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An Eco-efficiency Analysis of Space Agencies Launching Activities

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Abstract

In the last few years, countries and commercial firms are increasingly interested in space activities for civil, military, and commercial purposes (Undseth et al., 2020). As it has been shown in NASA report (2019), investment in space program drives to significant economic benefits to the whole society. We propose the first methodological paper to empirically study the efficiency of satellite launches employing the Data Envelopment Analysis input-oriented technique. We show that overall average efficiency is quite low and that it can significantly be improved by studying subsamples of DMUs according to user, purpose, and class of orbit. The most relevant results can be achieved in the communications purpose cluster where the bias corrected efficiency scores tripled with respect to average efficiency level reached by overall estimates. Hence, the scope of satellites seems to affect the mission efficiency and, even more relevant, the future creation of debris.

Keywords: efficiency; debris; space programs; space agencies; satellites.

JEL: D24, Q53, R41

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1. INTRODUCTION

In the last few years, countries and commercial firms are increasingly interested in space activities for civil, military and commercial purposes (Undseth et al., 2020). As it has been shown in NASA report (2019), investment in space programs drives to significant economic benefits to the whole society. Technology advancements needed for space exploration become applicable to several sectors such as agriculture, transport, energy and meteorology (OECD, 2020). For example, engineers working for NASA's Jet Propulsion Laboratory developed a ventilator for coronavirus patients in just 37 days. More directly, space activities positively affect GDP, by creating employment and generating revenues (OECD, 2019). To put things in perspective, during fiscal year 2019, NASA's agency activities produced more than 64,3 billions of dollars in total economic output, supporting thousands of jobs nationwide¹ (NASA Report, 2019).

Space-based infrastructures are essential for citizens' everyday lives. Nowadays, indeed, data resulting from space observation are used for weather forecasting, climate monitoring (Cheng et al., 2016) and, above all, telecommunications. For all these reasons, starting from the launch of Sputnik I, the use of Earth's orbits has expanded globally (Liou and Johnson, 2016) mainly boosted by lower launch costs and foreseen returns. Since 2010, NASA has recorded on average roughly 80 launches per year (Liou, 2017). Specifically, lower orbits are overpopulated due to a considerable rise in constellation satellites, replacing single satellites (Chrystal et al., 2018). The accumulation of man-made objects, defined as orbital debris, dramatically challenges the long-term sustainability of space operations, posing considerable risks to human space flight and robotic missions (Liou and Johnson, 2016). Beyond the already existing costs of satellites protection and mitigation, the costs resulting from accidental collisions with debris deserves special attention. First, collision generates additionally debris, leading to the so-called Kessler syndrome of self-generating collisions (Adilov et al., 2020). In fact, projections to simulate the future debris

¹ The Moon to Mars exploration program alone generated 69000 jobs nationwide (NASA Report, 2019).

patterns show that after 2055, though assuming no further satellites launches, the satellite population will increase due to the generation of new collision fragments, exceeding the quantity of decaying debris (Liou and Johnson, 2016). Second, not only satellites random collision with debris requires spacecraft replacement and triggers launch delays but, most important, it results in data loss with disastrous economic consequences for satellite communication (Undseth et al., 2020). For this reason, traffic management is becoming crucial to avoid collision and additional debris creation, increasing costs due to fuel consumption and delayed path of operational mission life. According to Christal et al. (2018), traffic management is one of the three existing alternatives to address debris collision risk, together with debris mitigation and remediation. While the former includes all guidelines which satellites follow to limit operational debris (e.g., Mejía-Kaiser, 2020), the latter consists of still hypothetical measures to remove debris. Although many debris removal measures have been proposed and tested (e.g., Nishida and Kawamoto, 2011; Kibe, 2003), none of them is both technically practicable and economic viable (Hall, 2014).

Based on the above, given the crowding of massive objects especially in low Earth orbit, satellites are always exposed to fatal collision risks (Wormnes et al., 2013). Christal et al. (2018) estimates the probability of collision as a function of spatial density, relative velocity, and collision cross-section. However, such probability is not linked to the launch costs. This represents a serious gap in the attempt at assessing the balance between revenues and costs related to launches of satellites or other publicly or privately funded space items. At the basis of each economic activity stands the relationship between revenue and cost or, to put differently, input and output leading to efficiency analysis. The pursue of high efficiency levels is the main goal of any organization. For, we believe that also in the space economy framework such aim should deserve a predominant attention to fill the existing gap.

The most common approach to assess efficiency of any organization is the well-known Data Envelopment Analysis (DEA), a mathematical programming technique designed to evaluate the relative efficiency for a group of comparable

decision-making units (DMUs). The aim of DEA is to measure productive efficiency through the estimation of a frontier envelopment surface for all DMUs by using linear programming techniques. In doing so, DEA allows for the identification of best practices and for the comparison of each DMU with the best possible performance among the peers, rather than just with the average. Once the reference frontiers have been defined, it is possible to assess the potential efficiency improvements available to inefficient DMUs if they were producing according to the best practice of their benchmark peers. From an equivalent perspective, these estimates identify the necessary changes that each DMU needs to undertake in order to reach the efficiency level of the most successful DMU (Fried et al., 2008). In addition, whereas DEA is, at the beginning, run under the constant returns to scale, it can be reformulated to account for variable returns to scale as well (Banker et al., 1988).

Following the DEA approach, we will consider launched satellite as a DMU in order to estimate the efficiency of its life cycle. This requires gathering as many information as possible on each launch. Specifically, technical information on the kind of object launched, monetary information on launch and maintenance on orbit, information on the flow of revenue eventually originated or expected to from each item, any changes from the scheduled satellite's duties during its life, if and when it has been hit by debris or other item, if and when it has produced debris, if the owner of the launched item is public or private body, the purpose of the item sent (e.g., commercial, military etc.). Likely important are the information regarding the existing debris at both LEO and GEO levels, focusing on their dimension, number and velocity. Gathering all the just described information would allow us to estimate the efficiency scores for each item and reporting the aspects to consider in order to increase the efficiency of future launches. Also, and maybe more relevant, by incorporating the data on debris, it may be possible to obtain estimates of 'eco-efficiency' pointing the best practices to adopt in order to account for both technical efficiency and eco-sustainability of space environment.

Such results may lead to relevant policy insights to space agencies involved in debris reduction activities and standard launching activity at the same time.

The rest of the paper is organized as follows. Section 2 reviews the related literature. In Section 3, we describe methods and data, whereas Section 4 discusses the results. Section 5 concludes the study.

2. LITERATURE REVIEW

To the best of our knowledge, little empirical research has been dedicated to the space debris problem. A three-dimensional debris model was developed by NASA using a MONTE CARLO approach to predict the development of future debris (Liou et al., 2004). Given the continuous collision and the deriving increasing production of debris, Christal et al. (2018) estimate the probability of collision for a satellite, dependent, among the other variables previously mentioned, on the number of debris. Specifically, debris collision risk, measured for all the phases of satellites life (i.e., from deployment to retirement, passing for operations), varies with the operational altitude, transit time, satellite's manoeuvre capability but mainly with its exposure to the background population. Although the aforementioned study also focuses on the consequences of a collision, the environmental impact of the space activity is specifically addressed by ESA (Colombo et al., 2017).

Notably, the European Space Agency successfully adopted Life Cycle Assessment methodology to assess the environmental footprint of the space projects, following their entire life cycle. A space debris indicator was defined as a function of casualty risk, orbital resource and debris risk. Additionally, the collision risk depends on the potential fragmentations of satellites and their probability to happen. The indicator is defined to drive preliminary mission design to reduce the satellites' environmental impact.

Missing from the reviewed studies, however, is any efficiency analysis of the space activity which we attempt to provide with the support of the DEA

technique, frequently used in other sectors. For example, Liang et al. (2006) measure supply chain efficiency in a seller-buyer context, developing numerous DEA models. The same approach is used by Grmanová and Ivanová (2017) to evaluate the efficiency of the banking sector in Slovakia. Another scenario where DEA approach resulted to be successful is solid waste management as shown by Marques and Simoes (2009) in the Portuguese context. Meng et al. (2016) highlight the ample scope of the well-known nonparametric technique, by providing a survey of all the empirical studies on China's regional energy and carbon emission sector, published between 2006 and 2015. In the same local context, Wang et al. (2016) assess the economic efficiency of the Chinese provincial museums. An extension of DEA is, instead, used by Falagario et al. (2011) to rank different bids in public procurement. Still focusing on the public sector, Finocchiaro Castro and Guccio (2014) apply DEA to assess the technical efficiency of Italian judicial districts. Finally, airport performances are evaluated resorting to the DEA models by Merkert and Assaf (2015). A more comprehensive review of DEA applications is provided by Liu et al. (2012). As can be inferred from the reported literature, DEA's most appreciated strength is the only need of identified inputs and outputs to be applied, regardless of the topic at hand. Also, it does not require any previous assumptions on specific production function, being in this case like a black box where pouring inputs to get outputs. Hence, we do believe we can use such technique to assess the efficiency of space items launching activity.

3. METHODS AND DATA

3.1 Methodological Framework

Each effective private or public service provision, such as health, educational, defense and space service, benefits from the support of rigorous measurement techniques. Data Envelopment Analysis (DEA) is a mathematical programming technique designed to evaluate the relative efficiency for a group of comparable decision-making units (DMUs). The mathematical programming technique can

take several forms according to different criteria, so it can be oriented to minimize input values or maximize output.

The DEA methodology calculates an efficiency frontier for a set of DMUs and the distance to the frontier for each unit. In the case of input-oriented approach, the distance (efficiency score) between the observed and most efficient DMU is the measure of the radial reduction in input for a given output. Our dataset calls for such approach, where for a given output level, the efficiency can be reached minimizing the inputs. Illustrating this point,² consider n DMUs for evaluation; a DEA input-oriented efficiency score h_i is calculated for each DMU, which solves the following program for $i = 1, \dots, n$ using the constant returns to scale (CRS) assumption.³

$$\begin{array}{ll} \text{Min}_{\lambda, \theta_i} & \theta_i \\ \text{subject to} & Y\lambda - y_i \geq 0 \\ & \theta_i x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \end{array} \quad (1)$$

x_i and y_i are the input and output, respectively, for the i^{th} DMU; X is the matrix for the input, Y is the matrix for the output, and λ is a $n \times 1$ vector of variables. The model (1) can be modified to account for variable returns to scale (VRS) by adding the convexity constraint $e\lambda = 1$ where e is a row vector with all elements unity, which distinguishes between Technical Efficiency (TE) and Scale Efficiency (SE).

DEA is a well-established and useful technique for measuring efficiency in public sector activities.⁴ The reasons for the widespread use of DEA are

² For more details, refer to Coelli (1998), Fried et al. (2008).

³ The acronyms CRS (constant returns to scale) and VRS (variable returns to scale) are often used with reference to the CCR and BCC models from the initials of the authors, Charnes et al. (1978), Banker et al. (1989).

⁴ DEA technique has been applied to several fields besides justice, such as regulation of water companies (Thanassoulis 2000), local police force (Garcia-Sanchez 2009), gas distribution industry (Erбетта and Rappuoli 2008), higher education (Johnes 2006), health (Hollingsworth et al.

summarized as follows: it can handle multiple inputs and outputs without a priori assumptions for a specific functional form of production technologies, it does not require a priori a relative weighting scheme for the input and output variables, it returns a simple summary efficiency measurement for each DMU, and it identifies the sources and levels of relative inefficiency for each DMU. However, some concerns should be addressed before the DEA is accepted as a routine tool in applied analysis. As DEA is an estimation procedure that relies on extreme points, it may be extremely sensitive to data selection, aggregation, and model specification. Typically, the selection of input and output variables is a major issue for efficiency measurements. The principal strengths of DEA, which include no a priori knowledge requirement for functional relationships, can be fully exploited under the premise that the input and output variables are relevant and sufficiently fair for all DMUs considered.

Another problem common to DEA studies is the relatively small number, n , of DMU with respect to the dimensionality space d (i.e., the number of input and output variables in the efficiency analysis) and the reliability of the results from the DEA model. However, for a given sample size, the rate of convergence depends on the dimensionality space d .⁵ This issue clearly represents a potential limitation of our work that may be solved only when more data will be available. Notwithstanding this, we do believe that our paper represents a first sound step to the analysis of launches efficiency. Finally, it is well-known that the DEA estimator for technical efficiency described earlier is biased in its construction (Simar and Wilson 2000b). This bias may be relevant and certain bootstrap methods that correct such bias have been used to investigate the bias, variance, and confidence intervals in efficiency scores, which generates more reliable efficiency rankings (Simar and Wilson 1998, 2000a).

1999; Tsekouras et al. 2010), heritage Authorities (Finocchiaro Castro et al. 2011) and care for the elderly sector (Borge and Haraldsvik 2009).

⁵ For a numerical example of the tradeoff between sample size and number of inputs and outputs used for consistency, see Simar and Wilson (2008, p. 439).

3.2 Data

Our sample has been built on the publicly accessible UCS Satellite Database of active satellites⁶ (<https://www.ucsusa.org/resources/satellite-database>) containing 3373 entries on the 01/01/2021. First, we selected the launches containing complete information on satellite's expected lifetime (measured in years), *Expectedlifetimeyrs*, that represents our output. Once satellites with such missing data were removed, we searched for those variables chosen as input: the launch mass, *Launchmasskg*, and the mission cost, *Cost*. Whereas the former has been directly taken from the UCS database, the latter has been taken from different sources provided in the UCS Dataset (e.g., [spaceflightnow.com](https://www.spaceflightnow.com)).

Hence, we restricted our dataset to 37 satellites, representing the DMUs under investigation. Table 1 provides a first description of sample composition. At a first glance, it appears that launches span on a quite wide period going from 2006 to 2020, although most of launches took place in the last five years and that several countries or multinational agency have been involved in the launches forming the sample under study. In details, 8 countries (Argentina, Australia, Canada, France, Germany, India, South Korea and USA) are involved in the space activities and 2 international agencies (ESA and EUMETSAT).

Moreover, the UCS dataset includes several additional basic information about the satellites and their orbits. Specifically, for each of the satellites it provides the country of owner, the users, and the purpose. For all of them, we built a set of dummy variables. For instance, considering the satellites' purpose, we obtained five dummy variables (technology development, communication, earth science and earth observation and navigation), taking the value 1 whether the satellite is used for that specific purpose and 0 otherwise. Table 2 provides the summary statistics for the variables used in our dataset.

⁶ The Union of Concerned Scientists is a national nonprofit organization founded more than 50 years ago by scientists and students at the Massachusetts Institute of Technology. For more details, see <https://www.ucsusa.org/about>

Table 1 – Sample composition

DMU	Name of Satellite, Alternate Names	Current Official Name of Satellite	Country/Org of UN Registry	Date of Launch
1	Prox-1 (Nanosat 7)	Prox-1	USA	25/06/2019
2	Calipso (Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation)	Calipso	France	28/04/2006
3	Aeolus	Aeolus	ESA	22/08/2018
4	Buccaneer RMM	Buccaneer RMM	Australia	18/11/2017
5	CSG-1 (COSMO-SkyMed Second Generation)	CSG-1	NR (12/20)	18/12/2019
6	FalconEye-2	FalconEye-2	NR (12/20)	02/12/2020
7	CSO-2 (Optical Space Component-2)	CSO-2	NR (12/20)	28/12/2020
8	Galileo FOC FM10 (0210, Galileo 13, PRN E01)	Galileo FOC FM10	NR	24/05/2016
9	Galileo FOC FM20 (0220, Galileo 24)	Galileo FOC FM20	NR	25/07/2018
10	Badr 7 (Arabsat 6B)	Badr 7	NR	10/11/2015
11	BulgariaSat-1	BulgariaSat-1	NR	23/06/2017
12	GEO-Kompsat-2B	GEO-Kompsat-2B	South Korea	18/02/2020
13	GOES 17 (Geostationary Operational Environmental Satellite GOES-S)	GOES-S	USA	01/03/2018
14	Göktürk 1	Göktürk 1	NR	05/12/2016
15	Grace Follow-on-1 (Gravity Recovery and Climate Experiment Follow-on-1)	Grace Follow-on-1	USA	22/05/2018
16	Grace Follow-on-2 (Gravity Recovery and Climate Experiment Follow-on-2)	Grace Follow-on-2	USA	22/05/2018
17	GSAT-11	GSAT-11	India	04/12/2018
18	GSAT-15	GSAT-15	India	10/01/2015
19	GSAT-18	GSAT-18	India	05/10/2016
20	Icesat-2	Icesat-2	USA	15/09/2018
21	Intelsat 30/DLA 1	Intelsat 30/DLA 1	NR	16/10/2014
22	Intelsat New Dawn (Intelsat 28)	Intelsat New Dawn	NR	22/04/2011
23	Iridium Next SV 102	Iridium Next 102	USA	14/01/2017
24	Jason 3	Jason 3	USA	17/01/2016
25	MetOp-C (Meteorological Operational satellite)	MetOp-C	EUMETSAT	06/11/2018
26	NOAA-20 (JPSS-1)	NOAA-20	USA	18/11/2017
27	PRISMA (PRecursore IperSpettrale della Missione Applicativa)	PRISMA	NR (12/20)	22/03/2019
28	RCM-1 (Radar Constellation Mission 1)	RCM-1	Canada	12/06/2019
29	SAOCOM-1A (Satélite Argentino de Observación Con Microondas)	SAOCOM-1A	Argentina	07/10/2018
30	Sentinel 1B	Sentinel 1B	ESA	25/04/2016
31	Sentinel 2B	Sentinel 2B	ESA	06/03/2017
32	Sentinel 5P (Sentinel 5 Precursor)	Sentinel 5P	ESA	13/10/2017
33	Sentinel 6 (Michael Freilich)	Sentinel 6	NR (12/20)	21/11/2020
34	Sky Muster 2 (NBN-1B)	Sky Muster 2	Australia	05/10/2016
35	South Asia Satellite (GSAT 9)	South Asia Satellite	India	06/05/2017
36	TerraSAR-X 1 (Terra Synthetic Aperture Radar X-Band)	TerraSAR X 1	Germany	15/06/2007
37	TESS (Transiting Exoplanet Survey Satellite)	TESS	USA	18/04/2018

Source: our elaboration on data provided by UCS; NR: the satellite has never been registered with the United Nations. ESA: European Space Agency; EUMETSAT: European Organisation for the Exploitation of Meteorological Satellites

Table 2 - Summary statistics

VARIABLES	Obs.	Mean	St.Dev.	Min	Max
usa	37	0.189	0.397	0	1
france	37	0.0270	0.164	0	1
australia	37	0.0541	0.229	0	1
nr	37	0.324	0.475	0	1
southcorea	37	0.0270	0.164	0	1
india	37	0.108	0.315	0	1
canada	37	0.0270	0.164	0	1
argentina	37	0.0270	0.164	0	1
germany	37	0.0270	0.164	0	1
agency	37	0.135	0.347	0	1
joint	37	0.108	0.315	0	1
multinational	37	0.0541	0.229	0	1
civil	37	0.0270	0.164	0	1
government	37	0.595	0.498	0	1
commercial	37	0.162	0.374	0	1
mixed	37	0.135	0.347	0	1
techologydevelopment	37	0.0541	0.229	0	1
earthscience	37	0.0541	0.229	0	1
earthobservation	37	0.541	0.505	0	1
navigation	37	0.0541	0.229	0	1
communication	37	0.270	0.450	0	1
leo	37	0.622	0.492	0	1
geo	37	0.297	0.463	0	1
meo	37	0.0541	0.229	0	1
longitudeofgeodegrees	37	10.57	48.54	-137	145
perigeekm	37	366.6	306.1	1.301	825
apogeekm	37	380.3	317.1	1.324	829
eccentricity	37	0.0269	0.157	0	0.953
inclinationdegrees	37	60.12	43.59	0	98.70
periodminutes	37	770.3	1,482	92.40	8,758
launchmasskg	37	176.2	293.8	1.060	860
drymasskg	5	238.9	329.6	1.283	678
powerwatts	5	224.2	275.6	4.800	550
expectedlifetimeyrs	37	8.899	4.908	0.250	20
cost	37	2.036e+09	3.711e+09	6.000e+07	1.280e+10

Source: our elaboration on data provided by UCS

Table 3 – Users, purpose and class of orbit

DMU	Users	Purpose	Class of Orbit
1	Civil	Technology Development	LEO
2	Government	Earth Science	LEO
3	Government	Earth Observation	LEO
4	Military/Civil	Technology Development	LEO
5	Military/Government	Earth Observation	LEO
6	Military	Earth Observation	LEO
7	Military	Earth Observation	LEO
8	Commercial	Navigation/Global Positioning	MEO
9	Commercial	Navigation/Global Positioning	MEO
10	Government	Communications	GEO
11	Commercial	Communications	GEO
12	Government	Earth Observation	GEO
13	Government	Earth Observation	GEO
14	Military	Earth Observation	LEO
15	Government	Earth Observation	LEO
16	Government	Earth Observation	LEO
17	Government	Communications	GEO
18	Government	Communications	GEO
19	Government	Communications	GEO
20	Government	Earth Science	LEO
21	Commercial	Communications	GEO
22	Commercial	Communications	GEO
23	Government/Commercial	Communications	LEO
24	Government	Earth Observation	LEO
25	Government/Civil	Earth Observation	LEO
26	Government	Earth Observation	LEO
27	Government	Earth Observation	LEO
28	Government	Earth Observation	LEO
29	Government	Earth Observation	LEO
30	Government	Earth Observation	LEO
31	Government	Earth Observation	LEO
32	Government	Earth Observation	LEO
33	Government	Earth Observation	LEO
34	Commercial	Communications	GEO
35	Government	Communications	GEO
36	Government/Commercial	Earth Observation	LEO
37	Government	Space Science	Elliptical

Source: our elaboration on data provided by UCS

Table 4 – Inputs and output

DMU	INPUTS		OUTPUT
	Launch Mass (kg.)	Cost in US \$ million	Expected Lifetime (yrs.)
1	70.00	185.00	0.25
2	587.00	298.00	3.00
3	1367.00	550.00	3.00
4	4.00	11300.00	5.00
5	2205.00	110.00	5.00
6	1180.00	407.00	5.00
7	3565.00	1500.00	10.00
8	723.00	8000.00	12.00
9	715.00	11700.00	12.00
10	5500.00	128.00	15.00
11	3669.00	235.00	15.00
12	3379.00	650.00	10.00
13	5211.00	11000.00	15.00
14	1060.00	300.00	7.00
15	600.00	430.00	5.00
16	600.00	430.00	5.00
17	5854.00	650.00	15.00
18	3164.00	128.00	12.00
19	3404.00	153.00	15.00
20	1515.00	1000.00	3.00
21	6220.00	250.00	15.00
22	3000.00	250.00	15.00
23	860.00	3000.00	15.00
24	553.00	364.00	5.00
25	4084.00	4000.00	5.00
26	2294.00	1600.00	7.00
27	550.00	143.00	5.00
28	1430.00	900.00	7.00
29	1650.00	600.00	5.00
30	2300.00	157.00	7.00
31	1130.00	150.00	7.00
32	820.00	284.00	7.00
33	1192.00	1000.00	5.00
34	6405.00	153.00	15.00
35	2230.00	60.00	12.00
36	1230.00	250.00	5.00
37	362.00	337.00	20.00

Source: our elaboration on data provided by UCS

Additional relevant satellites characteristics are reported in Table 3. Data show that most of the satellites (62%) are in the low earth orbit (LEO), 5% in medium earth orbit (MEO), 30% in Geostationary Earth Orbit (GEO) and the remaining 3% in Highly Elliptical Orbit (HEO). Satellites' use can be divided in governmental (59%), civil (3%), military (8%), commercial (16%) or mixed (13%). Regardless of the orbit (with the only exception of MEO, where there are only commercial satellites) their largest employment is for governmental purposes. Finally, as far as their purpose is concerned, the largest part of the satellites localized in LEO (78%) are developed for Earth Observation, whereas most of the satellites localized in GEO (82%) are developed for Communication.

Table 4 reports the values of the three variables included in our DEA model for each DMU. As previously mentioned, launch mass and cost values are used as inputs, while the satellites' expected life is considered as output. DMU are ordered according to their expected life from the smallest to the largest.

As we can observe, data are very heterogeneous across DMUs. This issue can be also noted looking at Table 5 referring to the average values of the sample. Launch mass (expressed in kilos) goes from 4 to 6405, mission costs (millions of dollars) go from 60 to 11700, while expected lifetime varies from four months to 20 years. Data heterogeneity is also shown by the high standard deviations for both inputs and output.

Table 5 – Sample statistics

Statistics	INPUTS		OUTPUT
	Launch Mass (kg.)	Cost in US \$ million	Expected Lifetime (yrs.)
Mean	2180.59	1693.30	8.90
St. Dev.	1830.43	3245.08	4.91
Max	6405.00	11700.00	20.00
Min	4.00	60.00	0.25

Source: our elaboration on data provided by UCS

4. RESULTS

Unfortunately, the available data are quite partial, and this represents a potential limitation to the analysis. As already mentioned, the available data moved us to choose satellite mass and mission cost as inputs and satellite expected life as output. Thus, it is reasonable to opt for an input-oriented estimation model, being more consistent with the objective of the analysis. The rationale for such choice is the following. For a given expected lifetime, the less resources in terms of mass launched into space and mission economic resources employed, the more efficient the satellite is.

This feature is relevant under a different point of view. A smaller mass implies fewer debris caused in the occurrence of collision. Hence, minimizing satellites' mass may positively affect the attempts at reducing the number of debris, and increasing the satellites' expected lifetime. In our estimate each satellite represents our DMU. In all our estimates we will employ the well-known DEA estimator, put forward by Charnes et al. (1978), measuring the efficiency in terms of Farrell (1957) input distance functions, which are the reciprocals of the Shephard (1970) input efficiency measures. Then, for a point contained within the convex hull of the reference observations the returned efficiency scores will be between 0 and 1. Larger is the efficiency score higher is the efficiency of DMU. Furthermore, we assume constant returns to scale (CRS). As already explained, DEA approach has, however, several problems that need to be addressed to obtain correct estimates. In particular, to account for possible bias in the estimates and the presence of outliers, we will also perform the bootstrap confidence interval for efficiency estimates (Simar and Wilson, 2000). Table 6 reports the efficiency estimates for each DMU. Column 2 shows the original efficiency scores; columns 3 and 4 provide the bias and bias-corrected efficiency scores. Columns 5 and 6 report the 95 % confidence intervals for the bias-corrected efficiency scores. As it can be seen, the value reported in the second column fall beyond the upper bound of the confidence intervals, revealing the presence of bias in the estimates. Both the levels of bias and bias corrected estimates significantly vary across the DMUs.

The greatest difference between the original and the bias-corrected efficiency scores is 0.40525 (DMU 4).

Table 6 – Efficiency estimates

DMU	DEA Eff. scores	Bias	Bias corrected Eff. scores	Lower bound (95% confidence)	Upper bound (95% confidence)
1	0.06381	0.01591	0.04790	0.03948	0.06177
2	0.16021	0.03106	0.12915	0.10548	0.15665
3	0.08411	0.01490	0.06922	0.05634	0.08217
4	1.00000	0.40525	0.59475	0.51151	0.89707
5	0.34105	0.07630	0.26475	0.21726	0.32728
6	0.18485	0.03132	0.15353	0.12564	0.18092
7	0.10348	0.01863	0.08485	0.06914	0.10101
8	0.27878	0.06706	0.21172	0.17453	0.26373
9	0.27167	0.06618	0.20549	0.16951	0.25740
10	0.58594	0.17058	0.41536	0.34434	0.56186
11	0.55024	0.11220	0.43804	0.36269	0.52920
12	0.20399	0.03367	0.17031	0.14224	0.19874
13	0.05163	0.01320	0.03843	0.03181	0.04971
14	0.33851	0.05608	0.28243	0.23162	0.33092
15	0.19188	0.04381	0.14807	0.12079	0.18571
16	0.19188	0.04381	0.14807	0.12079	0.18571
17	0.25568	0.04556	0.21011	0.17811	0.24680
18	0.61885	0.15163	0.46722	0.38364	0.59014
19	0.69108	0.16137	0.52971	0.43423	0.66144
20	0.04913	0.01058	0.03855	0.03140	0.04819
21	0.39443	0.09698	0.29745	0.24427	0.37546
22	0.58867	0.11165	0.47702	0.40156	0.56604
23	0.30963	0.07575	0.23389	0.19239	0.30032
24	0.22488	0.04835	0.17653	0.14378	0.22055
25	0.02215	0.00619	0.01596	0.01338	0.02096
26	0.07202	0.01610	0.05592	0.04555	0.07024
27	0.49844	0.08212	0.41632	0.34228	0.48623
28	0.12677	0.02671	0.10006	0.08149	0.12443
29	0.12650	0.02171	0.10479	0.08568	0.12356
30	0.39720	0.07933	0.31787	0.26422	0.38336
31	0.55215	0.09545	0.45670	0.38665	0.53406
32	0.37113	0.06292	0.30821	0.25219	0.36302
33	0.08360	0.02183	0.06177	0.05143	0.07903
34	0.49020	0.14310	0.34710	0.28808	0.46826
35	1.00000	0.29892	0.70108	0.58762	0.92050
36	0.26905	0.04427	0.22478	0.18719	0.26184
37	1.00000	0.28250	0.71750	0.60350	0.92805

Source: our elaboration on data provided by UCS

Looking at Table 7, the average values are displayed. The efficiency scores go from 0.71750 to 0.01596, showing a remarkably high degree of heterogeneity among DMUs. Also, the mean efficiency score across the sample is 0.2611, showing that on average inputs could be reduced altogether by roughly 74% to get full efficiency. Overall, the efficiency decreased slightly with a mean drop of slightly more than 8%.

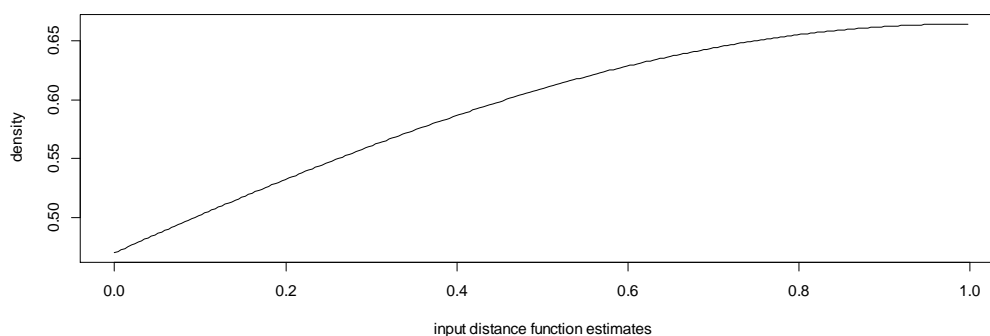
Table 7 – Summary statistics of the efficiency estimates

Statistics	DEA Eff. scores	Bias corrected Eff. scores	Lower bound (95% confidence)	Upper bound (95% confidence)
Mean	0.34442	0.26110	0.21681	0.32817
St. dev	0.26621	0.18682	0.15709	0.24635
Min	0.02215	0.01596	0.01338	0.02096
Max	1.00000	0.71750	0.60350	0.92805

Source: our elaboration on data provided by UCS

Figure 1 reports the Kernel density estimates of the efficiency scores that rely on the reflection method (Simar and Wilson 2008). The results are not significantly different from those reported in table 6.

Figure 1 – Kernel density of the DEA efficiency estimates



Source: our elaboration on data provided by UCS

The presence of bias in the original efficiency scores reported in Table 6 could be further investigated by decomposing the sample according to homogeneous characteristics of satellites. To do so, the following tables cluster the efficiency estimates according to user, purpose, and class of orbit. Table 8 reports the DMUs clustered by user. In more than half of the observations the Governments are the user with an average bias corrected efficiency score of 0.2628, with a small bias of 0.0798.

Table 8 – Efficiency estimates by User

User	Obs.	Mean DEA Eff. scores	St. Dev.	Mean Bias corrected Eff. scores	St. Dev.
Civil	1.0000	0.0638		0.0479	
Commercial	6.0000	0.4290	0.1360	0.3295	0.1133
Government	22.0000	0.3426	0.2915	0.2628	0.2112
Government/Civil	1.0000	0.0222		0.0160	
Government/Commercial	2.0000	0.2893	0.0287	0.2293	0.0064
Military	3.0000	0.2089	0.1193	0.1736	0.1003
Military/Civil	1.0000	1.0000		0.5947	
Military/Government	1.0000	0.3410		0.2648	
Whole sample	37.0000	0.3444	0.2699	0.2611	0.1894

Source: our elaboration on data provided by UCS

Differently, Table 9 refers to the clustering by satellites' purpose. In this case, there are two main groups. The first and more numerous is related to earth observation scope (54% of the sample) showing an average bias corrected efficiency score of 0.1799, with a very small bias of 0.0419. The second group refers to communications purpose showing an average bias corrected efficiency score of 0.4117, with a quite relevant bias of 0.1368.

Table 9– Efficiency estimates by purpose

Purpose	Obs.	Mean DEA Eff. scores	St. Dev.	Mean Bias corrected Eff. scores	St. Dev.
Communications	10.0000	0.5485	0.2114	0.4117	0.1473
Earth Observation	20.0000	0.2218	0.1511	0.1799	0.1257
Earth Science	2.0000	0.1047	0.0785	0.0839	0.0641
Navigation/Global Positioning	2.0000	0.2752	0.0050	0.2086	0.0044
Space Science	1.0000	1.0000		0.7175	
Technology Development	2.0000	0.5319	0.6620	0.3213	0.3867
Whole sample	37.0000	0.3444	0.2699	0.2611	0.1894

Source: our elaboration on data provided by UCS

Finally, Table 10 regards the cluster according to the class of orbit of the satellites. Also in this cluster, there are two main groups. The first one refers to LEO, showing an average bias corrected efficiency score of 0.1928, with a quite small bias of 0.0577, whereas the second cluster refers to GEO reporting an average bias corrected efficiency score of 0.3720, with a remarkable bias of 0.1217.

Table 10 – Efficiency estimates by class of orbit

Class of orbit	Obs.	Mean DEA Eff. scores	St. Dev.	Mean Bias corrected Eff. scores	St. Dev.
GEO	11.0000	0.4937	0.2603	0.3720	0.1854
LEO	23.0000	0.2505	0.2192	0.1928	0.1494
MEO	2.0000	0.2752	0.0050	0.2086	0.0044
Elliptical	1.0000	1.0000		0.7175	
Whole sample	37.0000	0.3444	0.2699	0.2611	0.1894

Source: our elaboration on data provided by UCS

Looking in depth at the results reported by previous Tables, it seems reasonable to perform new estimates focusing only on the most homogeneous groups of DMUs

to mitigate the bias. Thus, the following Tables report the efficiency estimates for the subsamples referring to earth observation and communications.

Table 11 reports the efficiency estimates for the subsample of satellites whose purpose is communications. The results show a quite remarkable increase in the average bias corrected efficiency scores of the subsample moving from 0.4117 to 0.5275. Also, the bias has significantly decreased from 0.1368 to 0.0970. It, thus, appears that we have been able to somehow mitigate the negative effect of DMU's heterogeneity on efficiency levels.

Table 11 – Efficiency estimates for subsample of communications satellite

DMU	DEA Eff. scores	Bias	Bias corrected Eff. scores	Lower bound (95% confidence)	Upper bound (95% confidence)
10	0.58594	0.08253	0.50341	0.41777	0.58131
11	0.74190	0.06870	0.67320	0.59130	0.73556
17	0.45157	0.04037	0.41120	0.36209	0.44631
18	0.69867	0.07830	0.62037	0.53771	0.69188
19	0.80943	0.08465	0.72479	0.62933	0.80406
21	0.44433	0.05018	0.39415	0.34126	0.43950
22	0.89641	0.07965	0.81676	0.71793	0.88714
23	1.00000	0.24053	0.75947	0.62411	0.97554
34	0.49020	0.07069	0.41950	0.34904	0.48502
35	1.00000	0.17386	0.82614	0.70412	0.98085
Mean	0.71185	0.09695	0.61490	0.52747	0.70272
St. Dev	0.20372	0.05866	0.16205	0.14045	0.19860
Min	0.44433	0.04037	0.39415	0.34126	0.43950
Max	1.00000	0.24053	0.82614	0.71793	0.98085

Source: our elaboration on data provided by UCS

Differently, Table 12 shows the efficiency estimates referred to the subsample of satellites whose purpose is earth observation. In this case, the average bias corrected efficiency score has tripled from 0.1799, as reported in Table 8, to 0.5401, whereas keeping the bias at a very low level (0.0835). As said before, running estimates on subsample to keep heterogeneity at minimum has dramatically helped in boosting bias corrected efficiency levels.

Table 12 – Efficiency estimates for subsample of Earth Observation satellite

DMU	DEA Eff. scores	Bias	Bias corrected Eff. scores	Lower bound (95% confidence)	Upper bound (95% confidence)
3	0.24140	0.02644	0.21497	0.18596	0.24009
5	0.97403	0.17063	0.80339	0.65915	0.96499
6	0.46610	0.05916	0.40694	0.35063	0.46197
7	0.30856	0.03278	0.27577	0.23897	0.30728
12	0.39190	0.06996	0.32194	0.27273	0.38185
13	0.31664	0.02223	0.29440	0.25893	0.31592
14	0.72642	0.12025	0.60616	0.52385	0.71503
15	0.91667	0.07035	0.84631	0.74029	0.91419
16	0.91667	0.07035	0.84631	0.74029	0.91419
24	0.99458	0.08024	0.91434	0.80185	0.99104
25	0.13467	0.00976	0.12492	0.11003	0.13436
26	0.33566	0.02612	0.30954	0.27073	0.33462
27	1.00000	0.18481	0.81519	0.70669	0.96590
28	0.53846	0.04489	0.49357	0.43385	0.53635
29	0.33333	0.03989	0.29345	0.25283	0.33127
30	0.95541	0.17755	0.77787	0.64491	0.93983
31	1.00000	0.21967	0.78033	0.66558	0.97141
32	0.93902	0.11851	0.82052	0.70647	0.93146
33	0.46141	0.03417	0.42724	0.37609	0.46021
36	0.52120	0.09186	0.42934	0.36444	0.50687
Mean	0.62361	0.08348	0.54012	0.46521	0.61594
St. Dev	0.30033	0.06048	0.25344	0.21734	0.29523
Min	0.13467	0.00976	0.12492	0.11003	0.13436
Max	1.00000	0.21967	0.91434	0.80185	0.99104

Source: our elaboration on data provided by UCS

5. CONCLUSION

Space activities are becoming crucial for many areas such as meteorology, navigation, communication and earth observation. For this reason, most countries are increasingly investing in the space sector to improve their space launching capabilities. The subsequent rising number of active satellites, responsible for the accumulation of orbital debris, challenges the space sustainability. Therefore, many studies address the problem, proposing possible solutions to debris creation. However, although some authors also attempt to estimate the probability of debris collision risk, none of them consider the satellites' characteristics and launch cost

(and more generally mission cost) which may instead be a key factor for an efficiency analysis. Our study tries to fill this gap, providing an efficiency analysis of the satellites' life cycle, by using a Data Envelopment Analysis technique. Specifically, by using a subsample of the UCS Satellite Database, we consider 37 satellites, launched between 2006 and 2020, as our Decision-making units, their launch mass and mission cost as inputs and finally their expected life expressed in years as output, for our input-oriented approach. Also, the mean efficiency score across the sample is 0.2611, showing that on average inputs could be reduced altogether by roughly 74% to get full efficiency. In second step, satellites are clustered according to their users, purposes and class of orbit respectively, to account for data heterogeneity. Then, the efficiency analysis is conducted for two subsamples referred to their purposes: earth observation and communications. As for the former, the results show a quite remarkable increase in the average bias corrected efficiency scores of the subsample moving from 0.4117 to 0.5275. Also, the bias has significantly decreased from 0.1368 to 0.0970. Focusing on the latter, the average bias corrected efficiency score triples from 0.1799 to 0.5401, whereas keeping the bias at a very low level (0.0835). Hence, it appears that the satellites whose purpose is communications are those where inputs are more efficiently employed, keeping the expected lifetime constant. In conclusion, results show that running estimates on subsample to keep heterogeneity at minimum significantly allows to boost bias corrected efficiency levels. However, our results should be read with caution. Several limitations affect our study being the main problem the reduced available sample set due to multiple missing variables in the UCS Database. Notwithstanding this, we do believe that our paper represents the first step in the efficiency analysis of satellites' launches, posing the attention on the problem of future debris creation.

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