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Two-Stage, Dynamic Data Envelopment Analysis of Technology Transition Performance in the U.S. Defense Sector

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Two-Stage, Dynamic Data Envelopment Analysis of Technology Transition Performance in the U.S. Defense Sector

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Abstract

This study aims to measure the technology transition performance of 252 small firms that won the U.S. Department of Defense (DoD) Small Business Innovation Research (SBIR) Phase II awards from 2001 to 2010 and filed more than 15 patents ("elite DoD SBIR awardees") and to explore how social, industrial, and geospatial contexts influence the performance. For the purpose, we first employ two-stage, dynamic Data Envelopment Analysis (DEA) that incorporates network building sub-process as well as R&D and commercialization sub-processes and then utilize Tobit regression analysis. We find two implications. One of them is that more than a quarter of the elite DoD SBIR awardees are efficient and their efficiency scores of about a half are higher than 60%. The other is that their strong networks with big-sized funders and their high-tech concentration are positively associated with the technology transition performance whereas locational factors are not significantly related with the performance.

Introduction

As a complex system, regional, industrial, or national innovation system involves many players who are interdependent with each other (Dougherty, 2017; Katz, 2016). Generally, the public sector (e.g., federal agencies with a substantial amount of extramural R&D budget) and non-profit organizations (e.g., private foundations) provide R&D funding to knowledge producers or technology developers. Universities and national and corporate research laboratories produce knowledge or develop technology depending on the funding. The private sector (e.g., small businesses) capitalizes on the produced and transferred knowledge and makes revenues and profits that are sources of investment and incentives to the players. While the segmentation of role responsibilities worked well in the era of the public sector-dominant R&D (particularly, in the wartime), the boundaries that were drawn for each player have been blurred (Kaufmann & Tödtling, 2001; Lundberg, 2013). For instance, the Department of Defense (DoD) develops technologies in house through Air Force, Army, and Naval research laboratories, outsources high-risk, high-return R&D projects to universities or corporations through the Defense Advanced Research Projects Agency (DARPA), and acquires state-of-the-art technologies from the private sector through the Defense Innovation Unit (DIU) and Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs. It stresses not only technology transfer (e.g., a knowledge flow from the DoD to small businesses) but also technology transition (e.g., a knowledge flow from small businesses to the DoD). It is especially true at the current times when the private sector is leading in many high-tech areas such as information and communications technology and biotechnology (Ryu, 2017). Nonetheless, most literature has paid attention to the former (particularly, technology transfer from universities or national laboratories to the private sector) whereas a paucity of literature has studied the latter (particularly, technology transition from small businesses to the public sector).

Innovation itself is also complex in that it entails various processes and sub-processes at multiple levels (Dias et al., 2014; Pelz, 1985). At the product level, for instance, it should pass along a series of product development processes from ideation to prototyping to testing in order to create a new product. To sell the new product, it should get through a chain of value-added processes from inbound logistics to operations to outbound logistics to marketing and sales to service. Innovation is affected by other upper-level characteristics (Autio et al., 2014; Tidd, 2001). For instance, organizational culture and institutions (e.g., incentive system) at the firm level, state government's business environment (e.g., tax credits and support for the public universities) at the regional level, and federal government's policy programs (e.g., R&D spending and procurement) at the national level can influence innovation. Given that innovation is affected by various contexts, policy-makers are responsible to reconstruct the contexts to attract more innovators to their jurisdictions and to grow their economies. Innovators (particularly, technology-based small businesses), on the other hand, tend to search better locations to operate their businesses considering not only government's support but also other factors (e.g., access to market and benefits resulted from agglomeration). In this vein, decision-makers who seek technological innovation in their organizations or jurisdictions may need to evaluate their current performance and find some entities to benchmark in order to improve their performance (Guan et al., 2006; Sun, 2011). That is why Data Envelopment Analysis (DEA) has been widely used to measure the innovation performance and identify leading entities at the firm-, regional-, and national levels.

With this background, this study seeks to (a) assess technology transition performance (as a special case of innovation) of technology-based small businesses that received the DoD SBIR awards, and (b) examine how social, industrial, and geospatial contexts influence the performance. For the purpose, we first employ two-stage, dynamic DEA to deal with the sub-processes of innovation in measuring technology transition performance and then Tobit regression analysis to determine what factors drive the performance.

The remaining sections of this research are organized as follows. The Literature Review section discusses a literature study. The Methodology section describes the methodology used in this study. The Empirical Study section summarizes empirical results. The last section concludes this research along with summary and future research.

Literature Review

DEA Applications to Measuring Innovation Efficiency

DEA, to date, has been utilized to measure innovation efficiency at multiple levels such as organization (e.g., firm and university), region, and country. At the microscopic level, for instance, Sueyoshi & Goto (2013) examined the firm-level efficiency by associating R&D expenditure with Tobin's q as an indicator for the corporate value. Kuah & Wong (2011) measured the university-level R&D efficiency by using multiple inputs (e.g., research grants and the numbers of research staff and students) and outputs (e.g., the numbers of publications, awards, and intellectual property rights). At the mesoscopic level, Zabala-Iturriagagoitia (2007) looked at the performance of regional innovation systems based on the European Innovation Scoreboard (EIS) data. At the macroscopic level, Sharma & Thomas (2008) explored the cross-national R&D efficiency of 22 countries. While they offer useful information about which entities lead in terms of the innovation performance and which entities can serve as benchmarks, they have some limitations: (a) they tend to regard the innovation process as a single big black box (and thus it is hard to understand the specifics of the innovation and to incorporate the time-consuming nature of the innovation), (b) although they seek to shed light on the specifics, they tend to focus on one specific segment of the whole value chain of innovation (and thus it is difficult to understand the interdependence between the innovation sub-processes), (c) they tend to stress only traditional production factors such as labor and capital materialized by financial resources (R&D personnel and expenditure in our case) ignoring the aspects of social capital, and (d) they tend to be general (particularly in the regional and country-level studies) and thus their frameworks need to be tailored to solving specific program-related performance measurement issues.

To address the aforementioned limitations (a) and (b), multi-stage and/or dynamic network DEA approaches have been recently developed and applied to measure the innovation efficiency. At the firm-level, for instance, Chun et al. (2015) and Wang et al. (2016) used two-stage DEA models by decomposing the innovation process into R&D and marketing/commercialization sub-processes and analyzed the innovation efficiency of Korean and Chinese companies. At the regional level, Chen and Guan (2012) and Chen et al. (2018) looked at the innovation efficiency of Chinese regions based on two-stage network DEA models. At the national level, Carayannis et al. (2016) and Kou et al. (2016) measured the innovation efficiency of European or OECD countries. All of these studies incorporate the systematic and dynamic aspects of the complex and non-linear innovation process. Along with the emerging concepts of Regional Innovation System (RIS) as well as the National Innovation System (NIS), those studies can better inform regional- and national-level policy-makers who desire to invigorate the economies of their jurisdictions through technological innovation. While achieving the desired result in the limitations (a) and (b), they are not still sufficient to address the remaining limitations (c) and (d).

As the position of this study is to fill this gap in the existing literature, we seek to incorporate the social capital dimensions into a two-stage, dynamic DEA model. Moreover, we seek to customize a general DEA model into addressing the technology transition issue, a special case of the innovation process but one of the objectives that the DoD SBIR program desires to achieve. Through the proposed DEA model, thus, we can better inform technology transition-related policy-makers and DoD SBIR program managers.

Role of Social Capital in Small Businesses' Innovation Context

There is a great body of studies on the corporate size of businesses. Most of them argued over the advantages and disadvantages of business size (e.g., MacMillan, 1975; Moen, 1999). For instance, large businesses can be price-competitive by reducing average cost through the economies of scale and also be technology- and market-competitive by investing more in R&D and marketing whereas they can suffer from bureaucracy, ineffective communication, and concerns about cannibalization or creative destruction. On the other hand, small businesses can take advantage of their flexibility, agility, and risk-taking innovation while they have to face many challenges such as lack of well-educated workers and well-secured financial resources and limited access to valuable information. One of the solutions to those challenges may be developing social networks (e.g., Miller et al., 2007; Lee, 2015). To hire qualified employees or to obtain useful information, for instance, small firms or their founders may be able to utilize their social networks (from strong and informal ties such as family and friends to weak and formal ties such as professional communities). They can also build social networks with potential funders to secure external financial sources. Particularly for startups and early-stage small businesses, securing funds through public venture programs such as federal-level Small Business Innovation Research (SBIR) grants/contracts and state-level SBIR matching grants and private equity such as investments from corporate venture capitals and angels are critical for their survival and growth.

Particularly, the SBIR program has contributed to facilitating the innovation of small businesses. Since the 1980s, the program has successfully attained its four objectives: 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 (Small Business Administration [SBA], 2014). Of them, the second objective is especially important to the DoD that accounts for almost half of the total SBIR budget. Unlike the past where the public sector (e.g., national laboratories) dominated technological innovation, the private sector is currently leading in the high-tech innovation (e.g., information and communications technology and biotechnology). It is essential for the DoD to acquire cutting-edge technologies from the private sector in order to maintain its military and technological leadership. In this regard, we define technology transition as a knowledge/technology flow from the private sector to the public sector (when compared to technology transfer indicating a knowledge/technology flow from the public sector to the private sector) following Dobbins's (2004) definition about technology transition: "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" (p. 14).

Considering both the importance of social networks among small business communities and the technology acquisition purpose of the DoD SBIR program, we include the technological distance from the DoD as one of the input variables and the number of small firms' connections to funders (captured by their eigenvector centrality in the SBIR funding network) as one of the intermediate variables. The rationale is that the DoD may seek novel technologies that are different from ones in its technology portfolio through the SBIR program. The technological distance measures the degree of dissimilarity between small firms' and the DoD's technological portfolios based on their patent distributions across the patent classification codes (e.g., Bar & Leiponen, 2012; Benner & Waldfogel, 2008). Our underlying concept is that the higher technological distance may lead to the more (or stronger) connections to the SBIR funders. To better reflect the reality of the SBIR budget allocation (where three services such as Air Force, Army, and Navy take a lion's share of the DoD SBIR budget), we use the eigenvector centrality (which counts the number of connections differently by placing more weights on the connections to big-sized funders and less weights on the connections to small-sized funders) instead of degree centrality (which counts the number of connections equally by placing the same weights on all connections). See Bonacich (2007) and Faulk et al. (2017).

Methodology

Primary

Nomenclatures used in this study are summarized as follows:

x_{ijt} is the observed *i* th input of the *j* th DMU (*i* = 1, …, *m* & *j* = 1, ..., *n*) at the *t* th stage, g_{rjt} is the observed *r* th output of the *j* th DMU (*r* = 1, ..., *s* & *j* = 1, ..., *n*) at the *t+1* th stage, y_{hjt} is the observed *h* th intermediate output of the *j* th DMU (*h* = 1, …, *z* & *j* = 1, ..., *n*) at the *t* th stage, y_{rjt+1} is the observed *h* th intermediate input of the *j* th DMU (*r* = 1, ..., *s* & *j* = 1, ..., *n*) at the *t+1* th stage, ξ is an inefficiency measure, d_{it}^{x} is an unknown slack variable of the *i* th input at the *t* th stage, d_{rt}^{g} is an unknown slack variable of the *r* th output at the *t* th stage, d_{ht}^{y} is an unknown slack variable of the *h* th intermediate output/input at the *t* and *t+1* th stages, λ_{jt} is an unknown intensity (or structural) variable of the *j* th DMU at the *t* th stage, ε_s is a prescribed very small number and J_t is a set of all DMUs at the *t* th stage. This study considers the first and second stage, so *t* = 1 and 2.

Before applying the proposed formulations, we need to specify the following data ranges on *X* (inputs) and *G* (outputs):

R_i^x is a data range on the *i* th input which is specified as

$$R_i^x = (m+s)^{-1}\left(\max_{jt}\{x_{ijt} \mid all\ j\ \&\ all\ t\} - \min_{jt}\{x_{ijt} \mid all\ j\ \&\ all\ t\}\right)^{-1} \qquad (1)$$

R_r^g is a data range on the *r* th desirable output which is specified as

$$R_r^g = (m+s)^{-1}\left(\max_{jt}\{g_{rjt} | all\ j\ \&\ all\ t\} - \min_{jt}\{g_{rjt} | all\ j\ \&\ all\ t\}\right)^{-1}. \qquad (2)$$

The data ranges are applied to the all DMUs (*j = 1, .., n*) in all periods (*t = 1, .., z*) in the proposed DEA models. The purpose of these data ranges is that DEA results can avoid an occurrence of zero in dual variables (i.e., multipliers). Such an occurrence implies that corresponding production factors (*X* and *G*) are not fully utilized in our DEA applications. Such an occurrence is problematic. To avoid the difficulty, this study incorporates the data ranges, (1) and (2), into the proposed formulations so that we can fully utilize available information on the two production factors.

Operational Efficiency Measurement

This research considers the operational performance of various entities. Each entity is considered as a DMU. In every DMU, the production technology transforms an input vector with m components ($X \in R_+^m$) into a desirable output vector with s components ($G \in R_+^s$).

The axiomatic form of Production Technology (PT) on a production possibility set (P) is expressed at the specific *t* th period as follows:

$$P_t = \{P_t(X) : X_t \text{ can produce } G_t\} \in \mathrm{R}_+^m \qquad (3)$$

within the framework of (3), the production possibility set at the *t* th period can be expressed as follows:

$$P_t^v(X_t) = \left\{ G_t \le \sum_{j=1}^n G_{jt}\lambda_{jt}, X_t \ge \sum_{j=1}^n X_{jt}\lambda_{jt}, \sum_{j=1}^n \lambda_{jt} = 1\ \&\ \lambda_{jt} \ge 0\ (j = 1,...,n) \right\} \qquad (4)$$

The expressions on *P* incorporate the assumption on variable Returns to Scale (RTS). Equation 4 incorporates the variable (v) RTS because Equation 4 has the side constraint (i.e., $\sum_{j=1}^n \lambda_{jt} = 1$). See Sueyoshi & Goto (2018) for a detailed mathematical description on RTS.

Figure 1 depicts the contract assessment used in this study. The contract consists of two staged processes. There is an intermediate stage that connects between them by considering a “time lag.” The first stage uses (a) the amount of SBIR awards, (b) the number of employees, and (c) the level of technology distance. There are two outputs: (a) the number of patents and the number of connections at the intermediate stage. After 5 years, the two outputs from the first stage serve as inputs at the second stage. The final output is the amount of federal procurement contract. Since the Empirical Study section provides a detailed description on inputs and outputs, this section focuses upon a description on the methodology.

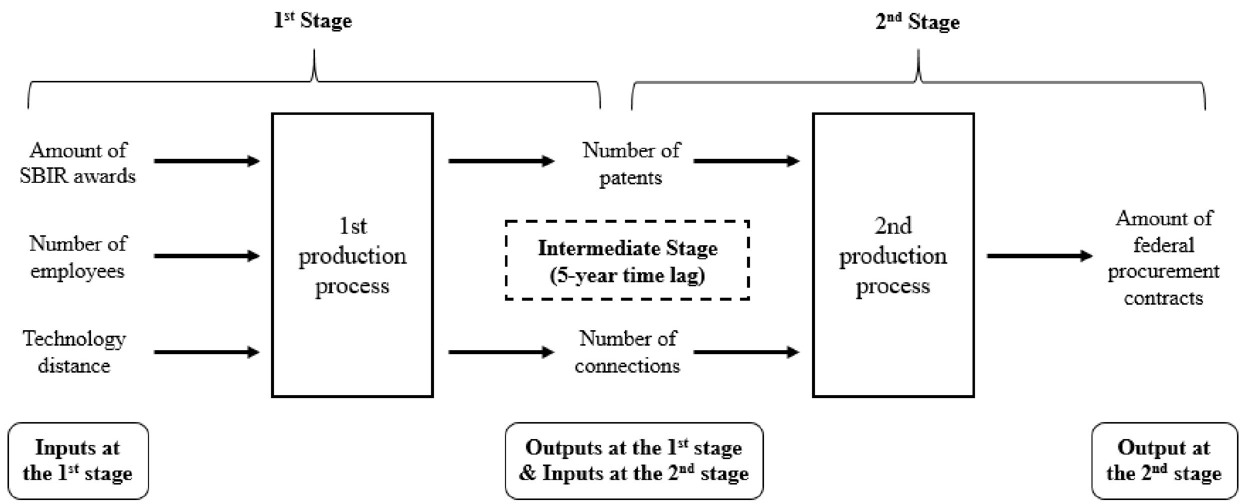

Figure 1. Two-Stage Analytic Framework

Note: (a) we collected data from various sources: (i) SBIR awards data from the Small Business Administration's (SBA) SBIR database, (ii) employment data from the System for Award Management (SAM), (iii) patent data from the Korea Intellectual Property Rights Information Service (KIPRIS, original data imported from the U.S. Patent and Trademark Office), and (ix) federal procurement contracts data from the Federal Procurement Data System-Next Generation (FPDS-NG). (b) There are three inputs at the first stage: the amount of SBIR awards (*ASA*), the number of employees (*EMP*), and technological distance from the DoD (*TDD*). Both *ASA* and *EMP* are measured at US$ million and full-time equivalent (*FTE*), respectively, while *TDD* is valued between 0 and 1. There are two variables at the intermediate stage (which act as stage-1 outputs and stage-2 inputs simultaneously): the number of patents (*PAT*) and the number of connections (*SEC*). The former is measured as the number of patent applications and the latter is valued between 0 and 1 and measured as the eigenvector centrality.[1] There is also one output at the second stage: the amount of federal procurement contracts (*FPC*). FPC is measured at US$ million. (c) It is also worth noting that there is a 5-year time lag between inputs and outputs. Given that technology transition takes a substantial amount of time.

To analyze the procurement process specified in Figure 1, this study uses a DEA-based radial approach to determine the level of Operational Efficiency (OE) on the specific *k* th DMU at the *t* th period. Given X_{kt} and G_{kt+1}, we evaluate the performance of the *k* th DMU to be examined. The subscription (j_t) is used to express each DMU ($j = 1, .., n$) in the total set (J_t).

Based upon the framework of Figure 1, this study proposes the following formulation to measure the level of Operational Efficiency (OE_{kt}^{v}) on the *k* th DMU at the *t* th period:

[1] There are several ways to calculate the number of connections in a network. For instance, degree centrality focuses on the absolute number of links while closeness centrality pays attention to the distance between nodes (that is why closeness centrality is often used for the analysis of information spread) and betweenness centrality stresses the path of pairs of nodes (that is why betweenness centrality is used for identifying brokers or intermediaries who can connect two different groups). In this study, we use eigenvector centrality because we believe the connections of small firms to big-sized funders are different from those to small-sized funders. We put more weight on the former connections. From a firm's perspective, for instance, connections to the Air Force, Army, or Navy may be more valuable than those to the Defense Logistics Agency or Missile Defense Agency.

$$
\begin{aligned}
&Maximize \;\; \xi+\varepsilon_s\Big(\sum_{i=1}^{m} R_i^x d_{it}^x+\sum_{r=1}^{s} R_r^g d_{rt+1}^g\Big)-\sum_{h=1}^{z}\big(d_{ht}^y+d_{ht+1}^y\big)\\
&s.t. \quad \sum_{j=1}^{n} x_{ijt}\lambda_{jt}+d_{it}^x+\xi x_{ikt} = x_{ikt} \quad (i=1,..,m),\\
&\qquad \sum_{j=1}^{n} y_{hjt}\lambda_{jt} - d_{ht}^y = y_{hkt} \quad (h=1,..,z),\\
&\qquad \sum_{j=1}^{n} y_{hjt+1}\lambda_{jt+1} + d_{ht+1}^y = y_{hkt+1} \quad (h=1,..,z),\\
&\qquad \sum_{j=1}^{n} g_{rjt+1}\lambda_{jt+1} - d_{rt+1}^g - \xi g_{rkt+1} = g_{rkt+1} \quad (r=1,..,s),\\
&\qquad \sum_{j=1}^{n} \lambda_{jt}=1 \; (j=1,..,n),\\
&\qquad \sum_{j=1}^{n} \lambda_{jt+1}=1 \; (j=1,..,n),\\
&\qquad \lambda_{jt}\ge 0 \; (j=1,..,n), \lambda_{jt+1}\ge 0 \; (j=1,..,n),\; \xi: URS,\; d_{it}^x \ge 0 \; (i=1,..,m),\\
&\qquad d_{ht}^y \ge 0 \; (h=1,..,z),\; d_{ht+1}^y \ge 0 \; (h=1,..,z) \;\&\; d_{rt+1}^g \ge 0 \; (r=1,..,s).
\end{aligned} \tag{5}
$$

The superscript (v) of OE_{kt}^v indicates variable (v) RTS.

The degree of OE_{kt}^v is measured by

$$
OE_{kt}^v = 1-\Big[\xi^*+\varepsilon_s\Big(\sum_{i=1}^{m} R_i^x d_{it}^{x*}+\sum_{r=1}^{s} R_{rt}^g d_{rt}^{g*}\Big)\Big], \tag{6}
$$

where the inefficiency score and all slack variables are determined on the optimality (*) of Model 5. Thus, the equation within the parenthesis is obtained from the optimality of the objective value of Model 5. The OE_{kt}^v is obtained by subtracting the level of inefficiency from unity. If the degree of OE_{kt}^v is unity, then it indicates the status of "full efficiency." On the other hand, the degree is less than unity, it includes some level of "inefficiency." If the degree is zero, it indicates "full inefficiency."

Here, it is important to note four concerns related to Model 5. First, as formulated in Equation 6, the degree of OE_{kt}^v is measured by the first groups of constraints (i.e., $\sum_{j=1}^{n} x_{ijt}\lambda_{jt}+d_{it}^x+\xi x_{ikt}=x_{ikt}$) on inputs at the *t* th period and the fourth groups of constraints (i.e., $\sum_{j=1}^{n} g_{rjt+1}\lambda_{jt+1}-d_{rt+1}^g-\xi g_{rkt+1}=g_{rkt+1}$) on outputs at the *t+1* th period. Both are used to determine a degree of the inefficiency measure in the whole process for the two (*t* and *t+1*) periods. Next, the second group of constraints (i.e., $\sum_{j=1}^{n} y_{hjt}\lambda_{jt}-d_{ht}^y=y_{hkt}$) indicates that intermediate factors functions as outputs at the *t* th period so that the frontier (i.e., $\sum_{j=1}^{n} y_{hjt}\lambda_{jt}$) locates above or on their observed values (y_{hkt}) because of $y_{hkt}+d_{ht}^y$. The slacks (d_{ht}^y) is minimized in Model 5. Meanwhile, the third group of constraints (i.e.,

$\sum_{j=1}^{n} y_{hjt+1}\lambda_{jt+1} + d_{ht+1}^{y} = y_{hkt+1}$) indicates that intermediate factors functions as inputs at the *t+1* th period so that the frontier (i.e., $\sum_{j=1}^{n} y_{hjt+1}\lambda_{jt+1}$) locates below or on their observed values (y_{hkt+1}) because of $y_{hkt+1} - d_{ht+1}^{y}$. The slacks (d_{ht+1}^{y}) is minimized in Model 5. Third, the fifth and sixth constraints ($\sum_{j=1}^{n} \lambda_{jt} = 1$ and $\sum_{j=1}^{n} \lambda_{jt+1} = 1$) indicate that the sum of these intensities (weights) is unit at the *t* th and *t+1* th periods, respectively. Such constraints imply that the degree of OE_{kt}^{v} is measured under variable RTS. Finally, it is necessary to describe that we are interested in the performance between initial inputs (X_t) and final outputs (G_{t+1}). So, Equation 6 measures $OE_{kt}^{v} = 1 - [\xi^{*} + \varepsilon_{s}(\sum_{i=1}^{m} R_{i}^{x} d_{it}^{x*} + \sum_{r=1}^{s} R_{rt}^{g} d_{rt}^{g*})],$ The intermediate factors (Y_t and Y_{t+1}) make a linkage between the two stages. Figure 1 visually describes such relationship among the three groups of factors.

Empirical Study

Data

This study uses a data set on 252 small firms that meet two criteria: (a) filed more than 15 patents, and (b) awarded the SBIR Phase II funding from the DoD over the decade (from 2001 to 2010). The criteria evidence their R&D and network building capacities because of the three rationales. First, Hicks & Hegde (2005) have defined firms with more than 15 patents as "serial innovators." Second, the SBIR Phase II is followed by the successful completion of Phase I that focuses on the assessment of technical feasibility. The SBIR funding usually entails close relationships between funders and awardees. Finally, the DoD SBIR program selects and announces very specific SBIR topics that require technical fit with awardees. While 2,889 firms meet the second criterion, only 252 firms meet both criteria. Hereafter, we call the 252 firms "elite DoD SBIR awardees."

For the analysis in the frame of multiple inputs and outputs across two stages, we collected data from various sources: (a) SBIR awards data from the Small Business Administration's (SBA) SBIR database, (b) employment data from the System for Award Management (SAM), (c) patent data from the Korea Intellectual Property Rights Information Service (KIPRIS, original data imported from the U.S. Patent and Trademark Office), and (d) federal procurement contracts data from the Federal Procurement Data System-Next Generation (FPDS-NG).

There are three inputs at the first stage: the amount of SBIR awards (*ASA*), the number of employees (*EMP*), and technological distance from the DoD (*TDD*). Both *ASA* and *EMP* are measured at US$ million and full-time equivalent (*FTE*), respectively, while *TDD* is valued between 0 and 1. There are two variables at the intermediate stage (which act as stage-1 outputs and stage-2 inputs simultaneously): the number of patents (*PAT*) and the number of connections (*SEC*). See Figure 1. The former is measured as the number of patent applications and the latter is valued between 0 and 1 and measured as the eigenvector centrality.[2] There is

[2] There are several ways to calculate the number of connections in a network. For instance, degree centrality focuses on the absolute number of links while closeness centrality pays attention to the distance between nodes (that is why closeness centrality is often used for the analysis of information spread) and betweenness centrality stresses the path of pairs of nodes (that is why betweenness centrality is used for identifying brokers or intermediaries who can connect two different groups). In this study, we use eigenvector centrality because we believe the connections of small firms to big-sized funders are different from those to small-sized funders. We put more weight on the former connections. From a firm's perspective, for instance, connections to the Air Force, Army, or Navy may be more valuable than those to the Defense Logistics Agency or Missile Defense Agency.

also one output at the second stage: the amount of federal procurement contracts (*FPC*). FPC is measured at US$ million.

It is also worth noting that there is a 5-year time lag between inputs and outputs. Given that technology transition takes a substantial amount of time, we collected input-related data as of 2010 and output-related data as of 2015. This approach has two advantages: (a) reflect more realistic conditions, and (b) avoid the endogeneity issue in the analysis. There are some studies supporting this. NASEM (2009, p. 230), for instance, showed a table describing the time elapsed between SBIR awards (R&D) and actual sales (commercialization), which tends to be 5–7 years. Xue & Klein (2010) also used a 5-year time lag between independent and dependent variables related to entrepreneurial activities. Seegopaul (2016) explored the time required for development/commercialization by industry (e.g., 0–2 years for software and 5–15 years for advanced materials).

Table 1 presents a summary of data descriptive statistics for DEA. The table shows detailed data and descriptive statistics of inputs and outputs at the first, intermediate, and second stages. Companies are listed in the alphabetical order of their names. On average, elite DoD SBIR awardees made approximately US$ 100 million worth of federal procurement contracts and filed approximately 50 patents while they have received approximately US$ 6 million of SBIR awards and employed 90 people.

Table 1. Descriptive Statistics of Data for DEA

Category	Variable	Descriptive Statistics				
		Obs	Mean	Max	Min	SD
Stage-1 inputs	ASA	252	5.78	103.27	0.29	11.21
	EMP	252	86.17	480.00	2.00	109.11
	TDD	252	0.38	0.88	0.00	0.21
Stage-1 outputs &	PAT	252	49.61	1,251.00	15.00	94.77
Stage-2 inputs	SEC	252	0.02	0.05	0.00	0.01
Stage-2 output	FPC	252	98.14	2,433.14	0.19	292.76

Note: *ASA*: amount of SBIR awards; *EMP*: number of employees; *TDD*: technological distance from DoD; *PAT*: number of patents; *SEC*: eigenvector centrality in the SBIR funding network; *FPC*: federal procurement contract

For the Tobit regression as a subsequent analysis, we also collected firms' demographic data, such as age (*AGE*), location (*HUB*: Historically Under-utilized Business Zones; *RUR*: rural area with less than 50,000 people; *LOC*: leading states such as California and Massachusetts; and *STE*: states), technological concentration (*HTC*: high-tech focus; and *IPC*: technical areas expressed by the international patent classification codes), and ownership (*MOW*: minority-owned firms; and *WOW*: women-owned firms), and calculated technological distance from prime contractors (*TDP*) and closeness centrality in the SBIR funding network (*SCC*). While *AGE*, *TDP*, and *SCC* are continuous variables, *HTC, RUR, LOC, HUB, MOW*, and *WOW* are binary (or dummy) variables. *STE* and *IPC* are categorical variables (but transformed into binary variables for the analysis). The former includes 33 states in which 252 elite DoD SBIR awardees are located while the latter includes 8 sections of technical fields (A: human necessities; B: performing operations and transporting; C: chemistry and metallurgy; D: textiles and paper; E: fixed constructions; F: mechanical engineering, lighting, heating, weapons, and blasting; G: physics; and H: electricity) in which the awardees are situated.

Table 2 presents a summary of Tobit regression data descriptive statistics. On average, elite DoD SBIR awardees are approximately 22 years old. A majority of them are nested in high-tech industries and situated in urban areas of leading states. Few of them are owned by minorities or women.

Table 2. Descriptive Statistics of Data for Tobit Regression

Category	Variable	Descriptive Statistics				
		Obs	Mean	Max	Min	SD
Continuous	AGE	252	22.17	122.00	2.00	14.93
	TDP	252	0.46	0.97	0.00	0.26
	SCC	252	0.88	1.00	0.51	0.12
Binary	HTC	252	0.86	1.00	0.00	0.35
	RUR	252	0.38	1.00	0.00	0.49
	LOC	252	0.72	1.00	0.00	0.45
	HUB	252	0.01	1.00	0.00	0.11
	MOW	252	0.04	1.00	0.00	0.20
	WOW	252	0.04	1.00	0.00	0.20

Note: *AGE*: age of firms; *TDP*: technological distance from prime contractors; *SCC*: closeness centrality in the SBIR funding network; *HTC*: high-tech concentration; *RUR*: location in the rural area; *LOC*: location in the leading states; *HUB*: location in Historically Under-utilized Business Zones (HUBZones); *MOW*: firms owned by minority; *WOW*: firms owned by woman

Results

Table 3 summarizes the OE measure of some companies measured by Model 3. Instead of listing all 252 companies' OE scores, we present those of 24 companies as an example. The first company (1st Detect Corp) of the table shows the status of full efficiency (OE = 1.00) while the second company (Aculight) exhibits the status of inefficiency (OE = 0.78). All firms are characterized by their OE measures. To visually summarize all the measures, Figure 2 exhibits the distribution of OE measures of all firms.

Table 3. Operational Efficiency of Some Companies

Company	OE	Company	OE
1st Detect Corp	1.00	Calspan Corporation	0.54
Aculight Corp.	0.78	Cambridge Scientific, Inc.	1.00
Ada Technologies, Inc.	0.83	Cape Cod Research, Inc.	1.00
Adaptive Materials, Inc.	0.20	Cascade Designs	0.28
Adesto Technologies	0.73	Ceradyne, Inc.	1.00
Advanced Ceramics Research, Inc.	0.36	Ceramatec, Inc.	0.43
ADVANCED CIRCULATORY SYSTEMS, INC.	0.50	CFD Research Corp.	1.00
Advanced Energy Systems, Inc.	0.27	CHEMIMAGE CORP.	1.00
Advanced Fuel Research, Inc.	1.00	CIPHERGEN BIOSYSTEMS, INC.	0.54
Advanced Mechanical Technology, Inc.	0.45	Cleveland Medical Devices, Inc.	0.29
Advanced Scientific Concepts, Inc.	0.65	Coherent Logix, Inc.	0.19
AEC-ABLE ENGINEERING CO., INC.	0.52	Coherent Technologies, Inc.	0.22

Note: OE = Operational Efficiency

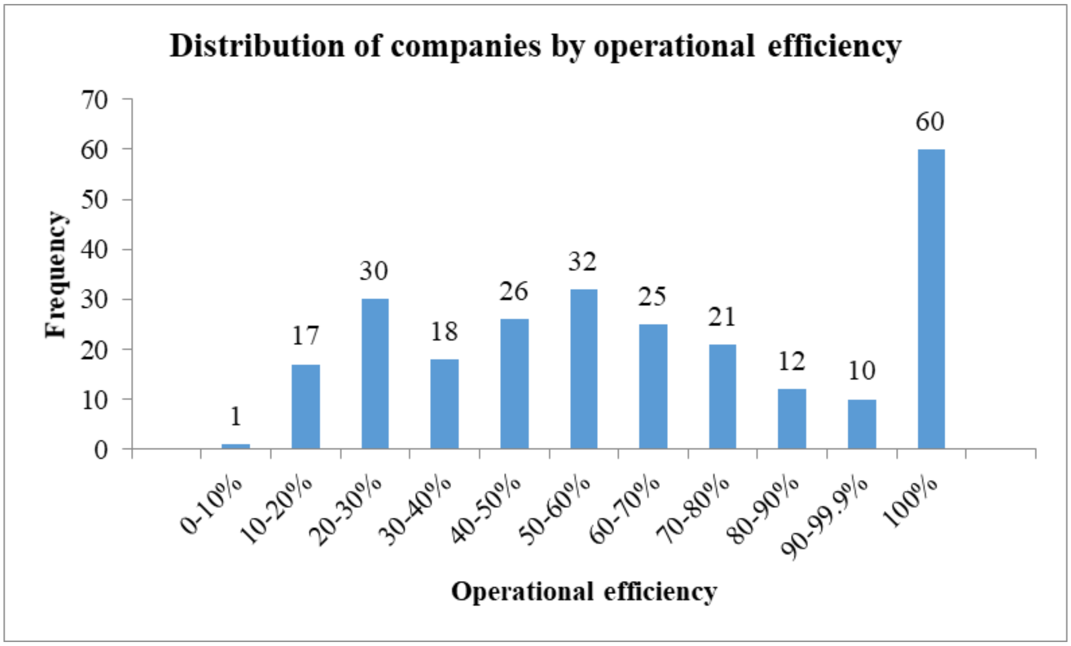

Figure 2. Distribution of Companies by Operational Efficiency

Statistical Analysis

Assuming that the operational performance of elite DoD SBIR awardees may be affected by not only input and output variables used in the DEA investigation but also their demographics, relationships to prime contractors, and agility in seeking external funding, this study constructs the following hypotheses. Since firm-level characteristics related to the transition from *R&D* to commercialization have been studied by other literature, we focus on firm-level traits related to the transition from *network building* to commercialization and contextual factors such as firms' technological concentration (industrial context) and location (geospatial context).

Hypothesis 1: *Small companies' network building capacity (captured by TDD, SEC, and SCC) is positively related to their operational performance.*

Sub-hypothesis 1a (H1a): *Small firms with higher TDD outperform those with lower TDD.* One of the primary objectives of the DoD SBIR program is acquiring R&D outcomes developed by the private sector (technology-based small businesses in this case) but not yet held by the public sector (DoD in this case). To fill the technological gap, the DoD may look for small firms with complementary technical assets so that small firms with different patent portfolios from the DoD's may be more advantageous in developing networks with the DoD than those with similar patent portfolios to what the DoD's are.

Sub-hypothesis 1b (H1b): *Small firms with higher SEC outperform those with lower SEC.* The amount of the SBIR budget (determined by the percentage of extramural R&D budget of SBIR-participating agencies) and procurement contracts depends highly upon the size of agencies. Given that three services (Air Force, Army, and Navy) are the largest DoD components and other components are relatively small, connections to big-sized components may be more valuable to small firms than those to small-sized components.

Sub-hypothesis 1c (H1c): *Small firms with higher SCC outperform those with lower SCC.* Social closeness often means better access to information that is critical for securing external funding. Thus, social adjacency to funders and small firms' agility in seeking funding sources may lead to better performance.

Hypothesis 2: *Small companies' high-tech concentration (captured by HTC and IPC) is positively associated with their operational performance.*

Sub-hypothesis 2a (H2a): *Small firms operating in the high-tech industries outperform those in the non-high-tech industries.* The R&D- and capital-intensive nature of high-tech industries tends to lead to higher value-added. Nowadays it is especially true since technology plays a pivotal role in firms' sustainable competitiveness. Thus, small firms with high-tech focus may achieve better performance than those with non-high-tech focus.

Sub-hypothesis 2b (H2b): *Small firms operating in the industries indexed by specific IPC codes outperform those in the industries indexed by other IPC codes.* According to the Eurostat indicators on high-tech industry and knowledge,[3] this study includes (a) computer and automated business equipment (indexed by G06C, G06D, etc.), (b) aviation (indexed by B64B, B64C, etc.), (c) micro-organism and genetic engineering (indexed by C40B, C12P, etc.), (d) lasers (indexed by H01S), (e) semiconductors (indexed by H01L), (f) communication technology (indexed by H04B, H04H, etc.), and (g) biotechnology (indexed by A61K, G01N, etc.) in the fields of high technology. In congruence with sub-hypothesis 2a, small firms with high-tech concentration (indexed by the aforementioned IPC codes) may perform better than those with non-high-tech concentration.

Hypothesis 3: *Small companies' location in better places (captured by HUB, RUR, LOC, and STE) is positively associated with their operational performance.*

Sub-hypothesis 3a (H3a): *Small firms located in the HUBZones or rural areas underperform counterparts.* Despite various incentive programs (e.g., tax credits) offered by governments for small firms located in the HUBZones or rural areas, small firms in those areas tend to have many disadvantages in conducting R&D, building networks, and commercializing R&D outcomes because of (a) limited access to a well-trained workforce, financial resources, and valuable information, (b) lack of knowledge spillover and infrastructure (e.g., broadband), and (c) distance to the market or customers. Thus, small firms situated in the HUBZones or rural areas may perform worse than counterparts do.

Sub-hypothesis 3b (H3b): *Small firms located in the economically or technologically leading states or states with business-friendly environment outperform counterparts.* Leading states such as California, New York, and Massachusetts tend to offer a better business environment to small firms than lagging states such as Mississippi, Montana, and Wyoming. Particularly financial resources such as venture capitalists and angels, which are critical for high-risk technology-based small businesses, tend to concentrate in the leading states. Moreover, leading states tend to have more prestigious research universities and large companies that play a role as anchor institutions in the regional innovation system or entrepreneurial ecosystem. Thus, small firms situated in the leading states may perform better than counterparts do.

To empirically test these hypotheses, we employ Tobit regression models that are appropriate for censored data considering the boundary of firms' efficiency scores (between 0 and 1; Bi et al., 2016). We test three different Tobit models (M 1–3) using efficiency scores as a dependent variable. The first model (M 1) includes only DEA input and output variables, the second (M 2) adds one more network building capacity-related variable (i.e., *SCC*), and the third

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[3] Eurostat indicators on High-tech industry and Knowledge-intensive services Annex 6 – High-tech aggregation by patents (https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an6.pdf)

adds contextual variables (i.e., *HTC*, *IPC*, *LOC*, and *STE*). Because of a long list of variables, we utilized the stepwise function that removes insignificant variables from a full model. We also dropped some variables due to the multicollinearity issue. Table 4 summarizes the Tobit analysis results.

Table 4. Results of Tobit Regressions

Variables		M 1		M 2		M 3	
Controls	ASA	0.0027	(1.48)	-0.0016	(-0.99)	-0.0017	(-1.06)
	EMP	-0.0011***	(-6.18)	-0.0010***	(-6.19)	-0.0010***	(-6.24)
	PAT	0.0009***	(3.66)	0.0009***	(3.86)	0.0009***	(3.97)
	FPC	0.0004***	(5.27)	0.0004***	(6.31)	0.0004***	(6.50)
Network building capacity	TDD	-0.3604***	(-4.48)	-0.3754***	(-5.39)	-0.3952***	(-5.58)
	SEC	1.0694	(0.67)	30.1008***	(8.78)	31.5687***	(9.17)
	SCC			-2.9771***	(-9.19)	-3.0433***	(-9.41)
High-tech focus	HTC					0.0989*	(1.94)
	IPC (Section A)					0.2308***	(2.87)
Location	HUB					0.0202	(0.16)
	RUR					-0.0471	(-1.58)
	LOC					-0.0389	(-1.16)
	STE (North Carolina)					-0.2742**	(-2.08)
Model fit	Pseudo R^2	0.56		1.20		1.32	
	AIC	66.86		-5.51		-7.47	
	BIC	95.10		26.25		45.47	

Note: (a) *ASA*: amount of SBIR awards; *EMP*: number of employees; *PAT*: number of patents; *FPC*: federal procurement contract; *TDD*: technological distance from DoD; *SEC*: eigenvector centrality in the SBIR funding network; *SCC*: closeness centrality in the SBIR funding network; *HTC*: high-tech concentration; *IPC*: international patent classification; *HUB*: location in Historically Under-utilized Business Zones (HUBZones); *RUR*: location in the rural area; *LOC*: location in the leading states; *STE*: state (b) Values in parenthesis are t-statistics. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Based on our hypotheses and the model fit, our interpretation follows the third model (M 3). According to the analysis results, operational efficiency of the elite DoD SBIR awardees has statistically significant relationships (a) positively with *PAT*, *FPC*, *SEC*, *HTC*, and *IPC (Section A)*, and (b) negatively with *EMP*, *TDD*, *SCC*, and *STE (North Carolina)*. Figure 3 visually summarizes results on the Tobin analysis and partly supports our three hypotheses. The empirical results are summarized as follows:

First, sub-hypothesis *H1b* is only supported and *H1a* and *H1c* are rebutted. *SEC* is positively related to efficiency, meaning that small firms' funding connections to big-sized DoD components enhance their operational performance. However, *TDD* and *SCC* are negatively related to efficiency, meaning that small firms' technological dissimilarity to the DoD and closer connections to more funding sources hurt their operational performance. Those results imply that (a) technological similarity (low technological distance) is better for small firms in building networks with funders, rather than technological dissimilarity (high technological distance), and (b) building a strong network with one of the big-sized DoD components and sticking to one funding source are better for small firms in terms of operational efficiency, rather than developing weak networks with multiple DoD components.

Second, sub-hypotheses *H2a* and *H2b* both are supported. *HTC* and *IPC (Section A)* are positively associated with efficiency, suggesting that small firms' high-tech concentration, particularly in biotechnology (e.g., IPC A61B: diagnosis and surgery; A61F: prostheses; and A61K preparation for medical and dental purposes), improves their operational performance. Those results confirm that industrial context plays an important role in determining small firms' operational performance.

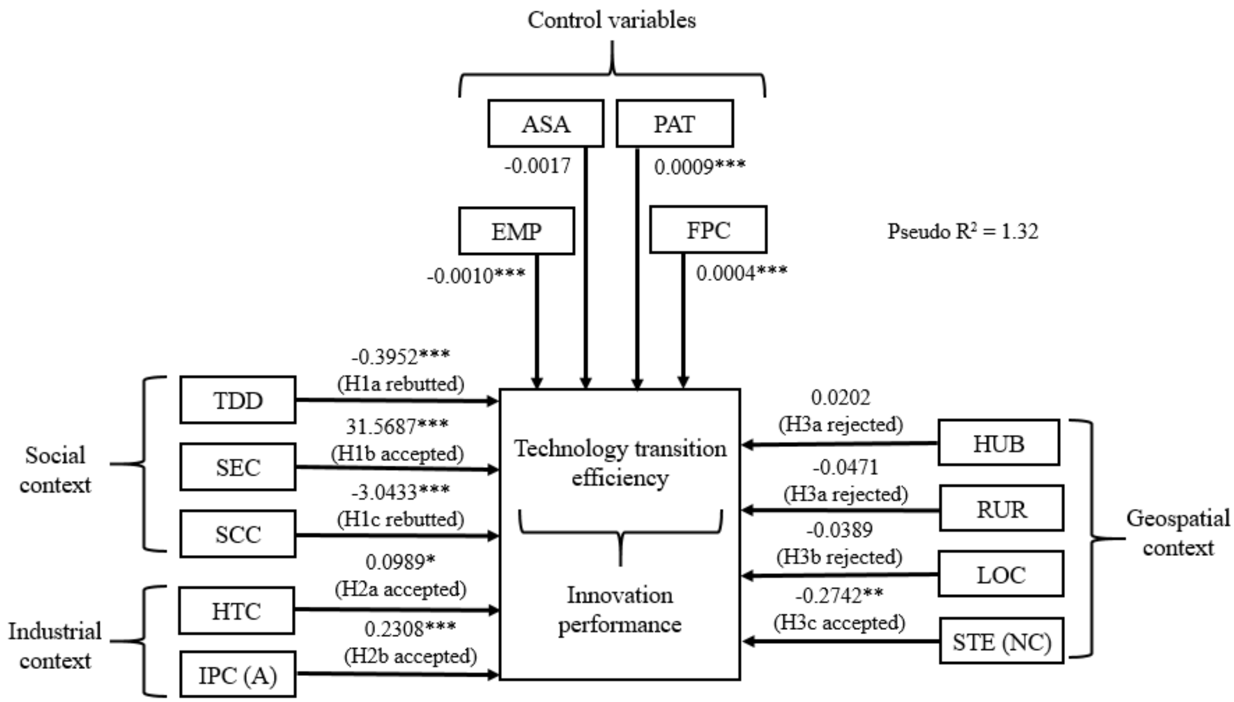

Figure 3. Concept and Result of Tobit Regression

Note: (a) *ASA*: amount of SBIR awards; *EMP*: number of employees; *PAT*: number of patents; *FPC*: federal procurement contract; *TDD*: technological distance from DoD; *SEC*: eigenvector centrality in the SBIR funding network; *SCC*: closeness centrality in the SBIR funding network; *HTC*: high-tech concentration; *IPC (A)*: international patent classification (section A); *HUB*: location in Historically Under-utilized Business Zones (HUBZones); *RUR*: location in the rural area; *LOC*: location in the leading states; *STE (NC)*: state (North Carolina).

(b) *** significant at 1%; ** significant at 5%; * significant at 10%.

Finally, sub-hypotheses *H3a* and *H3b* are not confirmed. *HUB*, *RUR*, and *LOC* do not have statistically significant relationships with efficiency while *STE (North Carolina)* is negatively associated with efficiency. Those results imply that geospatial context does play a substantial role in determining small firms' operational performance. There are some possible explanations: (a) the SBIR funding is geographically distributed on an equity basis or considering assistance for small firms located in disadvantageous areas, (b) lagging states, as well as leading states, are also active in offering business-friendly environment to small firms in their jurisdiction to invigorate their economies (e.g., the State of New Mexico is implementing the SBIR matching fund program), and (c) national laboratories and military bases located in remote areas contribute to R&D, network building, and commercialization (e.g., Sandia and Los Alamos

National Laboratories and Air Force Research Laboratories in New Mexico play a key role in the regional innovation system). On the other hand, it turned out that small firms located in the State of North Carolina underperform those in other states. It is rather contradictory considering its Research Triangle Park (RTP) that consists of three research universities (Duke University, the University of North Carolina at Chapel Hill, and North Carolina State University). We cautiously conjecture that (a) there may be an imbalance between R&D/network building and commercialization (i.e., the former is strong due to the existence of RTP but the latter may be relatively weak), (b) there may be lack of knowledge spillover from RTP or business and policy efforts in promoting entrepreneurial innovation, and (c) the proportion of small firms that specialize in high technology may be relatively small.

Conclusion and Future Extensions

This study first evaluated the innovation performance of 252 elite DoD SBIR awardees in the context of technology transition and then examined the impacts of social, industrial, and geospatial factors on the performance. For the first task, we employed a two-stage, dynamic DEA to reflect more realistic conditions of innovation (as a complex and time-consuming process that requires social capital as well as traditional input factors). According to the DEA result, more than a quarter of companies (60) turned out efficient while three quarters are not fully efficient. About half of companies showed efficiency scores that are higher than 60%. It implies that there is still significant room for improvement for many companies.

For the second task, we used Tobit regression analysis to deal with censored data (the upper limit of the 60 efficient companies in efficiency score is 100%). The statistical analysis demonstrated that our three hypotheses are partly supported. Our first hypothesis was that small companies with higher network building capacity outperform those with lower network building capacity. It turned out that small firms' connections to influential funders contributed to their performance but their heterogeneous technological portfolios and connections to multiple funders did not. It suggests that developing and strengthening networks with big-sized funders (focused networking rather than distracted networking) positively affects the technology transition performance. The second hypothesis was that small companies with high-tech concentration outperform those with low- or medium-tech concentration. It turned out true, particularly for biotech companies. It suggests that industrial context plays a significant role in the technology transition performance. The last hypothesis was that small companies situated in the preferred location outperform those in the unpreferred location. It turned out that locational factors were not critical. It suggests that the geospatial context plays a minor role in the technology transition performance.

While there are many studies on the knowledge generation function (e.g., Antonelli & Colombelli, 2018) and knowledge utilization or revenue/profit generation function (e.g., Lichtenthaler, 2005; Bergman & Usai, 2009), which account for the R&D sub-process at the first stage and commercialization sub-process at the second stage of our DEA framework, respectively, there are a relatively small number of studies on social link (or trust) generation function that represents the network building sub-process at the first stage. This study incorporated the concept of social capital into the DEA-based innovation performance measurement for the first time. In this study, we used technological distance based on the assumption that the DoD seeks small companies with different technological portfolios from its own portfolio as R&D partners (SBIR awardees in this case). Thus, we used technological distance as an input to the network building sub-process at the first stage of our DEA framework and eigenvector centrality as an output in the sub-process. However, there may be other alternative inputs that can better capture the input factors to the network building sub-process.

As the number of studies on social capital increases, we may be able to determine more suitable measures.

Appendix

All abbreviations used in this study are summarized as follows: DARPA: Defense Advanced Research Projects Agency, DEA: Data Envelopment Analysis, DIU: Defense Innovation Unit, DMU: Decision-Making Unit, DoD: Department of Defense, FPDS-NG: Federal Procurement Data System-Next Generation, EIS: European Innovation Scoreboard, KIPRIS: Korea Intellectual Property Rights Information Service, RIS: Regional Innovation System, RTS: Returns to Scale, NIS: National Innovation System, OE: Operational Efficiency, OECD: Organisation for Economic Cooperation and Development, PT: Production Technology, R&D: Research and Development, RIS: Regional Innovation System, RTP: Research Triangle Park, RTS: Returns to Scale, SAM: System for Award Management, SBA: Small Business Administration, SBIR: Small Business Innovation Research, STTR: Small Business Technology Transfer, and URS: Unrestricted.

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