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Keywords R&D output efficiency; Space industry; Clusters; Types of proximity; Public funding

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Highlights

- Estimates output efficiency of space R&D based on dynamic slacks-based DEA
- Finds that cognitive proximity exerts a positive influence on R&D output efficiency
- Finds that organizational distance negatively influences R&D output efficiency
- Reports lower R&D output efficiency in smaller firms and for larger amounts of public funding
- Finds that a mixture of space and non-space R&D contributes significantly to output efficiency

Within-cluster proximity and output efficiency of R&D in the space industry

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Abstract

Dynamic slacks-based data envelopment analysis is applied to measure output performance efficiency of space R&D active private firms. Truncated regression is used to identify associations between this firm level R&D output efficiency and cognitive, social and organizational proximity within geographical clusters.

Primary data collected for the entire population of space R&D active firms in Belgium for the period 2011-2015 reveals that an environment specialized in the focus firm's space activities (as a proxy for cognitive proximity) exerts a positive influence on R&D output efficiency. Organizational distance within the cluster negatively influences R&D output efficiency. No effect is found of the presence of anchor firms (as a proxy for social proximity). Firm size and a mixture of space and non-space R&D positively affect R&D output efficiency, whereas larger amounts of public funding induce lower efficiency, at least in a five year time-span.

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1. Introduction

This paper examines the determinants of firm level output efficiency of R&D. The focus is on the space industry in Belgium, a highly geographically concentrated industry. The paper takes a novel approach by looking at the role of cognitive (degree of overlap in knowledge base), organizational (extent to which relations are shared in an organizational arrangement), and social (embeddedness of actors) proximity (Boschma, 2005) within a geographically defined cluster of space R&D active firms. In addition, firm and public funding characteristics are taken into account.

The target population is all space R&D active private enterprises in Belgium in the period 2011-2015. The analysis includes the entire population of 122 private firms engaged in upstream or downstream space R&D activities. Upstream space activities include hardware and software products and services which enable the launch and operating of systems in space. Downstream space activities involve hardware and software producers and service providers which require the use of space systems and/or data for applications used on Earth (OECD, 2012).

The space sector is a largely publicly financed sector, and in the period 2011-2015, the Belgian federal government spent an average of 180 million euro per year on the European Space Agency

(ESA), representing six percent of the total ESA budget and making Belgium the sixth largest contributor. Via a "juste retour" system, the money flows back to private (close to four fifths of the budget) and public (including higher education - one fifth of the budget) space actors in Belgium. ESA funding is mainly oriented towards research and technology development activities. In the period 2011-2015, each of the 122 space R&D active firms in Belgium received funding from the European Space Agency (ESA). During that period, ESA funding represents three-fifth of the total internal R&D budgets of the space actors (Teirlinck et al., 2017).

The objective of this paper is to find out the determinants of performance efficiency in terms of space and non-space turnover of R&D inputs in private firms. At present, despite a clear policy need for evaluation of public funding of space R&D, hardly any empirical evidence exists in this regard (OECD, 2012). The paper contributes in two ways.

First, the paper contributes by providing a better measurement of output efficiency of R&D. R&D activities include an inherent characteristic which lags the influence of R&D contributions. Therefore, it is necessary to evaluate the efficiency and effectiveness of firms' performance using a multi-period efficiency approach over a certain time period. Furthermore, the R&D capital stock is a time-intermediate carry-over as it remains after R&D in previous periods, and it is an input for creating knowledge for the next period (Chen et al., 2018). Therefore, to evaluate the determinants of output efficiency of R&D in the space sector, we first calculate R&D output efficiency scores by applying a dynamic slacks-based model of Data Envelopment Analysis (DEA), as proposed by Tone and Tsutsui (2010), enabling to take into account the time change effect between two consecutive time periods. In a second step, in line with e.g. Sarkis and Cordeiro (2012) and Li et al. (2017), a truncated regression model is relied upon to determine the external factors that might affect the efficiency scores.

Second, based on the truncated regression model and while controlling for the influence of firm and funding characteristics, the paper sheds new light on the influence on R&D output efficiency of three different forms of proximity within the strongly geographically clustered space sector (Porter, 2000). It demonstrates a positive influence of cognitive proximity as approximated by specialization (Meardon, 2001), and a negative influence of organizational distance as approximated by the presence and importance of public actors (Meardon, 2001). It does not confirm positive influences of social proximity (Broekel and Boschma, 2011), approximated by the presence of anchor firms (Feldman, 2003).

The rest of the paper is organized as follows. A literature review of geographical cluster formation, different forms of proximity, firm and public funding characteristics, and the measurement of R&D output efficiency is presented in Section 2. The conceptual framework and a mathematical model of dynamic slacks-based DEA are constructed in Section 3. Empirical application based on the dataset of space R&D active firms in Belgium for the period 2011–2015 forms the subject of Section 4. Section 5 concludes the paper.

2. Literature review

The literature review addresses the measurement of output efficiency of R&D, followed by insights in the relation between output efficiency of R&D in the space sector and cognitive, organizational, and social proximity within geographical clusters.

2.1. Output efficiency of R&D

Measuring output efficiency of R&D activities by space actors is not that trivial. Firstly, in comparison to other areas, space programmes are rich in R&D, the impact of which develops over many years (Hsu, 2009). Second, space programmes are generally big industrial programmes involving an interplay between a broad range of industrial players in a variety of industrial activities (Spagnulo et al., 2013), and with spillovers to non-space industries (Venturini and Verbano, 2014). Third, the necessary modelling and measurement to isolate outputs which are the consequence of (public funding of) R&D is not available yet (Molas-Gallart and Davies, 2006), circumstances under which Rogers (2008) questions the use of a counterfactual approach (since no space R&D active firms can be identified without public support).

Existing literature illustrates that the evaluation of R&D active firms can be based on Data Envelopment Analysis (DEA). More particularly, dynamic DEA (Tone and Tsutsui, 2010) assumes that the R&D process is not a one-stage approach and it can take into account the interdependence of R&D activities between multi-periods. Since limited empirical literature is available in the field of R&D output efficiency, we will determine our variables based upon available research implemented by using dynamic and network DEA at either firm or regional level.

The selection of inputs, outputs and carry-overs to apply dynamic DEA is important. The most commonly used inputs are R&D expenditure, R&D employees, capital stock and assets (Li et al., 2017; Chen et al., 2018; Chun et al., 2015; Guan and Chen, 2010). The mainly applied outputs include marketable outputs such as export, sales, revenue and value added (Li et al., 2017; Chun et al., 2015; Hung and Wang, 2012; Guan and Chen, 2010). Patents and R&D capital stock are typically chosen as carry-overs or intermediate variables in order to apply dynamic DEA and/or network DEA (Li et al., 2017; Chen et al., 2018; and Chun et al., 2015).

Regarding the carry-over variable identification, Wang and Hagedoorn (2014) and Scotchmer (1991) explain that the R&D process is a cumulative knowledge stock. In other words, the input and output of the knowledge creation and R&D investment is the knowledge capital stock. Therefore, it is accounted for that the foundation of space firms is based on R&D activities that create knowledge during multiple periods. Through the process of R&D knowledge creation, the R&D capital stock encompasses the knowledge stock as an accumulated input and exerts influence on the process outputs (Chen et al., 2018). The R&D capital stock is the output of R&D investment. Table 1 gives an overview of the input, output, and intermediary/carry-over variables included in empirical literature relying on dynamic and network DEA at firm or regional level.

Table 1: Overview of R&D input, output, and intermediary variables used in dynamic or network DEA

Author	Input	Output	Intermediate inputs/ outputs	DEA model
Li et al. (2017)	Capital stock, R&D expenditure, Employment	Gross output value, Exports	Patents	Dynamic DEA
Chen et al. (2018)	R&D expenditure, R&D personnel	SCI papers, Domestic granted patents	R&D capital stock	Dynamic DEA
Chun et al. (2015)	R&D employees, Internal R&D investment, External R&D investment	Sales, Operating income	Process patent application, Product patent applications	Network DEA
Hung and Wang (2012)	Employees, Manufacturing Selling, R&D expense, Assets	Stock price, Earnings per share in the market	Revenue, Profit	Network DEA
Guan and Chen (2010)	Internal R&D expenditure, Full-time equivalent of R&D activities by employees	Profits, Export, Sale revenue of new product, Value-added	Applied patent	Network DEA

In this study, we focus on output efficiency in terms of space and non-space turnover (in line with the sales approach by Chun et al., 2015) that has been achieved by space firms' expenses on internal space and non-space R&D expenditures (Li et al., 2017; Chen et al., 2018; Chun et al., 2015; Hung and Wang, 2012; Guan and Chen, 2010) and space and non-space employment (in line with employment focused on by Hung and Wang, 2012).

2.2. Geographical cluster formation

The literature on geographical cluster formation puts a high emphasis on the importance for innovation of knowledge sharing through networks in regional economies, and on the influence of close geographical proximity on regional economic development (Broekel and Boschma, 2011). The cluster terminology was firstly defined by Porter (2000, p. 15) as a *"geographic concentration of interconnected companies"*. Porter (2000) explains that the motives of cluster formation might be supplying of specialized equipment, inter-firm local competition, infrastructure and labour pooling (Porter, 1994, 2000, 2003). A central idea in favour of geographical clustering is a positive relationship between geographical proximity and knowledge sharing (Boschma and Weterings, 2005; Feldman and Florida, 1994; Jaffe, 1989; Audretsch and Feldman, 1996). Audretsch and Feldman (1996) and Gertler (2003) emphasize the importance of geographical proximity by the opportunities of face-to-face contacts, enhancing the exchange of tacit knowledge. Niosi and Zhegu (2005) study the characteristics of aerospace clusters in Montreal, Seattle, Toulouse and Toronto. They find that the main drivers of firms' agglomeration in aerospace industry are regional pools of skilled labour. These agglomerations offer knowledge spillovers, specialization and labour economies (Meardon, 2001).

However, more recently, Niosi and Zhegu (2005) demonstrate that firm performance does not depend on links with local collaborators, and Ponds et al. (2007) argue that geographical proximity does not matter when research centres exchange their knowledge. Other studies argue that social, institutional and cognitive proximity are as effective as geographical proximity (Breschi and Lissoni, 2001; Boschma, 2005; Broekel and Binder, 2007; Isaksen 2001; Healy and Morgan, 2009). Moreover, geographical proximity may affect other forms of proximity and provide more potential opportunities for firms to exchange and share their knowledge, but innovative performance might also decrease due to excessive use of local linkages (Broekel et al., 2015).

Boschma and Frenken (2010) claim that there is a paradox in the fact that although (different forms of) proximity is a crucial dimension to exchange and share knowledge in a network, a high degree of proximity and connectivity does not guarantee enhancement of innovative performance and it even can cause a decline in performance.

In sum, in the literature, other forms of proximity have been opposed to geographical proximity (for the aviation industry, see Broekel and Boschma (2011)), and growing agreement has risen that a combination of various degrees of different kinds of proximity may enhance innovative and economic performance of firms. However, hardly any insights exist in how cognitive, social, and organizational proximity within geographical clusters influence the firm's R&D output performance. The focus of this paper is on the importance of cognitive, social and organizational proximity within geographically defined clusters of space R&D active firms.

First, regarding the cognitive proximity dimension, aerospace clusters mostly consist of small- and medium-sized companies, and some authors argue that the agglomeration of aerospace firms is not beneficial for performance (Lublinski, 2003), while in other industries there is a positive relationship between clustering and performance (Beaudry, 2001). Niosi and Zhegu (2005) explain the motives of industry clustering and dispersion by a regional pool of skilled and semi-skilled labour, the presence of entrepreneurial talent (Todd and Simpson 1986; Cunningham, 1951), and close geographical proximity to the original industries of the cluster. Meardon (2001) outlines that in the industrial district tradition, as defined by Alfred Marshall, the density of small- and medium-sized firms' location in a cluster is linked with the availability of the same or related industries. Broekel and Boschma (2011), in their study of the aviation industry in the Netherlands, follow this reasoning and expect to find a positive influence of technological similarity (defined as cognitive proximity) between actors on firm level innovative performance.

Research hypothesis 1: Geographical pooling of the same or related activities in the space sector (as a proxy for cognitive proximity) enhances output performance of R&D in the space sector.

Second, Feldman (2003) shows that firms agglomerate around a specific region due to the availability of anchor firms. Feldman (2003) defines an anchor firm as a firm that "*can attract skilled labour pools, specialised intermediate industries and provide knowledge spillovers that benefit new technology intensive firms in the region*" (p. 312). Other firms are interested to locate around anchor firms since they can benefit from specialised expertise, physical assets, infrastructure and positive spillovers (Feldman, 2003). Niosi and Zhegu (2005) argue that such anchor firms create a large labour pool and attract firms looking for these highly skilled employees. Further, these firms are strongly involved in outsourcing parts and final assembly from other areas, which requires adaptation of suppliers based on quality, cost and delivery. Agrawal and Cockburn (2003) highlight that the presence of anchor firms offers growth opportunities, and creates regional dynamics for other firms in a region. Agrawal and Cockburn (2003) define an anchor tenant as a firm which is heavily engaged in R&D activities and technological commercialization, which attracts high quality suppliers to the region, and which is heavily engaged in commercialization of technology. They illustrate an important role of the anchor tenant in receiving and transmitting spillovers through the local innovation systems. Their findings show a positive and significant influence of anchors on academic research and commercialization activity. Karlsen (2013) defines anchors as firms which play a prevailing role to affect the development of other firms in a regional innovation system or cluster. Karlsen (2013) measures the anchors using the share of firm turnover in total region turnover. Broekel and Boschma (2011) refer to the bankruptcy of the Fokker company in the Netherlands and the spread of Fokker employees in top management positions of other firms in the aviation industry as a proxy for social proximity connections between firms. We extent this reasoning and argue that anchor firms, by means of their role of provider of technology, employees, and training enhance social proximity within a geographical cluster of technology related firms.

Research hypothesis 2: The presence of anchor firms (as a proxy for social proximity) enhances output performance of R&D in the space sector.

Third, Feldman (2000) points out that, at the early stages of technological development, universities and government labs could play a role as technological knowledge sources. Broekel and Boschma (2011) also recognize this role of non-profit organizations. However, Meardon (2001) finds universities, government and public organizations do not significantly contribute through these clusters in case the cluster (mainly) is composed of (small- and medium-sized) private firms operating with similar specialized suppliers in the same markets. This can be related to absence of organizational proximity (Boschma, 2005). The divide between profit and non-profit organizations to identify organizational proximity is a standard practice in the empirical literature (Broekel and Boschma, 2011), and can be related to dissimilarities in routines and incentive mechanisms (Metcalfe, 1994). Since the space industry in Belgium mainly consists of medium-sized actors, we formulate a third hypothesis as follows (organizational proximity):

Research hypothesis 3: In an environment characterized by SMEs, a strong local public R&D base in space activities (organizational distance) hampers a firm's R&D output efficiency.

3. Method

3.1. Population of space R&D active firms

Space activities substantially differ by country (OECD, 2012). The focus of the space industry in Belgian is entirely on civil (opposed to military) space activities. Space activities are largely concentrated (over eighty percent of space – R&D – employment – Teirlinck et al., 2017) in the private business sector. Companies engaged in space activities in Belgium diversify into space markets, firstly by becoming involved in the creation of orbital infrastructures and means for access to space and then, more recently, in the development of space applications (such as telecommunications) and the services related to these applications. Firms involved in the Belgian space industry also play an active role in the exploitation and marketing of satellite data. Academic research in space activities largely is aligned with the business sector activities and is focused on observation and experimentation in orbit in order to broaden the scope of research and to enable participation in the design of complex instruments. Furthermore, various Belgian research centres are constantly performing testing, calibration or inspection activities, engage in designing microelectronic components for spatial systems, are involved in controlling orbiting (for the most part telecommunication) satellites, are active in the development of spot-vegetation instruments, solar physics, atmospheric studies and microgravity, and in real-time analyses of data coming from space (Belgian Science Policy Office - http://www.belspo.be/belspo/space/beIndu_en.stm).

Space activities are not a recognized category in the international industrial classification systems, and a diverse set of space activities are spread around aggregate manufacturing and services industries (OECD, 2012). Therefore, a major challenge is to identify firms engaged in space activities in the economy. The starting point for this paper is the population of 176 private actors involved in upstream or downstream space activities in Belgium, based on a repertory of actors known to be active in the space industry by the Belgian Space Agency, and complemented with information from the members of the space associations in Belgium; Belgospace, Bruspace, VRI

(Flemish Space Industry) and Wallonie Espace. The unit of analysis is the private firm involved in R&D in space activities.

The data relied upon in this paper are primary collected in an ESA-pilot harmonized survey, covering the period 2011-2015. The survey provides information for all members of the target population in terms of total and space employment, turnover, public-space funding, total and space related internal and external R&D expenditures. The electronic version of the survey has been launched February 2016, and two reminders were sent to those who had not responded. With the help of the space associations a full response rate for the variables of interest for this paper has been achieved. Based on the responses, out of the 176 firms, 122 firms can be considered R&D active in the space industry. The focus of this paper is on the 122 space research active private firms. Each of these firms received ESA funding during the period 2011-2015. This confirms that a large dependence on public funding is inherent to R&D in the space sector. In the period 2011-2015, these firms' employment in space activities augmented by 17 percent, equalling 2.453 full time equivalent employees in the year 2015 (Teirlinck et al., 2017).

3.2. Dynamic slacks-based DEA to determine output efficiency

DEA is a widespread efficiency approach to performance evaluation of decision making units (DMUs) using multiple inputs to generate multiple outputs during a single period of time (Cooper et al., 2000). It is a non-parametric approach introduced to evaluate the relative efficiency of a set of DMUs under the constant returns-to-scale (CRS) or variable returns-to-scale (VRS) assumption.

The conventional DEA model is not able to take into account the process of decision making in a multi-division system, because it is assumed that the production technologies are independent and static during a single period (Chen and van Dalen, 2010). The conventional DEA model computes the efficiency scores regardless of the internal operation of each DMU, which may lead to biased efficiency scores. Therefore, the standard DEA models are not proper methods to apply where DMUs are being assessed through a horizon planning with multiple periods (Khalili-Damghani et al., 2015), and it is required to apply a method which can evaluate the performance efficiency with respect to the dynamic component of R&D lagged effects (accumulated knowledge and R&D). Thus, the methodology needs to consider inter-temporal (carry-over) effects (dynamic component of R&D lagged effects) because the production process of accumulated R&D activities of high-tech firms, like firms in the aerospace industry which require a long time of investment, features lagged effects on outputs and eventually lead to productivity improvement (Adams, 1990; Romer, 1990; Huergo and Jaumandreu, 2004).

Concerning evaluation under dynamic circumstances, many authors apply window analysis and Malmquist productivity index (Malmquist, 1953; Färe et al., 1994). However, these methods overlook inter-temporal or carry-over activities between two consecutive periods (Hung et al., 2014). Färe and Grosskopf (1996) propose a dynamic DEA model and take into account how to deal with the carry-over variables. Their approach extends the dynamic model developed by Shephard and Färe (1980). Emrouznejad and Thanassoulis (2005) formulate the inter-temporal inputs and outputs of dynamic production systems as additional variables in the static DEA environment. However, the drawback of their model is that the discrimination power decreases by increasing the number of inputs, outputs and periods. Chen (2009) introduces a new performance evaluation method of a dynamic network system which includes interdependent multiple sub-units and enabling to measure the efficiency of all DMUs and sub-DMUs.

Tone and Tsutsui (2009) propose a slacks-based network DEA model which can calculate efficiency in each stage and efficiency over the entire period. Tone and Tsutsui (2010) further improve this model and propose a slacks-based dynamic DEA which computes carry-over to estimate efficiency in each period and efficiency over a certain period. Therefore, compared to window analysis and Malmquist index, dynamic DEA has the advantage to measure the relative efficiencies with respect to the time change effect between two or more consecutive single periods. In line with Tone and Tsutsui (2010), a dynamic slacks-based DEA for measuring efficiency changes of DMUs over time is applied. The dynamic slacks-based DEA model enables us to assess the DMUs during a planning horizon with multiple periods.

Suppose that n DMUs are operating in the dynamic production process over T terms where each DMU utilizes m inputs, p non-discretionary (fixed) inputs, s outputs and r non-discretionary (fixed) outputs[1]. Let $x_{ijt}(i = 1,...,m; j = 1,...,n; t = 1,...,T)$, $x_{ijt}^{fix}(i = 1, ...,p; j = 1,...,n; t = 1,...,T)$,

[1]Non-discretionary inputs/outputs are the fixed variables which cannot be changed or controlled by the decision maker (Saati et al., 2011). Good carry-over are carried to the next period (taken as outputs). Bad carry-overs are treated as inputs which cause inefficiency if they comparatively excess. Discretionary (free) carry-overs can be changed freely such that the change does not have any influence on evaluation, directly. Non-discretionary (fixed) carry-overs are the ones that the DMU cannot control. Discretionary (free) and non-discretionary (fixed) carry-overs indirectly impact on efficiency through the continuity condition between two periods (Tone and Tsutsui, 2010).

$y_{ijt}(i = 1, ..., s; j = 1,...,n; t = 1,...,T)$ and $y^{fix}_{ijt}(i = 1, ..., r; j = 1,...,n; t = 1,...,T)$ denote the observed (discretionary) input, non-discretionary input, (discretionary) output and non-discretionary output values of DMU j at term t, respectively. The four types of carry-overs are symbolized as $z^{good}_{ijt}(i = 1,...,ngood; j = 1,...,n; t = 1,...,T)$, z^{bad}_{ijt} $(i = 1,...,nbad; j = 1,...,n; t = 1,...,T)$, $z^{free}_{ijt}(i = 1,...,nfree; j = 1,...,n; t = 1,...,T)$, z^{fix}_{ijt} $(i = 1,...,nfix; j = 1,...,n; t = 1,...,T)$.

The variable returns to scale (VRS) output-oriented overall efficiency τ^*_o is given as the following linear program:

$$\frac{1}{\tau^*_o} = max\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s}\frac{w^+_i s^+_{it}}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s^{good}_{it}}{z^{good}_{iot}}\right)\right] \tag{1}$$

Subject to:

$$x_{iot} = \sum_{j=1}^{n} x_{ijt}\lambda^t_j + s^-_{it} \qquad (i = 1,..., m; t = 1,...,T) \tag{2}$$

$$x^{fix}_{iot} = \sum_{j=1}^{n} x^{fix}_{ijt}\lambda^t_j \qquad (i = 1,..., p; t = 1,...,T) \tag{3}$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt}\lambda^t_j - s^+_{it} \qquad (i = 1,..., s; t = 1,...,T) \tag{4}$$

$$y^{fix}_{iot} = \sum_{j=1}^{n} y^{fix}_{ijt}\lambda^t_j \qquad (i = 1,..., r; t = 1,...,T) \tag{5}$$

$$z^{good}_{iot} = \sum_{j=1}^{n} z^{good}_{ijt}\lambda^t_j - s^{good}_{it} \qquad (i = 1,..., ngood; t = 1,...,T) \tag{6}$$

$$z^{bad}_{iot} = \sum_{j=1}^{n} z^{bad}_{ijt}\lambda^t_j + s^{bad}_{it} \qquad (i = 1,..., nbad; t = 1,...,T) \tag{7}$$

$$z^{free}_{iot} = \sum_{j=1}^{n} z^{free}_{ijt}\lambda^t_j + s^{free}_{it} \qquad (i = 1,..., nfree; t = 1,...,T) \tag{8}$$

$$z_{iot}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix} \lambda_j^t \qquad (i = 1,..., nfix; t = 1,...,T) \tag{9}$$

$$z_{io0}^{good} \leq \sum_{j=1}^{n} z_{ij0}^{good} \lambda_j^1 \qquad (i = 1, ..., ngood) \tag{10}$$

$$z_{io0}^{bad} \geq \sum_{j=1}^{n} z_{ij0}^{bad} \lambda_j^1 \qquad (i = 1, ..., nbad) \tag{11}$$

$$z_{io0}^{free} = \sum_{j=1}^{n} z_{ij0}^{free} \lambda_j^1 + s_{i0}^{free} \qquad s_{i0}^{free} : free\ in\ sign\ (i = 1, ..., nfree) \tag{12}$$

$$z_{io0}^{fix} = \sum_{j=1}^{n} z_{ij0}^{fix} \lambda_j^1 \qquad (i = 1,...,nfix) \tag{13}$$

$$\sum_{j=1}^{n} z_{ijt}^{\alpha} = \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1} \qquad (\forall i; t = 1, ..., T-1), \tag{14}$$

$$z_{io0}^{good} \leq \sum_{j=1}^{n} z_{ij0}^{good} \lambda_j^1 \qquad (i = 1,...,ngood) \tag{15}$$

$$z_{io0}^{bad} \geq \sum_{j=1}^{n} z_{ij0}^{bad} \lambda_j^1 \qquad (i = 1,...,nbad) \tag{16}$$

$$z_{io0}^{free} = \sum_{j=1}^{n} z_{ij0}^{free} \lambda_j^1 + s_{i0}^{free} \qquad s_{i0}^{free}\ \ free\ in\ sign (i = 1,...,nfree) \tag{17}$$

$$z_{io0}^{fix} = \sum_{j=1}^{n} z_{ij0}^{fix} \lambda_j^1 \qquad (i = 1,...,nfix) \tag{18}$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 \qquad (t = 1,...,T) \tag{19}$$

$$\lambda_j^t \geq 0, s_{it}^{-} \geq 0\ , s_{it}^{+} \geq 0, s_{it}^{bad} \geq 0, s_{it}^{good} \geq 0, s_{it}^{free} : free (\forall i, t) \tag{20}$$

Where s_{it}^{-} , s_{it}^{+}, s_{it}^{good}, s_{it}^{bad}, s_{it}^{free} are slack variables denoting input excess, output shortfall, carry-over shortfall, carry-over excess and carry-over deviation.

Further, the weight to output i weighted by decision makers are respectively denoted as w_i^+, such that it is required to satisfy the following condition:

$$\sum_{i=1}^{s} w_i^+ = s \tag{21}$$

If the optimal solution (1) subject to (2)-(20) will be $(\{\lambda_o^{t*}\}, \{s_{ot}^{-*}\}, \{s_{ot}^{+*}\}, \{s_{ot}^{good*}\}, \{s_{ot}^{bad*}\}, \{s_{ot}^{free*}\})$, the output-oriented term efficiency for the term t would be obtained by:

$$\tau_{ot}^* = \frac{1}{1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{iot}^{+*}}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{iot}^{good*}}{z_{iot}^{good}}\right)}, \quad (t = 1,\ldots,T) \tag{22}$$

In other words, overall efficiency τ_o^* is the weighted average of the term efficiencies τ_{ot}^* that can be calculated as following:

$$\frac{1}{\tau_o^*} = \frac{1}{T} \sum_{t=1}^{T} \frac{w^t}{\tau_{ot}^*} \tag{23}$$

Figure 1 presents the conceptual scheme of the knowledge production process. The figure shows that not only dynamic DEA considers immediate inputs (space employment, non-space employment, internal R&D-space expenditure and internal R&D-non space expenditure) and outputs (space turnover, non-space turnover) in every period t, but also takes into account the embodied internal R&D-space and non-space capital stock as carry-overs from one period to the next period. We evaluate the performance of the space firms for the period 2012-2015 using dynamic DEA during a multiple period, and with the year 2011 as initial year.

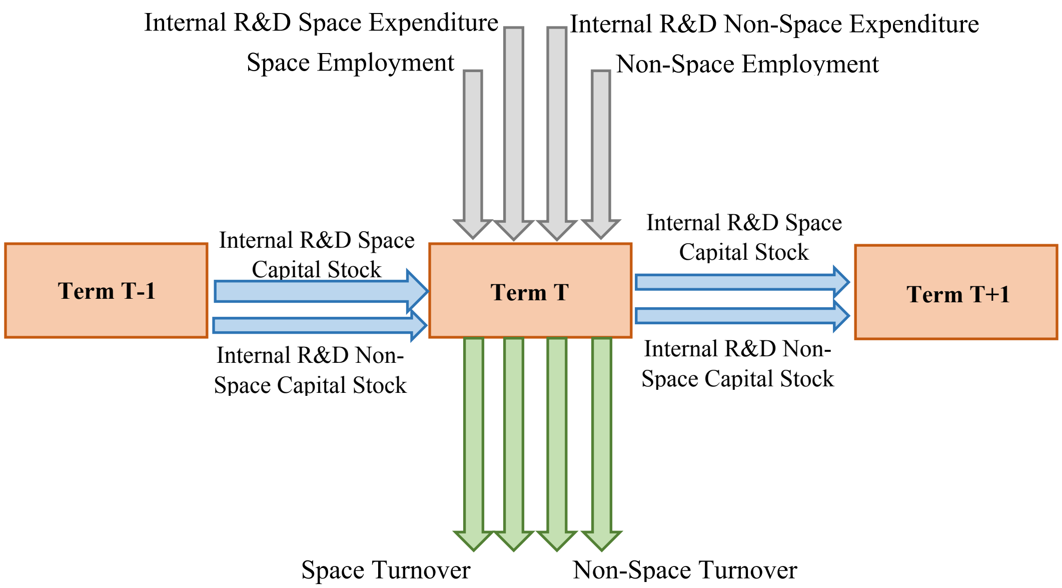

Figure 1: Dynamic slacks-based DEA research framework

The internal R&D-space capital stock and internal R&D non-space capital stock taken as carry-over variables are computed by the perpetual inventory method (PIM). The PIM assumes capital stock (investment) as an inventory and the amount of amortized capital stock is the depreciation rate.

The PIM model calculates the R&D capital stock in period t as a weighted total of previously created capital stock:

$$K_{(t)} = \sum_{i=0}^{\infty} (1-\delta)^{i} \times I_{(t-(i+1))} \tag{24}$$

Where $I_{(t-1)}$ is the R&D investment (period $t-1$), $K_{(t)}$ is the R&D capital stock (period t) and δ is the depreciation rate. The initial R&D capital stock is obtained by:

$$K_0 = \frac{I_{(0)}}{g+\delta} \tag{25}$$

Where g and δ are the R&D investment growth rate and R&D capital depreciation rate, respectively. Chen et al. (2018) point out that an arbitrarily depreciation rate can be selected between 10% and 15%. In line with Hall and Mairesse (1995) and Hu and Jefferson (2004), we have chosen 15% and 5% as depreciation and growth rate, respectively.

3.3 Truncated regression

The dependent variable, R&D output efficiency based on dynamic DEA, ranges between zero and one. A truncated regression model is tested in order to explain this firm level efficiency score by means of the central proximity topics, complemented with firm and public funding characteristics:

$$\text{Efficiency score} = c_t + \beta_1.\text{Within cluster proximity characteristics} + \beta_2.\text{Firm characteristics} + \beta_3.\text{ESA funding characteristics} \tag{26}$$

The starting point for the within geographical cluster characteristics is mapping the firms' location to depict the territorial space clusters in Belgium. The knowledge pool of human resource and knowledge exchange has been highlighted as main driver for geographical clustering of firms (Audretsch and Feldman, 1996; Porter, 1994; Niosi and Zeghu, 2005). Therefore, the geographical cluster is defined at the level of the urban area (morphological agglomeration defined by the continuity of residential dwellings around a central city characterized by a certain concentration of shops and services, a given density of population as well as the age and size of its dwellings), with inclusion of the - in particular in terms of socio-economic streams of people (and in particular labour forces) - closely connected suburban and commuter areas (Luyten and Van Hecke, 2007). As such, the population of space R&D active firms can be largely located in seven "urban" areas; Antwerp, Brussels, Ghent, Hasselt, Leuven, Liege, and Charleroi-Mons. The strong agglomeration of space activities in the mainly small- and medium-sized space R&D active firms in Belgium is in line with the strong agglomeration of the industry worldwide (Hickie, 2006).

At this point, it is interesting to recognize how output efficient space firms are operating in these functional geographical clusters. Therefore, we classify the firms' efficiency scores that we obtained based on the dynamic slacks-based DEA by geographical cluster. The cluster characteristics are specialization in the same industry as a proxy for cognitive distance, availability of anchors in the cluster as a proxy for social distance, and ESA funding received by public actors within the cluster as a proxy for organizational distance. Specialization is defined by the Hirschman-Herfindahl index (Herfindahl (1950) or Hirschman (1964)) which is commonly applied to measure market concentration, economic diversity and macroeconomic specialization (Beine and Coulombe 2006, Tauer 1992). For public funding, ESA funding received by public

actors in the region is obtained from the ESA contracts database. For social proximity, defining an anchor firm is not straightforward and many different approaches to do so exist (Feldman, 2000; Meardon, 2001; Niosi and Zhegu, 2005; Agrawal and Cockburn, 2003). Mostly, cut-off points to define anchor firms are set in terms of shares in sector turnover, or employment. In this paper, an anchor firm is defined as a firm with 5% or more of the total space employment in Belgium.
Firm level characteristics in terms of size, age, and sector are included as control variables. Scherer (1965), Schmookler (1972), Mansfield et al. (1971), Mansfield (1968) and Cooper (1964) state that medium- and small-sized firms are more motivated to perform R&D more efficiently. For the aviation industry in the Netherlands, Broekel and Boschma (2011) include firm size as a determinant for innovation performance. However, they did not find a significant influence of this variable on performance. Pradhan (2003) studies the determinants of the performance of R&D activities in the Indian pharmaceutical industry. Besides firm size, he finds that also age is positively related to R&D performance. To account for the large diversity in space activities, eight sub-sectors within the space sector are included: mechanical and industrial engineering; aviation aerospace; electrical and electronics; research; information, technology services; semiconductor industry; telecom services; and other manufacturing (OECD, 2012). Moreover, internal knowledge spillovers between space and non-space activities are an important issue in the sense of diversification of activities at firm level and spillovers between space and non-space activities (OECD, 2012; Venturini and Verbano, 2014).

Finally, since there is a large dependency of space R&D on public funding, characteristics of the public funding have to be taken into account. The amount of firm level government support for R&D is a first determinant to be taken into account. Griliches (1995) and Mamuneas and Nadiri (1996) explain that public support for private R&D activity and innovation can entail positive additionality effects in terms of performance. Czarnitzki et al. (2007) demonstrate the importance of public funding for R&D on firm performance. Czarnitzki and Hussinger (2004) indicate that both publicly and purely privately financed R&D exert a positive effect on innovative output. Additionally, through the output efficiency estimation process, the target of public funding for space R&D to address R&D activities in terms of technological readiness levels 5 and 6 (applied research) or level 7 or more (closer to market objectives) needs to be taken into account (OECD, 2012).

4. Empirical results

4.1. Descriptive

Dynamic slacks-based DEA is applied to evaluate the efficiency of the 122 space R&D active firms. Table 2 presents the results by geographical cluster (urban areas - following Niosi and Zhegu (2005)) for the period 2011-2015. It shows the output efficiency scores, the within-cluster proximity variables and the firm and public funding characteristics.

The results show that the average output efficiency differs by cluster, with the smaller clusters of Charleroi and Hasselt presenting higher average scores, and the cluster of Liège ranking lower in terms of average output efficiency.

Table 2: Descriptive of the firm and cluster characteristics by geographical cluster (mean, st. dev), 2011-2015

	Antwerp	Brussels	Charleroi -Mons	Ghent	Hasselt	Leuven	Liège	Belgium
Cluster size (N: number of space R&D active firms)	*19*	*37*	*6*	*12*	*5*	*20*	*23*	*122*
Output efficiency	0.42 (0.46)	0.39 (0.46)	0.59 (0.48)	0.48 (0.46)	0.81 (0.43)	0.48 (0.48)	0.25 (0.40)	0.42 (0.46)
Firm characteristics								
Firm size (Average number of employees)	215.98 (697.88)	486.88 (2272.24)	522.66 (935.91)	289.13 (555.40)	14.26 (27.22)	57.20 (84.84)	108.22 (269.01)	265.80 (1311.61)
Firm age (Number of years in 2011)	26.32 (24.79)	22.19 (0.40)	20.33 (10.86)	24.83 (16.48)	12.20 (9.26)	16.85 (8.16)	19.69 (12.75)	21.24 (17.52)
Aviation aerospace industry (Percentage of space firms active in aviation aerospace)	0.11 (0.32)	0.19 (0.40)	0.50 (0.55)	0.00 (0.00)	0.20 (0.45)	0.05 (0.22)	0.39 (0.50)	0.19 (0.39)
Telecom services (Percentage of space firms active in telecom services)	0.05 (0.23)	0.08 (0.28)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.05 (0.22)	0.00 (0.00)	0.04 (0.20)
Share of space R&D activities (share of internal space R&D in total internal R&D)	0.35 (0.34)	0.42 (0.34)	0.57 (0.49)	0.38 (0.36)	0.28 (0.44)	0.35 (0.34)	0.34 (0.32)	0.38 (0.35)
Cluster characteristics								
Cluster specialization (Specialization in the firm's space sector – cognitive proximity)	0.22 (0.05)	0.24 (0.05)	0.19 (0.03)	0.25 (0.06)	0.20 (0.03)	0.25 (0.05)	0.21 (0.05)	0.23 (0.05)
Private anchors (presence of anchor firm outside the proper company – social proximity)	0.89 (0.32)	0.91 (0.29)	0.83 (0.41)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.91 (0.29)	0.65 (0.48)
ESA funding received by public actors (keuro – period 2011-2015) – organizational distance	*	*	*	*	*	*	*	36554.29 (35429.65)
ESA Funding characteristics								
ESA funding at firm level (keuro – period 2011-2015)	*	*	*	*	*	*	*	4971.26 (13318.24)
TRL5_6_Share_ESA_Funding_2011-2015	0.21 (0.27)	0.21 (0.30)	0.18 (0.22)	0.03 (0.07)	0.24 (0.43)	0.24 (0.34)	0.26 (0.29)	0.20 (0.29)

Note: A handful of firms are located outside the sphere of the urban areas. These firms, mainly present in the South of the Liège cluster and in the West of the Ghent cluster are added to the geographical cluster the most nearby in terms of geographical distance. *For confidentiality reasons the amounts cannot be provided at cluster level.

The firm characteristics include age, size, engagement in aviation aerospace industry, telecom services industry, and share of space internal R&D activities in total internal R&D activities. Firm size is measured by total employment (full time equivalents). Age refers to the number of years of establishment. Engagement in aviation aerospace and telecom services industry are binary variables which show whether or not the main activity is related to the respective sub-industry of the aerospace industry. For reasons of absence of influence on output efficiency, all other space industry branches are taken together as the reference category.

The proximity dimensions are measured largely in line with Broekel and Boschma (2011). Cognitive proximity reflects closeness in space activities between the focus firm and all other firms surrounding this firm within the geographically defined cluster. Organizational distance indicates the importance of space activities in the public sector. Since no comprehensive data are available for space activities in the public sector, funding by ESA to public actors is taken as a proxy. This can be assumed a good proxy as the majority of space R&D is publicly funded. In total, there are 23 public organizations (10 universities and 13 public research centres) that were engaged in space R&D and that benefitted from ESA funding in the period 2011-2015. Together these organizations represent close to one fifth (equalling a yearly average of 36 million euro in the period 2011-2015) of the total budget spend by ESA on space R&D activities in Belgium. Social proximity is measured in terms of the presence of key players (anchor firms), defined in terms of employment (and related training, personal networks …), among the private actors surrounding (i.e. being located within the same geographical cluster as) the focal firm.

Finally, the influence of ESA funding is controlled for by including the firm level amount of ESA funding received during the period under consideration. In the period 2011-2015, on average a space R&D active firm received close to 5 million euro funding by ESA. Additionally, to take into account the shorter or longer term economic outputs, the technological readiness level (OECD, 2012) of the publicly funded R&D activities has been included, with applied research (TRL 5_6) being the reference category.

4.2. Determinants of R&D output efficiency

Table 3 demonstrates the outcomes of the truncated regression. Model 1 focuses on firm characteristics, particularly. In model 2, the within geographical cluster cognitive, social, and organizational proximity characteristics are added. The technological readiness level and amount of ESA funding at firm level have been added in model 3.

Table 3: Truncated regression model explaining output efficiency of space R&D active firms

	Model 1	Model 2	Model 3
Firm characteristics			
Firm size (natural logarithm)	0.29 (0.10)**	0.18 (0.06)**	0.13 (0.05)*
Firm age (natural logarithm)	-0.14 (0.23)	-0.07 (0.16)	-0.06 (0.12)
Aviation aerospace industry	0.57 (0.35)	0.59 (0.24)*	0.10 (0.21)
Telecom services	2.24 (0.79)**	1.83 (0.47)**	1.42 (0.42)**
Share of space R&D activities	-2.18 (1.45)	-0.95 (0.88)	-0.96 (0.72)
Share of space R&D activities (square)	3.09 (1.48)*	1.55 (0.86)°	1.41 (0.70)*
Cluster proximity characteristics			
Cluster specialization (cognitive proximity)		4.24 (1.94)*	3.93 (1.61)*
ESA funding received by public actors (organizational distance)		-0.11 (0.04)**	-0.08 (0.03)*
Anchor (social proximity)		-0.34 (0.23)	-0.22 (0.19)
ESA Funding characteristics			
Amount of ESA funding (natural logarithm)			-0.25 (0.10)*
Amount of ESA funding (square of natural logarithm)			0.03 (0.01)**
TRL5_6_Share_ESA Funding_2011-2015			0.05 (0.83)
TRL5_6_Share_ESA Funding_2011-2015 (Square)			0.24 (1.00)
Constant	-0.42 (0.55)	-0.07 (0.61)	0.30 (0.51)
Wald chi2 (sig)	16.27 (0.01)	36.63 (0.00)	51.21 (0.00)
Log pseudo likelihood	-38.42	-28.58	-22.88

Note 1: **,* denote 1% and 5% significance level respectively. Note 2: only "aviation aerospace" and "telecommunication services" space activities turned out to be significant, and for parsimonious reasons only these sector activities were included in the final models – all other space subsectors being the reference category. Cluster specialization is calculated for each of the seven clusters based on the eight space sub-industry activities. Note 3: cluster dummies have been included in the analysis and turned out not to be significant (and therefore not reported here). This can be seen as an indication that after controlling for within-cluster proximity, firm and public funding characteristics, little residual unexplained differences at geographical cluster level remain. The inclusion of these cluster dummies also avoids potential bias related to multi-level analysis. Note 4: correlation between the variables, and as such potential multicollinearity, is limited (average variance inflation factor of 1.92, with maximum of 3.97 – based on regression model).

Model 1 can be seen as the base model focusing on the relation between firm characteristics and R&D output efficiency. Contrary to the insights from the literature (Scherer, 1965; Schmookler, 1972; Mansfield et al., 1971) stating the small- and medium-sized firms are more motivated to perform R&D more efficiently, in the space industry, output efficiency of R&D tends to increase with firm size. This finding contrasts findings of absence of size effect in the Netherlands for a broader set of aviation and aerospace industries (Broekel and Boschma, 2011). The significant and positive influence of the space sub-sector dummies for being active in the aviation aerospace industry and in particular in telecom activities enforce the view of particularities by space sub-industry (OECD, 2012). In line with Broekel and Boschma (2011), but against the findings by Pradhan (2003) no positive effect is found of firm age. A stronger focus on internal R&D space activities in the overall internal R&D activities does not influence R&D output efficiency. However, the significant and positive square term of the share of internal R&D space activities points into the direction of the existence of an optimal balance between space and non-space R&D for, in our analysis within-firm, spillover effects positively affecting R&D output efficiency in terms of space and non-space turnover (Venturini and Verbano, 2014).

The sign and significance of the firm level characteristics are robust when adding the within geographical cluster proximity characteristics (Model 2). For the proxy variable for cognitive proximity, we find a significant positive effect of specialization of firms outside the focal firm in similar (at subsector level) space activities. This is in line with the idea by Simmie (2003) that regional specialization in a particular industry eases the occurrence of knowledge spillovers leading to innovation and economic growth. Therefore, the higher the similarity in the technological knowledge profile of firms in the space industry within the geographical cluster, the higher the firm level R&D output efficiency. Our findings go against the views by Feldman and Audretsch (1999) who state that geographical specialization does not guarantee innovative output enhancement. It has to be noted that we apply the regional specialization within the space industry and do not consider specialization of the space industry within the overall economic activities of the geographical cluster. These findings are also opposite to the findings by Broekel and Boshma (2011) who report a negative influence of cognitive proximity on innovative performance.

With regard to organizational distance we find a significant negative relation with innovative performance. This confirms the expectations that aligning private R&D with R&D in public organizations brings in its wake challenges in terms of management of knowledge exchange and induces higher transaction costs, in particular in an environment characterized by small- and medium-sized firms (Meardon, 2001). Alternatively, larger industry-science interactions might orient firms towards longer term basic research with less immediate output efficiency (Teirlinck and Spithoven, 2015). Our findings are in line with the theoretical expectations raised regarding organizational proximity by Broekel and Boschma (2011) for the aviation industry in the Netherlands. In contrast to their empirical findings (absence of influence for the aviation industry), we confirm this expectation for the space industry. We also confirm the argument by Meardon (2001) regarding the limited role of public actors for small- and medium-sized firms in a region. However, it cannot be ignored that it also might be that the five-year time span which we investigate here is not consistent with the time period such projects need to lead to output performance.

Within geographical clusters we cannot confirm the importance of social proximity (as found by Broekel and Boschma, 2011). As indicated before, the measurement of anchor firms is done quite arbitrary in the empirical literature. Therefore, we test other definitions of anchors (share of space R&D, 10% rather than 5% of total employment). Changing the measurement of the anchor firm does not influence the results. In addition, as an alternative proxy for social proximity, we tested participation in regional networks of space and aviation industry. Two such networks exist in Belgium: the FLAG and the SKYWIN cluster. Since 2006, the SKYWIN Aerospace Cluster in Wallonia offers substantial training activities and aims at developing technological niches for the future; at diversifying and creating new companies; and at meeting the market demand in terms of yet lighter components or increased performance in the structures (www.skywin.be). The Flemish Aerospace Group (FLAG) is a cluster organization for enterprises active in the aerospace market in the Flemish and Brussels Regions. FLAG supports the development of aviation and related technologies, improves the visibility of the Flemish aerospace globally aiming for a growing market share. FLAG caters for its members' interest on a political level, facilitates networking between its members and, develops business opportunities by organizing attendance to major business events and aims at a well-functioning triple helix structure (www.flag.be). The inclusion of dummy variables for participating in FLAG and SKYWIN confirmed absence of social proximity influence on R&D output efficiency.

In Model 3, ESA funding received by the individual firm during the period 2011-2015 is added. The magnitude and significance of the coefficient for firm and cluster level characteristics remain robust when adding the ESA funding at individual firm level. A negative effect of the size of ESA funding a firm received during the period 2011-2015 is found (indicating that a 1% increase in ESA funding leads to a 0.01*0.25 decrease in R&D output efficiency). This negative effect decreases with the size of the ESA budget (positive square term effect). The absence of significance of the lower TRL levels (ESA funding oriented towards applied research) indicates there is no difference according to whether public funding is oriented towards more applied research (TRL 5 and 6) or commercial development orientation.

5. Conclusions

This paper presented a new conceptual framework for the evaluation of firm level R&D output efficiency in the space industry. First, we have implemented a dynamic slacks-based DEA model to evaluate performance efficiency of space R&D active firms in Belgium. Next, we measured the influence of different forms of within-cluster proximity, firm, and public funding characteristics on this output efficiency.

Space activities in the small open Belgian economy are taken as a test case. These activities are largely concentrated in seven geographical clusters that can be defined according to urban areas and, in terms of streams of human resources, related suburban and commuter areas. The emphasis on human resources to define geographical clusters is in line with earlier work by Niosi and Zhegu (2005).

The paper adds to existing insights regarding the importance of different forms of proximity (Boschma, 2005) in explaining firm level performance. Besides firm characteristics, within geographical clusters, the role of cognitive, organizational, and social proximity for output efficiency of R&D is investigated. Since the space sector is a highly publicly funded sector, and all space R&D active firms receive funding from ESA, we also checked the influence of the height and the technological readiness level of public funding targeting space R&D.

For firm characteristics, first, against the ideas and findings based on initial work by Scherer (1965), output efficiency of internal space and non-space R&D is found to augment with firm size. So, a critical size for efficiently turning R&D into turnover is required in the space sector. Firm age turned out of no importance for output efficiency, and so we could not confirm positive (Pradhan 2003) nor negative (Shefer and Frenkel 2005) effects of potentially different dynamics between younger and more established firms. Space activities involve a broad variety of subsectors, and the firms active in telecommunication services, and to a lesser extent aviation aerospace, yield significantly higher R&D output efficiency compared to firms active in other subsectors of the space industry. In terms of knowledge spillovers between space and non-space

R&D, a balancing of space and non-space R&D activities yields higher output efficiency (Venturini and Verbano, 2014). The indication of positive effects on output efficiency of a mixture of space and non-space R&D activities indicates potential benefits of mixed (space and non-space) R&D activities.

For within geographical cluster proximity characteristics, first, cognitive proximity in terms of an environment specialized along the firm's sector activity (measured at the level of space subsectors) turns out to be highly beneficial for R&D output efficiency. This contrasts earlier findings by Broekel and Boschma (2011) reporting absence of cognitive proximity effects for the aviation industry in the Netherlands. So, for the space industry we do not find arguments that too much similarity of the knowledge base within a geographical cluster would be detrimental to performance (as expected by Nooteboom et al., 2007, and Boshma and Frenken, 2010).

For organizational distance, measured by the importance of public research in space in the geographical cluster, a significant negative influence on R&D output efficiency is found the higher the public space activities. In a sector in Belgium dominated by SMEs this confirms earlier findings by Meardon (2001), and goes against the absence of importance of organizational proximity reported by Broekel and Boschma (2011) for the aviation industry in the Netherlands.

Social proximity, measured in terms of the presence of anchor firms playing a key role in providing the cluster with socially connected human resources by means of flows and training of knowledge workers in the space industry, is not found to influence output efficiency. This goes against the expectations raised by Feldman (2003), and also does not confirm earlier findings by Broekel and Boschma (2011)).

Finally, given its highly publicly funded character, the influence of public support for space R&D cannot be ignored. Larger amounts of ESA funding allocated to the individual firm negatively relate to R&D output efficiency. Therefore, for R&D activities in the space sector, we do not confirm a positive relationship between performance and receiving public funding as reported by Czarnitzki and Hussinger (2004) and Czarnitzki et al. (2007). However, the negative effects seem to diminish with increasing amounts of funding. Whether this public funding is more applied research oriented (technological readiness level objectives 5 and 6) or more close to market (technological readiness level 7 and higher) does not matter for R&D output efficiency in terms of turnover.

The above presented findings yield important implications for managers and policy makers. First, geographical clustering policies in the space industry can be strengthened by taking into account cognitive and organizational proximity within these clusters. Next, an optimum level of funding for space R&D exists for maximizing firm level R&D output efficiency. Also, R&D output efficiency is higher for larger firms, for firms engaged in space aviation or telecom activities, and for firms combining space and non-space R&D.

Compared to previous research, the empirical analysis offers the advantage of having a relatively large number of firms in the narrowly defined space R&D active industry (e.g. three times more than the number in the study by Broekel and Boschma (2011) focusing on the aviation industry in a broad sense). However, further research for the highly internationalized space industry is necessary in order to address some of the limitations of this work. First, the measurement of the different forms of proximity, although highly in line with actual insights and practices in the empirical literature, could be further improved. This can be done by looking in more detail into the interactions between space and other actors or industries, both within and outside geographical clusters. The latter is important given the high international focus of the space industry and the necessity of a mixture of local buzz and global pipelines (Bathelt et al., 2004). Second, the dynamic slacks-based approach followed in this paper is novel and addresses the need to better take into account dynamics (as suggested by Broekel and Boschma, 2011), but longer time-lags between R&D and output performance need to be considered. Third, as highlighted by Broekel and Boschma (2011), a deeper investigation of the relationships between the different forms of proximity deserves further attention. Similarly, the relation between space and non-space activities should be further explored. Finally, the findings for the business dominated and largely SME-driven space sector in the small open Belgian economy need to be tested in other contexts. To do so, there is an urgent need for comparable data in different countries, and with systematic collection, preferably at ESA level.

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References

Adams, J. D. (1990). Fundamental stocks of knowledge and productivity growth. *Journal of Political Economy*, *98*(4), 673-702.

Agrawal, A., & Cockburn, I. (2003). The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems. *International Journal of Industrial Organization*, *21*(9), 1227-1253.

Audretsch, D. B., & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, *11*(2), 253-273.

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31-56.

Beaudry, C. (2001). Entry, growth and patenting in industrial clusters: A study of the aerospace industry in the UK. *International Journal of the Economics of Business*, *8*(3), 405-436.

Beine, M., & Coulombe, S. (2006). Economic integration and the diversification of regional exports: evidence from the Canadian–US Free Trade Agreement. *Journal of Economic Geography, 7*, 93-111.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional Studies*, *39*(1), 61-74.

Boschma, R. A., & Weterings, A. B. (2005). The effect of regional differences on the performance of software firms in the Netherlands. *Journal of Economic Geography*, *5*(5), 567-588.

Boschma, R. A., & Frenken, K. (2010). The spatial evolution of innovation networks. A proximity perspective. In R. A. Boschma, R. Martin (eds), *Handbook on Evolutionary Economic Geography*, pp. 120–135. Cheltenham: Edward Elgar.

Breschi, S., & Lissoni, F. (2001). Knowledge spillovers and local innovation systems: a critical survey. *Industrial and Corporate Change*, *10*(4), 975-1005.

Broekel, T., & Binder, M. (2007). The regional dimension of knowledge transfers—a behavioral approach. *Industry and Innovation*, *14*(2), 151-175.

Broekel, T., & Boschma, R. (2011). Knowledge networks in the Dutch aviation industry: the proximity paradox. *Journal of Economic Geography*, *12*(2), 409-433.

Broekel, T., Brenner, T., & Buerger, M. (2015). An investigation of the relation between cooperation intensity and the innovative success of German regions. *Spatial Economic Analysis*, *10*(1), 52-78.

Chen, C. M., & van Dalen, J. (2010). Measuring dynamic efficiency: Theories and an integrated methodology. *European Journal of Operational Research*, *203*(3), 749-760.

Chen, K., Kou, M., & Fu, X. (2018). Evaluation of multi-period regional R&D efficiency: An application of dynamic DEA to China's regional R&D systems. *Omega*, *74*, 103-114.

Chen, C. M. (2009). A network-DEA model with new efficiency measures to incorporate the dynamic effect in production networks. *European Journal of Operational Research*, *194*(3), 687-699.

Chun, D., Chung, Y., & Bang, S. (2015). Impact of firm size and industry type on R&D efficiency throughout innovation and commercialisation stages: evidence from Korean manufacturing firms. *Technology Analysis & Strategic Management*, *27*(8), 895-909.

Cooper WW, Seiford LM, Tone K. (2000). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. Dordrecht: Kluwer Academic Publishers.

Cooper, A. C. (1964). R&D is more efficient in small companies. *Harvard Business Review*, *42*(3), 75-83.

Cunningham, W. G. (1951). *The aircraft industry: a study in industrial location*. Los Angeles: Morrison.

Czarnitzki, D., & Hussinger, K. (2004). *The link between R&D subsidies, R&D spending and technological performance*. ZEW Discussion Paper 04–56, Mannheim.

Czarnitzki, D., Ebersberger, B., & Fier, A. (2007). The relationship between R&D collaboration, subsidies and R&D performance: empirical evidence from Finland and Germany. *Journal of Applied Econometrics*, *22*(7), 1347-1366.

Emrouznejad, A., & Thanassoulis, E. (2005). A mathematical model for dynamic efficiency using data envelopment analysis. *Applied Mathematics and Computation*, *160*(2), 363-378.

Färe, R., & Grosskopf, S. (1996). *Intertemporal production frontiers: with dynamic DEA*. Boston: Kluwer Academic Publishers.

Fare, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, *84*(1), 66-83.

Feldman, M. (2003). The locational dynamics of the US biotech industry: knowledge externalities and the anchor hypothesis. *Industry and Innovation*, *10*(3), 311-328.

Feldman, M. P. (2000). Location and innovation: the new economic geography of innovation, spillovers, and agglomeration. in Clark, G.L., Feldman, M. and Gertler, M. (Eds.), *The Oxford Handbook of Economic Geography* (pp. 373-394). Oxford: Oxford University Press.

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409-429.

Feldman, M. P., & Florida, R. (1994). The geographic sources of innovation: technological infrastructure and product innovation in the United States. *Annals of the association of American Geographers*, *84*(2), 210-229.

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography*, *3*(1), 75-99.

Griliches, Z. (1995). R&D and Productivity: Econometric Results and Measurement Issues. In P. Stoneman (Ed.), *Handbook of the Economics and Innovation and Technological Change* (pp. 52-89). Oxford, England: Blackwell.

Guan, J., & Chen, K. (2010). Measuring the innovation production process: A cross-region empirical study of China's high-tech innovations. *Technovation*, *30*(5-6), 348-358.

Hall, B. H., & Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics*, *65*(1), 263-293.

Healy, D., Morgan, R., & Chinnaswamy, S. (2009). Transient global amnesia associated with statin intake. *BMJ Case Reports*,2009.doi:10.1136/bcr.06.2008.0033.

Herfindahl, O. C. (1950). *Concentration in the steel industry*(Doctoral dissertation). Retrieved from Columbia University.

Hickie, D. (2006). Knowledge and competitiveness in the aerospace industry: The cases of Toulouse, Seattle and North-west England. *European Planning Studies*, *14*(5), 697-716.

Hirschman, A. O. (1964). The paternity of an index. *The American Economic Review*, *54*(5), 761-762.

Hsu, F. M., Horng, D. J., & Hsueh, C. C. (2009). The effect of government-sponsored R&D programmes on additionality in recipient firms in Taiwan. *Technovation*, *29*(3), 204-217.

Hu, A. G., & Jefferson, G. H. (2004). Returns to research and development in Chinese industry: Evidence from state-owned enterprises in Beijing. *China Economic Review*, *15*(1), 86-107.

Huergo, E., & Jaumandreu, J. (2004). Firms' age, process innovation and productivity growth. *International Journal of Industrial Organization*, *22*(4), 541-559.

Hung, S. W., & Wang, A. P. (2012). Entrepreneurs with glamour? DEA performance characterization of high-tech and older-established industries. *Economic Modelling*, *29*(4), 1146-1153.

Hung, S. W., He, D. S., & Lu, W. M. (2014). Evaluating the dynamic performances of business groups from the carry-over perspective: A case study of Taiwan′ s semiconductor industry. *Omega*, *46*, 1-10.

Isaksen, A. (2001). Building regional innovation systems: is endogenous industrial development possible in the global economy?. *Canadian Journal of Regional Science*, *24*(1), 101-120.

Jaffe, A. B. (1989). Real effects of academic research. *The American Economic Review*, 957-970.

Karlsen, J. (2013). The role of anchor companies in thin regional innovation systems lessons from Norway. *Systemic Practice and Action Research*, *26*(1), 89-98.

Khalili-Damghani, K., Tavana, M., Santos-Arteaga, F. J., & Mohtasham, S. (2015). A dynamic multi-stage data envelopment analysis model with application to energy consumption in the cotton industry. *Energy Economics*, *51*, 320-328.

Li, L. B., Liu, B. L., Liu, W. L., & Chiu, Y. H. (2017). Efficiency evaluation of the regional high-tech industry in China: A new framework based on meta-frontier dynamic DEA analysis. *Socio-Economic Planning Sciences*, *60*, 24-33.

Lublinski, A. E. (2003). Does geographic proximity matter? Evidence from clustered and non-clustered aeronautic firms in Germany. *Regional Studies*, *37*(5), 453-467.

Luyten, S., & Van Hecke, E. (2007). De Belgische stadsgewesten 2001. Statistics Belgium – Working Paper no. 14. FPS Economy (Direction for Statistics and Economic Information), Brussels.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Estadística*, *4*(2), 209-242.

Mamuneas, T. P., & Nadiri, M. I. (1996). Public R&D policies and cost behavior of the US manufacturing industries. *Journal of Public Economics*, *63*(1), 57-81.

Mansfield, E. (1968). *Industrial research and technological innovation; an econometric analysis*. New York: Norton

Mansfield, E. (1971). *Research and innovation in the modern corporation*. New York: Norton

Meardon, S. J. (2001). Modelling agglomeration and dispersion in city and country: Gunnar Myrdal, Francois Perroux, and the New Economic Geography. *American Journal of Economics and Sociology*, *60*(1), 25-57.

Metcalfe, J. S. (1994). Evolutionary economics and technology policy. *The Economic Journal*, *104*(425), 931-944.

Molas-Gallart, J., & Davies, A. (2006). Toward theory-led evaluation: The experience of European science, technology, and innovation policies. *American Journal of Evaluation*, *27*(1), 64-82.

Niosi, J., & Zhegu, M. (2005). Aerospace clusters: local or global knowledge spillovers?. *Industry and Innovation*, *12*(1), 1-25.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & Van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy*, *36*(7), 1016-1034.
Organisation For Economic Co-Operation Development. (2012). *OECD Handbook on Measuring the Space Economy*. OECD Publishing.
Ponds, R., Van Oort, F., & Frenken, K. (2007). The geographical and institutional proximity of research collaboration. *Papers in Regional Science, 86*(3), 423-443.
Porter, M. (2003). The economic performance of regions. *Regional Studies*, *37*(6-7), 549-578.
Porter, M. E. (1994). The role of location in competition. *Journal of the Economics of Business*, *1*(1), 35-40.
Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15-34.
Pradhan, J. P. (2002). Liberalization, firm size and R&D performance: A firm level study of Indian pharmaceutical industry. *Journal of Indian School of Political Economy, 14*(4), 647–666.
Rogers, P. J. (2008). Using programme theory to evaluate complicated and complex aspects of interventions. *Evaluation*, *14*(1), 29-48.
Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), 71-102.
Saati, S., Hatami-Marbini, A., & Tavana, M. (2011). A data envelopment analysis model with discretionary and non-discretionary factors in fuzzy environments. *International Journal of Productivity and Quality Management*, *8*(1), 45-63.
Sarkis, J., & Cordeiro, J. J. (2012). Ecological modernization in the electrical utility industry: An application of a bads–goods DEA model of ecological and technical efficiency. *European Journal of Operational Research*, *219*(2), 386-395.
Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. *The American Economic Review*, *55*(5), 1097-1125.
Schmookler, J., (1972). *Patents, Invention, and Economic Change*. Cambridge, MA: Harvard University Press.
Scotchmer, S. (1991). Standing on the shoulders of giants: cumulative research and the patent law. *Journal of Economic Perspectives*, *5*(1), 29-41.
Shefer, D., & Frenkel, A. (2005). R&D, firm size and innovation: an empirical analysis. *Technovation*, *25*(1), 25-32.
Shephard, R.W., and R. Färe (1980). *Dynamic Theory of Production Correspondences*, Cambridge MA: Oelgeschlager, Gunn and Hain Publishers.
Simmie, J. (2003). Innovation and urban regions as national and international nodes for the transfer and sharing of knowledge. *Regional Studies*, *37*(6-7), 607-620.
Spagnulo, M., Fleeter, R., Balduccini, M., & Nasini, F. (2013). Space program management. In *Space Program Management* (pp. 59-95). Springer, New York, NY.
Tauer, L. W. (1992). Diversification of production agriculture across individual states. *Journal of Production Agriculture*, *5*(2), 210-214.
Teirlinck, P. Praet, D., Nijskens, J. (2017). De door ESA gefinancierde ruimtevaartsector in België. Science Connection, Belgian Science Policy Office, 54, pp.12-17.
Teirlinck, P., & Spithoven, A. (2015). How the nature of networks determines the outcome of publicly funded university research projects. *Research Evaluation*, *24*(2), 158-170.
Todd, D. & Simpson, J. (1986) *The World Aircraft Industry*. Dover, MA: Auburn House Publ. Co.
Tone, K., & Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. *European Journal of Operational Research*, *197*(1), 243-252.

Tone, K., & Tsutsui, M. (2010). Dynamic DEA: A slacks-based measure approach. *Omega*, *38*(3-4), 145-156.

Venturini, K., & Verbano, C. (2014). A systematic review of the Space technology transfer literature: Research synthesis and emerging gaps. *Space Policy*, *30*(2), 98-114.

Wang, N., & Hagedoorn, J. (2014). The lag structure of the relationship between patenting and internal R&D revisited. *Research Policy*, *43*(8), 1275-1285.