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REGULAR ARTICLE

Earth Observation data, innovation and economic performance: a study of the downstream sector in Italy

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Abstract

The increasing availability of external data in the realm of big data significantly impacts the operations and performance of businesses. In this study, we focus on Earth Observation (EO) technology, which supplies an extensive range of data related to Earth's chemical, biological, physical, and societal aspects. Our primary goal is to understand how the utilisation of EO data affects companies operating in the *downstream* sector. These enterprises possess the expertise and capabilities to extract valuable insights and information from EO data. We use a rich and innovative dataset representing 74% of the Italian EO downstream sector. The results show that EO data have heterogeneous impacts across downstream firms. Economic performance and innovation are positively correlated only for a subset of firms, especially the ones in the northern regions. Firms in the centre of Italy exploit the spillover of being close to large space infrastructures, but their performance in economic and innovation terms is mixed. The sub-sample in the South of Italy innovates due to EO but performs poorly economically. We discuss the determinants of such discrepancies and suggest policy and managerial implications for the industry's future development.

Keywords IT firms · Big data · Digitalisation · Artificial intelligence · Satellites · Remote sensing · Earth Observation value

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1 Introduction

Data availability is the new form of capital for twenty-first-century knowledge economies (OECD, 2019). Different types of data significantly contribute to the world economy, enhancing the productivity and competitiveness of both the public and private sectors and creating a substantial economic surplus for consumers. The variety and velocity of big data generated mainly through social media, web platforms, and large research infrastructures such as the *EMBL's European Bioinformatics Institute*[1] is contributing to radically improving the efficiency and efficacy of different sectors, including health care, public administration, manufacturing, and services industry (McKinsey, 2011). Big data facilitates population segmentation to customise actions, supports human decisions and transparency and contributes to creating new business models, products and services. Indeed, big data is increasingly becoming a crucial asset for firms trying to innovate and grow (Damioli et al., 2021; Ghasemaghaei & Calic, 2020; Niebel et al., 2019).

A relevant share of potentially useful data is generated outside the firm, which can valuably use such data as direct and/or indirect input for the innovation process (McKinsey, 2011), in the context of an open innovation approach (Chesbrough, 2003; West & Bogers, 2014). However, even if freely available, external data may not benefit innovation if firms lack the relevant *absorptive capacity* (Cohen & Levinthal, 1990; Zahra & George, 2002). Small and Medium Enterprises (SMEs), in particular, must accumulate specific capabilities to overcome the barriers to managing and exploiting externally produced information (Huber et al., 2020). At the same time, innovation does not imply commercial success. Innovators may not profit from innovation because of appropriability conditions and the lack of relevant complementary assets, such as marketing know-how, manufacturing capabilities, distribution and service skills, that must accompany innovation (Kirchberger & Pohl, 2016; Teece, 1986). Profiting from data may not require innovation either, as firms may exploit their complementary assets without breakthrough innovations related to the use of data. In some cases, firms may act as data intermediaries (Van Schalkwyk et al., 2016), building their business model and source of competitive advantage as brokers between data providers and final users.

This paper aims to explore the various dimensions of external data impact on firm performance, distinguishing the implications for innovation and economic performance, and assessing at the same time the extent to which this impact is heterogeneous across firms and which firms' characteristics can explain such heterogeneity.

We focus on firms operating in the Earth Observation (EO) downstream sector as such firms possess the technology and the skills to transform raw EO data into services and applications for final users. EO downstream firms are businesses that specialise in utilising data and information derived from EO technologies and satellite systems. These companies focus on extracting valuable insights and information from EO data, creating applications, products, and services for various industries and purposes, such as environmental monitoring, agriculture, forestry, urban

[1] https://www.ebi.ac.uk/about.

planning, disaster management, and more. They add value to the raw EO data by turning it into actionable knowledge and solutions for their clients and end-users. The largest majority operate in the Information and Communication and Professional Scientific and Technical activities industries.[2]

The downstream sector is expected to contribute the most to the growth and maximisation of the socio-economic impact of EO (Pogorzelska, 2018), which in turn plays a vital role within the New Space Economy (Weinzierl, 2018). EO data come from observing planet Earth's chemical, biological and physical characteristics via remote sensing technologies[3] (GEO, 2020). This domain of the space industry has undergone dramatic changes since the beginning of this century (Craglia & Pogorzelska, 2019). It has rapidly developed during the last years, enabling various military and civil applications for governments, public and private firms, scientists, and citizens (Macauley, 2006; PwC, 2016; Tassa, 2019). While satellite technology is advancing fast, vast and varied amounts of new data are becoming increasingly available to solve critical socio-economic challenges, especially for civil purposes. In recent years, there has been a trend towards increasing the availability of EO data as open data. Many government space agencies and organizations, such as the National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA), provide a substantial amount of EO data freely and openly to the public, motivated by scientific research, environmental monitoring, and the benefit of society as a whole. However, there are also commercial satellite operators and data providers that sell data under various licensing arrangements. Once raw data are collected by satellites,[4] they must be stored, pre-processed and exploited to generate meaningful and usable information. Big data collection, storage and analysis through algorithms, artificial intelligence and computing power are needed to effectively manage and intersect a growing amount of information from different sources.

To achieve our objective, we conducted an exploratory study by collecting primary data through a novel survey with firms operating in the downstream sector to know the benefits of EO according to their perspective. Our research focuses on Italy, which, among European countries, is historically at the forefront of the EO satellite launches (Huadong, 2013). However, although the Italian space manufacturing sector is at the lead of the international space industry, little is known about the return of EO along the value chain, particularly for downstream operators and final users where the market potential and socio-economic impact are still underexploited.[5]

Our empirical analysis proceeds in three main steps. First, through exploratory factor analysis based on the survey responses, we identify two main factors behind an assortment of impact channels: *innovation* and *economic impact*.

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[2] Our elaborations based on the Italian market.

[3] Remote sensing is the process of detecting and monitoring an object at a distance.

[4] EO may include other means of data collection such as aircraft, drones, balloons etc. In this study we focus exclusively on satellites.

[5] In Europe, Italy is in 5th position in terms of number of companies. The ranking is led by the United Kingdom, followed by Germany and France, (EARSC, 2020).

Second, we perform a cluster analysis, which results in four groups of firms. While innovation and economic impacts are often positively associated, this is not always the case: some firms in our sample show a relatively high innovation performance, which does not necessarily translate into higher economic performance and vice-versa.

Third, we look at the determinants of innovation and economic performance using regression analysis. We find that micro and small firms benefit the most from EO data. Sector-specific human capital is also crucial to foster the impact of satellite data on firms' performance. Additionally, being a newcomer in the EO sector gives a "second mover" advantage in terms of economic impact. Finally, we investigate the cruciality of geographical location. Firms active in the South of Italy are innovative, but their financial performance appears modest, possibly due to the institutional environment in which such firms operate.

Our work can also be seen as an exploratory study on innovation and growth in an emerging data-based industry (OECD, 2015). When the data that are key for innovation are easily accessible, as in the case of EO, we can expect a sector to be highly competitive, with concentration of innovative activities being low, innovators of small economic size, stability in the ranking of innovators low and entry of new innovators high: all features that belong to the so-called Schumpeter Mark I pattern of innovation (Breschi et al., 2000). The descriptive evidence of EO downstream industry is consistent with this view. At the same time, when a given database is inspected by many potential innovators, each possessing idiosyncratic information, interests and capabilities, firms' heterogeneity can be persistent, both in terms of innovation and economic performance (Dosi, 2023). Our results are suggestive that this in the case of the EO downstream industry, although further evidence needs to corroborate the conclusions we reached in a cross-section of survey data.

This paper is organised into five sections. Section 2 briefly reviews the literature related to firms in the EO downstream sector and discusses the benefits that may arise from the increasing availability of EO data. Section 3 formulates the research questions and discusses the method and the survey design. Section 4 presents the results, whilst Sect. 5 concludes by suggesting some policy recommendations and future opportunities for research.

2 The EO downstream sector and the benefits of EO data

2.1 An overview of the EO downstream sector

The EO downstream sector mainly includes small and medium companies with high technological know-how, developing commercial applications from satellite data (*Value Added Services*), geo-information firms, consultancy companies, research institutes with artificial intelligence expertise and hardware/software development companies, among others (PwC, 2016). In this category, we also include units within large organisations that deal with data archiving, storage, pre-processing and delivery of middle services to facilitate and enable the creation of final services and applications (Pogorzelska, 2018; PwC, 2016) (this segment is sometimes called *midstream*).

The EO downstream sector is key to developing cutting-edge new services in various fields for the public and private sectors. Areas of application are numerous, including agriculture, urban planning, transport, land use, monitoring ocean activities, health and civil protection, and disaster management, among others (Daraio et al., 2014; NEREUS et al., 2018; PwC, 2019). For instance, in road infrastructure management, new mapping services showing ground motion based on EO data are increasingly supporting public administrations in building more efficient and resilient urban transport facilities. In Norway, the European Association of Remote Sensing Companies (EARSC) estimates the economic benefit of service of such type between €3.8 m and €8.7 m per year, mainly deriving from saving costs in construction and management of the road infrastructure (Sawyer et al., 2020).

According to Euroconsult (2020) the global market for value-added EO services was \$3.0 billion in 2019,[6] growing at a 5-year compounded average growth rate (CAGR) of 7%, and it is expected to reach about \$6 billion by 2030. The players' market is highly fragmented, with thousands of companies worldwide, primarily micro-companies (Euroconsult, 2020). At the European level, the 5th annual survey by EARSC (2020) estimates that the downstream EO industry in 2019 accounted for 1.38 billion in revenues and a 17% employment growth over 2018, mainly due to new micro-companies or startups entering the sector. Europe counts around 580 companies[7] with more than 8.000 employees, where 60% of the jobs created are from companies formed 4 and 5 years ago (EARSC, 2020).

2.2 The economics of data and the benefits of EO data for firm performance

The growing availability of data has ubiquitous effects in the economy, both at the macro and micro level (Veldkamp & Chung, 2023). When it comes to the impact of data, ownership stands out as a crucial aspect. At one end of the spectrum lie proprietary data held by companies. This type of data typically stems from essential business operations like transaction records. Its value lies in its potential to be sold or leveraged to enhance product quality and operational efficiency. As proprietary data quantity grows, so does its ability to boost quality and efficiency, creating a competitive advantage for established players. This advantage erects barriers to entry and secures a strong position in the market (Farboodi & Veldkamp, 2023). Conversely, at the opposite end, we find data commons—repositories of openly accessible data for innovation (Potts et al., 2023). Here, data serves as a raw material available for all companies to directly fuel the creation of innovative products and services. Data commons can emerge through private contributions, such as firms contributing to open-source software, or through government investment, like EO data.

The use of external data as an asset in the innovation process can be conceived within the *open innovation paradigm* (Chesbrough, 2003; West & Bogers, 2014).

[6] Figure referring to companies offering commercial solutions for data and services.

[7] 93% of firms have less than 50 employees, while around 70% are micro firms.

In this vast literature, researchers have investigated how firms can take advantage of external sources of innovation by integrating relevant pieces of knowledge outside the company's boundaries.

In a context where data availability is becoming a crucial asset, EO data are an example of external data that firms can use *directly* as input in the provision of innovative products and services. Indeed, firms operating in the EO downstream sector have the opportunity to exploit large volumes of high-revisit low-cost data jointly with the adoption of artificial intelligence techniques, contributing to the proliferation of new services and applications for final users. For instance, in Belgium, a new service called WatchITgrow (WIG) supports a group of potato farmers to get information on their fields for better management practices (Sawyer et al., 2019). Satellite imagery helps to monitor crop health, irrigation periods, and fertilisation needs, which is estimated to improve the quality of the product and the yields by up to 20%. Overall benefits along the value chain are estimated at around €1–€2 m without considering a range of not quantified benefits such as environmental gains (Sawyer et al., 2019). In this perspective, the increasing availability of free and open-source data sets, such as those provided by Copernicus of the European Space Agency (ESA), raises awareness of EO services and products, boosting the creation of value-added products (Robinson & Mazzucato, 2019).

However, the impact on innovation is not limited to the direct effect of using EO data. One of the most relevant benefits for firms is the *indirect* association with *learning by doing,* which refers to an increase in long-term performance achieved through practice (Arrow, 1971; Lucas, 1988). This benefit may stem from the new technological and challenging tasks firms face, such as creating cutting-edge EO service/applications or archiving, storing, and pre-processing large quantities of data with innovative, affordable, and smart solutions. As a result, firms will likely increase their R&D activity generating new knowledge, which may translate into an innovation or other spillovers in their processes (i.e., market, commercial or organisational effects). Thus, the ultimate impact is on their productivity and profitability (Edler & Georghiou, 2007; Edquist et al., 2015; Uyarra & Flanagan, 2010). Indeed, innovation is often pursued in response to unexpected, unfamiliar, or non-routine problems (Anderson et al., 2014) and involves learning and changing a firm's existing cognitive paradigms and resources (Damanpour & Gopalakrishnan, 2001; Ghasemaghaei & Calic, 2020).

In the context of open innovation through direct and indirect effects, a lack of *absorptive capacity* can be the main obstacle for firms to take advantage of external data. Cohen and Levinthal (1990) defined absorptive capacity as the firm's ability to value, assimilate and apply new knowledge. Zahra and George (2002) reviewed the early literature and reconceptualised absorptive capacity around four dimensions and capabilities, i.e. acquisition, assimilation, transformation and exploitation capabilities. In the context of open data, acquisition and assimilation capability is the ability to engage with data providers and understand the nature and relevance of data. Transformation capabilities are associated with attracting specialised human capital and integrating it into the organisation. Finally, exploitation capabilities are related to applying the transformed knowledge for innovation (Huber et al., 2020).

The ultimate criterion to assess the value of external data is their impact on commercial success. As extensive managerial literature has shown, profiting from learning and innovation cannot be taken for granted (Kirchberger & Pohl, 2016; Teece, 1986, 2006). The first concern is related to *appropriability conditions*, i.e. the extent to which firms can actually capture the value created through innovation. It is well known that industries (and firms) are heterogenous in their ability to profit from innovation and in the mechanisms they use to try to this such as patents, trade secrets and lead time (Cohen et al., 2000). The second concern refers to the possession of *complementary assets*, such as marketing know-how, manufacturing capabilities, distribution and service skills that firms have to access to transform innovation into economic value. The lack of appropriability and complementary assets may depend on firms' characteristics (such as size and age) and contextual factors as well, as firms may be unable to overcome the liability of being located in peripheral areas (Lagendijk & Lorentzen, 2007), for instance, in terms of bank funding or weak institutional contexts (Castelnovo et al., 2020; Lee & Brown, 2017).

At the same time, profiting from data may not require innovation. Besides the existence of complementary assets and capabilities that can be exploited even without innovation, an alternative viable business model is associated with firms acting as data intermediaries (Van Schalkwyk et al., 2016), for example, when firms build their competitive advantage by being brokers between data providers and final users, with limited data elaboration.

3 Research questions, method, data and preliminary summary statistics

Based on our discussion, this paper aims to answer three interrelated research questions: *(i) how EO data affect firms' performance?; (ii) how innovation and economic performance are linked? and (iii) are there similar characteristics of firms benefiting the most from the EO data?* First, we aim to answer such questions by exploiting the results from a novel survey on downstream firms. Then, by using exploratory factor analysis, we disentangle the benefits of EO data availability concerning innovation and economic performance. Moreover, we use cluster analysis to identify four groups of firms. The clusters are then compared, considering the firms' characteristics. Finally, a regression analysis identifies those firms' characteristics that are associated to innovation and economic performance.

In this study, we map firms operating in the downstream industry for the first time in the Italian context. We integrated information from different sources, including ASI (2020), the data users of prominent Italian EO satellite constellations, memberships to Italian associations active in the space sector[8] and the national cluster (*Cluster Tecnologico dell'Aereospazio – CTNA)*. Furthermore, we validated such sources with the help of interviews with key experts in the industry. Hence, we collected

[8] *Associazione delle Imprese per le Attività Spaziali* (AIPAS), *Federazione Aziende Italiane per l'Aerospazio, la Difesa e la Sicurezza* (AIAD) and *Associazione per i Servizi, le Applicazioni e le Tecnologie ICT per lo Spazio* (ASAS).

primary data through an online survey based on thirty semi-structured questions. The questionnaire is structured into four distinct sections: the first section focuses on gathering general information about the company, including its size, year of establishment, location, and more; the second delves into the specifics of EO activities, encompassing areas such as the services provided, types of EO data used, the industries served, and the clientele. The third section is dedicated to exploring the advantages derived from the utilization of EO data, with a particular emphasis on its contributions to market expansion, economic performance, and innovation in processes and services of the firm. Such advantages are investigated by considering the timeframe since the firms initiated their engagement with EO. Lastly, the fourth section is designed to investigate the primary obstacles hindering the development of this sector in Italy, as well as the wider dissemination of EO data-based services among final users. Most of the questions exploit answers based on a Likert scale.[9] Six pilot tests were also carried out with companies and other sector experts to verify the questions' clarity. The questionnaire was then administered between February 2021 and July 2021 through an online survey.

The final database consists of 89 companies which, as confirmed by the sector experts interviewed, represent the whole population of companies operating in the downstream sector in Italy. For 80 of them, we were able to retrieve balance sheet data from ORBIS,[10] spanning from 2012 to 2020. The average value added for employee is 68.000 EUR for a total value added of 1,9 billion EUR (also outside EO). The average value added in the EOemployees_2020_c period 2012–2020 is 29 million EUR. 43% of these companies operate in the IT sector (NACE rev2 code = J), particularly in computer programming activities and data processing, while 33% are engaged in professional, scientific, and technical activities, particularly related to engineering and architectural consultancies (NACE rev2 code = M). The remaining companies primarily operate in the manufacturing of computers, communication equipment, optical instruments, spacecraft, navigation devices, and other related areas.

Of these 89 companies, 63 firms participated in the survey, which recorded a response rate of approximately 74%. A unique study comparable to ours is available at the European level (EARSC, 2019, 2020) and reports information only for about forty Italian companies. Out of 63 companies we found balance sheet data from ORBIS for 56 of them. The total value added is 1.3 billion EUR (also outside EO) while the average value added in the period 2012–2020 is 28 million EUR. About half of the interviewed companies (45%) are micro-firms with less than ten employees. Around 32% of the sample consists of small firms (10–50 employees), 10% have between 50 and 250 employees, and 13% are large firms.[11] Besides micro and small firms, the composition of our sample highlights the critical role of medium and large IT firms, which penetrate the EO market by opening new EO units and divisions.

[9] This is a multidimensional scale that allows 'measuring' opinions and attitudes of the interviewees. It is made up of a series of statements semantically linked to the phenomena we want to investigate (e.g. I totally agree, I partially agrre, I am neutral, I partially disagree, I totally disagree).

[10] https://www.bvdinfo.com/it.

[11] Results from interviews are consistent with balance sheet data coming from ORBIS.

The average number of employees involved in EO activities is 21. At the same time, some firms declare zero employees devoted to EO as these companies use external collaborations, stressing the difficulties in finding the needed competencies internally, which is in line with the European situation (EARSC, 2020). 97%, of the sampled firms are primarily involved in the IT sector or engaged in professional, scientific, and technical activities. 63%, are dedicated to software development, 63%, are focused on creating applications utilizing EO data; 62% of these firms specialize in the processing and analysis of EO data. A slightly lower percentage, approximately 40%, offer consulting services, while an equivalent proportion, also around 40%, deliver Geographic Information System (GIS) services.[12]

As a result, the share of turnover deriving from EO activities varies between 1 and 25% in 48% of cases and is more than 76% for one-quarter of the firms. On the other hand, 17% of micro firms declare a percentage of EO turnover between 1 and 25% while 14% between 76 and 100%. As expected, the large majority of large firms show a share between 1 and 25%, confirming that large firms dedicate special units to EO, but, usually, this is not their core business. Additionally, 22% of firms define themselves as "startup", while 49% appear in the "*Registro delle start up e piccole e medie imprese innovative"*.[13] Innovative small and medium enterprises (SMEs) have consolidated business activity compared to startups. Therefore, this category of firms is crucial for the country's innovative development (MISE, 2021).

Concerning the final users to whom such EO services and applications are addressed, these are mainly Italian bodies operating in the public sector for 37% of the firms interviewed. Then, large Italian companies and foreign firms represent the final users for 27% of the firms surveyed, respectively. Regions (19%), provinces and municipalities (16%) and Italian SMEs (13%) are other firms' final users. Only 6% of firms work with the national government. Other clients and users include the European Commission, International Agencies, Multilateral Development Banks, and foreign governments. Hence, EO services in the Italian context seem to benefit mainly the public bodies, including the civil protection forces and Regional agencies for environment protection (ARPA).

4 The impact of EO data on firms' performance

4.1 Factor analysis

As mentioned in Sect. 3, we have explored the downstream firms' opinions concerning the benefits of EO data availability for firms operating in the downstream sector. Descriptive results from our survey highlight the critical contribution of EO to improving the operational processes of firms in the downstream sector. Indeed, the vast majority of companies (83%) agree (totally or partially) that the availability of EO data has contributed to improving the quality of their products and services. More than 80% of respondents declare that their R&D capabilities have improved

[12] Multiple answers were allowed.

[13] https://www.mise.gov.it/index.php/it/impresa/piccole-e-medie-imprese/pmi-innovative.

due to satellite data. A large number of firms, 75%, have also enhanced their technical know-how due to EO data, increasing their knowledge and technical skills within their industrial sector, even outside EO. More than half, 56%, have also improved their production processes, 44% their management and organisation skills, and 41% have opened new business units.

According to the interviewed firms, EO has also significantly contributed to improving corporate output and product innovation. Indeed, 86% of firms declare to have developed new services, while 31% have developed new trademarks and patents thanks to EO. Additionally, 50% of respondents have entered new markets or sectors.

Concerning the ultimate impact of EO in economic terms and employment, 65% of firms declare to have increased their long-term turnover, and 52% of companies agree (totally or partially) with the statement that, due to the EO, they have increased the number of permanent employees. In other words, the combination of EO data and artificial intelligence technologies that produces innovation in this industry turns out to be labour-friendly (Damioli et al., 2023).[14]

The results obtained from the survey are consistent with the balance sheet data obtained from ORBIS. In fact, for 56 interviewed firms for which we found information on ORBIS, we observed that the number of employees had grown by an average of 25%, and turnover had increased by more than 300% from 2012 to 2020.[15]

Considering this range of variables—capturing the impact on EO of firms' activity—all together into an analytical model can make the identification of the role of each variable particularly challenging due to multicollinearity issues.

For this purpose, we implement a factor analysis (FA) that compresses the number of variables capturing the effect of EO on firms' performance. The FA reveals how variables change and how they are associated. We follow an 'exploratory strategy analysis' where we reduce the variables by combining them within homogenous categories that share the same constructs. However, the methodological literature on the principal component and the factor analysis methods is mixed, and our results should be interpreted with caution. On the one hand, the factor analysis is a useful tool when analysing survey data to synthetize in meaningful factors the most relevant survey questions (Sharestha, 2021). On the other hand, composite indicators could be difficult to interpret and sometimes the signs on the loading are not well aligned with the literature. Greco et al (2019) provides and extensive description of the available methods and choice in such a context. The authors highlight that such techniques are sensitive to how the dataset is built, potentially biasing robustness of the results, and different choices could be made to lower. Recent literature proposes new strategies, such as a constrained principal component methods Boudt et al. (2022), to overcome the such limitations.

Before performing FA, we check if the data are suitable for this analysis. The first issue is that some variables suffer from partial correlations, sharing variance with

[14] Of course, a labour-saving effect may occur for final users of EO-based innovations (Dosi et al., 2021).

[15] On average, the years since the interviewed companies declared they started dealing with EO activities is 11 years.

one variable but not the remaining variables. Thus, we consider the Kaiser's Measure Olkin of Sampling Adequacy (KMO), which shows how severe this problem is for each variable. It represents the ratio of the squared correlation between variables to the squared partial correlations between variables (Field, 2009). The smaller the KMO, the greater the problem; a KMO above 0.5 is widely accepted and, in our case, is 0.79. The second issue is estimating the internal consistency of items in the model. The Cronbach Coefficient Alpha (C-alpha) is the most common internal consistency estimate. It is not a statistical test but a coefficient of reliability based on the correlation between individual indicators. Thus, if the correlation is high, there is evidence that the individual indicators measure the same underlying construct. In our case, the C-alpha is 0.85. Therefore, there is high reliability, and individual indicators measure the latent phenomenon well (OECD, 2008). Lastly, the Bartlett test of Sphericity rejects the null hypothesis that individual indicators are uncorrelated (OECD, 2008).

Table 1 presents factor loadings which indicate how well each variable fits to each factor, and they can be thought of as the Pearson correlation between a factor and a variable (Field, 2009). From the FA performed, it is possible to distinguish two main factors accounting for 92% of the variation of the data. The first one, defined "*Innovation impact*", is highly associated with six variables. The innovation impact factor captures both the direct contribution of EO data in creating new products and the indirect impact in learning and improving firms' processes. It mainly captures EO's contribution to enhancing the quality of products and services offered, the production processes, the R&D, management and organisation capacity.

The second factor, defined as "*Economic impact*", is linked with the economic effect of EO data in terms of medium and long-term turnover, the number of employees hired, the opening of new business units and penetration of new markets and sectors. Interestingly, this factor is also positively associated with patenting, an effective means for firms to boost economic success (Cefis & Ciccarelli, 2005; Kaiser, 2009). However, Fig. 1 shows that only 31% of firms registered new patents, probably due to the cost of patenting, which can be significant, especially for SMEs (Park, 2010).

By plotting our sample across the economic and innovation impact factors (see Fig. 2), several firms are positioned in the high innovation and economic area (41% of firms, quadrant on the top right) or the low innovation and economic impact area (32% of firms, quadrant bottom left).[16] However, others show mixed effects, such as high innovation impact and low economic effect, and the contrary. Therefore, we further investigated such firms' distribution in the cluster analysis presented in Sect. 4.2.

4.2 Cluster analysis

To further understand how our sample of firms is placed in terms of innovation and economic performance due to EO data use, and the relation between these two

[16] Vertical axis displays the factor loadings for innovation (Factor 1), while the horizontal axis shows the factor loadings for economic impact (Factor 2).

Table 1 Factor analysis results

	Channel of impact	Factor1 Innovation Impact	Factor2 Economic Impact	Uniqueness
Improved technical know-how	Indirect Effect	**0.6801**	0.0231	0.5245
Improved quality of products and services offered	Direct & Indirect Effect	**0.7670**	0.0840	0.3540
Improved production processes	Indirect Effect	**0.9012**	– 0.1228	0.2598
Improved R&D capacity	Indirect Effect	**0.7036**	0.1887	0.3647
Improved management and organisation capacity	Indirect Effect	**0.7364**	– 0.0254	0.4718
Developed new services	Direct Effect	**0.6781**	0.0209	0.5285
Increased number of permanent employees	Direct & Indirect Effect	0.1652	**0.6210**	0.5063
Increased medium and long term turnover	Direct & Indirect Effect	0.2680	**0.5849**	0.4626
Developed new patents	Direct & Indirect Effect	– 0.0284	**0.4386**	0.8167
Opened new business units	Direct & Indirect Effect	0.0095	**0.6732**	0.5416
Penetrated new markets	Direct & Indirect Effect	– 0.0996	**0.8743**	0.2943

Factor loadings > 0.40 in bold; Kaiser Rule applied (Eigenvalues > 1): 92% of the variance explained; Kaiser–Meyer–Olkin measure 0.79; Bartlett test of sphericity P-value = 0.00 Chi-square = 348.73

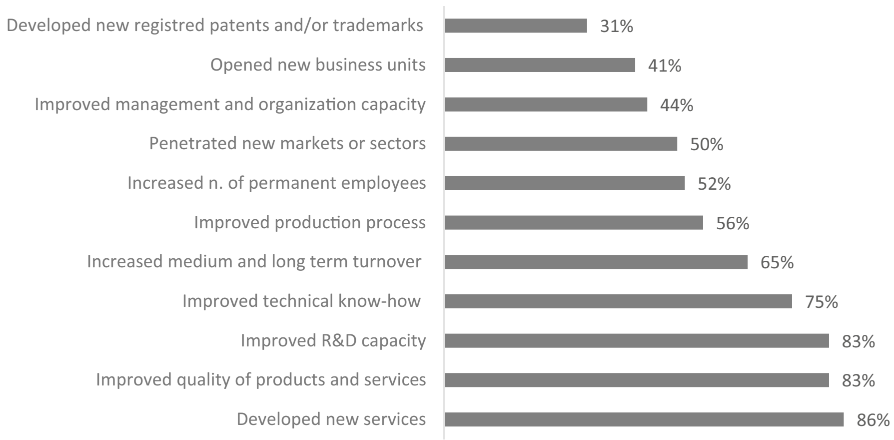

Fig. 1 The benefits of EO data availability according to the firm's view. % of companies that totally or partially agree (score 5 & 4 on the Likert scale)

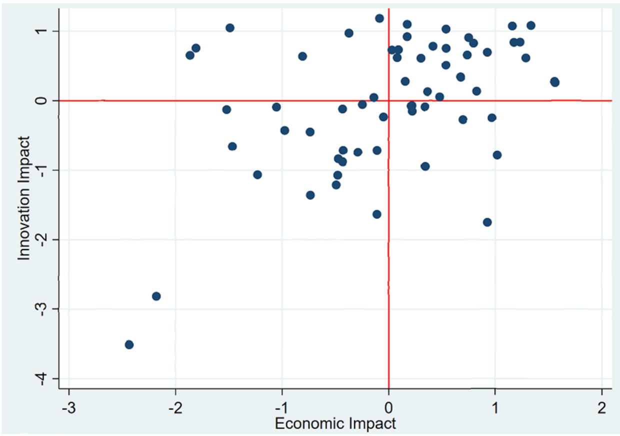

Fig. 2 Firms' distribution across two factors: innovation and economic impact

aspects, we perform a cluster analysis that relies on the factor analysis scores. We adopt a partition method to break the observations into a pre-set number of non-overlapping groups (Hamilton, 2013), performing a k-means cluster analysis (Everitt et al., 2011). We adopt statistical criteria to decide the most appropriate number of clusters, such as the distribution of observations across clusters and the variance between and within groups. From the analysis performed, we identified four clusters.

Cluster 1 (named for simplicity *EO winners*) groups 29% of firms in the sample that have reported a high impact of EO in terms of innovation and economic performance. Due to EO, these firms have innovated and experienced positive economic outcomes regarding higher turnover, employment, access to new markets, etc. Cluster 2 (named *EO performers*) groups those firms (27%) where the EO impact of innovation is relatively low, but firms have still improved their economic performance. Cluster 3 (named EO *losers*) groups firms (25%) whose neither economic performance nor innovation has improved due to EO. Lastly, Cluster 4 *(EO innovators)* groups companies (19%) that have innovated. However, most firms in this cluster have been unable to translate such innovation into higher economic performance (see Fig. 3).

Table 2 reports the descriptive statistics associated with each continuous variable across clusters to assess the characteristics of firms belonging to each group. We observe that EO winners tend to be *relatively* large firms with the highest level of EO-specialized human capital. Consistently with the extant literature (Zou et al., 2018), this may suggest that firms' size is a good proxy for the possession of the relevant absorptive capacity and complementary assets. In contrast, EO innovators tend to be small, young, and on average, born within the EO sector, while other firms joined the industry afterwards. They also own the highest share of specialised human capital out of the total number of employees.[17]

4.2.1 Cluster analysis: how firms differ across clusters

In terms of geographical distribution, the central Italian regions host most of *EO winners* (56%), *EO losers* (63%) and *EO performers* (53%). The higher concentration of firms in the centre of Italy is due to clusters of companies working in other space industry segments, the presence of the Italian Space Agency (ASI) and the ESA Centre for Earth Observation (ESRIN). The majority of *EO innovators*, instead, are mainly firms located in the South (50%). The category "other" includes firms with multiple locations (see Fig. 4).

Concerning the services offered, the clusters' distribution is consistent with the sample distribution. More specifically, 72% of the *EO winners* deal (often or always) with data elaboration and software/hardware production, while 83% of *EO innovators* design or produce EO applications and 58% offer consulting services.

Additionally, 66% of the firms in our sample declare to use freely available data. As expected, EO data from Copernicus Sentinels are the most used across all clusters. In particular, 44% *EO winners* and 58% *EO innovators* use mostly Copernicus data, while Cosmoskymed (the Italian Space Agency EO satellites constellation) covers smaller percentages (17% and 25%, respectively). This is because Copernicus data have the advantage of being open and free access to the public, private organisations and citizens, hence available as a public good.

[17] To check for any significant difference among firms in each cluster, we use the one-way analysis of variance (ANOVA) to determine whether the mean of a continuous variable is the same in two or more independent groups. Thus, the variables controlled are the number of employees, the age of the firms, the number of employees dedicated to EO activities and the years of firms' activity in EO. At the same time, our unrelated groups are categorical variables capturing firms in different clusters. We do not observe relevant differences among firms across clusters, possibly due to the small number of observations. The only exception is for the number of EO employees, which significantly differs between EO winners and EO losers and between EO winners and EO performers. The explanation behind this last result relies on the role of EO-related human capital in generating both innovation and economic impact from EO data (Bogers et al., 2018). Results of ANOVA are available upon request.

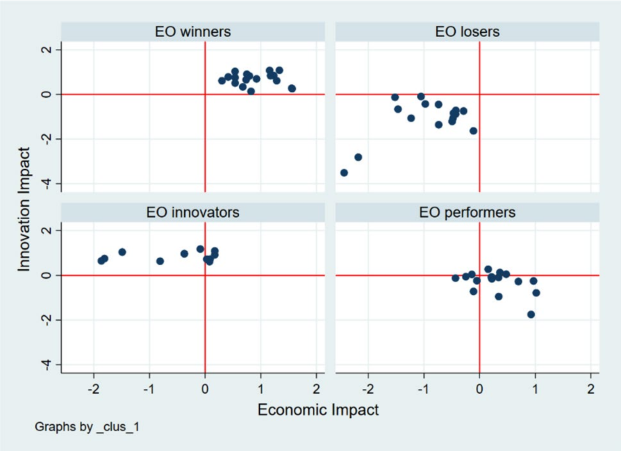

Fig. 3 Cluster Analysis: EO winners, losers, innovators and performers

In terms of turnover deriving from EO activities, half of the *EO innovators* cluster firms declare that more than 51% of the share of their turnover derives from EO activities. This percentage drops to 25% for *EO losers* and 18% for *EO performers*; 53% of the latter firms declare this share is between 1 and 25% (see Fig. 5).

78% of the *EO winners (*and 75% of *EO innovators)* deliver EO services for large Italian firms, while 72% for the public sector. A smaller percentage (67%) of winners also work with foreign firms, Italian SMEs, and regions (61%). At the same time, *EO innovators* and *EO performers* have less numerous business relationships with the public sector, a result we can associate to the well-established inefficiency of the Italian public administration. The main sectors their products and services address are Agriculture, Emergencies, Civil Protection, Security and Defence (see Fig. 6).

4.2.2 Cluster analysis: the main obstacles to the diffusion of EO products and services

The factors hindering the development of EO are of various types. In the survey, we also investigated the difficulties firms in the downstream sector encounter in developing EO services and applications and disseminating the latter among final users. In particular, we focus on the challenges in accessing EO data from a procedural and administrative point of view. Across clusters, accessing data is not problematic for most firms. In contrast, the cost of data access, including the cost to integrate the EO activities within the company, is critical for EO winners (56%), EO innovators (58%) and EO performers (59%). The term cost here is general, and it refers to the acquisition cost of data if not open source, and to the costs in terms of skills and time to engage with data providers and bureaucratic procedures to exploit EO data. Interestingly, the percentage is the lowest among EO losers, which suggests that the

Table 2 Summary statistics by cluster

	Age of the firm	Years of experience in the EO sector	N. of employees	N. of employees specialised in EO activities
EO winners				
Mean	23	15	3286	56
Median	15	12	16	6
Std. Dev	23	13	12,919	97
Min	5	2	3	1
Max	93	47	55,000	287
EO losers				
Mean	22	13	2871	5
Median	17	14	10	5
Std. Dev	113	10	11,235	3
Min	5	2	1	1
Max	48	32	45,000	13
EO innovators				
Mean	16	16	161	13
Median	17	17	10	6
Std. Dev	13	13	516	13
Min	1	1	1	1
Max	37	43	1800	50
EO performers				
Mean	20	10	249	6
Median	12	10	10	4
Std. Dev	37	6	967	6
Min	2	2	1	1
Max	161	23	4000	20

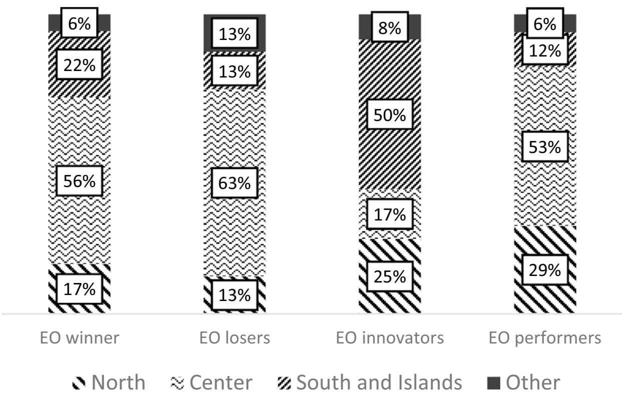

Fig. 4 Geographical distribution by cluster (%). % over the total number of firms included in each cluster

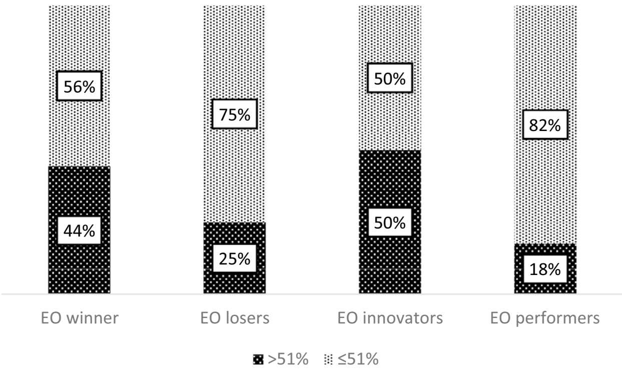

Fig. 5 Turnover related to EO by cluster (%). % over the total number of firms included in each cluster

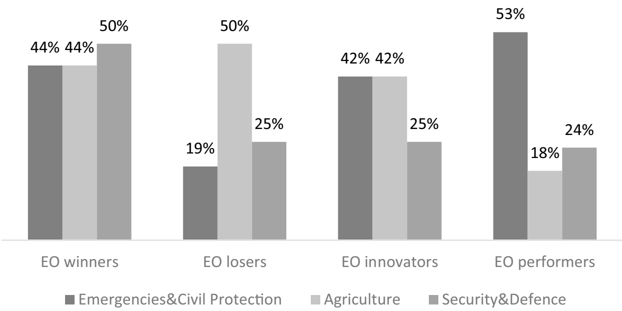

Fig. 6 Main Sectors of Clients by clusters (%). % over the total number of firms included in each cluster: multiple answers allowed

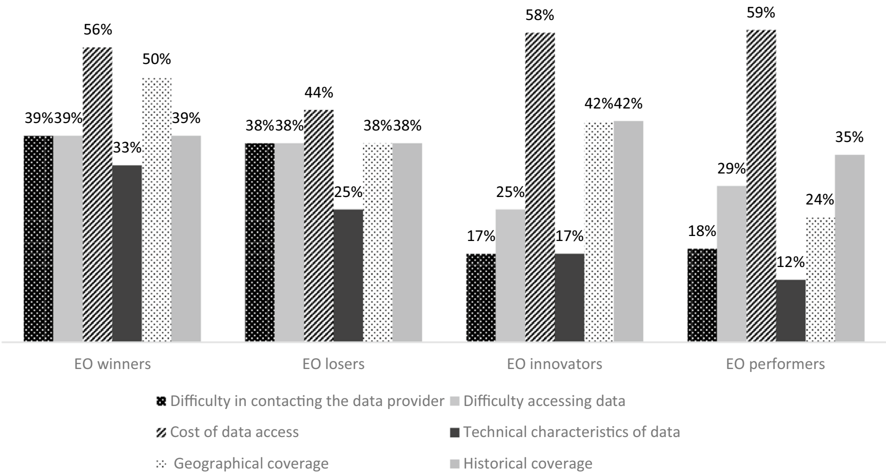

Fig. 7 Difficulties with EO data by cluster (%). % over the total number of firms included in each cluster: multiple answers allowed

Table 3 Obstacles to EO diffusion by cluster (%)

	Lack of personnel with technical skills	
	Yes	No
EO winners	78%	22%
EO losers	88%	13%
EO innovators	75%	25%
EO perfomers	94%	6%

cost is not the main reason why these firms fail to transform EO data into performance (see Fig. 7).

Another significant obstacle for Italian downstream firms is recruiting qualified personnel. As reported in Table 3, EO winners declare that finding adequate personnel is difficult for 78% of the firms in a such cluster. The analysis of the EO loser cluster (88%) lead to a similar conclusion as for the EO innovators (75%) and the EO performers cluster (94%). Overall, firms in the sample are mainly looking for professionals who deal with programming and development (84%), analytical skills (81%), managerial and organisational (48%) and communication and marketing skills (37%). Similar results are found at the European level (EARSC, 2019).[18]

Regarding the second type of barrier to sector development, firms express their opinions about factors hindering the diffusion of their EO services and applications among final users. The lack of knowledge regarding the opportunities deriving from EO is a crucial obstacle across clusters (see Fig. 8).

Such results are consistent with the taxonomy of obstacles defined by NEREUS (2016). In particular, the taxonomy identifies political barriers, e.g., low awareness at the political level concerning the social value of EO data; economic obstacles, e.g., concerning the efficient allocation of financial and human resources; social barriers, e.g. the reluctance to accept new tools of work and technological ones, e.g., lack of infrastructure to analyse the information to make decisions).

4.3 Innovation and economic impact of EO data: regression results

In this section we explore which firm's characteristics may influence the innovation and economic impact induced by working with EO data. We do not aim at identifying causal effects, but rather correlations. Thus, we implement two OLS models as follows:

$$\begin{aligned} Inn\_impact_j = \alpha + \beta_1 Empl_j + \beta_2 EO\_Empl_j + \beta_3 age_j + \beta_4 EO\_age_j + \beta_5 south \\ + \beta_6 Empl\_sq_j + \beta_7 EO\_Empl\_sq_j + \beta_8 EO\_x_j + \varepsilon \end{aligned} \tag{1}$$

[18] EARSC (2019) shows that 80 of the respondents to its survey have difficulties finding and hiring candidates, particularly people with suitable programming and development skills.

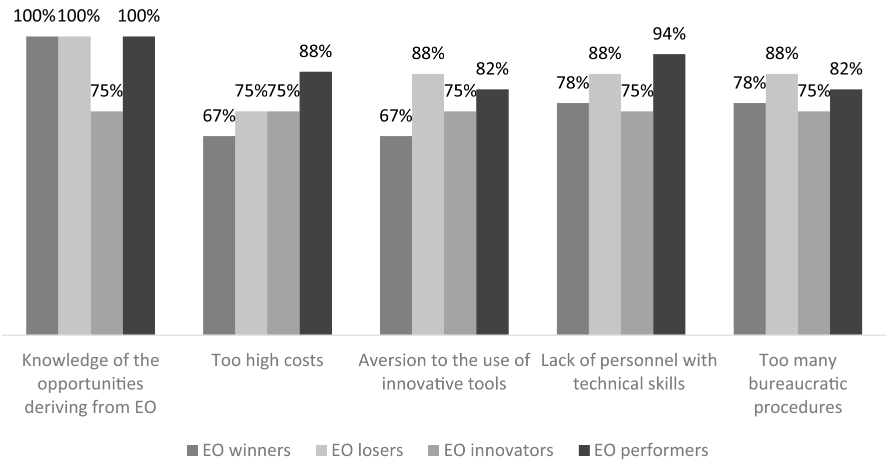

Fig. 8 Obstacles to EO diffusion by cluster (%). % over the total number of firms included in each cluster: multiple answers allowed

Table 4 Regressions—explanatory variables: summary statistics

Variables	Obs	Mean	Std. Dev	Min	Max	Dummy (1, %)
Empl	63	1765	8871.59	0	55,000	–
Age	63	20.54	23.778	1	161	–
EO_empl	63	20.667	56.013	0	287	–
EO_age	63	13.937	11.035	1	47	–
South	63	–	–	–	–	22
Copernicus	63	–	–	–	–	44
EO_data	63	–		–	–	62
Pubproc	63	–		–	–	73
Sec&Def	63	–		–	–	32
Emerg&Prot	63	–		–	–	40

$$Ec\_impact_j = \alpha + \beta_1 Empl_j + \beta_2 EO\_Empl_j + \beta_3 age_j + \beta_4 EO\_age_j + \beta_5 south + \\ + \beta_6 Empl\_sq_j + \beta_7 EO\_Empl\_sq_j + \beta_8 EO\_x_j + \varepsilon \tag{2}$$

In (1) and (2), the subscript j represents the firm. The dependent variables *Inn_impact* and *Ec_impact* are, respectively, derived from the previous factor analysis. Concerning the explanatory variables, *Empl* is the total number of employees in 2020, which is a proxy of the firm size. The variable *EO_Empl* represents the number of employees involved in EO activities. Then, *Empl_sq* and *EO_Empl_sq* are the corresponding squared terms to investigate possible nonlinearities; *Age* is the firm age and *EO_age* captures the number of years of the firms in the EO industry. Finally, *South* is a dummy variable for the firms' location in the South of Italy, and

Table 5 Regressions—Explanatory variables: correlation matrix

Variables	Inn_mpact	Ec_mpact	EO_empl	Empl	Age	EO_age	South	Copernicus	EO_data	pubproc	Sec&Def	Emerg&Prot
Inn_mpact	1.000											
Ec_mpact	0.449	1.000										
EO_empl	0.147	0.276	1.000									
Empl	– 0.159	– 0.126	0.410	1.000								
Age	– 0.026	0.054	0.421	0.342	1.000							
EO_age	0.126	0.034	0.623	0.198	0.465	1.000						
South	0.242	– 0.110	– 0.114	– 0.106	– 0.093	– 0.011	1.000					
Copernicus	0.187	0.003	– 0.060	0.194	– 0.179	– 0.044	0.060	1.000				
EO_data	0.285	0.103	0.089	0.133	– 0.097	0.103	0.105	0.241	1.000			
Pubproc	0.006	– 0.112	0.171	0.121	0.252	0.297	0.067	– 0.176	0.186	1.000		
Sec&Def	0.064	0.082	0.367	0.283	0.349	0.284	– 0.200	– 0.267	0.043	0.107	1.000	
Emerg&Prot	0.169	0.218	0.293	0.070	0.171	0.150	0.113	– 0.268	0.235	0.055	0.214	1.000

Table 6 Regressions results—Dependent variable: Innovation Impact

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Empl	– 2.64e–05* (1.53e–05)	– 2.51e–05* (1.50e–05)	– 0.000233** (0.000115)	– 0.000255** (0.000114)	– 0.000259** (0.000110)	– 0.000262** (0.000111)	– 0.000253** (0.000116)	– 0.000275** (0.000116)	– 0.000252** (0.000115)	– 0.000256** (0.000115)
EO_empl	0.00413 (0.00296)	0.00470 (0.00291)	0.00421 (0.00286)	0.0219** (0.0106)	0.0196* (0.0103)	0.0214** (0.0104)	0.0220** (0.0107)	0.0207* (0.0107)	0.0214* (0.0107)	0.0218** (0.0108)
Age	– 0.00282 (0.00597)	– 0.00209 (0.00584)	0.000430 (0.00589)	0.000700 (0.00579)	0.00316 (0.00572)	0.00342 (0.00581)	0.000780 (0.00588)	– 0.000156 (0.00585)	0.000289 (0.00585)	0.000803 (0.00588)
EO_age	0.00485 (0.0147)	0.00235 (0.0144)	0.000458 (0.0141)	– 0.00406 (0.0141)	– 0.00719 (0.0137)	– 0.00602 (0.0138)	– 0.00371 (0.0145)	– 0.00468 (0.0141)	– 0.00320 (0.0143)	– 0.00407 (0.0143)
South		0.555* (0.283)	0.514* (0.278)	0.489* (0.274)	0.428 (0.266)	0.460* (0.267)	0.492* (0.278)	0.534* (0.277)	0.459 (0.279)	0.484* (0.278)
Emplsq			4.07e–09* (2.24e–09)	4.50e–09** (2.21e–09)	4.48e–09** (2.14e–09)	4.48e–09** (2.15e–09)	4.48e–09* (2.24e–09)	4.87e–09** (2.24e–09)	4.46e–09** (2.22e–09)	4.53e–09** (2.24e–09)
EO_emplsq				– 6.80e–05* (3.94e–05)	– 5.94e–05 (3.83e–05)	– 6.36e–05 (3.84e–05)	– 6.83e–05* (3.98e–05)	– 6.51e–05 (3.94e–05)	– 6.80e–05* (3.96e–05)	– 6.79e–05* (3.97e–05)
EO_data					0.510** (0.233)					
Copernicus						0.466* (0.234)				
Pubproc							– 0.0345 (0.272)			
Sec&Def								0.287 (0.275)		
Emerg&Prot									0.166 (0.245)	
Agriculture										0.0387 (0.249)
Constant	– 0.0485 (0.209)	– 0.166 (0.213)	– 0.133 (0.209)	– 0.194 (0.209)	– 0.476* (0.240)	– 0.412* (0.231)	– 0.177 (0.251)	– 0.246 (0.215)	– 0.247 (0.224)	– 0.206 (0.226)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.084	0.142	0.189	0.231	0.294	0.284	0.231	0.246	0.238	0.232

Standard errors in parentheses

$***p<0.01$, $**p<0.05$, $*p<0.1$

Table 7 Regressions results—Dependent variable: Economic Impact

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Empl	– 3.31e–05** (1.39e–05)	– 3.35e–05** (1.40e–05)	– 0.000171 (0.000110)	– 0.000188* (0.000109)	– 0.000190* (0.000109)	– 0.000191* (0.000110)	– 0.000179 (0.000110)	– 0.000193* (0.000112)	– 0.000184* (0.000109)	– 0.000175 (0.000109)
EO_empl	0.00912*** (0.00270)	0.00894*** (0.00273)	0.00862*** (0.00272)	0.0223** (0.0102)	0.0212** (0.0102)	0.0221** (0.0102)	0.0227** (0.0103)	0.0220** (0.0104)	0.0215** (0.0102)	0.0235** (0.0102)
Age	0.00226 (0.00544)	0.00203 (0.00548)	0.00370 (0.00561)	0.00391 (0.00556)	0.00513 (0.00566)	0.00503 (0.00574)	0.00439 (0.00561)	0.00370 (0.00567)	0.00329 (0.00558)	0.00308 (0.00556)
EO_age	– 0.0230* (0.0134)	– 0.0223 (0.0135)	– 0.0235* (0.0134)	– 0.0270* (0.0136)	– 0.0286** (0.0136)	– 0.0278** (0.0136)	– 0.0248* (0.0139)	– 0.0271* (0.0137)	– 0.0257* (0.0136)	– 0.0269* (0.0135)
South		– 0.176 (0.265)	– 0.203 (0.265)	– 0.222 (0.263)	– 0.253 (0.264)	– 0.234 (0.264)	– 0.203 (0.265)	– 0.212 (0.268)	– 0.267 (0.266)	– 0.187 (0.263)
Emplsq			2.69e–09 (2.13e–09)	3.03e–09 (2.12e–09)	3.02e–09 (2.12e–09)	3.02e–09 (2.13e–09)	2.87e–09 (2.14e–09)	3.12e–09 (2.17e–09)	2.96e–09 (2.12e–09)	2.82e–09 (2.11e–09)
EO_emplsq				– 5.26e–05 (3.78e–05)	– 4.83e–05 (3.79e–05)	– 5.08e–05 (3.79e–05)	– 5.43e–05 (3.80e–05)	– 5.19e–05 (3.82e–05)	– 5.25e–05 (3.77e–05)	– 5.37e–05 (3.75e–05)
EO_data					0.254 (0.231)					
Copernicus						0.192 (0.231)				
Pubproc							– 0.209 (0.260)			
Sec&Def								0.0684 (0.267)		
Emerg&Prot									0.250 (0.234)	
Agriculture										– 0.310 (0.236)
Constant	0.145 (0.191)	0.182 (0.199)	0.204 (0.199)	0.157 (0.200)	0.0163 (0.237)	0.0671 (0.228)	0.261 (0.239)	0.144 (0.208)	0.0763 (0.214)	0.257 (0.213)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.187	0.193	0.215	0.242	0.259	0.252	0.251	0.243	0.258	0.266

Standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1

EO_x is a vector of variables capturing several aspects of the firm's EO activity, described below. We also report summary statistics and correlations among the variables in Table 4 and 5.

In Table 6, we report the results for the model described in Eq. (1). In column (1), we use *Empl* and *Age* as main regressors together with *EO_age* and *EO_Empl*. We find a negative correlation between the firm size and the innovation impact of EO data. This result is significant in all specifications. This result suggests two possible explanations: (i) larger and established firms do not invest in EO activities as the impact on innovation is expected to be small; (ii) other types of technologies are predominant for such firms, while EO activities are marginal for them.

Conversely, in specification (2), we find that firms located in the South of Italy benefit the most from EO in terms of innovation. Such firms are clustered mainly in Campania, Apulia and Basilicata. We explain this result due to large research and space infrastructures in the South of Italy. For example, we mention the Space Centre of Matera and the Geodesia of the Italian Space Agency act as innovation catalysts. In particular, the Matera Space Center is the central node of CosmoSkymed program, e.g. the Italian EO satellites constellation. It is also a station of the European Space Agency 's Core Ground Segment, devoted to the processing in real-time of the radar and optical data acquired by the Sentinel satellites, part of the European EO program Copernicus.

In specification (3), the number of workers involved in EO activities is positive and significant. An explanation is that the higher the investment in EO human capital, the higher the importance of such technology for the firm and, in turn, the impact of EO on firms' innovation.[19] The variable $EO\_Empl\_sq_j$ is negatively significant, while the coefficient for $Empl\_sq_j$ is positive and statistically significant at 10%. The effect of size on innovation, then, is negative but at a decreasing rate, while the effect on specialised human capital is positive but at a decreasing rate. The former effect suggests that the impact of EO data on innovation is particularly strong for very small firms; the latter identifies diminishing marginal returns in specialised human capital.

In specifications from (4) to (9), we include, in turn, additional regressors. For example, in specification (4), the dummy variable *EO_data* captures the main activity realised by the firm in EO, which is the elaboration of EO data and shows a positive and significant coefficient. The evolution of EO data through artificial intelligence techniques fosters innovation more than other EO activities, such as designing software or apps and providing GIS or consulting services. Indeed, it is possible that by pre-processing increasing quantities of EO data, firms face new technological challenges with a positive effect on the innovation process. In specification (5), we also find that including the variable *Copernicus,* a dummy describing firms' use of Copernicus data, contributes to the innovation impact for firms. That is the case because Copernicus Sentinels data[20] are open, free and easier to use than data from other satellites, such as CosmoSkymed. In specification (6) we investigate the

[19] It is worth highlighting that this effect is not due to a specialization effect measured by the share of EO workers out of total employees, as this share is never significant (results are available under request).

[20] https://sentinels.copernicus.eu/web/sentinel/home.

variable *Pubproc,* which describes whether firms working with the public sector such as regions, provinces, national government and other public entities, declare a higher impact in terms of innovation. We find a not significant coefficient. Therefore, public procurement does not deliver the expected positive effect, which may be due to the inefficiency of the Italian public administration. Moreover, in specifications from (7) to (9), we show that offering services which are the most requested among Italian final users of EO services and applications (in the field of Agriculture, Security and Defence, or Emergency and Civil Protection), does not help the explanation of firms' innovation.

Table 7 reports the results for the model specified in (2). From specification (1) onwards, we find a negative relation between the firm size and the economic impact of EO data. This effect extends the previous result on larger firms and innovation to economic performance. Conversely, *EO_empl* is always positive and significant, confirming that the higher the investment in human capital dedicated to EO, the higher the economic impact of EO data. Additionally, we find a negative and significant impact of *EO_age* on the economic impact. This result could be explained by a "second mover advantage" (Shankar et al., 1998). Firms that engaged in EO activities more recently may have higher capabilities to capture higher revenues, for example, by creating more flexible business models. In contrast, firms with a consolidated experience in EO, may prefer to stick to "old" business models that somehow hamper the economic performance. Finally, older firms, which are also larger, are extensively involved in public procurement activities. Thus, such firms could experience payment delays from public clients and, for this reason, declare less enthusiasm concerning the economic impact of EO activities.

Introduced in specification (2), the dummy variable *South* shows a negative sign but is not significant. The explanation is that firms based the South of Italy exploit EO in terms of innovation rate, but this advantage is not translated into a financial effect. Typically, firms in the southern Italian regions face several difficulties, such as financial constraints due to lack of credit, weaker institutional context or shortage of expertise to monetise innovation.

The remaining variables added from specification (4) to (10), including the main services offered, the squared terms of size and number of EO employees, the use of Copernicus data, working with public sector clients and the field of activity, do not generally contribute to explaining the economic impact of EO.

As a further check, we investigate which firms' characteristics influence the attribution to each cluster by using a logit model.[21] Although affected by the low number of observations and heterogeneity of clusters, and therefore overall quite weak, the results confirm that the higher the number of EO employees, the lower the probability of being a firm in the *Losers* cluster. Additionally, firms in the South are more likely to belong to the innovative cluster. We also find that the higher the EO age, the higher the probability of being in the cluster innovators.

[21] Details are available upon request.

5 Conclusions

This study contributes to understanding the importance of external data for innovation and economic performance of firms looking at the Italian EO downstream sector. EO is a growing, fast-changing and dynamic market with a substantial potential impact on how we will manage to challenge environmental and socio-economic issues shortly.

Thanks to a novel survey conducted for the first time in Italy, we find that the availability of EO data is beneficial to firms operating in this market of the digital domain as it contributes to their performance via different impact channels. Through exploratory factor analysis, we reduce the multiplicity of impact channels to innovation and economic impact. The first factor captures the direct and indirect contribution of EO, leading to learning and innovation. The second is more associated with the economic effects of EO data in terms of medium and long-term turnover, the number of new permanent employees that the firm has to hire to run the business, the opening of new business units and penetration of new markets and sectors.

While innovation and economic impact are usually positively associated, we identify firms for which a relatively significant improvement in innovation performance does not translate into higher economic performance. Conversely, thanks to EO, higher economic performance does not hang upon higher innovation performance. In other words, a positive impact of EO data on firms' innovation capabilities is not a sufficient nor a necessary condition for improved economic performance, and vice-versa.

We also find that, everything else constant, firms' overall size is negatively associated with both innovation and economic impact, so EO data strongly affect smaller firms. The number of employees in EO-related activity, a proxy of sector-specific human capital, positively affects innovation and economic performance. Surprisingly, experience in EO significantly negatively affects economic performance (while the effect is not significant for innovation). This suggests a late mover advantage at work, possibly related to cutting-edge business models that better fit the market. Additionally, being located in the South of Italy has a positive impact on innovation but a negative impact on economic performance, which we associate with the relative institutional and economic backwardness of the firms' environment.

Our work suggests several managerial and policy implications. Consistently with previous literature on open innovation (Huber et al., 2020), business models based on external data can be beneficial for small firms in terms of innovation and economic performance. As for the EO data, that is the case for open and accessible data like those provided by Copernicus Sentinels. Indeed, space agencies are increasingly moving toward an open data model after past privatisation and commercialisation trends with low success for the entire market (Borowitz, 2017). Accordingly, several countries and international organisations are promoting a full, free, open-access data policy of their satellites to maximise the return on public investment in EO (Harris & Baumann, 2015). In this way, firms receive crucial input for their activity in

Table 8 Innovation Impact (factor1) Subtracting EO employees from total employees

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Empl_minusEO	− 2.64e−05* (1.53e−05)	− 2.51e−05* (1.50e−05)	− 0.000233** (0.000115)	− 0.000255** (0.000114)	− 0.000259** (0.000110)	− 0.000262** (0.000111)	− 0.000253** (0.000116)	− 0.000275** (0.000116)	− 0.000252** (0.000115)	− 0.000256** (0.000115)
EO_empl	0.00410 (0.00296)	0.00468 (0.00290)	0.00398 (0.00287)	0.0217** (0.0106)	0.0193* (0.0103)	0.0211** (0.0104)	0.0217** (0.0107)	0.0204* (0.0107)	0.0211* (0.0107)	0.0215* (0.0108)
Age	− 0.00282 (0.00597)	− 0.00209 (0.00584)	0.000430 (0.00589)	0.000700 (0.00579)	0.00316 (0.00572)	0.00342 (0.00581)	0.000780 (0.00588)	− 0.000156 (0.00585)	0.000289 (0.00585)	0.000803 (0.00588)
EO_age	0.00485 (0.0147)	0.00235 (0.0144)	0.000458 (0.0141)	− 0.00406 (0.0141)	− 0.00719 (0.0137)	− 0.00602 (0.0138)	− 0.00371 (0.0145)	− 0.00468 (0.0141)	− 0.00320 (0.0143)	− 0.00407 (0.0143)
South		0.555* (0.283)	0.514* (0.278)	0.489* (0.274)	0.428 (0.266)	0.460* (0.267)	0.492* (0.278)	0.534* (0.277)	0.459 (0.279)	0.484* (0.278)
Emplsq			4.07e−09* (2.24e−09)	4.50e−09** (2.21e−09)	4.48e−09** (2.14e−09)	4.48e−09** (2.15e−09)	4.48e−09* (2.24e−09)	4.87e−09** (2.24e−09)	4.46e−09** (2.22e−09)	4.53e−09** (2.24e−09)
EO_emplsq				− 6.80e−05* (3.94e−05)	− 5.94e−05 (3.83e−05)	− 6.36e−05 (3.84e−05)	− 6.83e−05* (3.98e−05)	− 6.51e−05 (3.94e−05)	− 6.80e−05* (3.96e−05)	− 6.79e−05* (3.97e−05)
EO_data					0.510** (0.233)					
Copernicus						0.466* (0.234)				
pubproc							− 0.0345 (0.272)			
Sec&Def								0.287 (0.275)		
Emerg&Prot									0.166 (0.245)	
Agriculture										0.0387 (0.249)
Constant	− 0.0485 (0.209)	− 0.166 (0.213)	− 0.133 (0.209)	− 0.194 (0.209)	− 0.476* (0.240)	− 0.412* (0.231)	− 0.177 (0.251)	− 0.246 (0.215)	− 0.247 (0.224)	− 0.206 (0.226)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.084	0.142	0.189	0.231	0.294	0.284	0.231	0.246	0.238	0.232

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 9 Economic Impact: Subtracting EO employees from total employees

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Empl_minu-sEO	– 3.31e–05** (1.39e–05)	– 3.35e–05** (1.40e–05)	– 0.000171 (0.000110)	– 0.000188* (0.000109)	– 0.000190* (0.000109)	– 0.000191* (0.000110)	– 0.000179 (0.000110)	– 0.000193* (0.000112)	– 0.000184* (0.000109)	– 0.000175 (0.000109)
EO_empl	0.00909*** (0.00269)	0.00891*** (0.00272)	0.00845*** (0.00273)	0.0221** (0.0102)	0.0210** (0.0102)	0.0219** (0.0102)	0.0225** (0.0102)	0.0218** (0.0104)	0.0213** (0.0102)	0.0233** (0.0102)
Age	0.00226 (0.00544)	0.00203 (0.00548)	0.00370 (0.00561)	0.00391 (0.00556)	0.00513 (0.00566)	0.00503 (0.00574)	0.00439 (0.00561)	0.00370 (0.00567)	0.00329 (0.00558)	0.00308 (0.00556)
EO_age	– 0.0230* (0.0134)	– 0.0223 (0.0135)	– 0.0235* (0.0134)	– 0.0270* (0.0136)	– 0.0286** (0.0136)	– 0.0278** (0.0136)	– 0.0248* (0.0139)	– 0.0271* (0.0137)	– 0.0257* (0.0136)	– 0.0269* (0.0135)
South		– 0.176 (0.265)	– 0.203 (0.265)	– 0.222 (0.263)	– 0.253 (0.264)	– 0.234 (0.264)	– 0.203 (0.265)	– 0.212 (0.268)	– 0.267 (0.266)	– 0.187 (0.263)
Emplsq			2.69e–09 (2.13e–09)	3.03e–09 (2.12e–09)	3.02e–09 (2.12e–09)	3.02e–09 (2.13e–09)	2.87e–09 (2.14e–09)	3.12e–09 (2.17e–09)	2.96e–09 (2.12e–09)	2.82e–09 (2.11e–09)
EO_emplsq				– 5.26e–05 (3.78e–05)	– 4.83e–05 (3.79e–05)	– 5.08e–05 (3.79e–05)	– 5.43e–05 (3.80e–05)	– 5.19e–05 (3.82e–05)	– 5.25e–05 (3.77e–05)	– 5.37e–05 (3.75e–05)
EO_data					0.254 (0.231)					
Copernicus						0.192 (0.231)				
pubproc							– 0.209 (0.260)			
Sec&Def								0.0684 (0.267)		
Emerg&Prot									0.250 (0.234)	
Agriculture										– 0.310 (0.236)
Constant	0.145 (0.191)	0.182 (0.199)	0.204 (0.199)	0.157 (0.200)	0.0163 (0.237)	0.0671 (0.228)	0.261 (0.239)	0.144 (0.208)	0.0763 (0.214)	0.257 (0.213)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.187	0.193	0.215	0.242	0.259	0.252	0.251	0.243	0.258	0.266

Standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1

the form of a public good[22] and can boost applications in many fields (Pogorzelska, 2018). This aspect should be particularly taken care of in Italy, as the Italian Space Agency still provides data under a licence whose access is subject to a complex bureaucratic procedure.

At the same time, our results also highlight the importance of absorptive capacity, which influences learning by doing and data transformation and exploitation capabilities. Specialised human capital seems a crucial factor for firms to take advantage of EO data, not only for innovation but also for economic performance. Hence, a critical issue concerns recruiting qualified personnel, particularly professionals dealing with programming, development, and analytical skills. Promoting multidisciplinary groups from industry and academia could help to overcome these difficulties. This approach will help academia understand what courses and curricula should be encouraged and will support firms in finding suitable candidates, providing them with a fulfilling work environment, including training (see, for example, eo4geo[23]).

The benefit of EO also seems particularly relevant for micro, small and recently born firms where the dynamics of the sector and the capability to design new and innovative business models become crucial to capture new market niches. In contrast to what happens in the upstream space sector, public procurement does not seem to drive innovation and economic performance in the market; hence developing the private industry engagement within the new space economy paradigm is becoming increasingly critical. Additionally, to expand the industry and capture its full potential, there is a need to raise awareness of EO technology applications and benefits among potential final users. This could be achieved by building international networks and clusters to favour the connections between downstream players, bringing together the customers and the products available on the market, as the market at the moment is too fragmented. Several user uptake initiatives have been undertaken over the past years or are currently under development by the European Commission to facilitate the use of Copernicus data. Business incubators, networks and relays, training sessions, data handling tools and, recently, tailored cloud computing services (European Commission, 2016; Tassa, 2019) are at the disposal of the public, and this is the direction to pursue to exploit the enormous potential of this industry fully.

Lastly, our results suggest that firms with high innovation impact and low economic performance are mainly based in the South of Italy. The intuition is that the positive spillover effect of being clustered close to large research infrastructures dedicated to EO produce a trade-off in term of economic competition. Coherently, our results suggest that policies and interventions that spur innovation, as observed in the EO sector, do not necessarily translate into economic performance. Innovation and local development policies should then be combined to help innovative firms to better position in the market.

[22] A public good, such as knowledge, is a good for which exclusion from its consumption is impossible or too costly, and there is no rivalry in consumption among consumers (Samuelson, 1954).

[23] http://www.eo4geo.eu/about-eo4geo/.

Of course, our work is not without limitations. The most relevant one refers to the data available for the analysis. Based on questionnaire data observed in a particular moment of time, the relationships involving innovative and economic performance identified in the paper should be taken with caution, as they may suffer from omitted variables and a more extended time-span dimension could produce different results. As we argued throughout the paper, data to conduct statistical analyses based on objective measures in our context are basically non-existing. In that respect, future work may take advantage of the current efforts to measure properly the economic activities within the "New Space Economy" (OECD, 2022). Such a work could include a full-fledged investigation of the industrial dynamics of the sector, considering entry, exit, survival and growth (Malerba & Orsenigo, 1996). At the same time, (other) survey data may enlighten specific features of this industry. For instance, given the role of new firms in the EO downstream industry, it could be interesting to investigate the impact of founders' background on performance, to assess possible differences across spinouts from different industries (e.g. the upstream EO industry, ICT sectors, final users) (Costa & Baptista, 2023).

Appendix

In this Appendix, we report two robustness checks for the regressions presented in the main paper.

(a) We run the two models including a variable "Empl_minusEO" which represents total employees minus the EO employees (Tables 8 and 9). The results do not change significantly. The tables are reported in the Appendix as a further robustness check.

(b) We run the two models centering the variables (i.e., Empl and EO_empl) and their squared to the mean (Tables 10 and 11). The magnitude of the coefficients slightly changes but the significance of our results does not.

In a further robustness check we also included the ratio of EO-employees to the total number. However, the variable was not significant for each specification of the model, and so not reported here.

Table 10 Innovation Impact: centring employees and EO_employees and their squared variable in the mean to reduce multicollinearity

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
employees_2020_c	– 2.64e–05* (1.53e–05)	– 2.51e–05* (1.50e–05)	– 0.000219** (0.000107)	– 0.000239** (0.000106)	– 0.000243** (0.000103)	– 0.000247** (0.000104)	– 0.000238** (0.000108)	– 0.000258** (0.000108)	– 0.000236** (0.000107)	-0.000240** (0.000108)
EOemployees_2020_c	0.00413 (0.00296)	0.00470 (0.00291)	0.00421 (0.00286)	0.0191** (0.00908)	0.0171* (0.00883)	0.0187** (0.00884)	0.0192** (0.00917)	0.0180* (0.00914)	0.0186** (0.00916)	0.0190** (0.00920)
Age	– 0.00282 (0.00597)	– 0.00209 (0.00584)	0.000430 (0.00589)	0.000700 (0.00579)	0.00316 (0.00572)	0.00342 (0.00581)	0.000780 (0.00588)	– 0.000156 (0.00585)	0.000289 (0.00585)	0.000803 (0.00588)
Ageot	0.00485 (0.0147)	0.00235 (0.0144)	0.000458 (0.0141)	– 0.00406 (0.0141)	– 0.00719 (0.0137)	– 0.00602 (0.0138)	– 0.00371 (0.0145)	– 0.00468 (0.0141)	– 0.00320 (0.0143)	-0.00407 (0.0143)
South		0.555* (0.283)	0.514* (0.278)	0.489* (0.274)	0.428 (0.266)	0.460* (0.267)	0.492* (0.278)	0.534* (0.277)	0.459 (0.279)	0.484* (0.278)
emplsq_c			4.07e–09* (2.24e–09)	4.50e–09** (2.21e–09)	4.48e–09** (2.14e–09)	4.48e–09** (2.15e–09)	4.48e–09* (2.24e–09)	4.87e–09** (2.24e–09)	4.46e–09** (2.22e–09)	4.53e-09** (2.24e-09)
EOemplsq_c				– 6.80e–05* (3.94e–05)	– 5.94e–05 (3.83e–05)	– 6.36e–05 (3.84e–05)	– 6.83e–05* (3.98e–05)	– 6.51e–05 (3.94e–05)	– 6.80e–05* (3.96e–05)	-6.79e-05* (3.97e-05)
Eodata					0.510** (0.233)					
Copernicus						0.466* (0.234)				
Pubproc							– 0.0345 (0.272)			
Security_Defence								0.287 (0.275)		
Civil_Protection									0.166 (0.245)	
q20_1d										0.0387 (0.249)
Constant	– 0.00972 (0.235)	– 0.113 (0.236)	– 0.444 (0.294)	– 0.205 (0.321)	– 0.539 (0.346)	– 0.446 (0.335)	– 0.184 (0.363)	– 0.317 (0.338)	– 0.265 (0.334)	-0.223 (0.344)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.084	0.142	0.189	0.231	0.294	0.284	0.231	0.246	0.238	0.232

Standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1

Table 11 Economic Impact: centering employees and EO_employees in the mean and using the squared v.les to reduce multicollinearity

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
employees_2020_c	– 3.31e–05** (1.39e–05)	– 3.35e–05** (1.40e–05)	– 0.000162 (0.000102)	– 0.000177* (0.000102)	– 0.000179* (0.000102)	– 0.000180* (0.000102)	– 0.000169 (0.000103)	– 0.000182* (0.000104)	– 0.000173* (0.000102)	– 0.000165 (0.000102)
EOemployees_2020_c	0.00912*** (0.00270)	0.00894*** (0.00273)	0.00862*** (0.00272)	0.0202** (0.00871)	0.0192** (0.00874)	0.0200** (0.00874)	0.0204** (0.00875)	0.0199** (0.00885)	0.0193** (0.00874)	0.0212** (0.00869)
Age	0.00226 (0.00544)	0.00203 (0.00548)	0.00370 (0.00561)	0.00391 (0.00556)	0.00513 (0.00566)	0.00503 (0.00574)	0.00439 (0.00561)	0.00370 (0.00567)	0.00329 (0.00558)	0.00308 (0.00556)
Ageot	– 0.0230* (0.0134)	– 0.0223 (0.0135)	– 0.0235* (0.0134)	– 0.0270* (0.0136)	– 0.0286** (0.0136)	– 0.0278** (0.0136)	– 0.0248* (0.0139)	– 0.0271* (0.0137)	– 0.0257* (0.0136)	– 0.0269* (0.0135)
South		– 0.176 (0.265)	– 0.203 (0.265)	– 0.222 (0.263)	– 0.253 (0.264)	– 0.234 (0.264)	– 0.203 (0.265)	– 0.212 (0.268)	– 0.267 (0.266)	– 0.187 (0.263)
emplsq_c			2.69e–09 (2.13e–09)	3.03e–09 (2.12e–09)	3.02e–09 (2.12e–09)	3.02e–09 (2.13e–09)	2.87e–09 (2.14e–09)	3.12e–09 (2.17e–09)	2.96e–09 (2.12e–09)	2.82e–09 (2.11e–09)
EOemplsq_c				– 5.26e–05 (3.78e–05)	– 4.83e–05 (3.79e–05)	– 5.08e–05 (3.79e–05)	– 5.43e–05 (3.80e–05)	– 5.19e–05 (3.82e–05)	– 5.25e–05 (3.77e–05)	– 5.37e–05 (3.75e–05)
Eodata					0.254 (0.231)					
Copernicus						0.192 (0.231)				
Pubproc							– 0.209 (0.260)			
Security_Defence								0.0684 (0.267)		
Civil_Protection									0.250 (0.234)	
q20_1d										– 0.310 (0.236)
Constant	0.275 (0.214)	0.307 (0.221)	0.0881 (0.280)	0.273 (0.308)	0.107 (0.342)	0.174 (0.331)	0.399 (0.346)	0.246 (0.327)	0.183 (0.319)	0.419 (0.325)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.187	0.193	0.215	0.242	0.259	0.252	0.251	0.243	0.258	0.266

Standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

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Data availability The datasets analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors has no competing interests to declare that are relevant to the content of this article.

Ethical conduct This article does not contain any studies with human participants or animals.

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