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Abstract

This paper explores the phenomenon of mimicry in the selection of economic domains for Smart Specialisation Strategies (S3) and discusses the regional policy implications of strategic mimicry. By analysing S3 documents from European regions, we identify and distinguish between two general types of mimicry: 'Follow the Peers' and 'Follow the Role Models,' against the more desirable 'Follow the Indicators' priority selection strategy. Our findings reveal that although regions rely on their strengths by following the crucial indicators, thus exhibiting non-mimetic behaviour, there is a stronger tendency for regions to mimic popular domain portfolios, particularly those chosen by neighbouring regions and national strategies. Understanding these patterns in the selection of priority domains helps decision-makers balance mimicry and diversification, promoting specialization, new economic activities, and regional uniqueness.

Key words

smart specialisation, regional strategy, regional policy, innovation policy, mimicry

JEL codes

O25, O38, R11

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1. Introduction

Smart Specialisation Strategies (S3) are crucial in regional economic development, particularly in assessing and selecting economic domains with promising growth potential. The Entrepreneurial Discovery Process (EDP) lies at the heart of S3, guiding regions to prioritize domains aligned with their competencies for future prosperity. Despite the theoretical framework, scepticism persists about regions' involvement in the EDP and their efforts to identify domains with realistic prospects for success and economic returns (Di Cataldo, Monastiriotis, & Rodríguez-Pose, 2021). The complexity of the EDP, combined with the stringent EU requirements for developing S3, poses a significant challenge for regions, some of which may lack the necessary competences or motivation to fully engage in the process. On the other hand, regions are obliged to formulate S3 to benefit from EU funding, leading them to seek easier approaches to strategy development and domain prioritisation. Consequently, this can produce the phenomenon of mimicking the strategic choices of other regions.

While previous research has supported this tendency to benchmark or mimic regional priorities (Bellini, Lazzeri, and Rovai, 2021; Di Cataldo, Monastiriotis, and Rodríguez-Pose, 2021), the extent and mechanisms of such mimicry remain largely unexplored. To address this gap, our study explores two basic mimetic approaches: 'Follow the Peers' and 'Follow the Role Models,' along with a different, but complementary approach called 'Follow the Indicators.' These pathways represent different approaches that regions may adopt when developing their S3, including inspiration from similar regions and mimicking influential models to prioritise domains.

Understanding mimicry is crucial as it could challenge S3 effectiveness, revealing a policy competence gap where some regions innovate while others lag behind. Uncovering mimicry drivers is essential for successful S3 implementation and regional economic development. Mimicking strategies offer several benefits to regions. Aligning their domains with those of neighbouring regions or influential peers allows access to shared expertise, technologies, and innovations, enhancing their strategic initiatives and economic development. This alignment facilitates synergies, collaborative projects, joint ventures, and regional integration, fostering a more competitive economic environment. Additionally, choosing domains that have been successful elsewhere reduces the risk of investing in unproven areas, ensuring higher chances of success through shared experiences and proven results.

However, these benefits often come at the cost of long-term sustainability. A short-term focus on mimicry can undermine the development of resilient economic strategies and lead to homogenization, reducing the distinctiveness and diversity of regional specializations. This excessive mimicry may cause regions to overlook their unique strengths and local needs, resulting in overcrowded markets, increased competition, and diminished profitability. Additionally, regions relying heavily on mimicry may become vulnerable to external shocks and less incentivized to innovate or explore new domains.

We investigate the origins of domain selection using a dataset of 169 S3 documents from European regions, along with their creation dates, selected domains, and regional characteristics. Primarily, we find that regions rely on their existing strengths when selecting domains for their S3. However, our analysis also reveals a strong multi-faceted context in which regions follow different mimicry patterns. It seems that local peer influences and broader regional trends significantly shape domain choices. The 'Follow the Peers' model showed that regions tend to choose domains already selected by neighbouring regions and national strategies. Meanwhile, the 'Follow the Role Models' model indicated the strongest tendency to select domains popular among other regions that form attractive portfolios.

Our study enhances the understanding of S3 formulation by explaining mimicry patterns, addressing policy competence gaps, and strengthening regional development initiatives. Mimicry often stems from perceived domain constraints compounded by overlapping domains referred to as macro-portfolios, prioritizing domains based on technological and resource similarities. The following sections present the theoretical foundations of mimicry, our empirical strategy, research findings, and conclusions.

2. Understanding the causes and consequences of different mimicry forms in S3

2.1. Mimicry in S3: Challenges and implications for regional policy

Over the past decade, S3 has rapidly accelerated up the policy agenda, evolving from a theoretical concept developed by the expert group *'Knowledge for Growth'* to a key element of European regional development policy. This evolution is driven by the overarching goal of fostering innovation in Europe and addressing the growing productivity gap between the United States and the European Union (Marques Santos, Edwards and Neto, 2021; Gianelle, Guzzo and Mieszkowski, 2020). Essentially, smart specialisation embodies a place-based approach to economic development, focused on identifying strategic domains of intervention by analysing existing regional strengths and potentials (Tödtling and Trippl, 2005; Foray, David and Hall, 2011; Asheim, Grillitsch and Trippl, 2016; Rodríguez-Pose and Wilkie, 2016; Balland et al, 2019; Deegan, Broekel and Fitjar, 2021).

The creation of a S3 is based on EDP, conceptualised by Foray (2014) as the cultivation of 'entrepreneurial knowledge'. This unique knowledge links a region's vision to its ability to harness diverse stakeholder knowledge, including technological agility, entrepreneurial innovation and adaptability to changing market dynamics (Foray, 2014). Rooted in Schumpeter's notion of creative destruction, EDP advocates that regions challenge existing paradigms and take on new domains, fostering innovation and adaptability in response to changing economic landscapes (Perianez Forte & Wilson, 2021).

However, despite the apparent importance of smart specialisation in policymaking, concerns remain about the translation of theory into practice, highlighting the challenges of operationalising the concept. Critics point to unclear definitions of EDP and S3 design processes combined with ambiguous results, leading to a lack of clear guidance on how to plan, organise and implement these strategies. As a result, regions have adopted different methodologies, yielding inconsistent results (Boschma, 2021; Pylak & Warowny, 2021; Jordahl et al., 2023).

Moreover, alongside the practical challenges of implementation, doubts persist about the theoretical and empirical underpinnings of smart specialisation (Morgan, 2015; Iacobucci and Guzzini, 2016; Barbero et al., 2021). It has been criticised as insufficiently theoretical, being a *'perfect example of policy running ahead of theory'* (Foray, David and Hall, 2011; Boschma, 2014), leading to a lack of common understanding among researchers and practitioners about the nature and effective implementation of smart specialisation (McCann and Ortega-Argilés, 2015; Capello and Kroll, 2016; Griniece et al, 2017; Foray, 2019; Gianelle, Guzzo and Mieszkowski, 2019). Thus, there is an urgent need for greater theoretical coherence and empirical validation to strengthen the effectiveness and consistency of S3 across regions.

Despite these challenges, the growing literature on relatedness and S3 provides valuable insights for regions seeking to select areas that build on existing strengths, foster innovation and drive regional development. The related diversification approach has significantly deepened our understanding of the relationship between S3 and 'regional branching'. A key contribution by Boschma and Gianelle (2014) clarified this link by highlighting the key role of linkages between economic activities in regional development. Recent work by Balland et al. (2019) and Montresor and Quatraro (2017) has further enriched this discourse.

While S3 has become an integral part of regional innovation policy in Europe, serving as a prerequisite for accessing European structural and cohesion funds (Asheim, 2019; Deegan et al., 2021), there are ongoing debates about their conceptual and practical effectiveness (Foray, 2019; Hassink and Gong, 2019; Benner, 2020). A particularly controversial issue concerns the requirement for regions to develop S3 to access European funds (Iacobucci, 2014). While this condition seems logical in theory, it may inadvertently encourage regions to formulate S3 policies solely to meet regulatory obligations without concrete implementation plans and a strategic vision (Bellini et al., 2021).

In such scenarios, mimicry may emerge as an attractive strategy, especially for regions that designed their S3 after the initial ones became publicly available through the work of the Joint Research Centre of the European Commission (JRC) in Sevilla. Rather than investing time and effort in the time-consuming EDP and S3 development, regions may opt to align with strategies observed in comparable regions—a phenomenon known as territorial or yardstick competition (Gordon, 2010; Rodríguez-Pose and Arbix, 2001; Di Cataldo et al., 2020). Consequently, these regions may opportunistically select economic domain portfolios selected by others, viewing this approach as more pragmatic than formulating original selections (Di Cataldo et al., 2020). This "*copying of pre-packaged policy solutions rather than elaborating original ones or thoroughly adjusting others' practices*" (Bellini, Lazzeri, and Rovai, 2021, pg. 415) is facilitated by the inherent complexity and ambiguity inherent in EDP and S3 development.

Mimicry allows regions to bypass the demanding task of building competencies and investing significant resources in a complex policy design process. While policy learning is usually beneficial, it can be complex and costly, particularly within smart specialisation settings, where it must incorporate both endogenous and exogenous factors (Borrás, 2011; Dolowitz & Marsh, 1996). Consequently, the costs associated with developing such strategies can be significant and may require expertise that is not widely available in the regions.

However, S3 constructed by mimicking documents from other regions are often not long-lasting. Bellini, Lazzeri, and Rovai (2021) illustrate this with examples from three regions where there was a desire for standardization and continuity within and beyond regional administrations once the ex-ante conditions were met. Consequently, once the strategy-writing efforts were completed, there was a return to a less ambitious ‘business as usual’ approach, which ultimately reduced the expected innovativeness of the new interventions (p. 422).

Ultimately, the mimicry of S3 adopted by other regions undermines the uniqueness and adaptability inherent in the concept of smart specialisation, detracting from the potential benefits of region-specific policy design. The duplication of economic fields strengthens intra-European competition at the expense of global competitiveness. Moreover, mimicry can lead to unnecessary design efforts, diverting resources away from truly innovative and effective policy interventions. Taken together, these factors create conditions that may reduce the proposed positive effects of S3. Therefore, it becomes necessary to gain a deeper understanding of the practical manifestations of such mimicry and assess whether they are a significant cause for concern.

2.2. Exploring potential forms of mimicry in S3

The presence of incentives for regions to mimic the strategies of others prompts an examination of the different forms this mimicry can take. In the context of the development of S3, we propose two basic categories, together with a priority selection strategy, to illustrate the variety of approaches that regions can take in this process. The following section considers the complex nature of smart specialisation and the propensity of regions to combine different strategies.

2.2.1. ‘Follow the Peers’: Mimicry based on proximity and policy alignment

The first category of mimicry, referred to as ‘Follow the Peers’, involves regions developing their strategies by drawing inspiration from a reference group. This reference group can be defined based on spatial proximity, such as geographical neighbours, or economic proximity, where peer regions have similarities in terms of economic activities. In addition, the ‘Follow the Peers’ approach extends to considering the national context. National strategies, often based on comprehensive data analyses, expert consultations and accumulated best practices, often serve as critical reference points for regional strategies. Regions may mimic these strategies not necessarily due to direct structural similarities, but because of the guidance and familiarity they offer. National strategies often represent aggregated insights that transcend individual regional contexts, offering a form of mutual influence that is rooted in policy alignment rather than direct economic or geographical proximity.

This inclination towards adopting priorities chosen by similar peers is not merely coincidental; it is underpinned by the understanding that similar regional governments often confront comparable types of problems, as argued by Shipan & Volden (2012) and Holzinger & Knill (2005). Holzinger & Knill (2005, p. 786) aptly describe this phenomenon, namely that "*there is nothing too mysterious about a crowd of strangers all deciding to put up their umbrellas simultaneously as rain begins to fall.*" In the context of regional EDP, this analogy suggests that while the 'umbrellas'—or strategic priorities—may be tailored to each region's unique characteristics, the convergence on similar priorities is likely due to limited choice sets, analogous economic structures, and limited selection capabilities.

This category reflects what many might consider the typical form of mimicry: "simply peeking over the fence" to see what your neighbours are doing or following the lead or direction set by national-level policies (Borrás, 2011; Asheim, 2019; Deegan et al., 2021; Di Cataldo, Monastiriotis & Rodríguez-Pose, 2020; Prognos, 2021). It is grounded in insights from Marsh & Sharman (2009) and Bellini et al. (2021), who emphasize the role of geographic proximity in policy adoption, and Diemer et al. (2022), who stress the importance of regions recognizing their unique traits while also considering the broader national context in strategic planning.

2.2.2. 'Follow the Role Models': Mimicking influential models

In this approach, we explore mimetic strategies, whereby regions emulate not only proven or successful role models, but also those that are popular or widely adopted, regardless of their actual relevance. This approach highlights the broader dynamics of influencing policymaking, where regions may choose their benchmarks based on factors other than proximity, such as perceived success or widespread adoption of certain strategies.

The notion of a 'role model' traditionally refers to an exemplary entity – a region, strategy or policy – that others seek to emulate because of its demonstrated success or effectiveness. However, in the context of regional development and smart specialisation strategies, the concept of a role model goes beyond mere effectiveness. It also encompasses those models that, while perhaps not the most relevant in every context, have achieved a significant level of popularity or adoption within the policy-making community.

Regions may opt for this mimetic approach because it provides a convenient and resource-efficient solution to select priorities. They can choose priorities that have been commonly chosen by others in the past, as this requires minimal effort and is perceived to offer a high chance of success in obtaining the desired resources. By following successful role models, regions can easily access information about their choices that is well disseminated in the policy realm.

Moreover, this approach is appealing because of the perceived consistency with previous successes and the notion of *'wisdom of the crowd.'* Priorities that have previously proven successful are considered 'good' strategies, and those that are widely adopted by many regions are seen as indicative of what the European Commission favours, potentially unlocking additional funding opportunities in the future. As such, this form of mimicry involves a 'crowd' element, where regions adopt priorities that are popular and widely believed to align with future funding prospects.

However, this mimetic approach may prove detrimental to the effectiveness of S3, as it often overlooks the unique characteristics of individual regions. Rather than fostering regional specialisation and innovation, this approach risks perpetuating homogeneity and stifling the transformative potential that smart specialisation seeks to achieve. As Foray (2015, p. 11) argues, the essence of smart specialisation lies in encouraging regions to differentiate themselves by fostering new exploration and research activities related to existing productive structures, thus enabling transformative growth.

2.2.3. Data-informed priority choices: 'Follow the Indicators' approach

Unlike the two approaches outlined above, a third approach resembles an indicator-driven decision-making strategy. Regions following this approach will seek to identify ex-ante potential indicators used in the evaluation of strategies and opt for priorities that are likely to maximize these indicators. Hence, in contrast to the other approaches, in this case, decisions are made based on empirical evaluation rather than the exploratory method advocated by the policy. We term it the 'Follow the Indicators' approach.

In the context of smart specialization, the most prominent empirical translation aligns well with the previously discussed related diversification approach. That is, regions will identify priorities based on employment information focusing on sectors in which they are not yet specialized but that are highly related to their existing specialisations and that involve complex activities (see Balland et al., 2019).

This approach can align with the policy's intention when the empirical indicators accurately reflect the intended policy goals and, consequently, allow regions to play to their strengths.

However, it also bears two dangers. Firstly, the empirical indicators chosen by regions (or even those communicated by policymakers) may, in reality, not sufficiently align with policy intentions. Such situations are quite likely given the sparsity of available data sources and the complexities of contemporary policies. Secondly, the approach makes policy implementation subject to Goodhart's law, which postulates that *"when a measure becomes a target, it ceases to be a good measure"* (Oxford Reference, 2024). In the smart specialization context, these rationales might lead to: a) regions overemphasizing their strategies on existing strengths (for example, in terms of current employment levels) at the expense of less quantifiable targets such as future growth opportunities and b) choices of domains that are known to maximize the target indicators (e.g., employment growth) but not necessarily the goals desired by policy, e.g., development of sustainable and unique competitive advantages.

'Follow the Indicators' does not in itself constitute a form of mimicry, but it serves as a complimentary policy approach in the setting of this paper. It offers insights into what regions would likely do when they use regional data and the related diversification approach to make prioritization decisions.

3. Empirical strategy

In this section, we explore the empirical data on European regions' priority choices and our methodology for identifying mimicry. Most importantly, we lack insight into the selection process itself and instead must focus on evaluating the observed results. We utilise data from European territories that submitted S3 documents to the Smart Specialisation platform of JRC. Our dataset comprises 169 strategy documents published since January 2013[1], categorized as follows: 14 at the national level, 22 at NUTS1 level, 109 at NUTS2 level, and 24 at NUTS3 level. The regional specialisations in each document have been assigned by the JRC to 82 economic domains according to Eurostat's NACE Rev. 2.0 industry classification, which ensures the coherence of the process (Di Cataldo *et al.*, 2020).

Figure 1 shows the publication dates of these documents. The analysis shows that European regions published strategies at different times, with no clear spatial pattern in publication dates. It is worth noting that regions publishing strategies between 2014, and March 2019 cover most

[1] We searched for documents on the platform and territorial authority websites respectively. We excluded economic strategies, development plans, and strategies introduced before 2013 (eight from September 2010 to June 2012) as they did not accurately reflect the concept of smart specialization.

countries, with exceptions such as Ireland, Hungary, Moldova, Slovenia and the Baltic republics. While the bulk of such regions are in Eastern and South-Eastern Europe, Sweden and Finland, no distinct patterns within countries emerge.

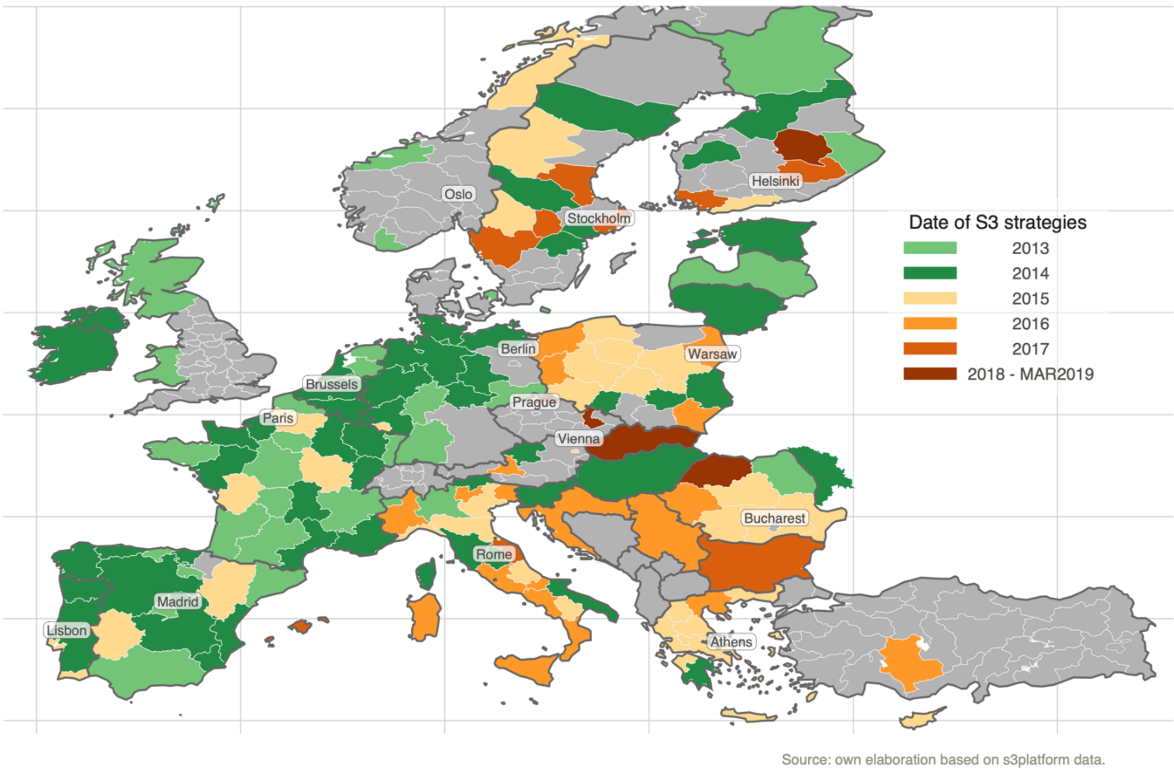

Figure 1. Publishing date of the S3.

Figure 1 illustrates the different publication periods of strategies and thus highlights the numerous opportunities available to regions to mimic economic domains from previously issued documents. Figure 1 also serves to illustrate the spatial patterns of our analysis, where we generally consider strategies at NUTS2 or NUTS3 level (if the S3 has been implemented at this level, as in the case of the Czech Republic, Finland, Norway, and Sweden) or at NUTS1 level (as in the case of Germany and Belgium). In addition, we adopted the national level (NUTS0) for countries that have only one NUTS2 region or there were no strategies available at regional level (such as Bulgaria, Hungary, Ireland, and Slovakia).

3.1. Approximating priority selection strategy and mimicry types

Our empirical strategy is designed to approximate the 'Follow the Indicators' and two types of mimicry models using variables that reflect real specializations or selected domains[2] in a focal region and other regions. All models are based on measures described below. All calculations were performed using R, particularly relying on the *EconGeo* package developed by Balland (2017).

3.1.1. Measures for the 'Follow the Indicators' priority selection strategy

The 'Follow the Indicators' approach evaluates how regions prioritize their domains based on existing specializations and relatedness density, employing two primary measures. The first measure assesses whether a domain i is an existing specialization in region r. This is quantified using the Location Quotient (LQ) indicator, represented as a binary variable. If the LQ for domain i in region r exceeds 1, the binary variable takes a value of 1; otherwise, it is 0. We calculate the LQs for all domains i in all regions at the time their strategies were issued. Although 82 economic domains were identified in the regions' S3, employment data from the Eurostat database is available for only 67 domains[3]. Consequently, our analysis focuses on these 67 domains. LQs are calculated separately for each NUTS level to ensure comparability.

The second measure evaluates the relatedness density of a domain i at time t when S3 was published, in relation to the region's overall specialization portfolio (Balland *et al.*, 2019). Relatedness density measures the proximity of domain i to other specializations in region r, for which the LQ is greater than 1. This is calculated using the sum of the relatedness of specialization i (measured by employment) to other specializations in region r at time t, divided by the sum of relatedness of specialization i to all other specializations in all regions at the corresponding NUTS level in Europe at time t. The formula for relatedness density is given by:

[2] It is important to note that the 'domains' referred to in this study, which correspond to codes from Eurostat's NACE Rev. 2.0, are not directly chosen by regional policymakers but are assigned by the JRC based on their interpretation of the S3 documents; this assignment carries a low risk of not fully matching the domains explicitly indicated in the S3 strategies.

[3] The missing data spans sections A (Agriculture, forestry, and fishing), K (Financial and insurance activities), O (Public administration), P (Education), Q (Human health and social work activities), R (Arts, entertainment, and recreation), and other services (sections S, T, and U).

$$RD_{irt} = \frac{\sum_{j \in r, j \neq i} \phi_{ijt}}{\sum_{j \neq i} \phi_{ijt}} \times 100\% \tag{1}$$

Here, ϕ_{ijt} represents the relatedness between a pair of specialisations i and j in time t computed as the minimum of the pairwise conditional probabilities of regions having specialisation in one economic domain i, given they have specialisation in another domain j during the same year (Hidalgo *et al.*, 2007). Relatedness matrix between N specialisations in domains is expressed mathematically as:

$$\mathbf{S} = (\mathbf{A}^T \cdot \mathbf{A}) \odot \mathbf{B} \tag{2}$$

Here, **S** is a square matrix of size N with an indeterminate diagonal (since similarity between specialisations in the same domain cannot be determined). **A** is a matrix of size $R \times N$, where R is the number of regions from a given NUTS level. The element $a_{ri} = 1$ if region r has a specialisation in domain i ($LQ_{ri} > 1$) and 0 otherwise. The symbol $\odot$ denotes an element-wise product of matrices. **B** is the matrix of the inverse of the maximum of the number of occurrences of the specialisation in domain i and the number of occurrences of the specialisation in domain j across all regions, ensuring the calculation of the minimum probability:

$$b_{ij} = \left[\max\left(\sum_{r=1}^{R} a_{ri}, \sum_{r=1}^{R} a_{rj}\right)\right]^{-1} \tag{3}$$

3.1.2. Measures for the 'Follow the Peers' mimicry model

Regions that adopt the 'Follow the Peers' mimicry strategy typically base their specialization choices on the economic activities of neighbouring regions or those selected earlier by these regions. Additionally, regions might align their domains with those prioritized in their national S3 before developing their regional strategies.

To determine the optimal number of nearest neighbours (NN) influencing these indicators, we compared models using the Akaike Information Criterion (AIC). We began with $k = 0$ NN, fitting a model without neighbour influence variables, which yielded an AIC of 9,732. We then incrementally increased the number of NN up to $k = 8$, observing a gradual improvement in the AIC. Our analysis identified the best fit at $k = 4$ NN, resulting in an AIC of 8,901. Consequently, the model incorporating four nearest neighbours will be presented in the findings section.

To capture this mimicry behaviour, we employ three indicators. The first indicator is maximum proximity to specializations of neighbouring regions. This indicator assesses how closely a region's specializations align with those of its neighbours. It is based on the relatedness density metric outlined in Equation 1 but focuses on the maximum proximity of domain i to the specialization portfolios of neighboring regions. This metric indicates whether a region r is attempting to harmonize its specialization portfolio with that of its neighbours, reflecting either intentional mimicry or inherent economic similarities among adjacent regions. This measure is calculated as follows:

$$MP_{ir} = \max_{n \in NN(r)} RD_{in} \tag{4}$$

where MP_{ir} is the maximum proximity of domain i in region r to its neighbouring regions' specializations, n represents each neighbouring region, and $NN(r)$ denotes the set of nearest neighbours to region r.

The second indicator reflects the proportion of neighbouring regions selecting the same domain. This indicator measures the popularity of a domain i among neighbouring regions by calculating the proportion of these regions that have already selected domain i as a priority in their S3. This measure, referred to as a 'buzzing domain,' captures the extent to which regional decision-makers are influenced by the choices made by their geographical peers. It is calculated as:

$$BUZZ_{NN_{it_r}} = \frac{\sum_{n \in NN(t_r)} d_{in}}{|NN(t_r)|} \times 100\% \tag{5}$$

where $BUZZ_{NN_{it_r}}$ is the proportion of neighbouring regions that have selected domain i before time t_r (i.e. when S3 of region r was published), d_{in} equals 1 if domain i was selected by neighbouring region n before t_r, and 0 otherwise. $|NN(t_r)|$ represents the total number of neighbouring regions that published S3 before t_r.

The third indicator illustrates domain choice in the national S3. This indicator reflects whether domain i was selected in the national S3 published prior to the regional S3. This measure is particularly relevant in countries where the national strategy sets a precedent for regional strategies. However, this indicator has fewer observations because it only includes regions in countries that published national S3 before the regional S3 were released. By this we must separate the model for regional and national contexts when presenting it in the results section. This indicator is given by the Equation:

$$NS_{ir} = \begin{cases} 1 \; if \; domain \; i \; is \; in \; the \; national \; S3 \\ 0 \; otherwise \end{cases} \tag{6}$$

3.1.3. Measures for the 'Follow the Role Models' mimicry model

The 'Follow the Role Models' mimicry model captures how regions may adopt strategic priorities based on the influence of successful or popular choices made by other regions. To quantify this behaviour, we use two primary indicators. The first indicator assesses how closely a region's selected domains align with popular domain portfolios, while the second indicator measures the overall popularity of a domain across all regions (except peers included in 'Follow the Peers' approach). These measures provide insights into how regions may be influenced by successful role models and contemporary policy trends.

Relatedness density of selected domains (RD_{ir}^{sel}) measures how well a selected domain i by region r fits into the portfolio of domains chosen by other regions (analogously to Balland *et al.*, 2019). It is calculated similarly to the relatedness density metric RD_{irt}, but focuses specifically on the domains that have been selected:

$$RD_{ir}^{sel} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}^{sel}}{\sum_{j \neq i} \phi_{ij}^{sel}} \times 100\% \tag{7}$$

Here, ϕ_{ij}^{sel} represents the relatedness between a pair of selected domains i and j, i.e., the minimum pairwise probabilities that domain i was selected by the regions conditional on domain j also being selected by the regions (Hidalgo *et al.*, 2007). The numerator sums the relatedness of domain i to other selected domains j within region r, while the denominator sums the relatedness of domain i to all other selected domains across all regions. This indicator equals one when region r has selected all domains with which domain i commonly co-occurs in other S3. High values of RD_{ir}^{sel} indicate that the selection process is highly aligned with common choices, suggesting less uniqueness and more conformity to popular domain portfolios. Low values suggest a more unique selection process.

The second indicator reflects the overall popularity of domain i based on its selection frequency in previously issued S3. It is analogous to the $BUZZ_{NN_{ir}}$ measure used in the 'Follow the Peers' model but considers other regions in addition to peers, thus complementing that approach:

$$BUZZ_{it_r} = \frac{\sum_{r \in R_{t_r}} d_{ir}}{R_{t_r}} \times 100\% \tag{8}$$

Here, $BUZZ_{it_r}$ is the proportion of regions that have selected domain i as a priority before t_r. d_{ir} equals 1 if domain i is selected by region r (which is not a neighbouring region or its country) and 0 otherwise. R_{t_r} is the total number of regions that published S3 before t_r. This measure indicates the extent to which a domain i has become a popular choice across all regions, serving as an indicator of the 'wisdom of the crowd.'

3.2. Empirical models to test the types of mimicry

In the empirical model, we aim to explain the selection of specific priority domains in S3 by using the indicators of mimicry defined in the previous section, along with a range of control variables. Specifically, we investigate which types of mimicry are significantly associated with the likelihood of a region r selecting an economic domain i. Our observations are N domain–regions, and to account for potential unobserved heterogeneity across regions and the hierarchical nature of the data (with multiple observations per region), we employ a Generalized Linear Mixed Model (GLMM) with a logit link function.

The GLMM framework allows us to handle the correlated nature of the data by incorporating random effects. These random effects capture differences in mimicry behaviour among regions (nested within countries) and domains that may not be fully explained by the observed variables. We chose random effects over fixed effects because not all countries, regions, and domains are included in the analysis, and random effects are better suited for capturing the variability within this context. The model specifications for the priority selection strategy model and the two types of mimicry (separately and together) are as follows:

$$logit(E[DS_{ir}|\mathbf{\Delta},\mathbf{Z}]) = \mathbf{FollowIndic}\,\beta_1 + \mathbf{\Gamma}\gamma + \mathbf{\Delta}\delta + \mathbf{Z}\zeta + \varepsilon \tag{9}$$

$$logit(E[DS_{ir}|\mathbf{\Delta},\mathbf{Z}]) = \mathbf{FollowIndic}\,\beta_1 + \mathbf{FollowPeers}\,\beta_2 + \mathbf{\Gamma}\gamma + \mathbf{\Delta}\delta + \mathbf{Z}\zeta + \varepsilon \tag{10}$$

$$logit(E[DS_{ir}|\mathbf{\Delta},\mathbf{Z}]) = \mathbf{FollowIndic}\,\beta_1 + \mathbf{FollowModels}\,\beta_3 + \mathbf{\Gamma}\gamma + \mathbf{\Delta}\delta + \mathbf{Z}\zeta + \varepsilon \tag{11}$$

$$logit(E[DS_{ir}|\mathbf{\Delta},\mathbf{Z}]) = \mathbf{FollowIndic}\,\beta_1 + \mathbf{FollowPeers}\,\beta_2 + \mathbf{FollowModels}\,\beta_3 + \mathbf{\Gamma}\gamma + \mathbf{\Delta}\delta + \mathbf{Z}\zeta + \varepsilon \tag{12}$$

Here, our dependent variable (DS_{ir}) is equal to 1 if region r has selected a domain i and 0 otherwise; $\mathbf{FollowIndic}$ denotes a $N \times 2$ matrix representing the 'Follow the Indicators' model described in Section 3.1.1, thus it is present in both specifications. $\mathbf{FollowPeers}$ and $\mathbf{FollowModels}$ are the matrices representing two mimicry types, 'Follow the Peers' described in Section 3.1.2 and 'Follow the Role Models' described in Section 3.1.3, respectively.

In the model equations, $\mathbf{\Gamma}$ and γ represent the fixed effects design matrix, and fixed effects, respectively, reflecting the political and economic context of region r. We use the measure of Quality of Government (QoG) (Crescenzi *et al.*, 2016; Rodríguez-Pose & Di Cataldo, 2015; Rodriguez-Pose & Garcilazo, 2015) at the time of S3 publication. Other control variables, following Di Cataldo et al. (2020) and Deegan et al. (2021), include agglomeration (population density), economic performance (GDP per capita growth and unemployment rates), and technological capabilities (patent applications per million inhabitants). $\mathbf{\Delta}$ and δ are the random effects design matrix and random effects, respectively, of economic domains; $\mathbf{Z}$ and ζ are the random effects design matrix and random effects, respectively, of regions; ε is the column vector of residuals. Descriptive statistics and a correlation matrix may be found in Tables A.1 and A.2 respectively in the supplemental data online.

In the results section, we present six models: Model (1) represents the 'Follow the Indicators' model (Equation 9), Models (2) and (3) refer to 'Follow the Peers' mimicry (Equation 10) separated by regional and country context, while Models (4) and (5) refer to 'Follow the Role Models' mimicry (Equation 11) divided by two measures. Model (6) combines both types of mimicry (Equation 12).

4. Results

Our primary findings address which types of mimicry influence the selection of domains in S3 according to Equations 9–11. The results are summarized in Table 1. All mimicry Models (2–6) achieve a lower Akaike Information Criterion (AIC) than the 'Follow the Indicators' Model (1) and the null Model (see Table A.3 in the supplemental data online), indicating their relevance. Additionally, the relatively low intraclass correlation (ICC) is lower than 0.4 in the models (except Model (4) with an ICC of 0.67) suggests that the group membership (domain, country, and region) has less impact on domain choice, allowing more emphasis on fixed effects. However, the relatively high variability in the intercepts between different domains (τ_{00}) implies that the baseline probability of domain selection varies significantly across domains, suggesting that domain-specific factors or inherent differences between domains play an important role in the selection process.

Predictors	Model (1) *Odds Ratios*	Model (2) *Odds Ratios*	Model (3) *Odds Ratios*	Model (4) *Odds Ratios*	Model (5) *Odds Ratios*	Model (6) *Odds Ratios*
'Follow the Indicators'						
Region has specialisation (LQ > 1) in a particular domain (dummy variable)	1.790 *** (0.109)	1.829 *** (0.116)	2.382 *** (0.296)	1.812 *** (0.128)	1.808 *** (0.111)	1.884 *** (0.138)
Proximity (relatedness density) to region's portfolio of specialisations	1.050 *** (0.006)	1.045 *** (0.006)	1.044 *** (0.010)	1.023 ** (0.007)	1.052 *** (0.006)	1.027 *** (0.008)
'Follow the Peers'						
Maximum proximity (relatedness density) to neighbours' portfolio of specialisations		1.000 (0.006)				0.990 (0.007)
Proportion of neighbours that have previously chosen a domain		1.021 *** (0.002)				1.016 *** (0.002)
A domain was selected in national S3 strategy			1.538 ** (0.275)			
'Follow the Role Models'						
Proximity (relatedness density) to a portfolio of domains selected by region				1.259 *** (0.013)		1.239 *** (0.014)
Proportion of all the regions (except peers) that have previously chosen a domain					1.070 (0.106)	1.097 (0.118)
Controls						
Population density	0.830 ** (0.066)	0.932 (0.114)	0.869 (0.079)	1.571 ** (0.270)	0.816 ** (0.065)	1.461 (0.387)
GPD per capita	1.297 ** (0.157)	1.201 (0.154)	1.078 (0.257)	0.357 *** (0.111)	1.393 ** (0.172)	0.334 *** (0.118)
Unemployment rate	1.311 ** (0.144)	1.309 ** (0.137)	1.233 (0.240)	0.659 * (0.149)	1.335 ** (0.145)	0.667 * (0.135)
Number of patents per capita	0.992 (0.108)	1.032 (0.114)	1.651 (0.598)	1.256 (0.273)	0.986 (0.107)	1.275 (0.244)
Quality of Government Index	1.000 (0.147)	1.036 (0.149)	0.607 (0.250)	1.484 (0.438)	0.994 (0.145)	1.657 * (0.455)
Intercept	0.030 *** (0.009)	0.030 *** (0.010)	0.026 *** (0.012)	0.000 *** (0.000)	0.029 *** (0.008)	0.000 *** (0.000)
Random Effects						
σ^2	3.29	3.29	3.29	3.29	3.29	3.29
τ_{00} (region:country)	0.51	0.56	0.26	2.14	0.52	1.46
τ_{00} (domain)	1.62	1.29	1.32	3.00	1.52	2.27
τ_{00} (country)	0.31	0.15	0.34	1.46	0.28	1.16
ICC	0.43	0.38	0.37	0.67	0.41	0.60
N (region)	155	143	46	149	154	138
N (country)	27	25	7	21	27	20
N (domain)	67	67	67	67	67	67
Observations	10,921	10,117	3,082	10,480	10,787	9,697
Marginal R^2 / Conditional R^2	0.061 / 0.460	0.079 / 0.427	0.111 / 0.439	0.501 / 0.834	0.068 / 0.454	0.483 / 0.792
Deviance	9,710.802	8,874.754	2,777.498	7,647.253	9,575.625	7,073.550
AIC	9,732.802	8,900.754	2,801.498	7,671.253	9,599.625	7,103.550
Log-Likelihood	–4,855.401	–4,437.377	–1,388.749	–3,823.626	–4,787.812	–3,536.775

Note: * p<0.1 ** p<0.05 *** p<0.001. The actual number of observations is lower than the number of regions and the number of domains multiplied. This is because not all regions provided data on specialisation as measured by employment in each domain.

Table 1. Analysis of mimicry patterns in smart specialisation strategies using Generalized Linear Mixed Model with logit link function.

Table 1 indicates that regions tend to consider their existing strengths when selecting domains in S3. It shows in all models (1–6) that having a specialization (LQ > 1) in a particular domain increases the odds of it being selected in S3 by approximately 79%. This clearly suggests that regions are making informed decisions when creating strategy documents.

Supporting the ‘Follow the Indicators’ approach, relatedness density, is identified as being significant. A 1% increase in the relatedness density of a domain to a region's overall specialization portfolio results in a 5% increase in the odds of that domain being selected. While this may seem modest in comparison to other variables’ effects, Figure 2 panel (a) shows that the increase in the odds of choosing a domain spreads considerably from almost 5% to 65% depending on the value of proximity to the region's portfolio of specialisations, which varies from 5.9% to 85.5%.

According to the ‘Follow the Peers’ mimicry type, regions are more inclined to select domains that neighbouring regions have previously chosen. We tested this in Table 1 Model (2). We don’t find a relationship between a region’s probability of selecting a domain and the proximity of this domain (relatedness density) to neighbours’ portfolio of specializations. In other words, regions don’t seem to select priorities in alignment with the industrial structure of their geographical neighbours.

In contrast, we find a significant coefficient for the proportion of neighbours previously chosen a domain. It means that independently of potential similarity in industrial structures, regions mimic (past) domain choices of their geographical neighbours. More precisely, the probability of selecting a domain when all neighbours have chosen it is more than 50%, as illustrated in Figure 2 panel (b). However, most regions do not have neighbours who have previously chosen a domain, therefore this effect is more hypothetical and has relatively little impact.

Another form of this mimicry type is shown in the significance of the coefficient for whether a domain is part of the priority portfolio of the corresponding national S3 strategy. Including a domain in a national strategy published before the regional S3 significantly increases the odds of regions considering this in their own selection (Table 1 Model (3)). However, the chances of selecting such a domain increase by only 0.4%, which is approximately one-tenth of the effect of a domain being part of a neighbouring region’s portfolio of priorities. Hence, mimicry of national strategies by regions seems to exist, but only to a limited degree.

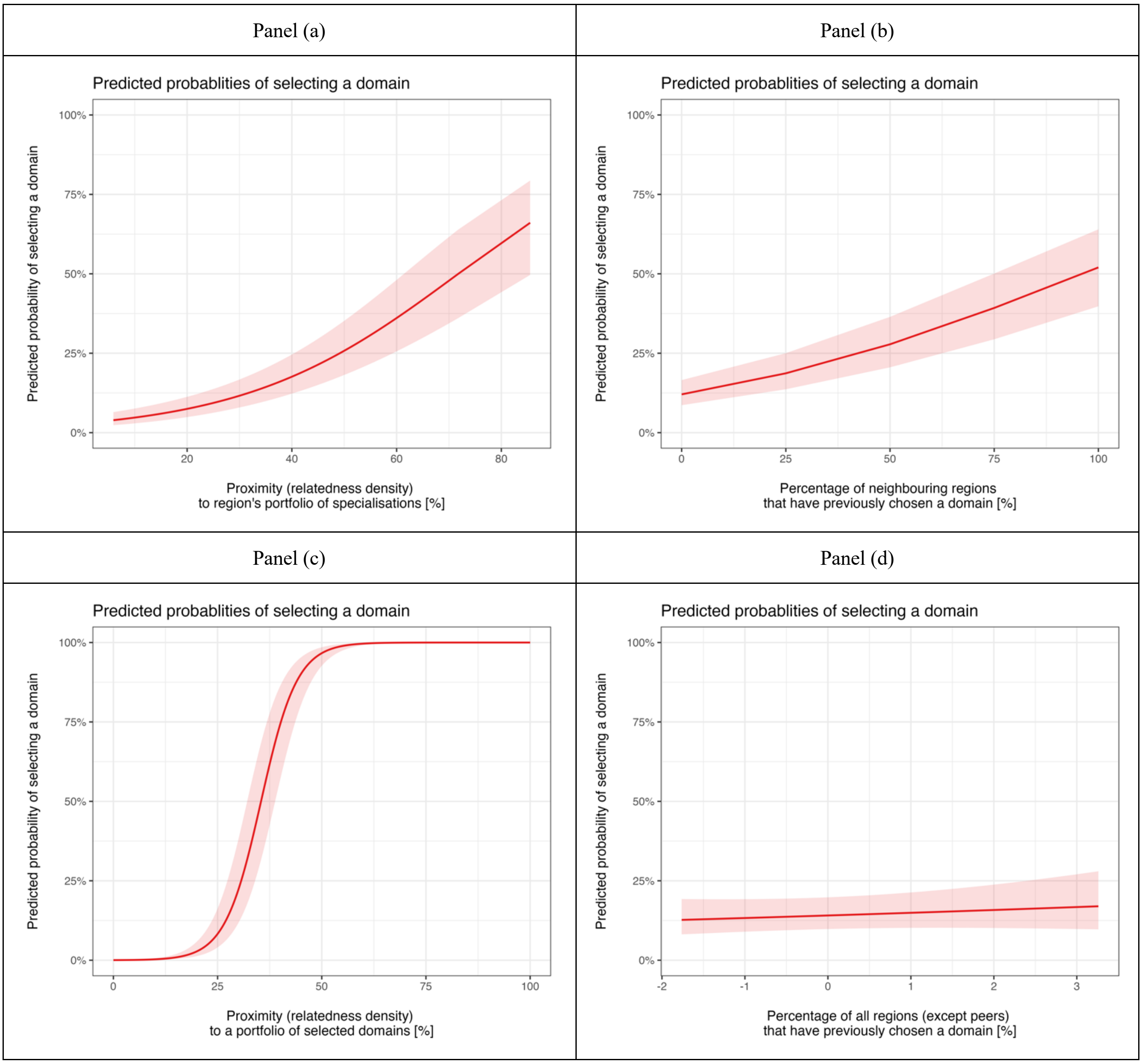

Figure 2. Predicted probability of selecting a domain based on various factors

Note: Panels show the predicted values (marginal effects) from the GLMM for specific model terms: (a) proximity (relatedness density) to region's portfolio of specializations [%]; (b) Percentage of neighbouring regions that have previously chosen a domain [%]; (c) Proximity (relatedness density) to a portfolio of selected domains [%]; (d) Percentage of all regions (except peers) that have previously chosen a domain [%].

Confirmatory results are also obtained for the 'Follow the Role Models' mimicry type (Table 1 Model (4)). In general, a 1% increase in the relatedness density of a domain to the portfolio of domains selected by other regions increases the chances of that domain being selected by

26%. This is the strongest effect among all models[4], as reflected by the highest marginal R^2. Regions rarely select domains that have not been chosen by other regions or only by a few. Figure 2 panel (c) shows the marginal effect of this variable. Up to the median value of this variable (21%), the predicted probability of selecting a domain is almost zero, indicating regions absolutely avoid niche, unique domains and those highly unrelated to frequently selected domains. For higher probability levels, the graph rises sharply, resulting in almost a 100% chance of selecting a particular domain for values above 50%, i.e., when its selected domains include at least 50% of highly related domains. However, such high values are extremely rare, with the third quartile starting at 30% and the last decile at 40.2%.

The final measure of this mimicry type indicates that regions are unlikely to select domains that were previously chosen as priorities by other than peer regions. While the relatedness density shows the proximity of a domain to other selected domains without directly indicating its selection, this measure focuses on the general attractiveness of a specific domain as expressed in the frequency with which it has been selected. High values of this variable may represent 'buzzing domains.' As Table 1 Model (5) shows, this effect is negligible, as the proportion of all the regions (except peers) that have previously chosen a domain is not statistically significant.

5. Discussion and conclusion

There has been considerable scholarly attention on which regions select which domains as priorities in the context of smart specialisation strategies (S3). From a theoretical perspective, Marrocu et al. (2020) suggest that regions should identify areas where they can develop a competitive advantage within their S3 strategies. Embedding smart specialisation within their current economic profiles can maximize synergies (Balland et al., 2019; Pylak and Warowny, 2021). Additionally, regions should target complex activities that are difficult for others to replicate (Deegan, et al., 2021). However, Di Cataldo et al. (2020) found that smart specialisation domains are often broad, multidimensional, and not well targeted, often

[4] The potential interdependence of DS_{ir} and RD_{ir}^{sel} in terms of their structure may cause some doubt. However, the moderate correlation between them (0.43, $p < 0.001$) suggests that it is a significant predictor without overwhelming the dependent variable, and the low variance inflation factor (VIF) = 1.13 supports its inclusion without risk of multicollinearity. Therefore, RD_{ir}^{sel} rather measures the fit of the selected domain in the context of regional portfolios, which is a significant and theoretically sound reason for its inclusion.

reflecting a mimicry of neighbouring regions' strategies rather than unique regional strengths. Consequently, the evidence is mixed regarding the effectiveness of these selections (Di Cataldo et al., 2020; Deegan et al., 2021; Pylak and Warowny, 2021; Gianelle, Guzzo, and Mieszkowski, 2020).

This paper explored a specific element of the domain selection in S3: mimicry. Specifically, we focused on two types of mimicry: 'Follow the Peers,' where regions choose priorities based on similarities with geographically or economically close regions and 'Follow the Role Models,' focusing on decisions influenced by regions acting as role models and popular choices of specializations. These two types were complemented by the 'Follow the Indicators' approach, highlighting reliance on empirical data for selecting priorities that align with empirical indicators (specialization and relatedness) associated with 'smart' domain selection.

Our analysis indicates that regions use a mix of these approaches to construct their S3 portfolios, however, their impact varies significantly in terms of magnitude and context. Notably, 'Follow the Role Models' demonstrates the most significant impact, where a 1% increase in relatedness density to other domains selected frequently corresponds to a 26% increase in the likelihood of domain selection. This highlights the strong influence of popular domains on regional decisions.

Conversely, the 'Follow the Peers' approach, while significant, demonstrates less explanatory power and reveals a more complex relationship. Regions tend to follow the domain choices of neighbouring regions; however, this type of mimicry is empirically less pronounced and harder to identify due to the limited number of cases where regions could have exhibited such behaviour. The 'Follow the Indicators' approach also plays a role, with a modest explanatory power suggesting that regions' strategic choices align with relevant empirical indicators (industrial relatedness and specialization) and that these indicators may have informed their choices in the first place. As a result, a good chunk of selected domains represents activities that are related to existing industrial competences in regions. Consequently, some parts of the domain selection process led to results supporting S3, further confirming the findings of Deegan et al. (2021).

However, mimicking successful role models and following broad policy consensus seem to be strong forces as well. These represent a tendency towards risk aversion and a preference for proven strategies. The evidence supporting the 'Follow the Peers' approach highlights the substantial similarity between domain choices of peer regions, which suggests that following peers is a strong mechanism shaping domain choices. Yet, the ‘Follow the Role Models’ approach, which incorporates inspiration from successful role models or broader policy consensus, demonstrated the most significant explanatory power regarding domain selection. Regions clearly tend to mimic domain portfolios that enjoy broad acceptance or proven success, avoiding niche selections that might require more resources or present higher risks.

This behaviour captures a realistic aspect of regional decision-making processes, where regions predominantly mimic others rather than making independent strategic choices. While this is a valid observation, it is crucial to contextualize it within the broader goals and implications of S3. The strong predictive power of this mimicry type should be interpreted carefully to understand its broader implications for regional strategies and policy recommendations. By recognizing these patterns, policymakers can better balance the benefits of proven strategies with the need for diversification and innovation in regional development.

In any case, our analysis revealed a complex landscape of decision-making, where regions utilize a combination of data analysis, peer influence, and broader sectoral trends to inform their S3. While proximity and the historical success of certain domains influence these decisions, the overarching trend is towards a broader integration of various types of information, including empirical data and peer strategies, to guide domain selection.

Turning then to what this means for policymakers, our research highlights the importance of a strategic approach to domain selection. To maximise the benefits from shared domains and avoid misdirected resources and unnecessary duplication, it is essential that policymakers provide adequate resources to support the place-based identification of relevant and suitable priorities. Regions may struggle in identifying relevant priorities due to limited capacity and a lack of the necessary competence, which can lead to mimicry.

By strengthening the mechanisms of selection and relying on a ‘Follow the Indicators’ approach, policymakers can mitigate some of these challenges. This approach avoids the drawbacks of mimicry. It is important for policymakers to design targeted policy interventions by assessing the potential for diversification, specialisation, and the emergence of new economic activities.

Policymakers should also highlight the importance of contextually appropriate strategies. Tailoring interventions to the unique circumstances of each region, including its economic structure, capabilities, and knowledge base, will ensure more effective interventions.

There are several limitations of the study. The analysis in this study heavily relies on the availability and quality of S3 documents. Also, it is important to note that the accuracy and completeness of these documents may vary across different regions, which could introduce biases or limitations in the analysis. The findings of this study are specific to the period examined (2014–2020) and the selected set of regions. Therefore, caution should be exercised when generalizing these findings to other time periods or regions with different socioeconomic characteristics or policy contexts. The unique context of each region should be considered when interpreting and applying the results.

Moreover, the operationalization of mimicry in this study relies on specific indicators and assumptions. While efforts were made to capture different dimensions of mimicry, it is possible that there are other aspects or nuances that are not fully captured by the selected indicators. The same applies to the measurement of mimicry, which may not capture all relevant nuances and is limited by the available data. For instance, the empirically observed dominance of the 'Follow the Role Models' approach could be due to a more technical reason: the limited number of selections, i.e., 82 domains, may restrict the diversity of choices available to regions, prompting them to emulate portfolios that have demonstrated success.

Hence, some caution must be exercised when interpreting the study's findings. The relationship between variables might also be influenced by other factors not included in the analysis, such as other economic policies. Hence, our findings provide insights into the nature of mimicry in the selection of smart specialization domains, but a comprehensive understanding of such processes in a wider policy context requires further research and analysis.

Future research on mimicry could explore several interesting avenues. Extending the analysis of non-deliberate mimicry regressors to more refined mechanisms of path dependence, such as the regional branching approach, could be valuable. This involves examining how regions' historical development trajectories, institutional settings, and other contextual factors influence the selection of economic priorities. By incorporating additional dimensions of path dependence, researchers could better understand the mechanisms driving economic priority selection and mimicry patterns across regions.

Another potential avenue for future research is to investigate whether the mimicry results for economic domains hold true for scientific domains and policy goals reported in S3. This would involve analysing the extent and nature of mimicry in areas such as research and innovation activities, scientific collaboration, and policy objectives related to social, environmental, or technological aspects. By examining mimicry patterns across different domains and policy goals, researchers could provide a more comprehensive assessment of the role of mimicry in shaping regional strategies and their outcomes.

A broad avenue is available in conducting comparative analyses across different countries or regions that could provide valuable insights into the variations in mimicry patterns and the factors driving them. By comparing regions (qualitatively or quantitatively) with diverse socioeconomic characteristics, institutional frameworks, and policy contexts, researchers can identify the contextual factors that influence the prevalence and nature of mimicry in S3. Complementing quantitative analysis with qualitative studies, such as interviews or case studies, can offer a deeper understanding of the motivations, decision-making processes, and mechanisms behind mimicry in S3. Qualitative research can uncover the perspectives of policymakers, stakeholders, and practitioners, providing rich insights into the contextual aspects and processes of mimicry.

Finally, it would be extremely interesting to assess whether regions that engage in mimicry achieve better or worse outcomes in terms of economic growth, innovation, or regional competitiveness. The performance of regions can be examined according to types of mimicry. Such research could inform policymakers about the effects of mimicry processes and guide the design and implementation of smart specialisation policies, facilitating the deliberate dissemination of successful strategies between regions.

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