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## Abstract

The Smart Specialization Strategy (S3) is a cornerstone of the EU's Cohesion Policy, with over €61 billion allocated for Research & Innovation from 2014 to 2020. This paper explores the prioritization of technological domains within regional S3 strategies and their influence on funding allocation of the European Regional Development Fund. Our findings indicate that while regions select a broad range of S3 priorities, they tend to prioritize those more related to their existing technological capabilities. This is particularly true for less developed and transition regions. The lack of selectivity in S3 strategies appears to be mitigated when these priorities are converted into funding allocations. There we observe that funding allocation appears to align more closely with regional capabilities than initial S3 priorities. We also find that, although the complexity of technologies is somewhat considered in selecting S3 priorities, it seems to gain importance when regions dedicate their funding to specific R&I projects.

## Introduction

The Smart Specialization Strategy (S3) plays a vital role in the European Union's (EU) Cohesion Policy. More than €61 billion in funding for Research & Innovation (R&I) was allocated to EU regions through S3 policy in Europe between 2014-2020 (European Commission, 2023). Therewith, smart specialization may well be one of the biggest multinational policy strategies aiming to boost regional innovation ever (Asheim et al., 2017). Smart specialization is a place-based approach that aims to spur economic growth by leveraging existing regional strengths. Therefore, regions should identify which specializations are most promising for the development of comparative advantage and prioritize those for policy intervention.

S3's relatively short journey from concept to policy has given it the reputation of being "a perfect example of a policy running ahead of theory" (Foray et al., 2011, p. 1). Thus far, only a few scholars have begun examining the policy's first programming period (2014-2020) by assessing how well selected specializations in regional S3 strategies reflect a region's capabilities (Gianelle et al., 2020b). Most of these focus on economic domains (Deegan et al., 2021; Marrocu et al., 2023), whereas this paper investigates the prioritization of technological domains. In doing so, we build on the smart specialization framework developed by Balland et al. (2019), which emphasizes as key principles both the relatedness of a technology to a region's existing capabilities and the complexity of that technology. By applying this framework, this paper is the first to analyze the extent to which S3 strategies prioritize technological domains that align with a region's technological profile and the complexity of the prioritized technologies.

In a next step, we investigate how regional S3 priority decisions influence a region's allocation of funding for R&I by the European Regional Development Fund (ERDF). R&I related projects account for around a fifth of all ERDF-funded projects. Accessing funding under the R&I thematic objective (TO1) requires that projects align with each region's or Member State's S3 strategy as an ex-ante condition (Abbott & Fitjar, 2024). By analyzing how S3 priorities are translated into the actual allocation of R&I funding, this study goes beyond most existing research, which primarily focuses on the formulation of priorities within S3 strategies. Therefore, this approach provides a deeper understanding of how S3 strategies affect financial investment into the regional development of technology.

The analysis is based on a novel integration of three datasets: 1) Eye@RIS3, which captures S3 priorities of 254 NUTS2 regions, 2) ERDF project data from Kohesio, adapted and extended following Bachtrögler-Unger et al. (2021), to analyze regional funding decisions, 3) the OECD's (2023) REGPAT dataset to measure regional technological capabilities.

While we find that regional S3 strategies tend to prioritize a wide range of technologies, regions generally consider the relatedness of technologies to their existing technological capabilities, particularly in less developed and transition regions where diversification is more path dependent (Pinheiro et al., 2021). However, there is room for improvement regarding prioritizing more complex technologies, as little variation in complexity-based prioritization was observed across regions at different development levels. Interestingly, the lack of selectivity and unclear consideration of complexity in S3 priorities is mitigated when it comes to funding decisions, with funding being more closely aligned with regional technological strengths than the initial S3 priorities. This is likely due to the greater availability of investment opportunities in technologies that are closely aligned with a region's technological profile.

The remainder of the paper is structured as follows. The next section describes the theory of smart specialization and briefly summarizes the concerns and critiques in the academic literature. This is followed by an overview of studies evaluating the implementation of the policy. Next, we describe the data sources used and how they were integrated to perform the analysis. The subsequent section discusses the results of this analysis, and the last section concludes.

## Theoretical background

### *What is S3?*

The concept of smart specialization stems from the idea that the evolution of a regional innovation system is inherently linked to its context. A region's development path depends on its ongoing economic dynamics and institutional structures. This is aptly illustrated by Boschma & Wenting (2007) in their study on the spatial evolution of the British automobile industry. They show that the automobile industry mostly thrived in the regions that were already heavily involved in industries closely related to the car industry, such as bicycle or coach making. Hence, regions should build on their existing strengths and capabilities (Boschma, 2024).

S3 diverges from a top-down one-size-fits-all policy towards a bottom-up innovation policy that is tailor-made to each region. Every region should concentrate its public resources on a limited set of well-defined economic, technological or scientific domains, in which it either shows a competitive advantage or a considerable growth potential (Foray et al., 2012).

These targeted domains are called *priorities* or *priority areas* and are identified via the *Entrepreneurial Discovery Process* (EDP) (Foray et al., 2012). The involvement of local entrepreneurial actors in the process of discovering priority areas is a key feature of S3. Its underlying rationale can be traced back to Storper's (1997) idea of regional economies as stocks of relational assets, i.e., local communities with their very own conventions, practices and (tacit) knowledge. Given their direct involvement in such communities, local entrepreneurial actors are probably better equipped than policymakers to understand these communities and identify the most promising paths for regional diversification (Foray et al., 2009; D'Adda et al., 2019).

A systematic identification of these diversification paths is a key challenge for smart specialization. Balland et al. (2019) developed a theoretical framework for regions to identify the most promising areas for smart specialization. Central to this framework are the concepts of relatedness and knowledge complexity. It is most interesting for regions to diversify into highly complex technologies, since these are hard to imitate, therefore sticky in space (Balland et al., 2020), and expected to generate the higher long-term returns. However, the knowledge and capabilities needed to diversify into these complex technologies, are hard to attain. Therefore, regions have the most potential to develop new complex technologies in those areas related to existing capabilities (Boschma, 2017; Hidalgo et al., 2018), as shown in Figure 1. There is a large strand of literature showing empirical evidence in support of this framework (Hausmann et al., 2006; Hidalgo & Hausmann, 2009; Neffke et al., 2011; Essletzbichler, 2015; Kogler et al., 2013; Rigby, 2015; Boschma et al., 2015; Montresor & Quatraro, 2017; Petralia et al. 2017; Rigby et al., 2022; Antonelli et al., 2022; Mewes & Broekel, 2022).

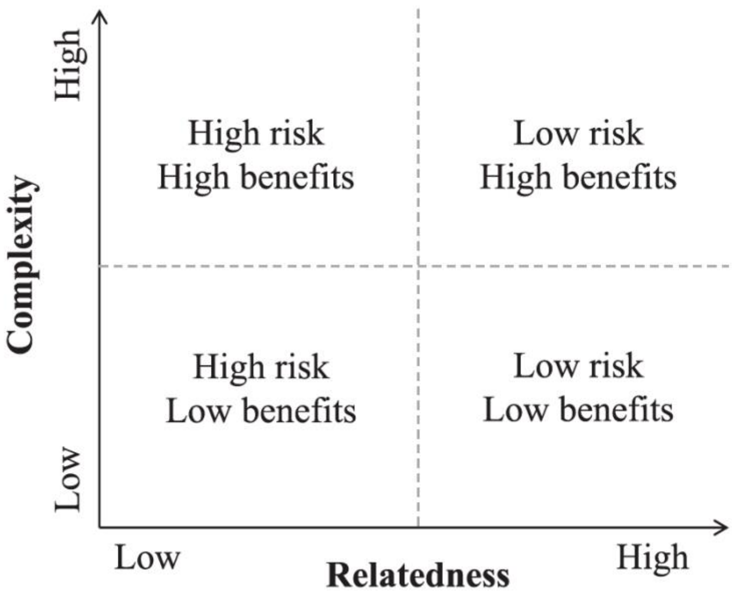


*Figure 1. Framework for smart specialization (Balland et al., 2019).*

## *Concerns and critiques about S3*

Smart specialization gained its importance in a relatively short period of time. It was first coined by the Knowledge for Growth Expert Group around 2009 (Foray, 2014) and initially implemented only 5 years later. This short journey from concept to policy raised a range of concerns among experts (McCann et al. 2017; Marques and Morgan 2018).

Hassink & Gong (2019) argue that the smart specialization became to be an umbrella term for various concepts in economic geography. Therefore, it is often not well understood by those responsible for its implementation (Kroll, 2015; Capello & Kroll, 2016; Pugh, 2018). Others are concerned that involving local stakeholders in regional innovation policy entails the risk of rent-seeking behavior, corruption, and regional lock-ins (Camagni & Capello, 2013; Boschma, 2014; Rodríguez-Pose et al., 2014; Grillitsch, 2016; Trippl et al., 2020).

Moreover, there are several concerns about S3 related to governance institutions (Morgan 2015). Rodríguez-Pose et al. (2014) show that a high quality of regional governmental institutions seems to be crucial for a successful implementation. On top of that, the EU is characterized by diverse structures of governance within its Member States. Embedding S3 in these various institutional contexts can be challenging (Kroll, 2015; Capello & Kroll, 2016; Pugh, 2018; Benner, 2019). This also relates with Hassink & Gong's (2019) concern of how well S3 works next to already existing innovation policies.

Lastly, several scholars point out that, while the Cohesion Policy tends to strengthen weaker regions, the logic behind S3 favors more advanced regions. The elements crucial for the policy's implementation are exactly those that are missing in lagging regions (Boschma 2014; McCann & Ortega-Argilés, 2015; Capello & Kroll, 2016; Iacobucci & Guzzini, 2016; Papamichail et al. 2023). This may drive these regions to set many broad priorities instead of a few well-defined ones (Boschma, 2014; Capello & Kroll, 2016; Di Cataldo et al., 2021).

### *Evaluations of S3 implementation*

There is a growing body of literature evaluating the implementation of S3. These studies can be divided into two groups: studies examining regional S3 priorities (see Table 1), and studies investigating regional S3 strategies and regional funding decisions (see Table 2).

As can be seen in Table 1, most studies examine how well regional S3 priorities reflect regional capabilities. They vary in their geographical scope and type of priority, the latter determining the data used (e.g., employment data for economic domains and patent data for technological domains). Moreover, the second column shows that researchers use different indicators to evaluate S3 priorities. Some look at the relatedness between priorities (Iacobucci & Guzzini, 2016; D'Adda et al., 2020), whereas others measure the relatedness of chosen priorities to a region's technological or economic profile (Deegan et al., 2021; Kramer et al., 2021; Marrocu et al., 2023). Kim et al. (2024) also evaluate to what extent regions prioritize technological domains that have a central position in the knowledge network. Location quotients or revealed comparative advantages are used to compare priorities to regional capabilities (D'Adda et al., 2019; Kramer et al., 2021; Marrocu et al., 2023; Kim et al., 2024). Following Balland et al.'s (2019) framework, two studies also considered the complexity of prioritized domains (Deegan et al., 2021; Kramer et al., 2021).

*Table 1. Overview of studies evaluating S3 prioritization in alphabetic order.*

| **Study** | **Focus / aim** | **Geographical scope** | **Type of priority** | **Data** |
|---|---|---|---|---|
| Biagi et al. (2021) | The rationale of regions for prioritizing tourism in S3 | 191 EU regions | Tourism | Regional tourism statistics |
| Buyukyazici (2023) | Do priorities reflect regional workplace knowledge and skills? | 20 Italian regions | Economic domains | Italian Sample Survey on Professions and Italian Labor Force Survey |
| D'Adda et al. (2019) | Do priorities reflect regional innovative capabilities? | 23 Italian regions | Technological domains | Patent data |
| D'Adda et al. (2020) | The relatedness between priorities | 19 Italian regions | Technological domains | Patent data |
| Deegan et al. (2021) | The relatedness and complexity of priorities | 128 European regions | Economic domains | SBS employment data |
| Di Cataldo et al. (2021) | Do priorities reflect economic characteristics? | All regions and countries in the Eye@RIS3 dataset | Economic and scientific domains, and policy objectives | GDP, population, unemployment, EU QoG index, patents per inhabitant, tertiary educated |
| Farinha et al. (2020) | Do priorities reflect regional stakeholders' perceptions? | 7 Portuguese regions | Priorities in general | Survey among stakeholders |
| Gianelle et al. (2020a) | How are priorities indicated and described? | 39 Italian and Polish regions | Priorities in general | Descriptive analysis of RIS3 documents |
| Iacobucci & Guzzini (2016) | The relatedness of priorities and their potential interregional links | 16 Italian regions | Technological domains | Descriptive analysis of RIS3 documents |
| Kim et al. (2024) | The centrality of prioritized domains and their potential for regional diversification. | 164 European regions | Technological domains | Patent data |
| Kramer et al. (2021) | Do priorities reflect regional capabilities? | 185 European regions | Technological, economic, and scientific domains | Patent data, SBS employment data, and scientific publication data |
| Lopes et al. (2018) | Do priorities reflect regional stakeholders' perceptions? | 7 Portuguese regions | Priorities in general | Survey among stakeholders |
| Marrocu et al. (2023) | Do priorities reflect regional capabilities? | 243 European regions | Economic domains | SBS employment data |
| Pylak et al. (2025) | Do regions mimic other regions in priority selection? | | Economic domains | Employment data |
| Sörvik & Kleibrink (2015) | What are the most common (combinations) priorities? Do priorities reflect economic characteristics? | 174 EU regions, 18 non-EU regions | Economic domains | Descriptive statistics of Eye@RIS3 data and SBS employment data |

Several scholars point out that a systematic analysis of S3 priorities is challenging because priorities are defined in a non-codified way (Iacobucci & Guzzini, 2016; D'Adda et al., 2019; Marrocu et al., 2023). This methodological problem is less of an issue for analyzing economic domains since regions also have to select the associated NACE sectors for each priority[1]. However, this is not the case for the analysis of technological domains. In their analysis of Italian regions, D'Adda et al. (2019) and D'Adda et al. (2020) overcome this issue by matching priorities to three-digit IPC codes using WIPO's automatic categorization assistant[2]. Alternatively, Kramer et al. (2021) use a less fine-grained codifying method, by matching priorities with Schmoch's (2008) technology classes via automatic text mining. In contrast, this study creates a technological taxonomy that is tailored to S3 priority data by thoroughly analyzing all S3 priorities, as outlined in the Data and Methods section. Therewith, the correspondence between prioritized technological domains and a region's technological capabilities can be measured more accurately.

Some syntheses about S3 priorities can be drawn from the studies in Table 1. First, Marrocu et al. (2023) find that most regions tend to prioritize economic domains that are not very related to their economic profile. The results of Deegan et al. (2021) indicate a stronger relation between economic relatedness and selected priorities. Second, Deegan et al. (2021) also show that regions tend to prioritize more complex economic domains. However, overall, regions do not consider relatedness and complexity in tandem when selecting priorities, as proposed by Balland et al. (2019), but rather independently. Third, studies notice that regions often mimic neighboring regions in their S3 strategies (Deegan et al., 2021; Di Cataldo et al., 2021; Pylak et al. 2025). Fourth, there is a moderate degree of coherence between each region's prioritized technological domains and the domains in which they possess a comparative advantage, with a slightly higher degree for more developed regions (D'Adda et al., 2019; Kramer et al. 2021). This degree tends to be lower for prioritized economic domains (Kramer et al. 2021; Marrocu et al. 2023). Moreover, Kramer et al. (2021) note that the regions that define more broad and vague priorities often have a better correlation between priorities and regional capabilities. This relates to the commonly shared notion that regions are not selective in their priority setting, and that most priority areas are broadly defined (Iacobucci & Guzzini,

[1] See Data and Methods section for a more detailed description of S3 priority data.

[2] Categorization Assistant in the International Patent Classification (IPCCAT), see www.wipo.int/ipccat/.

2016; Gianelle et al., 2020a; Di Cataldo et al., 2021; Marrocu et al., 2023). This seems to be more of an issue for regions with a weaker quality of governance (Di Cataldo et al., 2021).

As shown in Table 2, a relatively small body of literature is concerned with how S3 influences regional funding decisions. D'Adda et al. (2021) investigate to what extent S3 changed the allocation of structural funds in Italy by comparing S3's first programming period of 2014-2020 with the preceding one. They find that the changes are modest, and the extent of change varies among regions. The other studies focus on the alignment between S3 priorities and a region's funding decisions by analyzing regional project selection procedures using data from calls for proposals. In a similar vein as D'Adda et al. (2021), both Giannelle et al. (2020a) and Fratesi et al. (2021) conclude that S3 did not engender much change from former more horizontal industry intervention policies. They argue that this is caused by the lack of selectivity in S3 priorities, as well as the fact that most calls for proposals address all S3 priorities of a region collectively. Kramer et al. (2021) add that this is more prevalent in less developed regions.

*Table 2. Overview of studies evaluating S3 funding in alphabetic order.*

| **Study** | **Focus / aim** | **Geographical scope** | **Data** |
|---|---|---|---|
| Crescenzi et al. (2020) | What is the effect of a S3 forerunner programme on firm performance? | Italian regions | Firm level project data from a S3 forerunner programme |
| D'Adda et al. (2021) | To what extent is the allocation of structural funds changed because of S3? | 15 Italian regions | ESF project data, ERDF projects are excluded. |
| Fratesi et al. (2021) | Are calls for proposals aligned with priorities? Do they favor collaborative projects? Do they stimulate entry into new activities? Do they support stakeholder communities? | 6 EU countries and 17 EU regions | Calls for proposals and RIS3 documents |
| Gianelle et al. (2020a) | How are priorities defined? Are calls for proposals aligned with priorities? How specific are calls for proposals? | 21 Italian and 16 Polish regions | Calls for proposals and RIS3 documents |
| Kramer et al. (2021) | Are calls for proposals aligned with priorities? Are funded projects aligned with priorities? | 185 European regions | Calls for proposals, ERDF project data |

Additionally, Kramer et al. (2021) study the alignment of S3 priorities and funding decisions by examining the actual projects that are funded by the ERDF using a dataset provided by JRC (see Bachtrögler-Unger et al. 2020). They clearly show that the use of funded projects gives a more accurate picture of how well funding is aligned with S3 priorities. Where they find that 84% of the calls for proposals correspond to S3 priorities, only 54% of the funded projects are aligned. This paper adopts a similar approach by leveraging a more up to date ERDF project dataset that encompasses nearly all projects from the 2014–2020 programming period. By applying a technological taxonomy tailored to S3 priority data, we aim to offer a more accurate assessment of the alignment between S3 priorities and the projects that received funding.

The studies presented above provide a detailed picture of S3's first programming period. We will move along the same lines, aiming to fill the following gaps. 1) An EU-wide analysis of the consistency of regional S3 priorities with each region's technological capabilities, using a taxonomy that accurately fits S3 priority data. 2) An analysis of how regional S3 priorities are translated into the allocation of ERDF funding to R&I projects.

## Data and methods

To analyze regional technological capabilities, S3 priorities and ERDF funding allocation we combine three datasets: 1) the Eye@RIS3 dataset (European Commission, 2018) which lists all regional S3 priorities; 2) the OECD REGPAT database (OECD, August 2023) to measure regional technological capabilities; and 3) the European Commission's Kohesio database[3] enriched by Bachtrögler-Unger et al. (2021) which provide funding information about nearly all projects funded by the ERDF.

To enable a coherent analysis across these three datasets, we first integrate them by developing a taxonomy of technologies with which we can categorize each dataset into the same technological domains. This taxonomy, comprising 33 technological domains, is based on a thorough analysis of all regional S3 priorities in the Eye@RIS3 dataset. By doing so, we make sure that both our patent and funding data aptly fits the S3 priority dataset, and therewith, overcome the problem emphasized by D'Adda et al. (2019) of having non-standardized S3 priorities. While most of the technological domains are relatively specific, some priorities encompass broad categories, such as "ICT" or "sustainable energy." Therefore, the taxonomy both includes specific as broad domains (see Figure 10 in the Appendix).

The following three subsections will provide a detailed discussion of each dataset and explain how they are operationalized into the variables needed for the empirical analysis.

[3] https://kohesio.ec.europa.eu/en/

### *S3 priorities (Eye@RIS3 dataset)*

Eye@RIS3 is an online database, available at the European Commission's S3 Platform[4], containing all the S3 priorities defined by national and regional authorities in RIS3 documents. The strategies differ in territorial level, but most are on a NUTS2 level[5]. Each priority comprises the following pieces of information: the region or Member State, a free text description of the priority, the associated economic domains (based on the 2-digit NACE sectors), the associated scientific domains (based on NABS2007 categories), and the associated policy objectives (based on societal grand challenges identified in Horizon2020 and the headline policies in the Innovation Union Flagship Initiative).

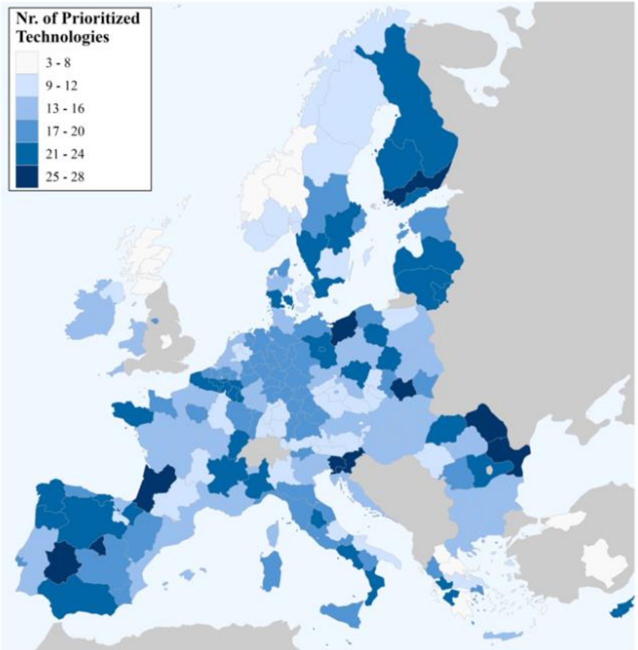


*Figure 2. The total number of prioritized technological domains per NUTS region.*

Priorities were matched to technological domains through a combination of automatic text mining, manual content analysis of free-text descriptions, and an examination of selected economic and scientific domains as well as policy objectives. On average, regions identify 5.8

[4] https://s3platform.jrc.ec.europa.eu/map

[5] Most S3 strategies were developed at the NUTS2 level, though some were at NUTS1, NUTS3, or national levels. For consistency, all strategies were standardized to NUTS2 by duplicating NUTS1 strategies across subordinate NUTS2 regions and aggregating NUTS3 strategies to their corresponding NUTS2 regions. National strategies were excluded (e.g., Austria, Germany, Greece, Denmark, Spain, Poland, Portugal, Romania, and Sweden) except for cases like Luxembourg and Latvia, where national and NUTS2 levels coincide.

priorities, with 93.7% of these successfully covered by the technological taxonomy. As previously discussed, regions often define very broad priorities, with each individual priority associated with an average of 4.6 technological domains. Consequently, the total number of prioritized technological domains per NUTS2 region averages 15.8.

However, as illustrated in Figure 2, there is significant variability across regions. For example, South Finland (FI1C) prioritized 28 out of 33 technologies, while Extremadura (ES43), Aquitaine (FRI1), Northeast Romania (RO21), and Eastern and Western Slovenia (SI03 and SI04) each prioritized 26 technologies. In contrast, Trøndelag (NO06) prioritized only 3 technologies. Several studies have highlighted that the lack of selectivity in S3 strategies may undermine their effectiveness (Gianelle et al., 2020a; Di Cataldo et al., 2021; Marrocu et al., 2023).

To explore whether selecting many priority areas has a rationale, we plotted the total number of prioritized technologies against several regional characteristics (see Figure 11 in the Appendix). The analysis reveals a weak correlation between the total number of priorities and population size (panel a), and an even weaker correlation with the number of incumbent technological specializations (panel b). These findings are consistent with Deegan et al. (2021), who conducted a similar analysis for the prioritization of economic domains. Furthermore, while Di Cataldo et al. (2021) suggest that a lack of selectivity in S3 strategies is more pronounced in regions with lower government quality, our findings do not support this relationship (panel c). Additionally, there seems to be no relation between each region's GDP per capita and the number of prioritized domains (panel d).

### *Regional technological capabilities (REGPAT dataset)*

The OECD's REGPAT database is used to measure each region's technological capabilities. This dataset contains all patent applications to the European Patent Office between 1977 and 2020. The patent applications are regionalized at the NUTS2 level using the address of their inventor(s) and categorized according to this study's technological taxonomy (Figure 2) using their Cooperative Patent Classification (CPC) codes.

To measure each region's technological capabilities, we take all patents filed within a 5-year window preceding the start of the S3 programming period, i.e. 2009-2013 (Boschma et al., 2015; Balland et al., 2019). With these patents, we compute a region's Relative Technological Advantage (RTA) in each technological domain and the degree of relatedness of each domain to a region's technological profile, also known as the relatedness density

(Boschma et al., 2015). Based on Hidalgo et al. (2007), region $r$ has an RTA in technology $i$ at time $t$ if the share of patents in technology $i$ in region $r$ is greater than the share of patents in technology $i$ in the entire sample. More formally, $RTA = 1$ if

$$RTA = \frac{patents_{i,r,t} / \sum_i patents_{i,r,t}}{\sum_r patents_{i,r,t} / \sum_r \sum_i patents_{i,r,t}} > 1 \tag{1}$$

Then, following Hidalgo et al. (2007) and Boschma et al. (2015), the density around technology $i$ in region $r$ at time $t$ can be computed using the relatedness $\phi_{ij}$ of technology $i$ to the technologies $j$ in which region $r$ has an RTA at time $t$, divided by the sum of technological relatedness of technology $i$ to all the other technologies in the entire sample:

$$Relatedness\ Density_{i,r,t} = \frac{\sum_{\epsilon r, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} \times 100 \tag{2}$$

Next, an index of technological complexity is constructed for each technological domain, by following the work of Hidalgo & Hausmann (2009) on economic complexity. We start with a $n \times k$ two-mode binary adjacency matrix ($M$) with $n = 254$ regions and $k = 33$ technological domains, where $M$ has a value of 1 if a region exhibits an RTA in a certain technology. From this matrix, we compute two metrics: diversity ($D_r$), which measures the number of technologies in which a region has an RTA, and ubiquity ($U_i$), which indicates how common a given technological specialization is across regions:

$$D_r = \sum_i M_{ri} \tag{3}$$

$$U_i = \sum_r M_{ri} \tag{4}$$

Based on $D_r$ and $U_i$, we construct a regional complexity index (RCI), revealing the complexity of a region's technological capabilities, and a technological complexity index (TCI), showing the knowledge complexity of a technology. The RCI is the average complexity of all technologies where a region has an RTA. And, vice versa, the TCI of a technology is the average complexity of the regions (i.e., their RCI) specialized in that technology. Hence, this results in the following iterative arguments:

$$RCI_r = \frac{1}{D_r} \sum_i M_{ri} TCI_i \tag{5}$$

$$TCI_i = \frac{1}{U_i} \sum_r M_{ri} RCI_r \tag{6}$$

Then, by substituting equation (5) into equation (6), we derive an eigenvalue equation. The solution to this equation yields the technological complexity index (TCI) for each technology:

$$TCI_i = \sum_r \frac{M_{ri}}{U_i D_r} \sum_i M_{ri} TCI_i \tag{7}$$

This approach allows us to quantify the complexity of a given technology based on the diversity of regions specializing in it and the ubiquity of those specializations. The resulting eigenvector corresponds to the complexity of each technological domain, providing a measure of how advanced or knowledge-intensive a specific technology is. Table 5 in the Appendix shows the TCI for each technology.

### *S3 and R&I funding (ERDF dataset)*

S3 priorities form the guiding foundation for the allocation of the European Regional Development Fund (ERDF) under the thematic objective 1 (TO1) 'Strengthening research, technological development and innovation'. For this study, the regularly updated Kohesio database[6] was used enriched following Bachtrögler-Unger et al. (2021)[7]. The dataset contains 778,391 projects from the 27 EU Member States over the programming period of 2014-2020.

For each project in this dataset, the following pieces of information are relevant: the NUTS2 region in which the project was carried out, a dummy variable indicating whether the project is R&I-related based on the reported field of intervention (for more information, see Bachtrögler-Unger et al. (2021)), the ERDF co-funding amount, and a free text description of the project. The latter is used to categorize projects into technological domains that correspond with S3 priorities.

Before the projects are categorized, the dataset is restricted in two ways. First, all non-R&I-related projects were removed, excluding 68.6% of the total projects. Second, some

[6] The version published on 26th of July 2023, see https://kohesio.ec.europa.eu/en/.

[7] The enrichment and cleaning process involved the following steps: 1) supplementing missing project descriptions, 2) adding missing information on the type of fund and NUTS2 region codes using details from the operational programme, 3) supplementing data on Swedish projects based on the original list of operations, and 4) checking for duplicates.

projects shared the same, often generic, descriptions that did not target a technology in specific. To reduce the risk of miscategorization, these projects were also excluded. This is done by identifying the most frequently occurring project descriptions and manually removing those that did not target a specific technology. The resulting dataset comprised 181,031 projects (74% of all R&I projects). Figure 12 in the Appendix illustrates the percentage of R&I projects associated with each technology.

To categorize these projects into technological domains, we followed a systematic text mining process. For each technological domain, we manually compiled a list of keywords from various glossary websites[8], ensuring that overly broad terms were avoided. These keywords were then used to search through the ERDF project descriptions. The results were reviewed, and the keyword list was refined iteratively until satisfactory outcomes were achieved. Through this process, 92,278 projects (38% of all R&I projects) were matched to one or more technological domains. On average, the categorized projects were associated with 2.7 domains. It is difficult to state anything decisive about the R&I projects that went through the text mining process but were not matched to any technological domain (32% of all R&I projects), as this could be due to inadequacies in either the project description or the text mining process.

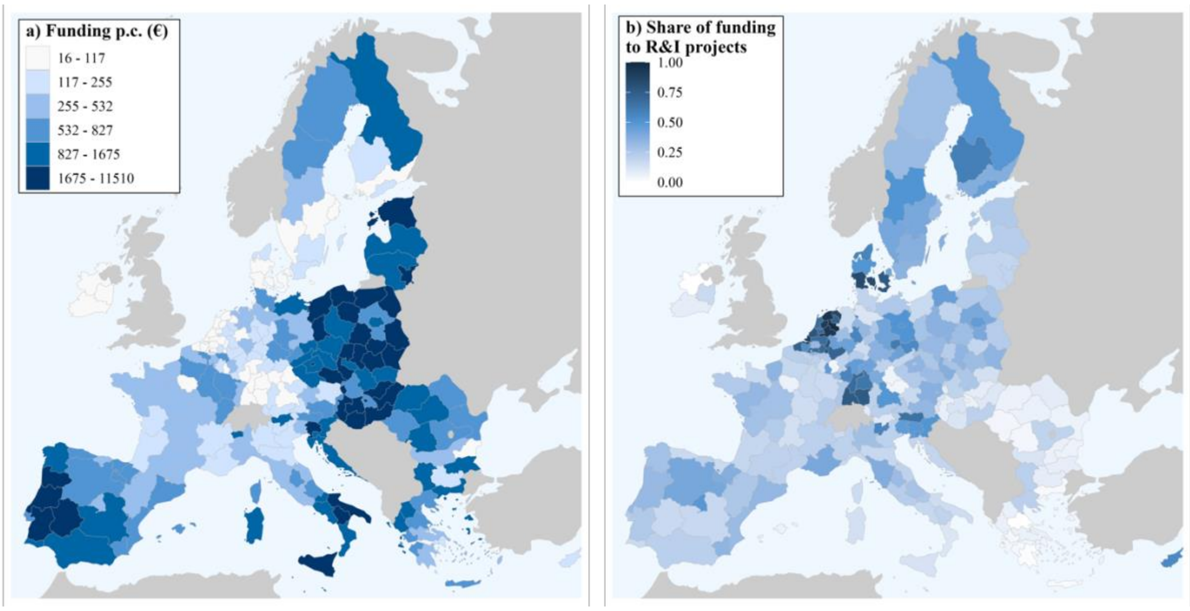


*Figure 3. The total amount of ERDF funding per NUTS2 between 2014-2020 (a) and the share of ERDF funding dedicated to R&I projects (b).*

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[8] For example, https://en.wikipedia.org/wiki/Glossary_of_artificial_intelligence and https://www.expert.ai/glossary-of-ai-terms/ were, among others, used to gather keywords associated with Artificial Intelligence.

As depicted in Figure 3a, the total amount of ERDF funding between 2014-2020 varies significantly among regions. In general, less developed and transition regions receive more funding, while more developed regions tend to dedicate a larger share of their funding to R&I projects (see Figure 3b). This may be due to the greater prevalence of R&I activities in more developed regions, making it easier to identify and support R&I-related projects.

In order to determine whether a region dedicates a considerable amount of funding to a specific technological domain, we build a variable that, in a similar fashion as RTA, measures a region's Relative Funding Advantage (RFA). In other words, region $r$ has an RFA in technology $i$ if the share of ERDF funding to technology $i$ in region $r$ is greater than the share of ERDF funding to technology $i$ in the entire sample. Therefore, $RFA = 1$ if

$$RFA = \frac{funding_{i,r} / \sum_i funding_{i,r}}{\sum_r funding_{i,r} / \sum_r \sum_i funding_{i,r}} > 1 \qquad (8)$$

### *Empirical strategy*

The key objective of this paper is twofold: 1) to examine the extent to which S3 priorities align with regional technological capabilities; and 2) to assess the degree to which ERDF funding allocation corresponds to these S3 priorities. To empirically test these two objectives, we use the smart specialization framework by Balland et al. (2019), as depicted in Figure 1. Specifically, we analyze whether regions consider two critical factors in their S3 priority selection and funding allocation: the relatedness of a technological domain to their existing technological profile, and the complexity of each technology.

To evaluate the alignment of S3 priorities with regional technological capabilities, we use a linear probability model (LPM) to estimate the probability of a technology being prioritized. In this specification the unit of analysis is at the region-technology level. The econometric equation to be estimated can be written as follows:

$$Priority_{r,i,t} = \beta_1 RD_{r,i,t-1} + \beta_2 Complexity_{i,t-1} + \gamma_{r,t-1} + \varphi_r + \alpha_i + \varepsilon_{r,i,t} \qquad (9)$$

where $Priority_{r,i,t} = 1$ if technology $i$ is prioritized by region $r$ during time $t$ (i.e. the programming period 2014-2020). The main explanatory variables are $RD_{r,i,t-1}$, which indicates the degree of relatedness of technology $i$ to the technological specializations of region $r$ at time $t-1$ (i.e. 2009-2013), and $Complexity_{i,t-1}$ which measures the complexity of technology $i$ at time $t-1$. $\gamma_{r,t-1}$ is a vector of regional characteristics that serve as control variables, specifically GDP per capita, population size and density, and an index for a region's institutional quality[9]. $\varphi_r$ is a region fixed effect, $\alpha_i$ is a technology fixed effect, and $\varepsilon_{r,i,t}$ represents the error term.

Next, to assess each region's correspondence between the allocation of ERDF funding to R&I projects and their S3 priorities, we construct a linear probability model (LPM) to estimate the probability of a technology receiving a considerable amount of funding. As in the previous model, the unit of analysis is at the region-technology level. We formalize the following econometric specification:

$$ERDF_{r,i,t} = Priority_{r,i,t} + \beta_1 RD_{r,i,t-1} + \beta_2 Complexity_{i,t-1} + \gamma_{r,t-1} + \varphi_r + \alpha_i + \varepsilon_{r,i,t} \quad (10)$$

where $ERDF_{r,i,t} = 1$ if region $r$ allocates a higher share of its total funding to technology $i$ compared to the average share of funding dedicated to technology $i$ across the entire sample[10]. $Priority_{r,i,t} = 1$ if technology $i$ is prioritized by region $r$ during time $t$ (i.e. the programming period 2014-2020). $RD_{r,i,t-1}$ indicates the degree of relatedness of technology $i$ to the technological specializations of region $r$ at time $t-1$ (i.e. 2009-2013), and $Complexity_{i,t-1}$ measures the complexity of technology $i$ at time $t-1$. $\gamma_{r,t-1}$ is a vector of regional characteristics that serve as control variables, specifically GDP per capita, population size and density, and an index for a region's institutional quality. $\varphi_r$ is a region fixed effect, $\alpha_i$ is a technology fixed effect, and $\varepsilon_{r,i,t}$ represents the error term.

# Results

## *S3 priorities and technological capabilities*

In this section, we examine whether regional S3 priorities align with each region's technological profile. We do so by evaluating two aspects: the extent to which the selected priorities are related to the region's existing technological specializations (i.e., relatedness density) and the level of complexity of the chosen priorities.

[9] Institutional quality is measured using the Quality of Government index by Charron et al. (2019).

[10] As a robustness check Table 7 in the Appendix shows the same model with an alternative version of the dependent variable, namely the logarithmic transformation of the amount of funding allocated to a technology by a region + 1.

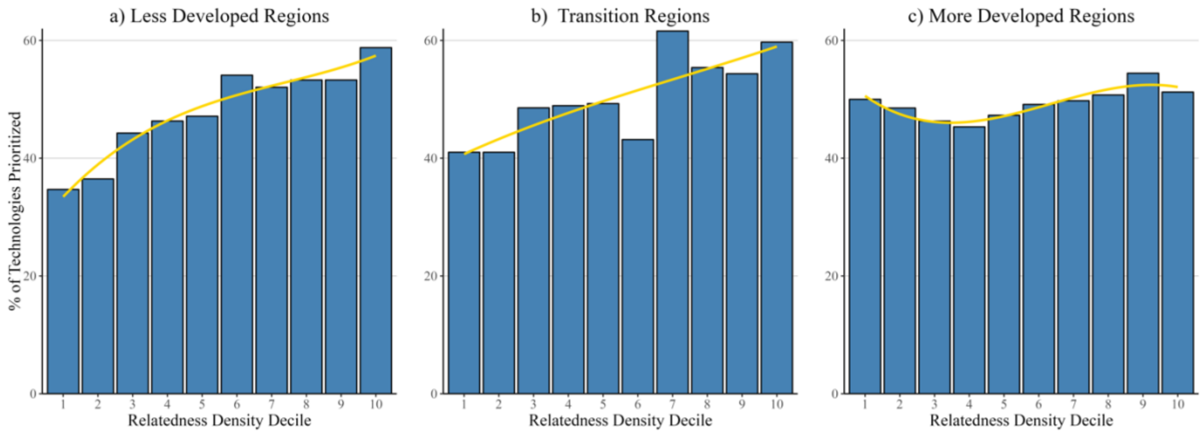


*Figure 4. The share of technologies prioritized by relatedness density decile for less developed regions (a), transition regions (b), and more developed regions (c). All region-technology observations (254 regions * 33 technologies) are divided into deciles based on their relatedness density score.*

First, in Figure 4, we visualize the relatedness of S3 priorities by dividing all region-technology observations into deciles by their degree of relatedness density score. For each decile, we display the share of technologies that are prioritized. The sample is divided into three panels representing regions at different development levels[11] to highlight differences in priority selection strategies. For example, in less developed regions (panel a), 35% of the technologies in the lowest relatedness density decile are prioritized, whereas 57% of those in the highest relatedness density decile are prioritized.

Both less developed and transition regions (panels a and b) exhibit an increasing trend, indicating that the higher the relatedness density of a technology, the more likely it is to be prioritized. In contrast, more developed regions seem to place less emphasis on relatedness when selecting S3 priorities. This may be because these regions have a broader range of capabilities and more resources available, making it easier for them to explore and develop new, unrelated technological domains. Indeed, Pinheiro et al. (2021) demonstrate that unrelated diversification is more feasible for more developed regions.

[11] We use the Cohesion Policy's classification of regions to determine eligibility for structural funds. Less developed regions are defined as those with a GDP per capita below 75% of the EU-27 average, transition regions have a GDP per capita between 75% and 90% of the EU-27 average, and more developed regions are those with a GDP per capita above 90% of the EU-27 average.

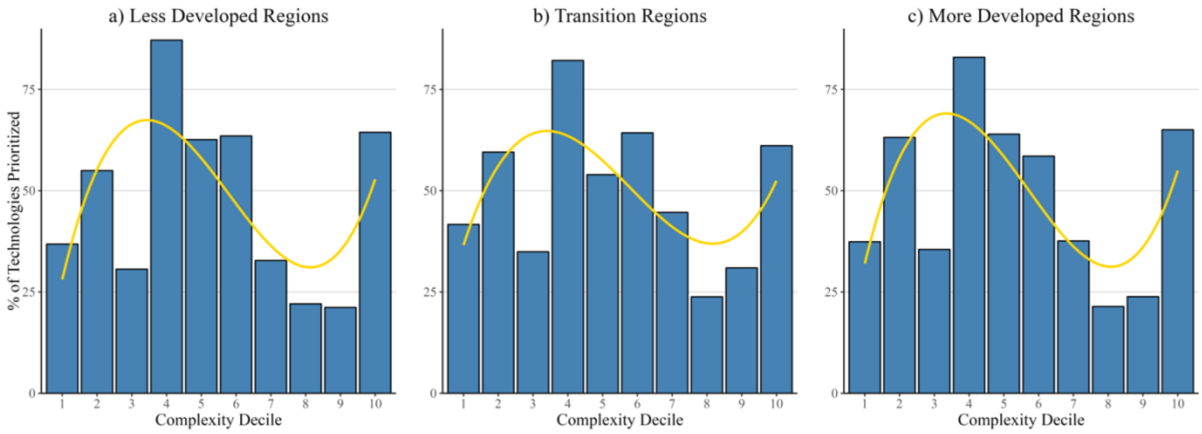


*Figure 5. The share of technologies prioritized by complexity decile for less developed regions (a), transition regions (b), and more developed regions (c). All region-technology observations (254 regions * 33 technologies) are divided into deciles based on their complexity score.*

In a similar fashion, Figure 5 illustrates how the complexity of technologies is considered during priority selection. One would expect that less developed regions target technologies of a lower complexity, whereas more developed regions prioritize more complex domains (Pinheiro et al. 2022). However, it is strikingly difficult to discern any differences in priority selection strategies regarding complexity among the three types of regions. Most regions appear to emphasize technologies in the midrange of the complexity spectrum.

To test the use of these concepts in the selection of S3 priorities more thoroughly, we estimate Equation (9). The results in Table 3 support the findings depicted in Figures 4 and 5. Notably, *Relatedness density* is both positive and significant, even under a strict specification including both region and technology fixed effects (Table 3; column 5). This indicates that regions actually consider the relatedness of technologies when selecting S3 priorities. In contrast, the interpretation of *Complexity* is a little less straightforward since its coefficient only turns positive when technology fixed effects are added (Table 3; column 5). This may imply that, in the earlier specifications, the *Complexity* coefficient is capturing other technology-specific characteristics, such as the trendiness or popularity of a technology, which may influence the likelihood of it being prioritized. For instance, regions might favor green technologies due to their popularity or usefulness, despite these technologies generally being less complex than digital technologies (Bachtrögler-Unger et al., 2023). By controlling for such characteristics through the inclusion of technology fixed effects, we observe that complexity positively affects the selection of priorities. This also clarifies why it is challenging to identify clear strategies regarding complexity among different types of regions in Figure 5.

*Table 3. Correspondence between regional S3 priorities and technological profiles.*

| | Dependent variable: Priority (= 1) | | | | |
|---|---|---|---|---|---|
| VARIABLES | (1) Baseline | (2) Controls | (3) Full Model | (4) Full Model (Region FE) | (5) Full Model (Region & Tech. FE) |
| Relatedness density | 0.03778*** | | 0.02841*** | 0.07844*** | 0.02092* |
| | (0.00001) | | (0.00163) | (0.00000) | (0.09165) |
| Complexity | -0.01581** | | -0.01274* | -0.00552 | 0.05768* |
| | (0.01056) | | (0.05183) | (0.43262) | (0.08194) |
| GDP per capita | | -0.00878 | -0.01206 | -2.09313*** | -0.73016** |
| | | (0.58149) | (0.43803) | (0.00000) | (0.01331) |
| Population density | | -0.00957 | -0.00945 | 5.40380*** | 1.95796*** |
| | | (0.41480) | (0.38247) | (0.00000) | (0.00871) |
| Population size (log) | | 0.04193*** | 0.03239*** | -3.99194*** | -1.37784** |
| | | (0.00000) | (0.00055) | (0.00000) | (0.01485) |
| Institutional quality | | 0.01269 | 0.00723 | -4.57640*** | -1.59471** |
| | | (0.27665) | (0.53388) | (0.00000) | (0.01346) |
| Constant | 0.47984*** | 0.49621*** | 0.49636*** | -2.92029*** | -1.10262** |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.01835) |
| Observations | 8,382 | 7,722 | 7,722 | 7,722 | 7,722 |
| R-squared | 0.007 | 0.008 | 0.011 | 0.084 | 0.481 |
| Region FE | NO | NO | NO | YES | YES |
| Technology FE | NO | NO | NO | NO | YES |

Notes: The dependent variable Priority = 1 if a region ($n$ = 254) prioritizes a technology ($n$ = 33), and 0 otherwise. All independent variables are standardized to have a mean of 0, and a standard deviation of 1. Coefficients are statistically significant at the *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ level. Heteroskedasticity-robust standard errors (clustered at the regional level) are in parentheses.

To illustrate the different approaches regions may take in S3 priority selection regarding relatedness and complexity, Figure 6 positions each region within Balland et al.'s (2019) smart specialization framework. For each region, we calculate the difference between the average relatedness density of its prioritized and non-prioritized technologies, and similarly for complexity. This method adjusts for differences in average relatedness and complexity across regions at different development levels.

The categorization reveals several insights. First, most regions fall on the right side of the framework, supporting the finding that regions tend to prioritize technologies aligned with their existing knowledge base. Second, as expected, the southeast quadrant ("Low risk, low benefits") is predominantly occupied by less developed and transition regions. For these regions it entails less risk to prioritize domains closely embedded in their technological structure, while they may lack the capacity to pursue more complex technologies, leading them to focus on simpler domains. A notable example is the Spanish region of Castile-La Mancha (ES42), which prioritizes domains like Solar Energy and Advanced Robotics, both closely related to their technological capabilities and less complex compared to other technologies. Third, as touched upon before, more developed regions are the ones that can take more risks and therefore can take bigger leaps in terms of unrelated diversification into more complex technologies. As such, the northwest quadrant ("High risk, high benefits") is expected to be dominated by these regions. Surprisingly, this is not consistently the case, apart from notable examples like Dresden (DED2) and Lyon (FRK2). However, the southwest quadrant ("High risk, low benefits") features a significant share of more developed regions, such as North-Brabant (NL41) and Antwerp (BE21). This suggests that while these regions are engaging in unrelated diversification, they are not necessarily doing so with the explicit aim of increasing the complexity of their knowledge stock.

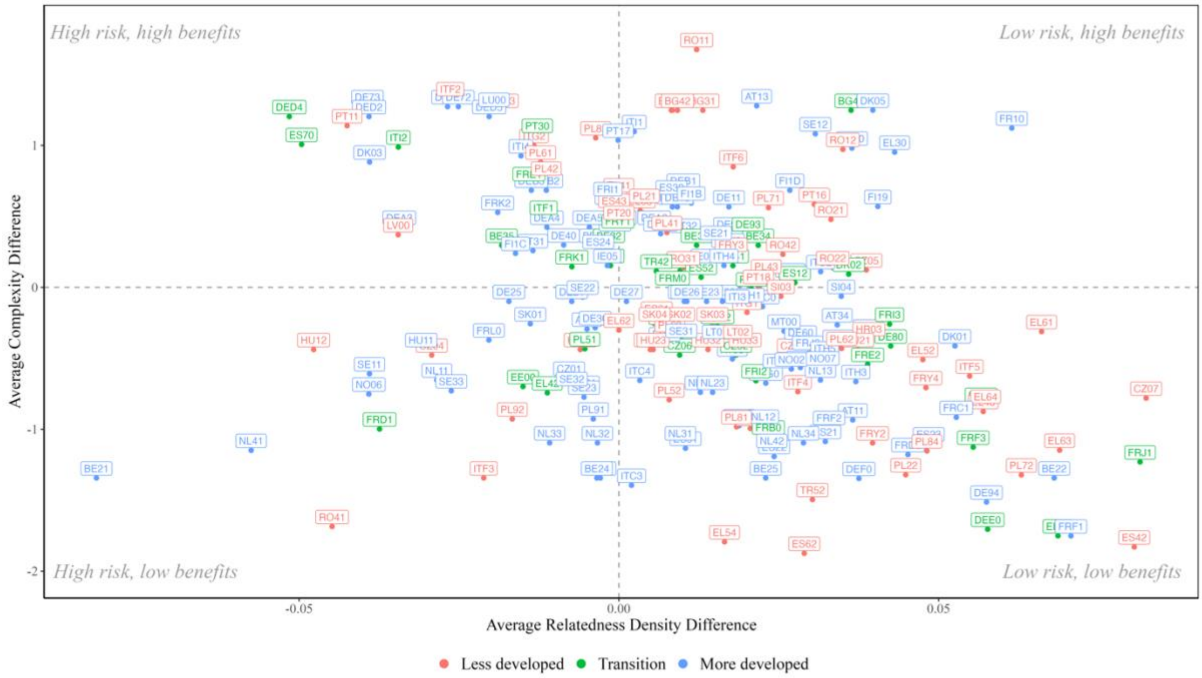


*Figure 6. A mapping of each region's approach to selecting S3 priorities based on the framework by Balland et al. (2019). The x-axis reflects the difference between the average relatedness density of a region's prioritized and non-prioritized technological domains, while the y-axis shows the same for complexity.*

## S3 Priorities & R&I funding

The next step is to analyze how regions translate their S3 priorities into the allocation of ERDF funding to regional R&I projects. Overall, 94% of all categorized R&I projects are related to a region's S3 priorities. This is a very high percentage, but it should be treated with some caution. As explained in the method section, we were only able to categorize 38% of all R&I projects.

26% of R&I projects were removed from the dataset before the text mining procedure, because the descriptions were too general and did not target any technology in specific. On 35% of R&I projects, we applied text mining, but without success. It is hard to say anything decisive about these uncategorized projects, as the cause could be either the inadequacy of the text mining process or the inadequacy of the text descriptions of these projects. The latter could imply a poor alignment with S3 priorities. Analogous to the previous section, Figure 7 visually presents the relatedness density of technologies that receive a considerable amount of ERDF funding[12]. Again, we divide all region-technology observations into deciles based on their relatedness density. However, instead of showing the share of region-technology combinations being prioritized within each decile, we now present the share that receive considerable funding.

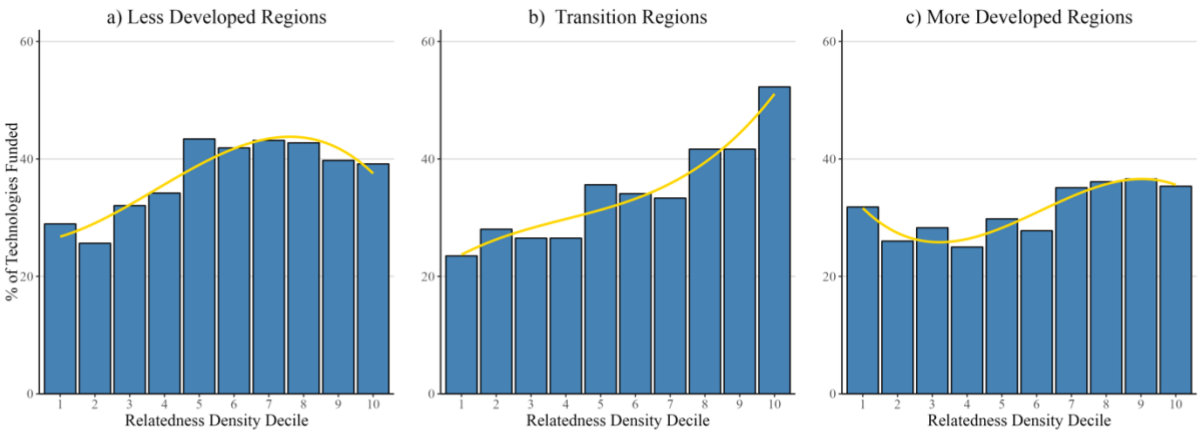


*Figure 7. The share of technologies that receive a considerable amount of ERDF funding by relatedness density decile for less developed regions (a), transition regions (b), and more developed regions (c). All region-technology observations (231 regions * 33 technologies) are divided into deciles based on their relatedness density score.*

Similar to Figure 4, Figure 7 shows that relatedness density is more important for less developed and transition regions than for more developed regions. However, a striking difference between both figures is that, while the shares of nearly all deciles in Figure 4 exceed 40%, most deciles in Figure 7 fall below that threshold. As noted previously and highlighted by others (Gianelle et al., 2020a; Di Cataldo et al., 2021; Marrocu et al., 2023), regional S3 strategies often lack selectivity. The contrast between these figures suggests that while a region may prioritize numerous technologies in its S3 strategy, the regional presence of capabilities related to those prioritized technologies is critical for finding R&I projects eligible for funding.

[12] By "considerable", we specifically mean that a region allocates a higher share of its total funding to a particular technology compared to the average share of funding dedicated to that technology across the entire sample. See *Equation 8* in the Method section for a more formal specification.

Consequently, the average relatedness density of prioritized technologies that receive considerable funding is higher than that of the priorities which do not receive funding (though differences are small with averages of 0.36 as compared to 0.34)[13]. This indicates that the issue of unselective S3 strategies is, to some extent, inevitably mitigated in the translation from S3 priority selection to actual funding decisions.

A comparison of the complexity of prioritized versus funded technologies (see *Figures 5* and *8*) also suggests that funding decisions tend to be more closely aligned with a region's technological capabilities than a region's S3 priority selection. While Figure 5 shows little distinction in priority selection strategies regarding complexity across the three types of regions, Figure 8 reveals greater variation. Although the trends are not as pronounced as they are for relatedness density, we observe that more developed regions tend to allocate their ERDF funding toward more complex technologies, whereas transition regions focus their funding more toward the center of the complexity spectrum.

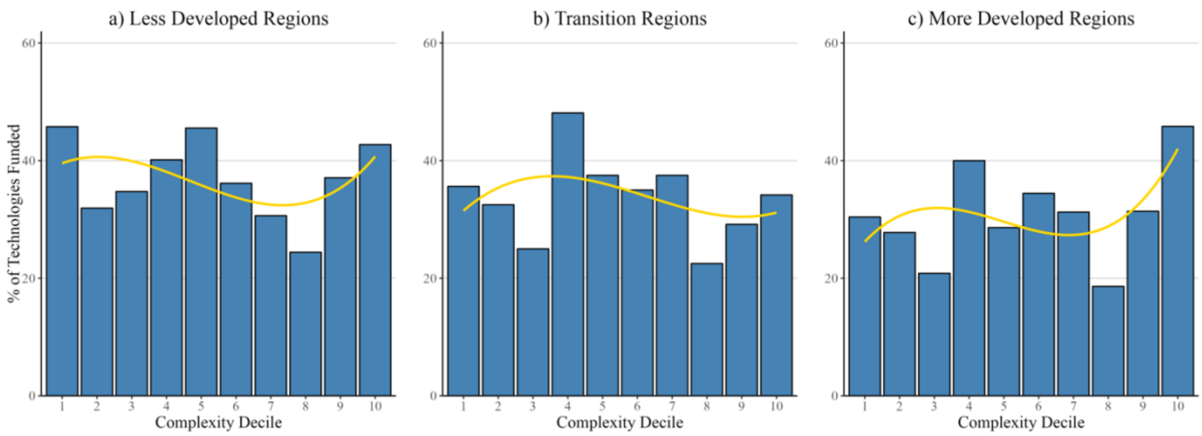


*Figure 8. The share of technologies that receive a considerable amount of ERDF funding complexity decile for less developed regions (a), transition regions (b), and more developed regions (c). All region-technology observations (231 regions * 33 technologies) are divided into deciles based on their complexity score.*

To examine regional funding decisions in more depth, we estimate Equation (10). As expected, Table 4 shows a positive and significant coefficient for *Priority*, indicating that S3 priorities do influence ERDF funding allocation. Moreover, *Relatedness density* and *Complexity* are also positive and significant. As emphasized before, it seems that funding allocation more truly reflects regional technological capabilities than S3 priorities, since both

[13] To corroborate this, Table 6 in the Appendix shows a linear probability model that estimates the probability of a prioritized technology receiving considerable ERDF funding by relatedness density and complexity.

the size and significance of *Relatedness density* and *Complexity* seem stronger in this model compared to the model in Table 3. Since all independent variables are standardized, the coefficient sizes suggest that *Relatedness Density* plays a more important role than whether a technology was prioritized. Furthermore, *Complexity* has the largest impact on the likelihood of a region allocating considerable funding to a particular technology.

*Table 4. Correspondence between a region's ERDF spending and S3 priorities.*

| | Dependent variable: ERDF Advantage (= 1) | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) Priority | (2) R.D. & Complexity | (3) Priority, R.D. & Complexity | (4) Controls | (5) Full Model | (6) Full Model (F.E.) |
| Priority | 0.05808*** | | 0.05648*** | | 0.05533*** | 0.02656*** |
| | (0.00000) | | (0.00000) | | (0.00000) | (0.00040) |
| Relatedness density | | 0.03598*** | 0.03179*** | | 0.04162*** | 0.07275*** |
| | | (0.00000) | (0.00003) | | (0.00000) | (0.00003) |
| Complexity | | 0.02088** | 0.02251*** | | 0.02398*** | 0.19933*** |
| | | (0.01230) | (0.00659) | | (0.00341) | (0.00009) |
| GDP per capita | | | | -0.01640 | -0.02039* | -3.45897*** |
| | | | | (0.18647) | (0.05192) | (0.00000) |
| Population density | | | | -0.00116 | 0.00049 | 6.51950*** |
| | | | | (0.89885) | (0.94898) | (0.00000) |
| Population size (log) | | | | 0.02534*** | 0.00711 | -6.99077*** |
| | | | | (0.00015) | (0.29057) | (0.00000) |
| Institutional quality | | | | -0.01682* | -0.02622*** | -8.10981*** |
| | | | | (0.09152) | (0.00644) | (0.00000) |
| Constant | 0.33438*** | 0.33438*** | 0.33438*** | 0.33438*** | 0.33438*** | -6.40421*** |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 7,623 | 7,623 | 7,623 | 7,623 | 7,623 | 7,623 |
| R-squared | 0.015 | 0.007 | 0.021 | 0.007 | 0.028 | 0.099 |
| Region FE | NO | NO | NO | NO | NO | YES |
| Technology FE | NO | NO | NO | NO | NO | YES |

Notes: The dependent variable ERDF Advantage = 1 if a region ($n$ = 231) allocates a higher share of its total funding to a specific technology ($n$ = 33) than the average share allocated to that technology across the entire sample, and 0 otherwise. All independent variables are standardized to have a mean of 0, and a standard deviation of 1. Coefficients are statistically significant at the *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ level. Heteroskedasticity-robust standard errors (clustered at the regional level) are in parentheses.

### *From S3 Priorities to Funding Allocation*

Lastly, to synthesize our findings, we assess how regions shift within the smart specialization framework when translating their S3 priorities into ERDF funding allocation. Similar to Figure

6, we position each region in the framework by calculating the difference in average relatedness density and complexity between the technologies that receive funding and those that do not. It is particularly interesting to compare a region's funding approach with its initial S3 prioritization approach. Therefore, in Figure 9, we illustrate this by plotting the movement of regions within the smart specialization framework as they translate their S3 priorities into funding allocation. Each dot represents a region's position based on its S3 priorities (as in Figure 6), while the arrow indicates the shift in position based on R&I funding decisions. For readability, we divided all regions into four panels based on their direction of movement.

For example, consider the region of Île-de-France (FR10). In panel c, the trajectory of Île-de-France shows a shift from the top-right quadrant of the framework to the bottom-left. This indicates that Île-de-France initially prioritized technologies that are both highly complex and strongly related to its existing technological specializations. However, when these priorities are translated into funding decisions, the region tends to allocate funding to technologies that are less related to its incumbent specializations and relatively less complex compared to the technologies it does not fund.

Although *Priority* is a strong predictor of funding allocation (as shown in Table 4), the length of the arrows in Figure 9 suggests substantial differences between each region's priority selection and funding decisions. A possible explanation is that regions tend to be broad when selecting S3 priorities, with an average of 15.8 priorities per region. However, as the analysis above suggests, regions are probably unable to allocate substantial funding across all these prioritized domains. Therefore, when comparing the average relatedness and complexity of all prioritized technologies with those of the funded technologies, a noticeable difference emerges. This discrepancy is particularly intriguing, as it shows how regions translate their strategic plans (S3 priorities) into practical actions (funding allocation).

For instance, many regions make a significant upward shift within the framework, indicating that their funding allocation focusses on more complex technologies compared to those selected in their S3 priorities. This explains why complexity is the most important predictor of where R&I funding is allocated (Table 4; Column 6). Moreover, while some less developed and transition regions move from the southeast to the northwest quadrant (panel a), indicating a leap towards more complex and unrelated technologies, many others follow the reverse path (panel d). In fact, the southeast quadrant remains largely populated by these regions, as focusing on highly related but less complex technologies is both safer and more feasible for them. Additionally, most regions avoid the "high risk, low benefits" (southwest) quadrant. More specifically, only 17% of regions adopt this seemingly less favorable strategy. This indicates that regions generally aim for approaches that balance risk and potential benefits.

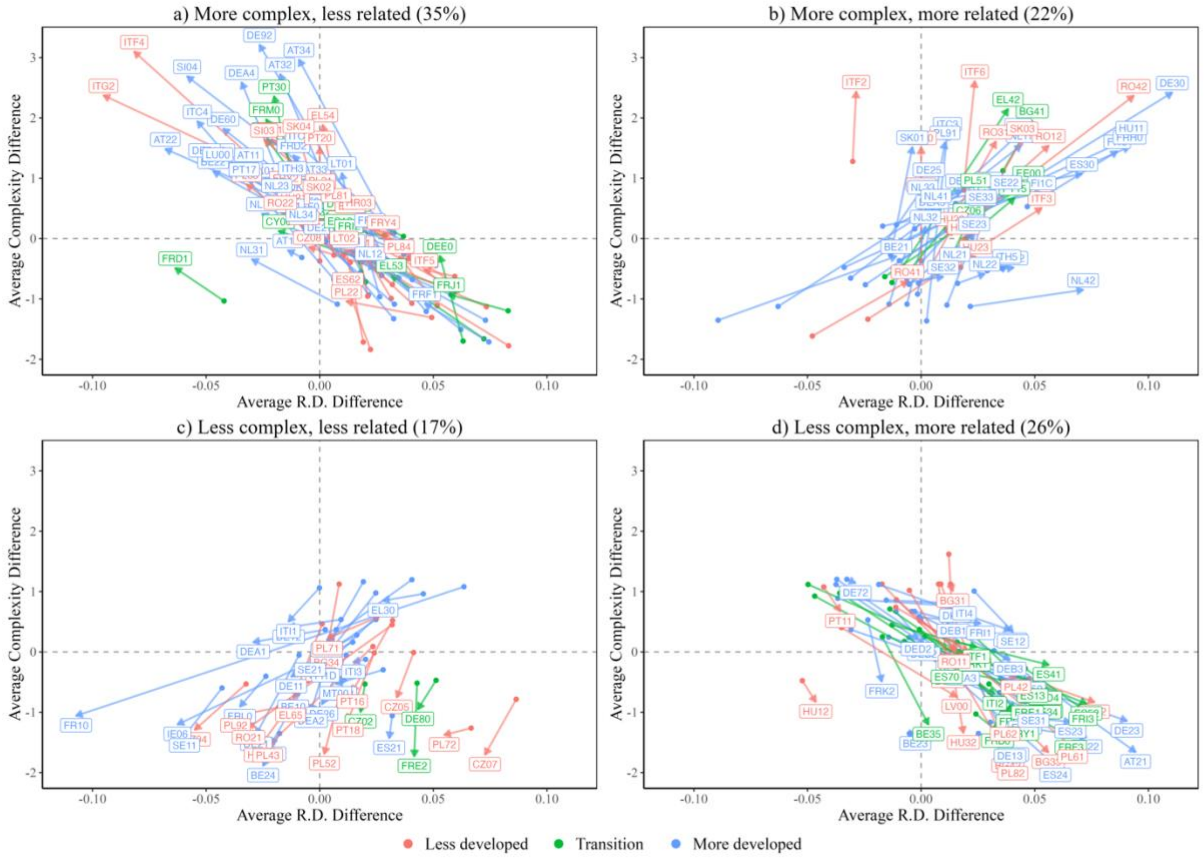


*Figure 9. An illustration of how each region's funding decisions differ from their initial S3 priority selections, by mapping their position in the smart specialization framework based on the ERDF funding allocation (arrow end) relative to their position based on S3 priorities (dot). The x-axis reflects the difference between the average relatedness density of a region's funded and non-funded technological domains, while the y-axis shows the same for complexity. Regions are divided into four panels based on their direction of movement within the framework.*

# Discussion and conclusions

This paper examined two key aspects of the first S3 programming period: the alignment between S3 priorities and regional technological capabilities, and the relationship between S3 priorities and R&I funding allocation. We found that while regional S3 strategies are not highly selective in terms of the number of prioritized technologies, regions do consider the relatedness of a technology to their existing technological profile, especially in less developed and transition regions, where technological diversification is more path dependent.

The tendency of S3 strategies to lack selectivity is well-documented (Iacobucci & Guzzini, 2016; Gianelle et al., 2020a; Di Cataldo et al., 2021; Marrocu et al., 2023). However, this study takes a step further by examining what happens after the selection of S3 priorities.

The findings reveal that this lack of selectivity is somewhat mitigated during the transition from priority selection to funding allocation. A possible explanation for this difference between S3 priorities and funding allocation is that regional authorities deliberately stay broad when defining S3 priorities in order not to limit opportunities for regional actors such as firms or research institutes. However, it is more likely that regional actors who apply for the funds have capabilities closely related to the region's technological profile. In other words, while a region may prioritize many unrelated technologies, it is more likely to fund R&I projects in areas closely related to its existing technological strengths.

A similar pattern emerges concerning the complexity of prioritized technological domains. Contrary to expectations, regions with varying levels of development show little difference in their prioritization of complex technologies. Yet, complexity becomes more pronounced in the funding stage, indicating that regions emphasize more advanced technologies when translating broad priorities into funding decisions.

To address these challenges, the adoption of user-friendly, data-driven tools could help regions identify technological domains with high development potential. Such tools would not only make the Entrepreneurial Discovery Process more evidence-based, but it would also create a unified understanding of key S3 concepts like relatedness and complexity, which are often not fully understood by regional administrators (Kroll, 2015; Capello & Kroll, 2016; Pugh, 2018). The tool proposed by Kim et al. (2024) serves as an excellent example.

Future research could provide deeper insights by qualitatively examining how regional policymakers perceive and apply S3 concepts. Like several other studies (Deegan et al., 2021; Di Cataldo et al., 2021; Marrocu et al., 2023; Kim et al., 2024), this analysis takes S3 priority data at face value. However, a deeper understanding of the process behind the development of these priorities would greatly enhance the ability to interpret them accurately. Moreover, to prevent misinterpretations of S3 priorities, studies like this one would greatly benefit from a more accurately categorized S3 priorities dataset.

It is important to bear in mind the potential bias in these findings, stemming from the inability to categorize all ERDF-funded R&I projects. Specifically, 26% of R&I projects were excluded before applying the text-mining procedure due to general and frequently occurring project descriptions that did not target any specific technology. Another 36% of R&I projects went through the text mining process, but without successful categorization. The cause of this inability to categorize is unclear, as it may stem from limitations in either the project descriptions or the text-mining methodology. Consequently, it is uncertain how including these uncategorized projects might affect the results. However, we do not have no strong reasons to believe that their inclusion would significantly alter the overall findings.

Lastly, this study does not assess the success of regional S3 strategies (Uhlbach et al., 2022); rather, we analyzed the extent to which the policy was implemented in line with the smart specialization logic (see also Rigby et al. 2022). At this stage, it may be too early to draw conclusions about its performance or efficacy, leaving it to future research to evaluate the success of S3's first programming period.

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# Appendix

| Specific Technologies | Broad Technologies |
|---|---|
| Additive Manufacturing | |
| Aeronautics & Space | |
| Advanced Robotics | Advanced Manufacturing |
| Biotechnology | |
| Nanotechnology | |
| Quantum Computing | |
| Artificial Intelligence | |
| Blockchain | |
| Cloud Computing | ICT |
| Cyber Security | |
| Internet of Things | |
| VR & AR | |
| Biofuel & Biomass | |
| Fuel Cells | |
| Hydro Energy | |
| Nuclear Power | Sustainable Energy |
| Solar Energy | |
| Thermal Energy | |
| Wind energy | |
| Advanced Materials | |
| Autonomous Mobility | |
| Civil Engineering | |
| Energy Conservation | |
| GHG Capture | |
| Health | |
| Optics & Photonics | |
| Smart Grids | |
| Sustainable Agriculture & Forestry | |
| Sustainable Transport | |
| Waste Management | |

*Figure 10. Technological taxonomy.*

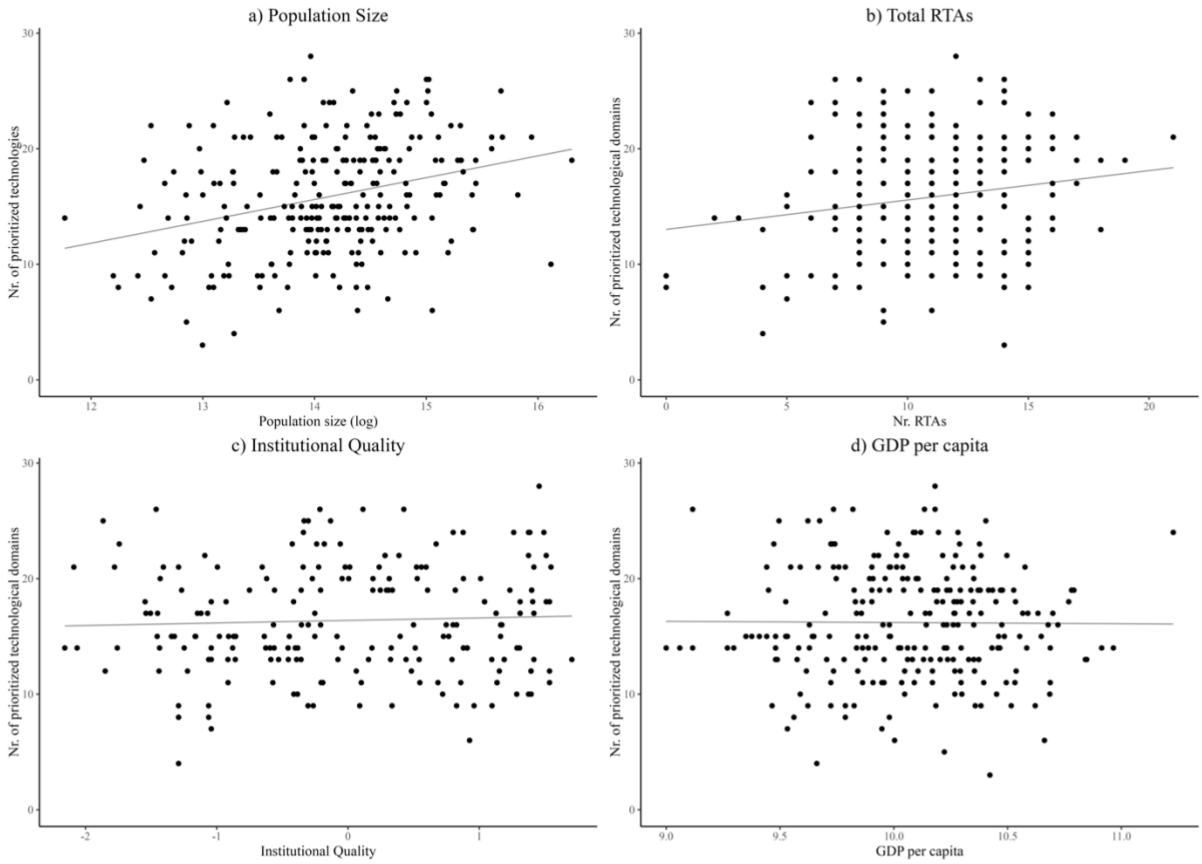


*Figure 11. The number of prioritized technological domains per NUTS2 region by population size (a), number of incumbent specializations or RTAs (b), institutional quality (c), GDP per capita (d).*

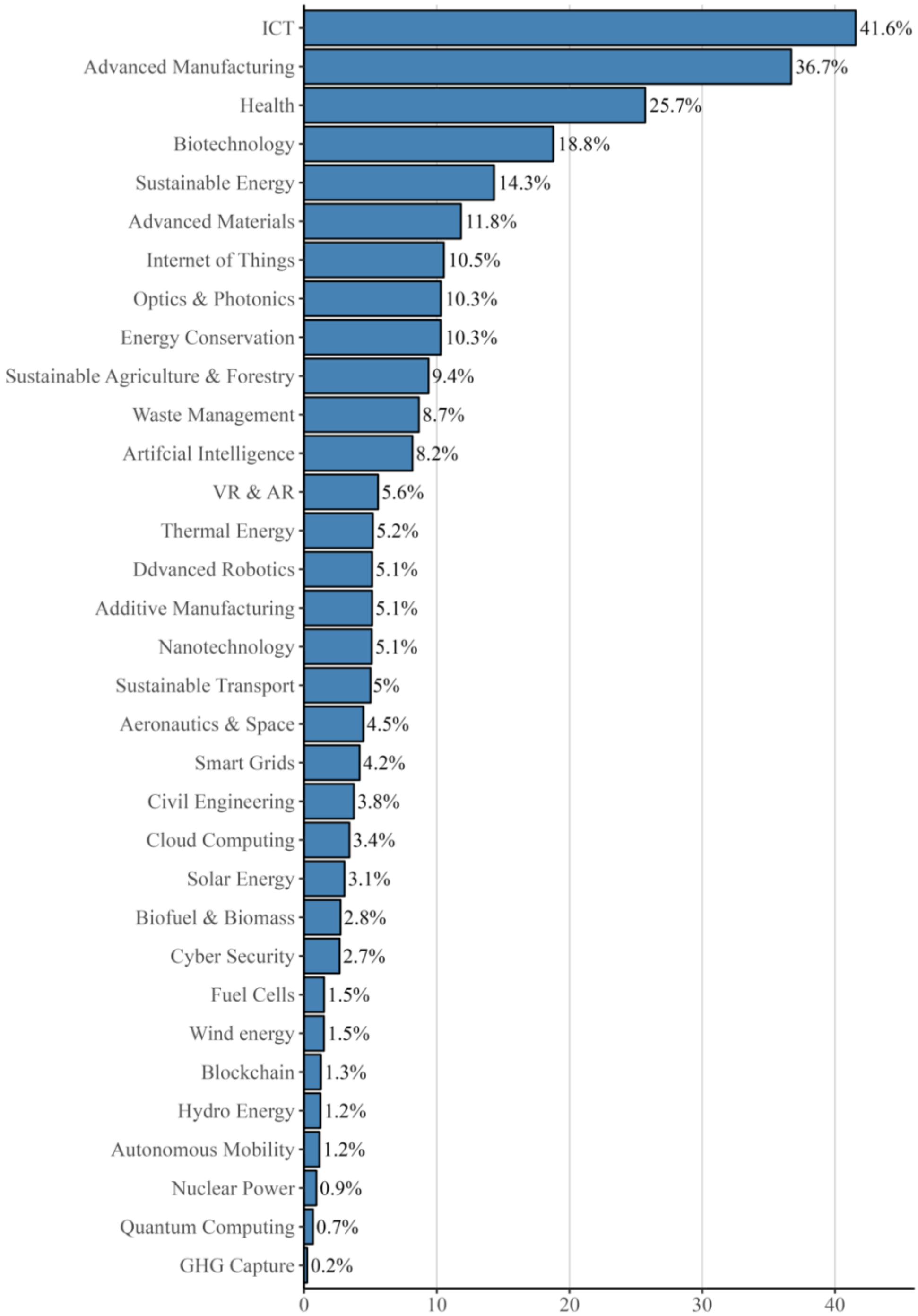


*Figure 12. Percentage of all categorized ERDF R&I projects per technological domain. Projects can be matched to more than one domain, so percentages do not add up to 100%.*

*Table 5. Technological Complexity Index. The higher the score, the more complex a technology is.*

| | ***Technology*** | ***TCI*** |
|---|---|---|
| *1* | Sustainable Energy | -1.789 |
| *2* | Thermal Energy | -1.630 |
| *3* | Solar Energy | -1.617 |
| *4* | Advanced Robotics | -1.279 |
| *5* | Fuel Cells | -1.229 |
| *6* | Wind Energy | -1.206 |
| *7* | Energy Conservation | -1.186 |
| *8* | Civil Engineering | -1.153 |
| *9* | Advanced Materials | -1.113 |
| *10* | GHG Capture | -0.949 |
| *11* | Advanced Manufacturing | -0.681 |
| *12* | Health | -0.645 |
| *13* | Waste Management | -0.610 |
| *14* | Optics Photonics | -0.522 |
| *15* | Hydro Energy | -0.516 |
| *16* | Sustainable Agriculture & Forestry | -0.510 |
| *17* | Biofuel & Biomass | -0.497 |
| *18* | Smart Grids | -0.487 |
| *19* | Sustainable Transport | -0.379 |
| *20* | Biotechnology | -0.245 |
| *21* | Nanotechnology | 0.097 |
| *22* | Aeronautics & Space | 0.166 |
| *23* | Autonomous Mobility | 0.260 |
| *24* | Additive Manufacturing | 0.304 |
| *25* | Nuclear Power | 0.418 |
| *26* | Quantum Computing | 0.521 |
| *27* | Artifcial Intelligence | 1.478 |
| *28* | VR & AR | 1.763 |
| *29* | Blockchain | 3.330 |
| *30* | Cloud Computing | 4.162 |
| *31* | Cyber Security | 4.290 |
| *32* | ICT | 4.424 |
| *33* | Internet of Things | 4.909 |

*Table 6. Which S3 priorities receive considerable funding?*

| | Dependent variable: ERDF Advantage (= 1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | R.D. | Complexity | R.D. & Complexity | Controls | Full Model | Full Model (F.E.) |
| Relatedness density | 0.03140*** | | 0.03596*** | | 0.04946*** | 0.09383*** |
| | (0.00183) | | (0.00056) | | (0.00000) | (0.00001) |
| Complexity | | 0.02090* | 0.02659** | | 0.02869*** | 0.17020 |
| | | (0.05020) | (0.01377) | | (0.00707) | (0.24584) |
| GDP per capita | | | | -0.01868 | -0.02418** | -4.97182*** |
| | | | | (0.14079) | (0.04444) | (0.00000) |
| Population density | | | | -0.01042 | -0.01076 | 12.04344*** |
| | | | | (0.20121) | (0.15001) | (0.00000) |
| Population size (log) | | | | 0.00851 | -0.00542 | -9.65276*** |
| | | | | (0.32914) | (0.52908) | (0.00000) |
| Institutional quality | | | | -0.01751* | -0.02504** | -10.88549*** |
| | | | | (0.07613) | (0.01051) | (0.00000) |
| Constant | 0.39011*** | 0.39343*** | 0.39082*** | 0.39178*** | 0.39017*** | -8.10039*** |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 3,803 | 3,803 | 3,803 | 3,803 | 3,803 | 3,803 |
| R-squared | 0.004 | 0.002 | 0.007 | 0.006 | 0.016 | 0.095 |
| Region FE | NO | NO | NO | NO | NO | YES |
| Technology FE | NO | NO | NO | NO | NO | YES |

Notes: The dependent variable ERDF Advantage = 1 if a region (n = 231) has a relative comparative advantage (RCA) in their ERDF spending on a technology (n = 33), and 0 otherwise. Only region-technology observations where Priority = 1 are included. Each independent variable has been standardized to have a mean of 0 and a standard deviation of 1. Coefficients are statistically significant at the *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ level. Heteroskedasticity-robust standard errors (clustered at the regional level) are in parentheses.

*Table 7. Correspondence between a region's ERDF spending and S3 priorities.*

| | Dependent variable: log(ERDF + 1) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | Priority | R.D. & Complexity | Priority, R.D. & Complexity | Controls | Full Model | Full Model (F.E.) |
| Priority | 1.91118*** | | 1.84854*** | | 1.71107*** | 0.20905** |
| | (0.00000) | | (0.00000) | | (0.00000) | (0.01063) |
| Relatedness density | | 1.14673*** | 1.00964*** | | 0.97255*** | 0.23923* |
| | | (0.00000) | (0.00002) | | (0.00000) | (0.05636) |
| Complexity | | 0.36244*** | 0.41569*** | | 0.40444*** | 3.49655*** |
| | | (0.00004) | (0.00000) | | (0.00000) | (0.00000) |
| GDP per capita | | | | -1.01781** | -1.10296*** | -33.35696*** |
| | | | | (0.02926) | (0.00758) | (0.00000) |
| Population density | | | | -0.17956 | -0.13262 | 93.23583*** |
| | | | | (0.60691) | (0.65125) | (0.00000) |
| Population size (log) | | | | 2.22132*** | 1.76060*** | -62.73883*** |
| | | | | (0.00000) | (0.00000) | (0.00000) |
| Institutional quality | | | | -0.71805** | -0.94796*** | -75.36592*** |
| | | | | (0.04655) | (0.00565) | (0.00000) |
| Constant | 11.83490*** | 11.83490*** | 11.83490*** | 11.83490*** | 11.83490*** | -41.59017*** |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |
| Observations | 7,623 | 7,623 | 7,623 | 7,623 | 7,623 | 7,623 |
| R-squared | 0.077 | 0.028 | 0.100 | 0.153 | 0.234 | 0.621 |
| Region FE | NO | NO | NO | NO | NO | YES |
| Technology FE | NO | NO | NO | NO | NO | YES |

Notes: The dependent variable is the natural logarithm of each region's ($n$ = 231) ERDF spending on a technology ($n$ = 33) plus 1. All independent variables are standardized to have a mean of 0, and a standard deviation of 1. Coefficients are statistically significant at the *** $p$ < 0.01, ** $p$ < 0.05, * $p$ < 0.1 level. Heteroskedasticity-robust standard errors (clustered at the regional level) are in parentheses.