# Skills for Smart Specialization: Relatedness, Complexity and Evaluation of Priorities

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**Abstract**

The present study provides a framework to empirically integrate regional workplace knowledge and skills with the smart specialization concept. It evaluates the smart specialization priorities of regions with respect to skill relatedness and skill complexity measures to analyze to what extent they build on the regional skill base. It shows that leading and lagging regions strongly differ in their strategies. Leading regions tend to prioritize domains in which they have some experience and related capabilities while lagging regions choose domains in which they do not possess experience and capabilities.

**JEL-Codes:** R11; O38; R58.
**Keywords:** skills, complexity, relatedness, smart specialization, diversification.

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# 1 Introduction

In the advent of the fourth industrial revolution, the footsteps of fundamental transformation in labor markets are already evident. More than 43% of the European Union (EU) workers experience changes in the technologies and methods used in their workplace (Cedefop, 2018). The soon-to-come higher integration to the ground-breaking technologies, including the internet of things, artificial intelligence, neurotechnologies, blockchain, and big data, will undoubtedly introduce new non-ignorable challenges to labor markets. The transformation induced by these technologies will not only affect labor markets but also industry dynamics, innovation, growth and development, thereby regional and national policies. The regional impact of these changes is expected to vary across regions, depending on regional capabilities and competencies as well as policy response and flexibility. Regions that can accurately evaluate the ongoing process are more likely to take necessary actions to retain or enhance their position.

The policy sphere seems to acknowledge the central position of workplace skills in such a transformation period. European Commission (EC) has launched 'The New Skills Agenda' in 2016 to strengthen human capital, employability and competitiveness across Europe (European Commission, 2016). In 2019, the European Training Foundation (ETF) started to develop a guide to collect data and analyze workplace skills at the national and subsectoral levels in Montenegro (ETF, 2020) and Moldova (ETF, 2021). Moreover, skills for innovation took part as a priority in the proposals for the post-2020 Cohesion Policy (Hazelkorn and Edwards, 2019). 'Skills for Smart Specialisation, Industrial Transition and Entrepreneurship' has been proposed as a new Specific Objective for regions to fulfill to be funded by the EU. Accordingly, skill development, up-skilling, and re-skilling of the workforce through Vocational Education and Training (VET) or formal education are likely to be an essential part of the near-future smart specialization (SS) policies. In this context, analyzing the regional status quo with respect to specific skills, i.e. digital, technical, or soft skills, occupations, and sectors to take necessary measures is increasingly becoming a necessity rather than a choice.

Apart from the recent advancements, a central pillar of the SS concept is a rigorous analysis of regional capabilities and competencies upon which place-based innovation policies can be built. In this regard, the SS guide (Foray et al., 2012) suggests the revealed skill relatedness (RSR) as an effective method to measure relatedness between specialization areas to identify the regional potential for innovation. However, to the best of our knowledge, no study has applied the RSR method to the SS analyses thus far. Prior research generally employed technological relatedness to analyze regional capabilities and potential (Balland et al., 2019). Hence, regional workplace knowledge and skills stay rather obscured in the empirical SS literature.

By considering the aforementioned aspects, we empirically incorporate regional workplace knowledge and skills into the SS literature. We provide a framework that can be used for both SS policy design and evaluation with the help of skill relatedness and skill complexity concepts by drawing on Balland et al. (2019) and Buyukyazici et al. (2022). We compute skill relatedness and complexity measures at the industry-region-year level by using workplace skills data on the Italian labor market. By doing so, we aim to quantify the unique and place-based combination of a variety of spatially-sticky competencies that embed useful information not only on the branching opportunities but also on the intrinsic innovative capacity of regions. We argue that regional workplace skills are good proxies of regional assets. For instance, if a region has high technological development and related physical infrastructure, i.e. broadband internet, then technical and digital skills are expected to be cultivated in that region. We then use skill relatedness and complexity measures to evaluate the coherence of the SS strategies of Italian regions with their regional knowledge and skill bases for the policy period 2014-2020. Overall, we find that regions tend to prioritize industries that are skill-related to other industries in the region, while skill complexity does not affect the priority choices of regions. However, the picture changes when we consider regional heterogeneity, which is substantial in Italy. High-income, i.e. leading, regions prone to target highly skill-related, yet less skill-complex industries. Low-income, i.e. lagging regions, tend to choose non-skill-related industries, while skill complexity does not affect their choices. We also find that leading regions prioritize industries they already have some experience and specialization, while this is not the case for lagging regions. Accordingly, leading regions define more realistic and accurate SS policies in terms of regional capabilities and strengths, yet they follow a rather conservative path by choosing less-complex industries. Lagging regions, on the other hand, are risk-takers. They target industries cognitively distant from their capabilities and current specializations. In addition, we find that regions, both leading and lagging, generally choose industries that are mostly chosen by other regions, raising the concern of whether regional SS strategies are really region-specific.

We contribute to the literature methodologically and empirically. At the methodological level, we integrate the SS concept with skill relatedness measure which has been underlined to be one of the most convenient methods for SS analyses (Foray et al., 2012; Boschma and Gianelle, 2014; D'Adda et al., 2019). Correspondingly, the present study provides the first attempt to empirically evaluate whether regions choose SS priority domains in accordance with their capabilities, i.e. knowledge and skills, which is an essential criterion of the SS concept. Moreover, our method can be used ex-ante for policy design and ex-post for policy evaluation. It may be useful to examine skills, occupations, industries, and regions in a comparative and non-aggregative way, providing an analytical tool for policymakers to define necessary up-skilling and re-skilling measures to take through formal, non-formal or VET according to sectoral, regional and local needs, thus advancing policy design. It also can be used for policy evaluation by providing a framework to observe variations in regional skill, occupation, and industry spaces conditional on policy choices.

The rest of the paper is constructed as follows. Section 2 provides brief overviews at the intersection of relatedness, complexity, workplace skills and SS. Section 3 describes the data sources and methods we employ. Section 4 conducts the econometric analyses and discusses the main findings. Section 5 concludes.

# 2 Literature

## 2.1 In Search of an Empirical Framework: Relatedness, Complexity and Smart Specialization

Smart specialization (SS) is a policy concept characterized by the identification of strategic economic, technological, and political domains for intervention, based on a thorough evaluation of regional capabilities, strengths, and potential upon which new specializations can be established to reach innovation-led growth (Foray et al., 2011). SS prioritizes place-based strategies for sustainable regional growth and development, representing a deviation from the 'one-size-fits-all' and 'picking winners' policy approaches.

The SS concept has been widely discussed since its introduction by Foray and Ark (2007). Some scholars criticized it to be highly enthusiastic and rhetorical rather than being theoretical and empirical (Marques and Morgan, 2018; Hassink and Gong, 2019). The absence of a widely accepted empirical framework to quantitatively identify, analyze, and evaluate SS policies is highlighted many times. Nevertheless, SS has quickly become a central plank of the EU's Cohesion Policy since its introduction in the 2014-2020 cycle (Barzotto et al., 2019) and preserves its place after 2020. In this regard, Foray et al. (2011) describe this defacto situation as "a perfect example of policy running ahead of theory" (Foray et al., 2011, pp. 1). However, recent years have witnessed a flourished literature on empirical SS, especially after the application of the regional diversification approach alongside relatedness and complexity methods.

In search of an empirical framework following early discussions (Iacobucci, 2014), scholars started to link SS with the concept of regional diversification (McCann and Ortega-Argilés, 2011; Boschma and Gianelle, 2014; McCann and Ortega-Argilés, 2015). Regional diversification is a dynamic process through which new activities emerge from the existing ones that are built upon specific regional capabilities. In other words, diversification is a recombination of regional sources to reach new activities. Allegedly weak empirical underpinnings of SS have been strengthened with the application of the regional diversification concept. Balland et al. (2019) made an important step forward to close the gap between theory and policy by proposing a framework to design and evaluate SS policies which is built on the concepts of relatedness (Hidalgo et al., 2007; Hidalgo et al., 2018) and economic complexity (Hidalgo and Hausmann, 2009) combined with the regional diversification approach. They use the relatedness-complexity diagram, which is introduced in the Atlas of Economic Complexity (Hausmann et al., 2014), to explore the diversification opportunities of European regions.

They argue that relatedness and complexity are key building blocks of SS so that the SS literature is actually built around these concepts without naming them. Indeed, an essential part of SS strategy is identifying high value-added (complex) activities in which regions are more likely (related) to establish a comparative advantage. This simple yet powerful observation has opened a new research agenda with the possibility of addressing the most central components of SS strategy. The non-aggregative nature of relatedness and complexity concepts has advanced SS policy recommendations to be custom-made for each location and activity, creating possibilities for diversified growth paths which were previously rather global and homogeneous, such as prioritizing high-tech sectors, i.e. AI, biotechnology, regardless of regional perspective (Hidalgo, 2022).

Apart from theoretical and empirical advancements in the SS literature, scholars underline that there is a disconnection between the ambitious rhetoric of SS and the reality of SS policies mainly due to the lack of institutional capacity (Uyarra et al., 2018) and ill-equipped public sector (Morgan, 2017; Marrocu et al., 2022) to identify the most promising fields to be invested in. Evaluation of the design, impact, and effectiveness of SS strategies unveil that they are defined based on anecdotal evidence rather than theoretically grounded methodologies such as relatedness (Iacobucci and Guzzini, 2016) and are loosely connected to the unique and place-based conditions of regions, mostly mimicking other regions' strategies (Di Cataldo et al., 2021). Moreover, many European regions seem to be incapable of defining specific priorities and policy objectives (Gianelle et al., 2020), probably due to the lack of widely accepted methods and analytical tools to truly analyze the conditions, potentials, and strengths of regions. Furthermore, the SS framework suggesting that regions should prioritize both related and complex domains does not seem to be applied by regional authorities (Deegan et al., 2021). All in all, the empirical evidence demonstrates that the underlying logic of relatedness and complexity for SS does not appear to be embraced by policymakers.

## 2.2 Skill Relatedness, Skill Complexity, and Smart Specialization

The literature theoretically agrees on the ability of relatedness and complexity measures to grasp the underlying logic of the SS concept while little discussion has been devoted to the different types of relatedness and complexity measures. A particular focus is directed towards technological sources as core capabilities of regions, generally addressed by patents and technological relatedness (Santoalha, 2019a, 2019b; D'Adda et al., 2020; Balland and Boschma, 2021; Rigby et al., 2022; Kogler et al., 2022). Nevertheless, the SS strategy of a region is not solely based on technologies, thus, it should be designed by accounting for a variety of regional assets that range from tangible assets, i.e. physical capital, labor force, to intangible assets, i.e. norms, institutions, knowledge and skills. Hence, the diversified nature of regional capabilities should be captured with different measures not to have a potential failure at the first and most important step of SS design: identification of regional assets. In this regard, the SS guide (Foray et al., 2012) suggests the RSR as the most effective method to identify the regional potential for innovation.

The RSR method (Neffke and Henning, 2013) uses labor flows to capture skill similarity among industries at the national level. The aggregative nature of the method, conflicting with the SS concept, and the absence of detailed labor flow data for many countries have prevented scholars to integrate skill relatedness with the SS literature. Recently, Buyukyazici et al. (2022) provided a measure of skill relatedness at the industry-region-year level based on workplace skills data. In their method, the exact skills that make two industries related can be observed and analyzed, paving the way to identify the skill-development needs of occupations, industries or regions. Moreover, skill relatedness can be defined between skills, occupations, industries, and regions, enabling a thorough and multi-dimensional analysis with the same data. Accordingly, this method is particularly suitable for the SS concept for both policy design and evaluation. By using skill relatedness as an analytical tool, local authorities can foster human capital formation according to the needs of the regional industry mix rather than pursuing one-size-fits-all skill-formation policies.

When skill relatedness is defined between skills, higher skill relatedness indicates higher similarity to the skills missing in the region or the industry and occupation, depending on the input data. This is to say that the region can easily and less costly acquire the necessary skills for new specializations, implying that the region has enough flexibility to effectively adapt to changes in industry and job space with less possibility to experience skill shortages. Moreover, it introduces easier up-skilling of the workforce, especially advantageable for micro, small, and medium enterprises (MSME), the main source of job creation who have limited sources for vocational training.

When skill relatedness is defined between industries, higher skill relatedness indicates higher similarity between the skill sets of an industry and others in the region. This is to say that these industries use similar and/or complementary knowledge and skills to conduct their activities. Hence, investing in a skill-related industry will more likely create an easier specialization, higher knowledge spillovers, greater cross-fertilizing among industries and thereby a more sustainable regional growth and development. Consequently, during the first step of SS implementation, i.e. identifying regional potential and priority areas via the entrepreneurial discovery process[1] and at the last step, i.e. monitoring and evaluation, skill relatedness would make a useful tool for policymakers and researchers.

The second building block of the SS framework is the economic complexity approach. In the SS literature, similar to relatedness, complexity has generally been measured with patents at the regional level (Balland et al., 2019), named knowledge complexity. By the same token we discussed for relatedness above, other regional assets should also be considered for SS strategy. Skill complexity is a relevant indicator since it quantifies the sophisticatedness

[1]Entrepreneurial discovery process includes various actors —such as local authorities, public sector, universities, research institutes, firms, and the like— collaborating each other to identify and explore the potential domains of innovation and R&D in which the region is most likely to establish a comparative advantage conditional on its existing capabilities (Morgan, 2017).

level of an industry and/or region's knowledge and skills, providing an industry-region level measure, unlike other complexity measures. Industries with higher skill complexity are likely to produce higher value-added goods and services, therefore, investing in them is more rewarding. In addition, establishing a comparative advantage in a skill-complex industry is naturally more difficult, limiting the competition with neighboring and other regions.

# 3 Data and Methods

We use several data sources for the present study. The data on SS priorities come from the database *Eye@RIS3: Innovation Priorities in Europe* provided by the Smart Specialization Platform of EC[2]. In the database, SS strategy documents of all countries for the policy period 2014-2020 are coded under three priority domains: economic, scientific, and policy. We consider the economic domain which is based on NACE two-digit sectors in both manufacturing and services, summing up to 80 sectors. Economic domain priority indicates whether a region has selected a particular industry as a target in its SS strategy document. The present study covers Italy which has 491 economic domain priorities in total at the NUTS 2 territorial level. Accordingly, our analysis encompasses 20[3] Italian regions for the period 2014-2017[4].

We do not exactly know how regional SS priorities have been chosen and what kinds of factors are considered by local authorities when designing regional strategies (McCann and Ortega-Argilés, 2015). Each region has a different number of priorities in accordance with its SS strategy, yet they do not seem to follow a clear pattern. As Table 1 indicates, Calabria, Campania, Veneto, and Emilia Romagna have the highest number of priorities, while Lombardia, Molise, Umbria, and Basilicata have the lowest. Figure 1(a) displays an almost neutral relationship between the number of SS priorities and GDP per capita based on purchasing power parity (PPP). Figure 1(b) exhibits a slightly positive relationship between the number of priorities and population density. Consequently, there is not any clear evidence whether the number of chosen priorities reflects regional characteristics.

The data on workplace skills, *the Italian Sample Survey on Professions* (ICP), is obtained from the National Institute for Public Policies Analysis (INAPP). ICP data set is the Italian version of O*net survey and includes detailed information on the characteristics of all professions existing in the Italian labor market[5]. We use 161 skill variables from the ICP survey that is unfolded in Table A1. Each skill has two dimensions in the survey: importance and complexity[6]. We multiply the scores of these dimensions to create a skill

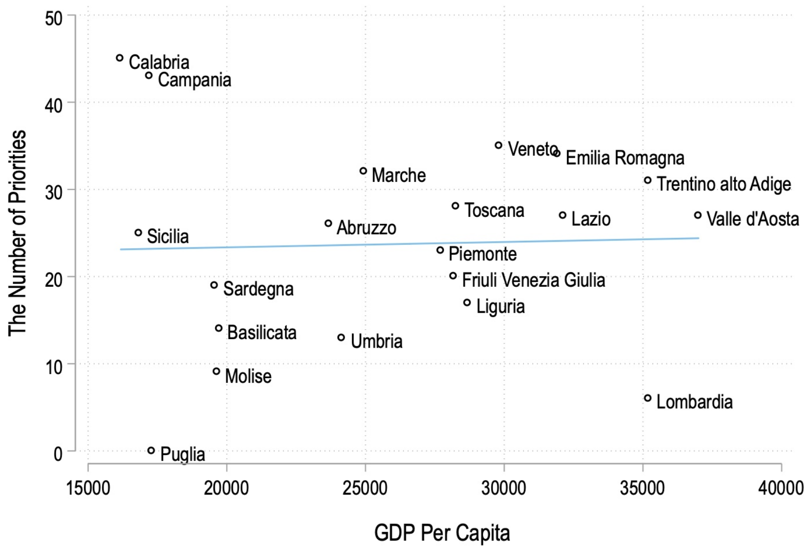
[2]https://s3platform.jrc.ec.europa.eu/map/-/eye3/y/2014-2020

[3]The database does not contain information on Puglia.

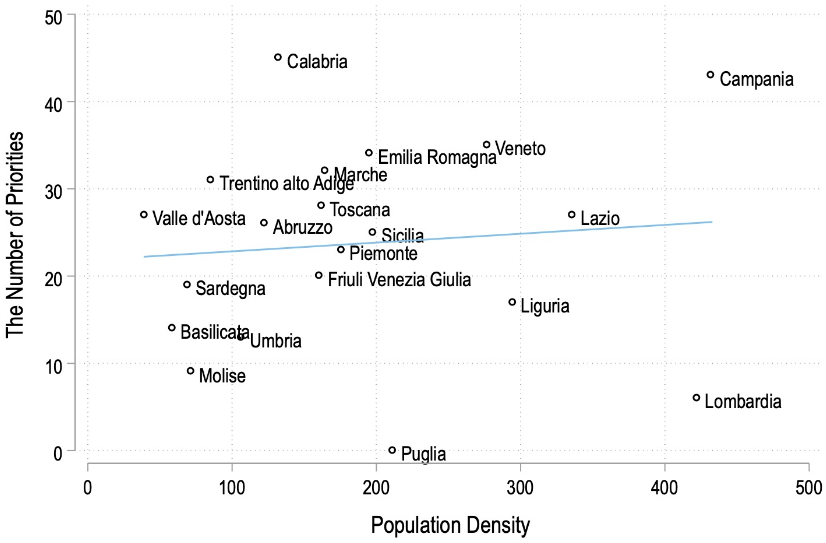
[4]SS strategies of Italian regions target these years.

[5]ICP data does not include information on agriculture, thus, we have to exclude agricultural SS priorities from the analysis, leaving us with 474 priorities in total.

[6]Importance question: *How important is competence in carrying out your current profession?* Level question: *Among those indicated below, at what level is this competence necessary for the development of*




(a)




(b)

**Figure 1. The Number of SS Priorities with Respect to Regional Characteristics GDP per capita and Population Density**

intensity variable for each skill.

The source of occupational and industrial data is *the Italian Labor Force Survey* (ILFS) provided by the National Institute of Statistics of Italy (ISTAT). We cross ICP and ILFS to obtain the distribution of skill intensity scores for industries to be able to construct the independent variables[7]. To this end, we create industry-skill matrices for each region in

*your current profession?* Importance questions are rated on a scale from 1 (not important) to 5 (extremely important), while complexity level questions are rated on a scale from 1 (least complex) to 7 (most complex). Then they are rescaled to be between 0 and 100.

[7]The detailed information on ICP data and how we merge the two data sets can be found in Buyukyazici et al. (2022).

each year whose each cell is the skill intensity score of skill $s$ for industry $i$. Accordingly, we end up with 20 input matrices (80x161) for each year. We then use these input matrices to construct skill relatedness and complexity variables as defined below.

## 3.1 Skill Relatedness

We estimate skill relatedness based on the framework proposed by Hidalgo et al. (2007) and Buyukyazici et al. (2022). We first define the effective use of skills with the relative skill advantage (RSA), a measure based on the Balassa index. RSA is the share of the relative importance of skill $s$ to industry $i$ (the numerator in equation 1) to the relative importance of skill $s$ to all industries $I$ (the denominator).

$$RSA(i,s) = \frac{icp(i,s) \setminus \sum_{s' \epsilon S} icp(i,s^{'})}{\sum_{i' \epsilon I} icp(i^{'},s) \setminus \sum_{i' \epsilon I, s' \epsilon S} icp(i^{'},s^{'})} \tag{1}$$

where $icp(i,s)$ is the skill intensity score of skill $s$ for industry $i$. An industry effectively uses a skill if $RSA > 1$, denoted as $e(i,s) = 1$. We compute skill relatedness between a pair of skills based on the minimum conditional probability of their effective use co-occurrences in industry classes as formulated in equation 2.

$$R(s,s^{'}) = \frac{\sum_{i \epsilon I} e(i,s).e(i,s^{'})}{max(\sum_{i \epsilon I} e(i,s), \sum_{i \epsilon I} e(i,s'))} \tag{2}$$

The resulting skill relatedness index is an adjacency matrix of skills. We, thus, define an average skill relatedness density (ASRD) measure by using RSA (equation 1) and the skill relatedness index (equation 2) to consider skill relatedness in the industrial and regional context.

$$ASRD^{r}_{i,t} = \frac{\sum_{s \in i} \left( \frac{\sum_s \phi_{s,j,t} RSA_{s,i,t}}{\sum_s \phi_{s,j,t}} \times 100 \right)_{s,i,t}}{\sum_{s \in i} s} \tag{3}$$

where $r$ is region, $\phi_{s,j,t}$ refers to relatedness between skill $s$ and $j$ at time $t$. Higher ASRD indicates higher proximity between the skill portfolios of an industry and other industries in the region. In other words, ASRD quantifies how close a potential new industry is to the region's existing industry mix in terms of human capital.

### 3.2 Skill Complexity

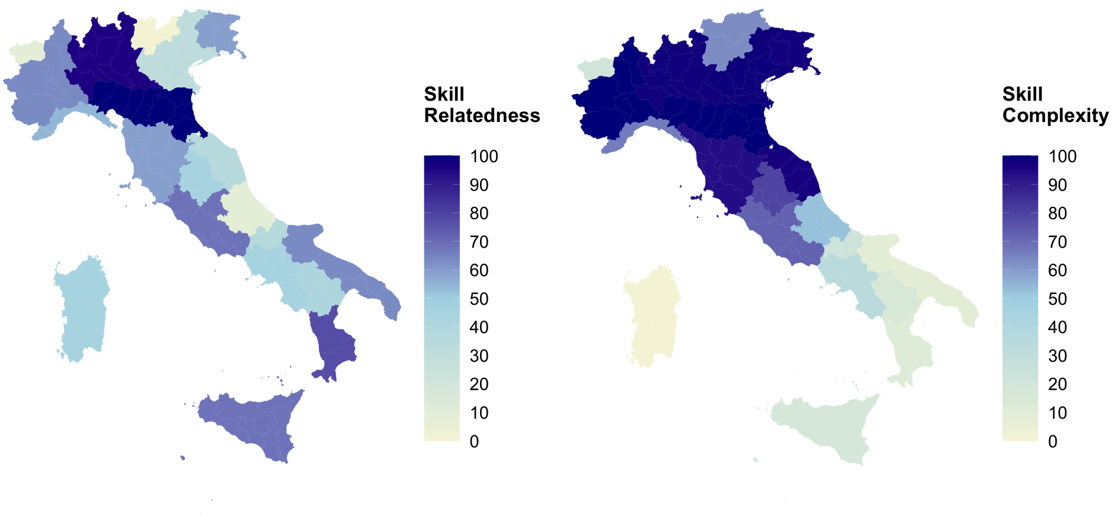
We use *the method of reflections* (MOR), introduced by Hidalgo and Hausmann (2009) to quantify the complexity, i.e. sophisticatedness, level of an industry's skill portfolio. MOR is defined as theoretically infinite iterative linear equations that sequentially combine two measures: diversity and ubiquity. In our analysis, diversity is the number of skills effectively used ($RSA > 1$) by industry $i$. Ubiquity is the number of industries that effectively use a particular skill $s$.

$$Diversity = k_{i,0} = \sum_{s} M_{i,s} \tag{4}$$

$$Ubiquity = k_{s,0} = \sum_{i} M_{i,s} \tag{5}$$

where $M_{i,s}$ is an adjacency matrix of industries and skills, resulting from equation 1. $M_{i,s} = 1$ if industry $i$ effectively uses ($RSA > 1$) skill $s$, and $M_{i,s} = 0$ otherwise.

Higher order iterations of diversity and ubiquity can be interpreted as a linear combination of the information on skill usage patterns of all industries in a region that we briefly name skill complexity. The complexity score converges to a certain value as the number of iterations increases. A higher skill complexity score indicates that industry $i$ effectively uses a relatively higher number of skills (diversity) that are effectively used by a relatively small number of industries (ubiquity).

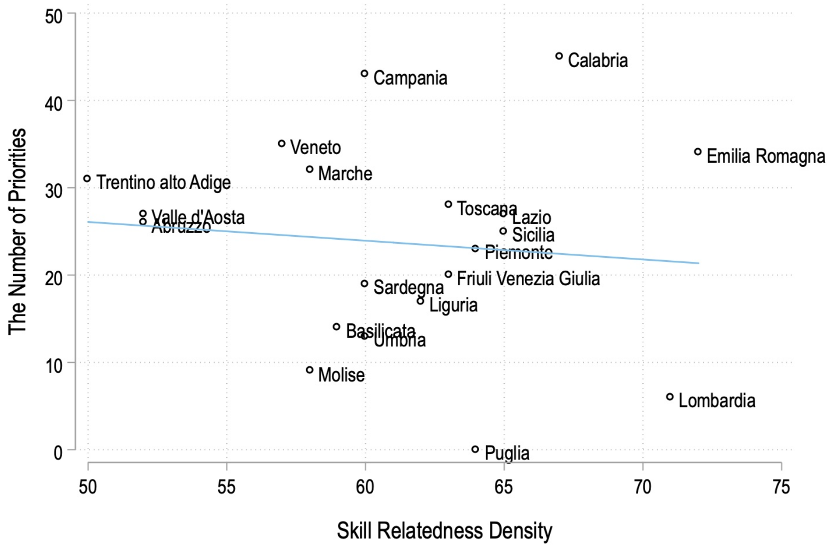



(a) (b)

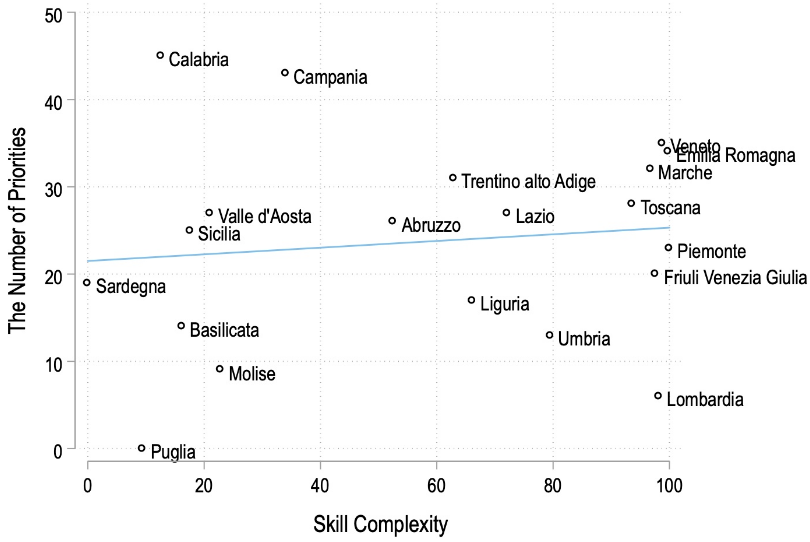
**Figure 2. ASRD and Skill Complexity Scores of Italian Regions**

Figure 2(a) demonstrates ASRD scores of industries averaged for Italian regions. The higher the ASRD of a region, the closer its existing set of effectively used skills (by industries located in that region) to the missing skills in the region. This is to say that the region is closer to forming the necessary capabilities to specialize in new industries that require different sets of workplace skills than the existing ones. The figure displays considerable differences in the branching potentials of regions.

Figure 2(b) presents the skill complexity index of industries averaged for Italian regions. A higher skill complexity score for a region indicates diverse and exclusive workplace skills in the regional industry mix. Apparently, the northern and central regions have higher complexity scores than the southern regions.




(a)




(b)

**Figure 3. The Number of SS Priorities with Respect to ASRD and Skill Complexity**

In Figure 3, we analyze whether the number of chosen SS priorities by regions varies with regional ASRD and skill complexity. There is a weak negative relationship between the number of priorities and ASRD (Figure 3(a)); while it is positive for skill complexity (Figure 3(b)).

**Table 1. Number of Priorities by Quartiles of Skill Relatedness and Complexity**

| | Skill Relatedness | | | | | Skill Complexity | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Quartiles | 1st | 2nd | 3rd | 4th | Total | 1st | 2nd | 3rd | 4th | Total |
| Piemonte | 0 | 7 | 8 | 8 | 23 | 7 | 7 | 8 | 1 | 23 |
| Valle d'Aosta | 16 | 7 | 2 | 2 | 27 | 12 | 5 | 8 | 2 | 27 |
| Lombardia | 1 | 0 | 3 | 2 | 6 | 2 | 0 | 3 | 1 | 6 |
| Trentino alto Adige | 11 | 6 | 7 | 7 | 31 | 9 | 5 | 11 | 6 | 31 |
| Veneto | 1 | 8 | 9 | 17 | 35 | 16 | 7 | 9 | 3 | 35 |
| Friuli Venezia Giulia | 2 | 7 | 7 | 4 | 20 | 5 | 4 | 8 | 3 | 20 |
| Liguria | 5 | 4 | 5 | 3 | 17 | 4 | 4 | 7 | 2 | 17 |
| Emilia Romagna | 9 | 8 | 7 | 10 | 34 | 10 | 6 | 12 | 6 | 34 |
| Toscana | 8 | 4 | 11 | 5 | 28 | 13 | 7 | 6 | 2 | 28 |
| Umbria | 7 | 6 | 0 | 0 | 13 | 0 | 0 | 6 | 7 | 13 |
| Marche | 3 | 5 | 9 | 15 | 32 | 11 | 9 | 9 | 3 | 32 |
| Lazio | 5 | 3 | 14 | 5 | 27 | 4 | 6 | 12 | 5 | 27 |
| Abruzzo | 8 | 9 | 4 | 5 | 26 | 4 | 5 | 8 | 9 | 26 |
| Molise | 4 | 2 | 1 | 2 | 9 | 1 | 1 | 5 | 2 | 9 |
| Campania | 13 | 12 | 10 | 8 | 43 | 15 | 13 | 10 | 5 | 43 |
| Basilicata | 5 | 5 | 1 | 3 | 14 | 3 | 2 | 6 | 3 | 14 |
| Calabria | 14 | 12 | 12 | 7 | 45 | 17 | 10 | 12 | 6 | 45 |
| Sicilia | 6 | 4 | 10 | 5 | 25 | 6 | 5 | 9 | 5 | 25 |
| Sardegna | 10 | 2 | 4 | 3 | 19 | 1 | 6 | 8 | 4 | 19 |
| Total | 128 | 111 | 124 | 111 | 474 | 140 | 102 | 157 | 75 | 474 |

Table 1 provides further insights by summarizing the number of regional priorities with respect to their ASRD and skill complexity in more detail. First, the quartiles of each measure are computed by regions. Then ASRD and skill complexity of chosen SS priorities are distributed to the quartiles. For Piemonte, Lombardia, Veneto, Fruili Venezia Giulia, Toscana, Marche, Lazio, and Sicilia, the majority of priority industries are skill related to other industries in the region since they belong to the third and fourth-quartile. These regions can relatively easily increase innovation and specialization in priority industries given that they possess, or can nurture, the necessary human capital. The rest of the regions have chosen industries that are less skill related to their existing industry mix meaning that developing a specialization is rather challenging for these industries since the region does not have the necessary workforce and human capital. Hence, their SS strategy should also include plans on how to nurture the skills of regional workforce in accordance with target industries. Regarding skill complexity, Piemonte, Valle d'Aosta, Veneto, Toscana, Marche, Campania, and Calabria have chosen less complex industries with respect to their industry mix given that the majority of their SS priorities fall into the first and second-quartile. The rest of the regions have more complex SS priority sets, thus, they are more likely to reach economic activities with higher value-added and enjoy a more specialized and sophisticated workforce if their SS strategies are properly implemented. Overall, Figure 2 and Table 1 reaffirm the argument that regions do not follow a clear pattern in their SS strategies with respect to measures we consider.

### 3.3 Smart Specialization and Regional Skills: A Framework

By drawing on the relatedness-complexity diagram (Hausmann et al., 2014; Balland et al., 2019), we propose a skill relatedness-skill complexity (SRSC) diagram on which SS priorities of regions can be defined and analyzed in line with regional skill bases which embody regional capabilities. The SRSC diagram is divided into four quadrants by plotting reference lines for the mean of skill relatedness (vertical line) and the mean of skill complexity (horizontal line). To interpret these four quadrants, we refer to Figure 4 which is a schematic representation of regional industry space based on regional skill base and portrayed as a framework for SS.


**Figure 4. Regional Skill Relatedness-Skill Complexity Diagram**

The top-left quadrant accommodates industries that effectively use a relatively complex set of skills that are not much related to skills effectively used by the majority of industries, including cognitive skills, scientific and academic knowledge, programming, and technology design, which means more complexity in necessary tasks to perform a job. Generally, service industries such as financial activities and insurance, scientific research and development, production of software and programming, advertising and market research are located in this quadrant. The top-right quadrant shows industries whose skill sets are more complex and similar to other existing industries in the region. These industries generally effectively use mental process and complex problem solving skills alongside other skills. In the bottom-right quadrant, we find non-complex but mostly used skills by the majority of industries including physical, sensory, psychomotor, work output, and a high fraction of technical skills. Generally, manufacturing industries such as food, beverage and textile industry, metallurgy, and service activities such as wholesale trade, restaurant services and accommodation are located in this quadrant. The bottom-left quadrant hosts industries that effectively use non-complex skills required by a relatively small number and non-complex industries. These are generally manufacturing industries, such as packaging of textile, repair of goods, installation of equipment, and water supply, demanding physical, sensory, and some technical skills related to physical activities. These examples are given with a high level of generalization for explanatory purposes. Industries located in each quadrant and skills effectively used by these industries are likely to change by region and time.

The SRSC diagram can be operationalized in two main ways. First, industries that do not have a comparative advantage ($RCA < 1$)[8] in the region can be plotted to evaluate (1) which industries are more likely to fit in the regional industry mix in terms of regional capabilities and human capital, i.e. higher relatedness; (2) which industries are more sophisticated and more likely to create cross-fertilizing and spill-overs among industries, i.e. higher complexity, to induce high value-added production and growth. This method is useful when defining regional innovation and industrial policy since it provides a place-specific, non-aggregative, and data-based assessment of which industries are more rewarding to invest in. Second, industries that have a comparative advantage in the region ($RCA > 1$) can be plotted to examine (1) the existing structure of skill-related industry space in terms of policy targets; (2) the effects of a policy decision and implementation. Correspondingly, the before-policy and after-policy structure of the SRSC diagram may shed light on the effectiveness of the implemented policy. The first approach can be used for policy design while the second approach is useful for policy evaluation.

In this study, we analyze the accuracy of chosen SS priorities in terms of regional capabilities. Hence, we opt for the second way and operationalize the SRSC diagram for regional SS policy evaluation. Figure 5 exhibits the results. Each subfigure represents a region's industry space built upon regional skill base characterized by skill relatedness and complexity. Each circle stands for a particular industry at the two-digit NACE level, while red circles represent industries chosen as SS priority in regional SS strategy documents. The figure demonstrates that each region has a unique industry space with the distribution of SS priorities. Notwithstanding, some similarities across regions can be detected. For instance, high-income regions such as Piemonte, Veneto, Friuli Venezia Giulia, and Toscana have

[8]Comparative advantage can be defined in terms of the number of people employed in that industry and region.

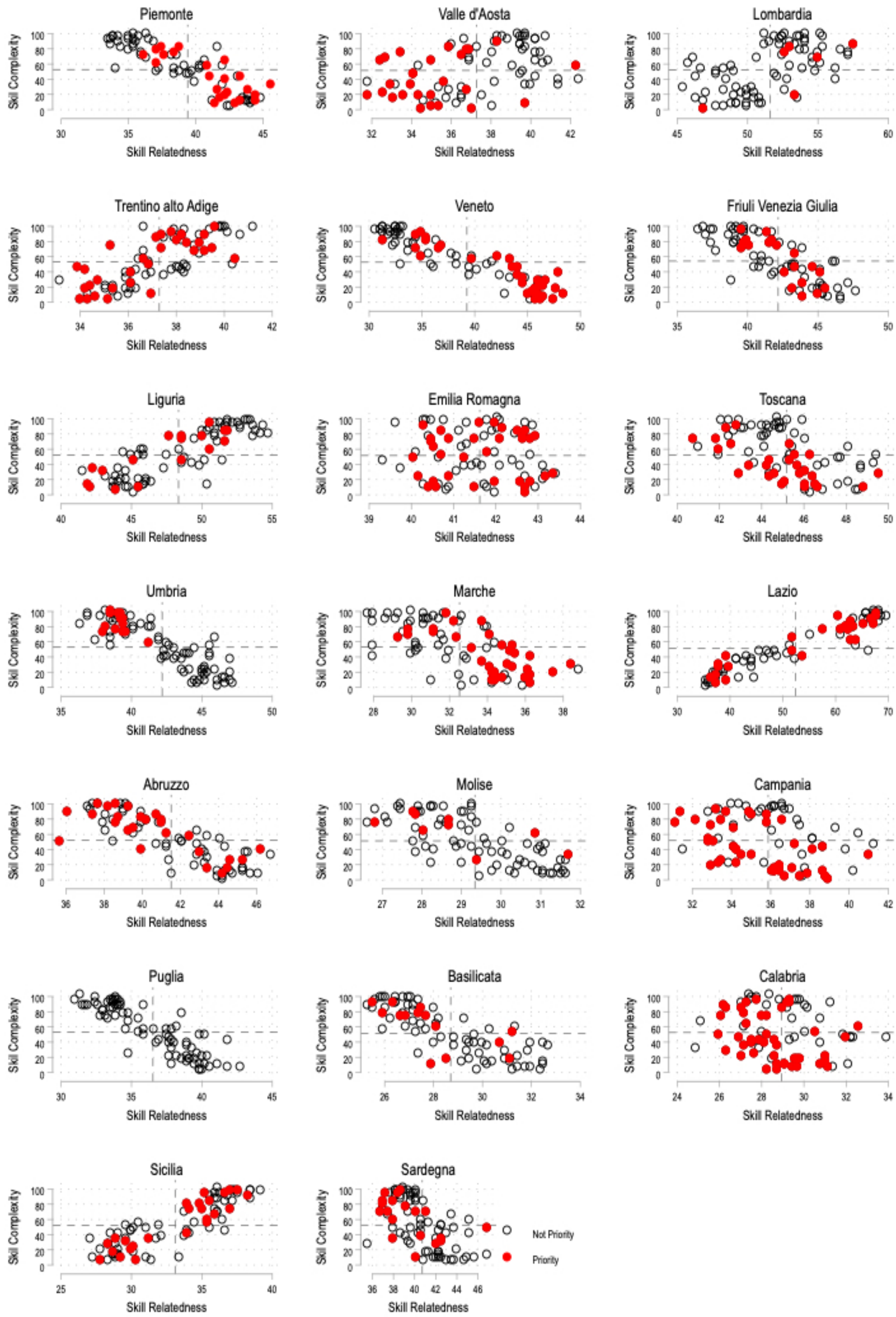



**Figure 5. Priority Industries' Position in Regional Skill Relatedness-Skill Complexity Diagrams**

resembling industry spaces with the majority of their SS priorities located in the bottom-right quadrant. Accordingly, these regions targeted skill-related but non-complex industries. Other high-income regions, Lombardia, Trentino alto Adige, Liguria, and Lazio opted for industries the majority are located in the top-right quadrant. These regions have chosen both skill-related and complex industries which are most rewarding. Regarding low-income regions such as Umbria, Abruzzo, Molise, Basilicata, and Sardegna, the general pattern is targeting industries that are complex and not skill-related to the region's industry mix given that the majority of their SS priorities are located in the top-right quadrant. This is to say these regions aimed high by choosing highly complex industries but they do not possess enough regional knowledge and skills, i.e. human capital and workforce, to be specialized in these industries. Other low-income regions, Marche, Campania, and Calabria have chosen industries from almost each quadrant.

# 4 Econometric Analysis

In this section, we conduct econometric analyses to better assess whether regions have chosen SS priorities in accordance with their regional knowledge and skill base. The dependent variable is *Priority* which takes the value of 1 if a region has selected a particular industry as a target in its SS strategy document, and takes the value of 0 otherwise. The SS strategy documents of Italian regions have been released only once in the policy period 2014-2020. Nine regions released it in 2014, three regions in 2015, seven regions in 2016, and one region in 2017. Correspondingly, SS priority data do not have a panel structure, we thus estimate a cross-sectional logistic model.

The main independent variables are ASRD (*ASRD*) and skill complexity (*SkillComplexity*) that are defined as explained in Section 3. We expect *ASRD* to be positive and significant if regions tend to choose industries that are skill-related to other industries in the region as SS priorities. In other words, if the regions' industrial portfolios include similar and/or complementary knowledge and skills required by the industries chosen as regional SS targets, *ASRD* will be positive. *SkillComplexity* is expected to be significant and positive if regions are prone to target industries that effectively use diverse and non-ubiquitous skill sets, thus, are able to produce high value-added goods and services. We also include an interaction term for *ASRD* and *SkillComplexity* to the model since the empirical SS framework suggests targeting industries that are both related and complex. We expect to see a significant and positive interaction term if this theoretical suggestion translates into regional policy choices.

We control for potential confounding factors with two sets of variables. Regional controls, *GDP (log)*, *PopDensity (log)*, and *HighTech*, account for the general characteristics of regions. *GDP (log)*, GDP per capita PPP, controls for the economic development level. *PopDensity (log)*, the number of inhabitants per square kilometre per region, controls for agglomeration. *HighTech*, the employment share of high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services) in the region, accounts for technological capabilities. The second set, SS controls, are *SharePriority* and *TargetIndustry*. *SharePriority*, target industry's employment share in the region, controls for the importance of target industry for the region. *TargetIndustry*, the number of regions that have chosen a particular industry as a SS target, accounts for general tendencies towards specific industries among regions. We also control for the total number of priorities the region has chosen (*TotalPriority*). In addition, we include regional fixed-effects to account for time-invariant confounding factors. Correspondingly, we estimate the following specification with the logistic model.

$$\begin{aligned} logit(Priority_{r,i}) = \beta_1 ASRD_{r,i} + \beta_2 SkillComplexity_{r,i} + \\ \beta_3 ASRD_{r,i} * SkillComplexity_{r,i} + \beta_4 \boldsymbol{RegionControls}_r + \\ \beta_5 \boldsymbol{SSControls}_{r,i} + \beta_6 TotalPriority_r + \rho_r + \varepsilon_{r,i} \end{aligned}$$

where $r$ is region, $i$ is industry, $\rho_r$ is regional fixed-effects. Errors are likely to be correlated within groups since the data we use has a grouped structure. Therefore, all estimates are performed with robust standard errors clustered at the industry-region level.

Regional authorities are likely to consider regional economic performance and economic indicators in recent years when designing regional SS strategies. Hence, we compute independent variables by taking the averages of the three years prior to the date of the regional SS strategy document. For instance, for regions that released their SS strategy document in 2014, independent variables are averaged in 2013, 2012, and 2011. In addition, measuring variables in the period prior to the SS strategy implementation eliminates endogeneity concerns. All independent variables are mean-centered before regressions.

Table 2 reports the results from the econometric model defined above. The specification in column 1 considers only the main independent variables of interest. *ASRD* is insignificant while higher *SkillComplexity* negatively affects the probability of an industry being chosen as a SS target. In column 2, we include an interaction term for *ASRD* and *SkillComplexity* which is weakly significant. The specifications in columns 3 and 4 include control variables for regional characteristics. *ASRD* stays insignificant, *SkillComplexity* and the interaction term stay robust. The overall picture changes when we add further controls to account for SS policy tendencies. As indicated in column 5, *SkillComplexity* is not significant anymore, while *ASRD* becomes highly significant. A ten percent increase in an industry's *ASRD* increases its probability of being chosen as a SS priority by 4.9%. The interaction term becomes insignificant in column 6, while the effect of *ASRD* is significant. For an industry with average *SkillComplexity*, a ten per cent increase in its *ASRD* increases the probability of that industry being chosen as SS priority by 3.9%. The SS framework suggests targeting industries that are complex and related to the existing regional industry mix to reach the most rewarding strategy. However, non-robust and insignificant interaction terms in Table 2 suggest that this proposition has not been applied in regional SS strategies.

**Table 2. Skill Relatedness, Skill Complexity and SS Priorities**

| | (1) prior | (2) prior | (3) prior | (4) prior | (5) prior | (6) prior |
|---|---|---|---|---|---|---|
| *ASRD* | 0.01581 | 0.00713 | 0.01581 | 0.00713 | 0.04796*** | 0.03877** |
| | (0.01378) | (0.01472) | (0.01378) | (0.01472) | (0.01689) | (0.01827) |
| *SkillComplexity* | -0.00588*** | -0.00602*** | -0.00588*** | -0.00602*** | -0.00104 | -0.00121 |
| | (0.00182) | (0.00183) | (0.00182) | (0.00183) | (0.00235) | (0.00236) |
| *ASRDxSkillComplexity* | | 0.00050* | | 0.00050* | | 0.00055 |
| | | (0.00027) | | (0.00027) | | (0.00034) |
| *GDP (log)* | | | 27.78315*** | 28.14484*** | 20.86870 | 13.30104 |
| | | | (7.65690) | (7.69592) | (28.70818) | (29.44650) |
| *PopDensity (log)* | | | 5.52050*** | 5.43417*** | 4.49856 | 2.83914 |
| | | | (1.39456) | (1.39599) | (5.76819) | (5.93950) |
| *HighTech* | | | -7.38561*** | -7.40289*** | -5.69964 | -3.59993 |
| | | | (1.92069) | (1.92820) | (7.57806) | (7.79145) |
| *SharePriority* | | | | | 0.07474** | 0.07329** |
| | | | | | (0.03632) | (0.03636) |
| *TotalPriority* | | | | | 0.05537 | 0.07247 |
| | | | | | (0.05559) | (0.05750) |
| *TargetIndustry* | | | | | 0.36127*** | 0.36086*** |
| | | | | | (0.02036) | (0.02029) |
| *Constant* | -0.92522*** | -0.87197*** | 3.84191*** | 3.88780*** | 2.29498 | 0.99713 |
| | (0.24382) | (0.24496) | (1.25791) | (1.26268) | (4.82777) | (4.95644) |
| *Regional FE* | yes | yes | yes | yes | yes | yes |
| *N* | 1520 | 1520 | 1520 | 1520 | 1520 | 1520 |
| *Pseudo $R^2$* | 0.072 | 0.073 | 0.072 | 0.073 | 0.396 | 0.397 |
| *Log Likelihood* | -875.49 | -873.94 | -875.49 | -873.94 | -569.85 | -568.67 |

Notes: Robust standard errors clustered at the region and industry level are in parentheses. All specifications include fixed effects for regions. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Among control variables, *TargetIndustry* is highly significant and sizable, implying that regions tend to choose priority domains that are highly chosen by other regions. In addition, regions are more likely to choose industries that have a higher share of employment in the region, as indicated with significant *SharePriority* coefficients.

Overall, Table 2 displays rather inconclusive results that might stem from the heterogeneity among regions. Indeed, Figure 5 analyzed above demonstrates substantial differences between high and low-income regions. We, therefore, consider these regional disparities below.

## 4.1 Regional Disparities: Leading and Lagging Regions

Some regions are more prosperous than others, thereby they possess healthy innovation and entrepreneurship ecosystems, well-connected industry and knowledge networks, diverse and valuable capabilities including well-developed human capital, supportive institutional environment, and technological diversity, which enable them to create new innovation-led growth paths. These regions are called 'leading' regions. In contrast, some regions have below-average income due to limited and ubiquitous capabilities, underdeveloped innovation and entrepreneurship ecosystems, and disconnected industry and knowledge networks which cause them to lag behind other regions. As befits the name, these regions are called 'lagging' regions. Due to their differences, SS strategy formation and targets might significantly differ between leading and lagging regions. In order to evaluate the potential differences, we reestimate the model separately for leading and lagging regions.

We define leading and lagging Italian regions based on average GDP per capita PPP for the observation period. The regions placed in the upper half-percentile are leading regions[9], while the ones in the lower half-percentile are lagging regions[10].

Table 3 displays the results. The substantial differences between lagging and leading regions are evident at first sight. First of all, *ASRD* is significant and negative for lagging regions, indicating that these regions tend to target industries that are not much skill-related to their existing industry mix. In column 3, a ten per cent increase in *ASRD* decreases the probability of an industry being chosen as SS priority by 9%. In other words, lagging regions seem to prioritize industries in which they do not have enough capabilities and skilled labor force to specialize in. Therefore, their SS strategy may not introduce the expected innovation level and growth. Interestingly, *SkillComplexity* is insignificant, not affecting SS priority choices of lagging regions. The interaction term for *ASRD* and *SkillComplexity* is positively significant. The higher the *SkillComplexity*, the higher the effect of *ASRD* on the probability of an industry being selected as a SS target and vice versa. An industry with average *ASRD* located in a lagging region has a higher probability of being chosen as SS priority by 1.3% if its *SkillComplexity* increases by ten per cent. Correspondingly, the effect of skill complexity appears to be conditional on the level of skill relatedness for lagging regions.

Regarding leading regions, *ASRD* is significant and positive in all models, meaning that leading regions tend to target industries in which they have enough capabilities, knowledge, and skills. The probability of being chosen as SS priority increases by 11% when *ASRD* increases by ten per cent. In contrast to lagging regions, leading regions have a higher chance to trigger innovation-led growth via SS strategy since they possess the necessary competencies to do so. Unlike lagging regions, leading regions tend to choose less complex industries, indicated by negative and significant *SkillComplexity* coefficients in all models.

[9] Emilia Romagna, Friuli Venezia Giulia, Lazio, Liguria, Lombardia, Piemonte, Toscana, Trentino alto Adige, Valle d'Aosta, Veneto.

[10] Abruzzo, Basilicata, Calabria, Campania, Marche, Molise, Puglia, Sardegna, Sicilia, Umbria.

Nevertheless, the effect size of *SkillComplexity* is less potent than *ASRD*. Another difference between lagging and leading regions is the interaction term, which is insignificant for leading regions. However, the main effects are significant. An industry with average *SkillComplexity* (*ASRD*) in a leading region has a higher (lower) probability of being chosen as SS priority by 10% (1.1%) if its *ASRD* (*SkillComplexity*) increases (decreases) by ten per cent. Recall that lagging regions are more likely to target complex industries if they are skill-related on average, indicated by the positive and significant *SkillComplexity* coefficient in column 4.

**Table 3. Regional Disparities: Skill Relatedness, Skill Complexity and SS Priorities**

| | Lagging Regions | | | | | Leading Regions | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) prior | (2) prior | (3) prior | (4) prior | | (5) prior | (6) prior | (5) prior | (6) prior |
| *ASRD* | -0.10177*** | -0.07492* | -0.08633* | -0.03871 | | 0.04624*** | 0.03766** | 0.10195*** | 0.09482*** |
| | (0.03766) | (0.03866) | (0.04787) | (0.04840) | | (0.01536) | (0.01776) | (0.01961) | (0.02355) |
| *SkillComplexity* | -0.00464 | 0.00240 | 0.00143 | 0.01285** | | -0.01057*** | -0.01222*** | -0.00952*** | -0.01116*** |
| | (0.00292) | (0.00371) | (0.00353) | (0.00514) | | (0.00250) | (0.00300) | (0.00359) | (0.00432) |
| *ASRDxSkillComplexity* | | 0.00150*** | | 0.00235*** | | | 0.00046 | | 0.00043 |
| | | (0.00052) | | (0.00066) | | | (0.00045) | | (0.00063) |
| *GDP (log)* | 3.55034 | 5.88974 | -24.86241* | -14.00643 | | 12.57384 | 11.82566 | 28.54236 | 27.48698 |
| | (4.06543) | (4.22403) | (15.05478) | (15.03624) | | (12.87134) | (12.82244) | (24.30307) | (24.29084) |
| *PopDensity (log)* | 0.31022 | 0.79310 | -6.50829 | -3.97837 | | -6.79645 | -6.45222 | -6.89389 | -6.74212 |
| | (0.93941) | (0.97143) | (4.04931) | (3.98539) | | (9.23692) | (9.19575) | (5.23912) | (5.22109) |
| *HighTech* | -1.54981 | -2.48125* | 11.34913 | 6.54841 | | 0.83451 | 0.75835 | 0.33804 | 0.30431 |
| | (1.30899) | (1.37449) | (6.91704) | (6.81191) | | (1.40142) | (1.39560) | (0.35963) | (0.36320) |
| *SharePriority* | | | 0.03426 | 0.03612 | | | | 0.13745** | 0.13484** |
| | | | (0.04523) | (0.04614) | | | | (0.05757) | (0.05876) |
| *TotalPriority* | | | 0.22419** | 0.17416* | | | | -0.18503 | -0.17657 |
| | | | (0.09393) | (0.09105) | | | | (0.26486) | (0.26420) |
| *TargetIndustry* | | | 0.30144*** | 0.30802*** | | | | 0.44213*** | 0.44144*** |
| | | | (0.02639) | (0.02732) | | | | (0.03115) | (0.03107) |
| *Constant* | -1.16808** | -0.97801* | -2.36397*** | -1.86465** | | -2.36911 | -2.20386 | -4.46895* | -4.29261* |
| | (0.55050) | (0.55914) | (0.84249) | (0.89054) | | (1.63130) | (1.62829) | (2.28426) | (2.30102) |
| *Regional FE* | yes | yes | yes | yes | yes | yes | | | |
| *N* | 720 | 720 | 720 | 720 | | 800 | 800 | 800 | 800 |
| *Pseudo $R^2$* | 0.097 | 0.105 | 0.347 | 0.360 | | 0.069 | 0.070 | 0.476 | 0.476 |
| *Log Likelihood* | -404.37 | -400.72 | -292.69 | -286.86 | | -461.23 | -460.74 | -259.67 | -259.45 |

Notes: Robust standard errors clustered at the region and industry level are in parentheses. All specifications include fixed effects for regions. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Regional control variables are almost always insignificant, implying that the number of selected priorities does not relate to regional characteristics, which is in line with the prior research (Di Cataldo et al., 2021; Deegan et al., 2021). *TargetIndustry* is highly relevant for both lagging and leading regions, while more sizable for leading regions, reaffirming the finding that regions generally prioritize industries that are chosen by other regions.

This aligns with the prior work underlining that regions generally, especially the ones with low-quality governance, mimic the SS strategies of neighboring and other regions instead of adopting well-tailored and place-based policies (Di Cataldo et al., 2021). Leading regions also tend to prioritize industries with higher employment share in the region, evidenced by the significant and positive coefficients for *SharePriority*. Accordingly, leading regions design their SS strategy by targeting industries in which they already have some experience and specialization (positive employment share) and competencies (positive skill-relatedness). D'Adda et al. (2019) underline that there is a trade-off between the two suggestions of the SS guide: maximizing the relatedness and maximizing the coherence between chosen domains and actual domains the region already specialized in. Our findings suggest that there might not be necessarily a trade-off since leading regions tend to choose priorities with higher skill relatedness and higher employment share. On the contrary, negative *ASRD* and insignificant *SharePriority* for lagging regions support the idea that they tend to choose industries by which they can more easily receive funding, such as high technology and knowledge-intensive industries, even though they do not possess enough competencies to establish a comparative advantage in these sectors.

Based on these findings, it can be said that leading regions have defined more realistic and accurate SS policies in terms of regional capabilities and strengths, yet follow a conservative path by targeting non-complex industries. Conversely, lagging regions target skill-complex industries when they are skill-related on average, following the suggestion of the empirical SS literature (Balland et al., 2019). However, they are risk-takers, prioritizing unrelated industries which conveys the risk of building cathedrals in the desert since relevant capabilities are not present. It has been stated that lagging regions might benefit from unrelated diversification (Di Cataldo et al., 2021), especially when regions are over-specialized or trapped in low-complex activities (Boschma, 2021). From this perspective, choosing priorities inversely vary with skill relatedness may not be necessarily an ill-design for lagging regions. It is important to emphasize that the present study evaluates the design of SS strategies, not the effects of implemented SS strategies. Indeed, we do not know whether the SS strategies declared in regional SS plans have actually been implemented since our data set does not include such information. Hence, the question of 'does lagging regions benefit from investing in non-skill-related domains?' remains unexplored in this study.

# 5 Conclusion

The SS concept puts regional capabilities at the center. In order to build comparative advantage in new activities, either related or unrelated to existing activities, regions must have the necessary capabilities to combine. Even though workplace skills have been recognized as crucial for SS, they are seldom included in the analysis. Regional capabilities and knowledge bases are generally quantified with patent data, measuring patentable technological aspects

(Balland et al., 2019). In this study, we argue that regional workplace knowledge and skills are important indicators of regional capabilities. We synthesize the SS concept with skill relatedness and skill complexity measures to provide a framework for policy design and evaluation. We then operationalize this framework to analyze to what extent the regional SS policy in Italy is coherent with regional knowledge and skill bases. In this context, we analyze the SS policy choices, i.e. targeted sectors, of each Italian region by shedding light on their place in the current specialization pattern of regional industry space.

We find that regional heterogeneity plays an important role in designing SS strategies. Lagging, i.e. low income, regions tend to choose industries that are not skill-related to their industrial skill base. On the other hand, leading, i.e. high income, regions are prone to choose skill-related industries as SS targets. Skill complexity does not affect SS targets of lagging regions if the industries in question have below-average skill relatedness. Conversely, if an industry in a lagging region has average skill relatedness, the probability of that industry being chosen as a SS target increases with its skill complexity. Accordingly, lagging regions are prone to target more skill-related and complex industries after a certain relatedness level, as evidenced by positive and significant interaction terms. On the contrary, leading regions tend to choose less complex industries with no interaction effect. Prior research found that the optimal SS strategy defined by Balland et al. (2019), i.e. targeting both related and complex domains, has not been implemented by regions (Deegan et al., 2021). We show that lagging regions seem to implement it while leading regions do not.

Overall, leading regions prioritize SS domains on which they have similar or complementary capabilities alongside some degree of regional experience. Hence, they aim at strengthening the existing productive structure. Lagging regions seem to target domains in which they may not have enough experience, knowledge and skills, potentially looking for new productive paths. These findings underline the importance of regional disparities when examining regional SS strategies. As shown in our analyses, high level of aggregation might obscure crucial information. Correspondingly, future studies should consider taking regional heterogeneity into account to better observe regional SS strategies. In this regard, more sub-national studies, rather than Europe-wide, are needed to improve our understanding of SS strategy design.

Our findings convey further implications and questions for future research. For instance, why lagging regions are more likely to target unrelated domains? Why do lagging regions tend to choose skill-complex domains when there is enough skill relatedness while leading regions choose non-skill-complex domains regardless of the skill relatedness level? Another interesting question is why leading regions' priority selection is more affected by the choices of other regions. Is it a coincidence or lagging regions' governing bodies are more successful at designing place-based SS strategies?

The framework provided in this study can be used by policymakers to identify and evaluate regional SS strategies in coherence with regional knowledge and skill bases. A potential limitation might be the lack of workplace skills data which is essential to operationalizing our method. It is known that ICP and O*net-like surveys are not conducted in many countries. However, it is advisable for local policymakers to start the necessary procedures to collect data on regional workplace knowledge and skills as they are crucial for regional human capital formation, industry dynamics, innovation, and thereby, growth.

# A Supplementary Material

**Table A.1. ICP Categories**

| | |
|---|---|
| **1.Knowledge** | (B1) Administration and Management, (B2) Office Work, (B3) Economics and Accounting, (B4) Sales and Marketing, (B5) Services to Customers, (B6) Human Resources Management, (B7) Production and Processing, (B8) Food Production, (B9) IT and Electronics, (B10) Engineering and Technology, (B11) Technical Design, (B12) Building and Construction, (B13) Mechanical, (B14) Mathematics, (B15) Physics, (B16) Chemistry, (B17) Biology, (B18) Psychology, (B19) Sociology and Anthropology, (B20) Geography, (B21) Medicine and Dentistry, (B22) Therapy and Counseling, (B23) Education and Training, (B24) Italian Language, (B25) Foreign Language, (B26) Fine Arts, (B27) History and Archaeology, (B28) Philosophy and Theology, (B29) Civil Protection and Public Safety, (B30) Legislation and Institutions, (B31) Telecommunications, (B32) Communication and Media, (B33) Transportation |
| **2.Skills** | |
| 2.1 Basic Skills | (C1) Reading Comprehension, (C2) Active Listening, (C3) Writing, (C4) Speaking, (C5) Mathematics, (C6) Science, (C7) Critical Thinking, (C8) Active Learning, (C9) Learning Strategies, (C10) Monitoring |
| 2.2 Social Skills | (C11) Social Perceptiveness, (C12) Coordination, (C13) Persuasion, (C14) Negotiation, (C15) Instructing, (C16) Service Orientation |
| 2.3 Complex Problem | (C17) Complex Problem Solving |
| 2.4 Technical Skills | (C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C21) Installation, (C22) Programming, (C23) Quality Control Analysis, (C24) Operation Monitoring, (C25) Operation and Control, (C26) Equipment Maintenance, (C27) Troubleshooting, (C28) Repairing |
| 2.5 Systems Skills | (C29) Systems Analysis, (C30) Systems Evaluation, (C31) Judgement and Decision Making |
| 2.6 Resource Management Skills | (C32) Time Management, (C33) Management of Financial Resources, (C34) Management of Material Resources, (C35) Management of Personnel Resources |
| **3.Attitudes** | |
| 3.1 Cognitive | (D1) Oral Comprehension, (D2) Written Comprehension, (D3) Oral Expression, (D4) Written Expression, (D5) Fluency of Ideas, (D6) Originality, (D7) Problem Sensitivity, (D8) Deductive Reasoning, (D9) Inductive Reasoning, (D10) Information Ordering, (D11) Category Flexibility, (D12) Math Reasoning, (D13) Number Facility, (D14) Memorisation, (D15) Speed of Closure, (D16) Flexibility of Closure, (D17) Perceptual Speed, (D18) Spatial Orientation, (D19) Visualisation, (D20)Selective Attention, (D21) Time Sharing |
| 3.2 Psychomotor | (D22) Arms-Hand Steadiness, (D23) Manual Dexterity, (D24) Finger Dexterity, (D25) Control Precision, (D26) Multilimb Coordination, (D27) Response Orientation, (D28) Rate Control, (D29) Reaction Time, (D30) Wrist-Finger Speed, (D31) Speed of Limb Movement |
| 3.3 Psychical | (D32) Static Strength, (D33) Explosive Strength, (D34) Dynamic Strength, (D35) Trunk Strength, (D36) Stamina, (D37) Extent Flexibility, (D38) Dynamic Flexibility, (D39) Gross Body Coordination, (D40) Gross Balance Body Equilibrium |
| 3.4 Sensory | (D41) Near Vision, (D42) Far Vision, (D43) Visual Colour Discrimination, (D44) Night Vision, (D45) Peripheral Vision, (D46) Depth Perception, (D47) Glare Sensitivity, (D48) Hearing Sensitivity, (D49) Auditory Attention, (D50) Sound Localisation, (D51) Speech Recognition, (D52) Speech Clarity |
| **4.Work Activities** | |
| 4.1 Information Input | (G1) Getting Information, (G2) Identifying Objects, Actions, and Events, (G3) Monitor Processes, Materials or Surroundings, (G4) Inspecting Equipment, Structures or Material, (G5) Estimate the Quantifiable Characteristics of Products, Events, or Information |
| 4.2 Mental Process | (G6) Judging the Qualities of Things, Services or People, (G7) Evaluating Information to Determine Compliance with Standards, (G8) Processing Information, (G9) Analysing Data or Information, (G10) Making Decisions and Solving Problems, (G11) Thinking Creatively, (G12) Updating and Using Relevant Knowledge, (G13) Developing Objectives and Strategies, (G14) Scheduling Work and Activities, (G15) Organising, Planning, and Prioritising Work |
| 4.3 Work Output | (G16) Performing General Physical Activities, (G17) Handling and Moving Objects, (G18) Controlling Machines and Processes, (G19) Interacting With Computers, (G20) Operating Vehicles, Mechanised Devices, or Equipment, (G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment, (G22) Repairing and Maintaining Mechanical Equipment, (G23) Repairing and Maintaining Electronic Equipment, (G24) Documenting/Recording Information |
| 4.4 Interacting with Others | (G25) Interpreting the Meaning of the Information for Others, (G26) Communicating with Supervisors, Peers, or Subordinates, (G27) Communicating with Persons Outside Organisation, (G28) Establishing and Maintaining Interpersonal Relationships, (G29) Assisting and Caring for Others, (G30) Selling or Influencing Others, (G31) Resolving Conflicts and Negotiating with Others, (G32) Performing for or Working in Directly with the Public, (G33) Coordinating the Work and Activities of Others, (G34) Developing and Building Teams, (G35) Training and Teaching Others, (G36) Guiding, Directing, and Motivating Subordinates, (G37) Train and Nurture Other People, (G38) Provide Consultation and Advice to Others, (G39) Performing Administrative Activities, (G40) Staffing Organisational Units, (G41) Monitoring and Controlling Resources |

Author's own elaboration on ICP 2013[11] and O*NET data descriptors[12].

**Table A.2. Skill Relatedness, Skill Complexity and SS Priorities**

| | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| *Prior* | 1,600 | 0.296 | 0.457 | 0 | 1 |
| *ASRD* | 1,600 | 39.202 | 7.776 | 24.923 | 69.88 |
| *SkillComplexity* | 1,600 | 52.311 | 31.099 | 0 | 100 |
| *GDP (log)* | 1,600 | 25551 | 6614 | 15966 | 37000 |
| *PopDensity (log)* | 1,600 | 186.332 | 112.441 | 39.233 | 433.667 |
| *HighTech* | 1,600 | 2.517 | 1.446 | 0 | 6.667 |
| *TotalPriority* | 1,600 | 23.7 | 11.428 | 0 | 45 |
| *SharePriority* | 1,600 | 1.25 | 1.895 | 0 | 13.020 |
| *TargetPriority* | 1,600 | 5.925 | 5.088 | 0 | 17 |

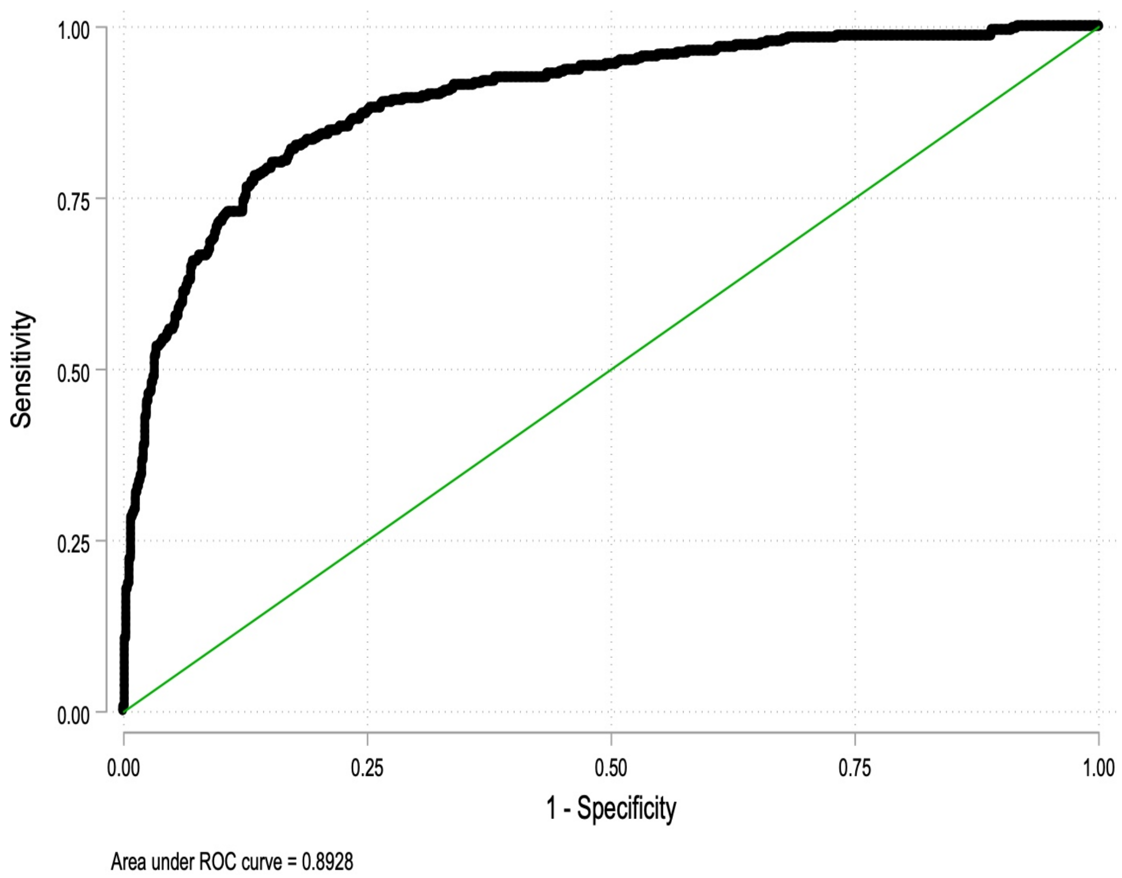



**Figure A.1. ROC Curve After Logistic Model 6 in Table 2**

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