging states but urban areas are more likely to be efficient in the technology transition. It may be because there are more DoD-related facilities (e.g., military bases and research labs) in the lagging states and TBSBs in the central area of those states take advantage of their geographic proximity.
6. *Primary affiliation with the DoD agencies (DOD)*. Although the degree varies by agencies, TBSBs' affiliation with them is negatively associated with the efficiency. As shown in the previous sub-sections, many firms and their affiliated agencies are relatively inefficient. Particularly, TBSBs primarily affiliated with MDA and OSD tend to be more inefficient.

Conclusion

Summary

The objective of this study was to examine the technology transition efficiency of the DoD SBIR program. Through the program, TBSBs provide the DoD with solutions to technical problems that are critical to national security. Because of not only its contribution to technological innovation and national security but also its significant amount of federal spending, it is important to examine the technology transition efficiency of the DoD SBIR program at firm (SBIR awardees) and agency (e.g., Air Force, Navy, and Army) levels.

Instead of using a simple efficiency metric such as ROI, this study employed a DEA approach to measure the relative efficiency of firms and agencies in comparison with the most efficient ones on the efficiency frontier. To do that, this study kept track of 252 "serial innovators" that have been awarded the DoD SBIR awards, and calculated their efficiency score across three stages: R&D, network building, and commercialization. At each stage, this study used various input (e.g., the amount of SBIR awards and the number of employees) and intermediate and final output indicators (e.g., the number of patent applications and the amount of federal procurement contracts).

Based on the computed efficiency scores, this study explored which factors influence the scores. To do that, this study employed Tobit regression models using firm-level characteristics such as location, industrial focus, and affiliated agency.

Findings of this study are as follows: First, firm-level efficiency scores range from 30% to 60%, while agency-level scores are between 70% and 90%; 2) commercialization efficiency is relatively higher than the other two efficiencies at the firm level, whereas network building efficiency is relatively higher at the agency level; second, efficiency-related significant factors include the number of employees, degree of technology distance relative to the DoD, location (particularly, leading versus lagging states and urban versus rural areas), industrial focus (particularly, information and communication technology versus medical and mechanical technology), and primary affiliation with the DoD agencies.

Table 7. Results of Tobit Regression Analyses

Efficiency	Model I		Model II		Model III		Model IV	
PAT	-0.0001	(-0.0014***)			-0.0002	(-0.0019***)		
SEC	-0.6394	(-0.5872)			-0.4845	(-0.2115)		
ASA	0.0002	(0.0009)			-0.0001	(0.0006)		
EMP	-0.0006***	(-0.0004***)	-0.0006***	(-0.0006***)	-0.0005***	(-0.0003***)	-0.0006***	(-0.0006***)
TDD	-0.1786***	(-0.1532***)	-0.2627***	(-0.2624***)	-0.1661***	(-0.1394**)	-0.2347***	(-0.2176***)
TDP					-0.0377	(-0.1394)		
AGE					0.0004	(0.0003)		
WOW			0.0755*†	(0.0609)	0.0598	(0.0649)		
MOW					0.0680	(0.0493)		
VOW					-0.0015	(-0.0030)		
MFG					-0.0168	(-0.0383**)		
IPC_A							0.1674***	(0.1847***)
IPC_B							0.0819**	(0.0954***)
IPC_G			-0.0620**	(-0.0677***)				
IPC_H			-0.0587**	(-0.0638***)				
HTC					-0.0051	(-0.0041)	0.1058**	(0.1228***)
LOC					0.0023	(-0.0028)	-0.0983***	(-0.0844**)
RUR			-0.0369*†	(-0.0344*†)	-0.0206	(-0.0271)	-0.0464**	(-0.0425**)
HUB					0.0928	(0.1540*)		
STE_AL							-0.2124**	(-0.1917**)
STE_MI							-0.1534*	(-0.1452*†)
STE_NC							-0.2649***	(-0.2511***)
STE_NJ							-0.0953*†	(-0.0860*†)
STE_NY							-0.1096**	(-0.1123**)
STE_OH							-0.1066**	(-0.0990**)
STE_TX							-0.0815**	(-0.0661*†)
DOD_AirForce							-0.1756**	(-0.1738**)
DOD_Army							-0.1771**	(-0.1660**)
DOD_DARPA							-0.1748**	(-0.1711**)
DOD_MDA							-0.2135***	(-0.2022***)
DOD_Navy							-0.1892**	(-0.1817***)
DOD_OSD							-0.2866*†	(-0.2854**)

Note: Statistical significance = *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.10$
† = 95% confidence interval ranges between negative number and positive number
Numeric values in the parenthesis represent heteroscedasticity-adjusted coefficients.

Policy Implications

The technology transition performance of DoD SBIR awardees is relatively low. Averaged R&D, network building, and commercialization efficiency scores are between 30% and 60%. A majority of R&D inefficiencies arise from IRS, implying that firms operate at sub-optimal scale. As the SBIR budget increases over time, federal agencies may have two options: 1) increasing the number of awards, or 2) scaling up the amount of awards. To improve the R&D inefficiencies by scaling up the firms, it may be better to pursue the second option rather than the first one, while minimizing the crowd-out effect. Another way to address this issue is for federal agencies to cooperate with state and local governments or the private sector. For instance, state governments can offer SBIR match grants to TBSBs located in their states. DoD agencies can provide the SBIR awardees with opportunities to attract more private R&D funds such as venture capitals and angels, or to work with prime contractors (generally, well-established large companies with sufficient R&D funding). In this sense, the DoD needs to strengthen the current Mentor–Protégé Program and make efforts to involve more prime contractors in the program.

The network building inefficiencies stem from both IRS and DRS. To address the IRS-inducing inefficiencies, government agencies need to offer more networking events that aim to make matches between the SBIR awardees and government agencies that can afford to procure small business products or services. To that end, the DoD needs to take advantage of the network of procurement technical assistance centers and procurement technical assistance programs located across states. In the case of DRS-inducing inefficiencies where the SBIR awardees have larger networks than the optimal scale, the DoD needs to pay attention to the SBIR mills that highly rely on their connections with program officers and politics (Lerner, 2000). If the excessive network scale arises from the SBIR awardees' generic technologies, government agencies may help them transform to specialized suppliers with strong connections to a few influential agencies.

Like R&D inefficiencies, most commercialization inefficiencies result from IRS. To increase the scale of SBIR awardees to the optimal level, the government agencies need to expand the procurement quota from small businesses or promote more agencies to procure more small business products or services. For instance, it is encouraging that the Air Force SBIR program is recently collaborating with General Services Administration in SBIR Phase III acquisition from small businesses ("New Agreement Allows Air Force," 2018).

At the agency level, while three services have relatively low R&D efficiency scores, other DoD components such as DARPA, CBD, and MDA have relatively low commercialization efficiency scores. Both inefficiencies tend to arise from IRS, so these services need to beef up the R&D scale, whereas other DoD components need to ramp up the commercialization scale. Given that the SBIR program budget is slated to increase over time, the SBA needs to sustain this increasing trend through active coordination with Congress. On the other hand, relatively small–sized DoD components need to conceive a plan that facilitates the procurement of small business products or services.

In addition, Tobit analysis results suggest that TBSBs' internal capacity (particularly how to manage employees) and external environment (particularly where to locate their companies and in which industry they are nested) are important for their technology transition performance that is represented by the average of three efficiency scores. Given that they are also essential ingredients for firms' strategy formulation, the DoD agencies need to imbue their SBIR awardees with a strategic mindset through various training and mentorship programs.

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