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**Abstract**

In this paper we explore the impact of place-based innovation policy in Europe. We focus on the effects of Smart Specialisation strategies on the labour productivity of regional economies. We design an analytical framework that takes into account the entrepreneurial discovery process through which the policy is implemented, and connect the technological relatedness of regions with their specialisation choices. We use an IV estimation approach capable of handling endogeneity problems, and apply it to an extensive dataset of 102 NUTS2 regions extracted from the European Commission Smart Specialisation Portal. The results show that Smart Specialisation strategies increase labour productivity as long as the priorities are set in sectors related to pre-existing technological capabilities, indicating the fundamental importance of path-dependency in diversification choices. The findings deepen our understanding of regional development and innovation strategies, and have relevant implications for the implementation of appropriate policy instruments.

**Keywords:** Related diversification; Specialization; Regional policy; Innovation policy; Place-based Policies

**JEL codes:** O33; R11

# Introduction

How do regional economies evolve their industrial structures and areas of relative specialisation? And when regions diversify their activities, what impact should we expect on the performance of local economies? These questions have long been the focus of much research as well as intense policy debate. On the one hand, there are comparative advantages stemming from specialisation, and on the other there are opportunities for Schumpeterian structural change associated with the exploration of new sources of competitive advantage. These two potential drivers of growth often coexist across a number of regional development policy interventions, and it has proved very difficult to identify robust and generalisable solutions. Europe is an interesting case because it has experienced significant change in its policy approaches, and because it contains highly heterogenous institutional and economic contexts on which EU policies apply. In the wake of the Lisbon's agenda, renewed attention was given to the design of place-based development strategies (Rodríguez-Pose and Wilkie, 2019; Barca, 2009). These strategies are thought of as policies adapted to idiosyncratic characteristics of regions which cannot be completely designed and implemented from the top-down. Thus, the third European Union Cohesion Policy cycle (2014-2020) kept as its key target the promotion of sustainable, smart, and inclusive growth across all EU regions, but introduced the principle that in order to obtain policy support, each region had to develop and submit the the EU its own Regional Innovation Strategy. This is the so-called 'Smart Specialisation' strategy of the region (Foray, P. A. David, and B. Hall, 2009).

The premises of the policy rely on the ex-ante identification of the economic strengths and potential of the region, and on the expansion of the growth opportunity set in the direction of new competitive advantage in high-value activities (Boschma, 2014; Deegan, Broekel, and Fitjar, 2021). The regions' potential must be translated into priorities, i.e. into choices about the economic sectors in which each region should invest. The identification of priorities occurs through a bottom-up approach known as the Entrepreneurial Discovery Process (Foray, P. A. David, and B. H. Hall, 2011; Foray, Goddard, and Beldarrain, 2012). This process outlines a path of specialisation or diversification guided by the decision to explore new production possibilities, which should be negotiated with a broad range of entrepreneurial stakeholders, including firms, higher education institutions, research organisations, and independent innovators. Through the Entrepreneurial Discovery Process, regions assess their existing knowledge assets and explore in which complementary and more or less adjacent domains they should expand their technological capabilities (P. David, Foray, and B. Hall, 2009). The process implies that Smart Specialisation cannot be implemented as a "one-size-fits-all" policy (Kroll, 2015) because regions have different past and present industrial structures and technological trajectories. Regions can choose only a limited amount of priorities, and the selection and implementation of Smart Specialisation objectives has not been easy for local policy-makers, especially in regions with poor-quality governance (Aranguren et al., 2019).

An interesting aspect of Smart Specialisation policy is also that, while it was rooted in an economic geography framework (McCann and Ortega-Argilés, 2011; McCann and Ortega-Argilés, 2015; Boschma, 2017), it was developed alongside a growing and variegated stream of literature on the concept of economic 'relatedness' (Content and Frenken, 2016; Boschma, 2017)). By the principle of relatedness regions can diversify into technologies and industries that are contiguous and complementary to their existing capabilities, rather than diversify on a portofolio basis through investments in domains that are unrelated, but potentially profitable given that positive growth outcomes may be observable in other regions (Balland et al., 2019).

To the best of our knowledge, a very limited amount of research focuses on the link between the mechanisms of priorities selection and the performance effects of the policy. In particular, if the priorities that are chosen through the technological relatedness principles translate into a symmetrical and effective evolution of the regional industrial structure. Following this line of inquiry, Bathelt and Storper (2023) points out that relatively little attention has been given to the contexts and mechanisms through which related variety shapes regional economic development. While research efforts on this topic have noticeably accelerated, there is a risk of misalignment between theory, evidence and policy design, if one cannot disentangle the endogeneity of diversification choices from their economic consequences. Doing so requires the development of a framework that can bring together the selection and the development sides of the policy, thus providing at the same time the means to identify the effects of specialisation choices, and in particular the role of relatedness, and the means to measure the economic effect of the policy.

To address this gap in the literature, we build a novel analytical framework that links together technological capabilities, regional industrial structures and economic performance. This approach can have general applicability in the evaluation of place-based innovation policies because it accounts for the ex-ante trajectories of technological and industrial evolution of the region. Moreover, we make a novel empirical contribution by showing whether and how the Smart Specialisation policy has been effective in European regions. We show that regions that operated a place-based selection of priorities outperformed regions that made similar choices unconditionally with respect to their existing capabilities. Moreover, multiple development paths, i.e. paths shaped by very different choices of priorities, have proved effective in the European area.

The paper is organised as follows. In the next section, we provide a concise review of the theoretical foundations of Smart Specialisation. We then describe the data and empirical strategy. Next, we present our findings on regional specialisation decisions and their impact on regional performance. The paper concludes by discussing the implications of Smart Specialisation policies and their development.

## Literature Review

Economic geographers and economists interested in technical change have long argued that both space and history matter in the production, diffusion and use of knowledge (Dosi et al., 1988; Feldman and Kogler, 2010). Moreover, space and history interact deeply with the cognitive dimension of economic activities so that, because of the tacit nature of an important share of productive knowledge (Polanyi, 2012), economic agents absorb and share knowledge in specific local contexts so that local economies can construct comparative advantage by intensifying social (informal) network interactions (Breschi, Lissoni, et al., 2003), investing in knowledge exchanges with universities and research organisations (R. N. Freeman, 1987), and by adapting their institutional frameworks (R. R. Nelson, 1995). Comparative advantages can be built by strengthening existing specialisations or by expanding into new knowledge domains (Foray, P. A. David, and B. H. Hall, 2011). The expansion into new domains can entail different diversification choices depending on the distance of these domains from existing areas of specialisation. The literature on 'related diversification' stresses the idea that there are advantages in diversifying in sectors, technologies, skills, and output with characteristics that are similar or complementary to the ones that already exist in the region (Frenken, Van Oort, and Verburg, 2007; Boschma and Iammarino, 2009). Scholars have identified different approaches and different levels of analysis to study regional diversification trajectories (Teece et al., 1994; Neffke, Henning, and Boschma, 2011; Boschma, Minondo, and Navarro, 2013; Boschma, 2015). These approaches rely on the intuition that technological classes, new products, workers' skills, and traded goods and services are parts of complex systems whose components can be more or less related to one another (Hidalgo et al., 2007). From a policy perspective, the concept of related diversification can help to understand the direction in which new specialisations could – or should, in normative terms – evolve (Iacobucci and Guzzini, 2016).

The empirical literature has analysed extensively the concept of relatedness and its role in economic growth (see the review papers by Content and Frenken (2016) and Boschma (2017)). The literature tends to conceptualise relatedness as a measure of the cognitive proximity between different components of a complex system. There is evidence of positive effects of relatedness on economic performance. Related industrial structures have been associated with higher employment rates (Frenken, Van Oort, and Verburg, 2007; Bishop and Gripaios, 2010; Rigby, Roesler, et al., 2022), higher GDP growth rates (Saviotti and Frenken, 2008), increments in labour productivity (Boschma and Iammarino, 2009), and stronger economic performances after crises (Rocchetta and Mina, 2019; Rocchetta, Mina, et al., 2022). Moreover, regions characterised by a higher degree of relatedness in their industrial structure are more likely to branch into new related industries (Neffke, Henning, and Boschma, 2011). For example, Neffke and Henning (2013), using data on labour force flows across industries, shows that firms are more likely to branch into sectors whose workers' skills are more similar to their core activities. These results are corroborated by the empirical literature on technological diversification, which exploits the high dimensionality of patent data to characterise the knowledge base of regions (Feldman and Kogler, 2010). This evidence tends to confirm that a region is more likely to acquire new specialisations in new technological fields if these are closer to the pre-existent knowledge bases (Kogler, Rigby, and Tucker, 2013; Rigby, 2015; Balland et al., 2019).[1] The notion of related variety has acquired over time more relevance in the justification of Smart Specialisation policy, even though a strong connection with the innovation systems literature emerged only later (McCann and Ortega-Argilés, 2011; McCann and Ortega-Argilés, 2015). Once this link was made, scholars often conceptualised Smart Specialisation borrowing from the literature on the construction of regional comparative advantages (Boschma, 2014), and on the role of related diversification (Asheim, Grillitsch, and Trippl, 2017; Santoalha, 2019).

The development of Smart Specialisation can be considered as an explicit declination of the idea of place-based policy for the European area (Barca, 2009). Smart Specialisation was conceived as an innovation-enhancing policy that aimed to create self-sustaining,

[1]It is also possible to detect non-linearities. For example, Rocchetta, Ortega-Argilés, and Kogler (2022) highlights that relatedness is likely to have an inverted U-shaped effect on economic performance, because a minimum degree of proximity is desirable to enhance knowledge diffusion, but excess proximity might lead to negative economic outcomes. Too much technological relatedness, indeed, negatively correlates with the ability of regions to adjust to emerging disruptive sectors (De Noni, Ganzaroli, and Pilotti, 2021) and may lead to lock-in (Boschma and Iammarino, 2009; Broekel and Boschma, 2012).

knowledge-based growth, built on existing capabilities (Foray, P. A. David, and B. Hall, 2009; Foray, 2009; Foray, Goddard, and Beldarrain, 2012). It is place-based precisely because it is designed to match the local "skills' supply with skills' future demand" in order to increase productivity (P. David, Foray, and B. Hall, 2009). As a policy, Smart Specialisation was intrinsically linked with the third cycle of European Cohesion Policies (2014-2020) and for this reason this particular policy wave is referred to as "S3". During this policy cycle, the European Commission conditioned access to the European Regional Development Fund (ERDF) to the submission of a Regional Innovation Strategy (RIS) (European Union, 2013a; European Union, 2013b). Interestingly, however, the deployment of RIS documents occurred at a time when there was no clear theory behind it, marking Smart Specialisation as a "policy running ahead of theory" (Foray, P. A. David, and B. H. Hall, 2011). Place-based policies can indeed be versatile tools to exploit local characteristics to achieve sustainable growth (Barbieri, Perruchas, and Consoli, 2020) and Smart Specialisation in particular has been seen as a useful approach for pursuing the EU wide-ranging sustainability targets (Mazzucato, 2013). In this respect, Smart Specialisation policies are also attracting more and more attention outside the EU area (Veldhuizen and Coenen, 2022).

One essential stage in the implementation of the policy is the decision-making process that generates the set of region-specific priorities on which funding will be spent. This process is described in the Smart Specialisation guidelines (Foray, Goddard, and Beldarrain, 2012) as the Entrepreneurial Discovery Process (EDP). Priorities should be set for those sectors in which each regional economy has more potential to gain new competitive advantage. This might be – but does not have to be – in related areas of activity. Interestingly, it is not a given that all stakeholders share the same idea of where 'related' growth opportunities might reside, and whether relatedness should concern purely technological capabilities rather than innovation design and market capabilities (Castaldi and Drivas, 2023). Moreover, the challenge of selecting appropriate priorities might be especially difficult for laggard regions with lower-quality governance (McCann and Ortega-Argilés, 2015; Aranguren et al., 2019).

A few empirical studies have recently focused on the role of relatedness in regional growth within a Smart Specialisation strategy framework. Rigby, Roesler, et al. (2022) employs a relatedness-complexity framework (Balland et al., 2019) to model Smart Specialisation and to study its effects on regional employment. Rocchetta, Ortega-Argilés, and Kogler (2022) finds evidence that the development of related technologies improves labour productivity. Deegan, Broekel, and Fitjar (2021) shows that the likelihood of including an economic domain (NACE sector) in RIS is positively correlated to skill relatedness and complexity of such a sector, and there is no substitution nor complementary effect among these two dimensions. Marrocu et al. (2023) evaluated the specialisation paths of regions, comparing policy decisions with regional comparative advantages and related diversification paths. Panori, Kakderi, and Dimitriadis (2022) attempts to identify the possible specialisation decisions of 16 regions based on technological opportunities. In so doing, they propose a method to link the IPC codes of patents produced in the region with NACE2 codes. Di Cataldo, Monastiriotis, and Rodríguez-Pose (2022) assesses instead how S3 strategies are influenced by differences in economic and institutional characteristics across regions of Europe. All these analyses provide very interesting insights. However, as noted by Bathelt and Storper (2023) with respect to related diversification strategies, robust evidence is still lacking on the mechanism through which the selection of investment priorities endogenously affects technological diversification and how this translates into economic performance.

In this paper, we aim to fill this gap by building first an analytical framework that takes into account the ex-ante selection of industrial strategies. This framework explicitly links the industrial side of the policy with the regions' technological capabilities as they enter the Entrepreneurial Discovery Process. This allows us to identify how policy implementation affects economic performance conditional on the selection of appropriate investment targets. It is now possible to conduct robust policy evaluations because we have enough observations coming from the diffusion of the policy (2014-2020), and enough years to detect effects.[2]

[2] An interesting exception is Crescenzi and Giua (2020), who evaluated a programme of subsidies for

Building on insights from both the related diversification and the Smart Specialisation literature, we are now going to illustrate our empirical approach, which we believe could have broader and more general applicability in the evaluation of other place-based innovation policies.

# Data and Econometric Strategy

A key challenge for evaluating place-based policies is to identify the channels and the mechanisms behind the policy decision. In the case of Smart Specialisation the decisions are made through the Entrepreneurial Discovery Process. This makes it necessary to identify which prescriptions the EDP should follow. In principle, Smart Specialisation through EDP should prioritise sectors close to the ones where innovators already operate and with more favourable growth expectations. However, this does not necessarily happen in practice, and local stakeholders can make a variety of choices. In evaluating the policy, we must take into account three specific features of its design.

Firstly, Smart Specialisation rejects the idea of 'one-size-fits-all" policies (Di Cataldo, Monastiriotis, and Rodríguez-Pose, 2022). This means that every region will design a specific innovation strategy. One aspect of such strategies concerns the choice of industries to include. We are going to refer to the specific decision to include a sector in the strategy as an 'industrial specialisation decision' or 'industrial inclusion'. Thereby, regions combine these decisions to create a unique strategy depending on regional-specific factors. Secondly, we need to disentangle the effects of underlying technological dynamics on industrial specialisation decisions. These dynamics can affect estimates in two ways. On one hand, regions select industries according to the potential they see in them. For this reason, regions (should) choose industry fields that are expected to contribute more than the others to growth. On the

collaborative industrial research co-funded by Cohesion Policy instruments in less developed Italian regions in the period 2007-13. This programme can be considered an early application of Smart Specialisation principle, even though it was not part of S3 policies.

other hand, underlying technological capabilities influence simultaneously specialisation decisions and economic growth. The trajectory of development that is chosen is path-dependent and shapes future growth prospects (Rigby and Essletzbichler, 1997). The EDP is then at the same time determined by the regional industrial evolution, and a determinant of future developments. Thirdly, S3 strategies may not be fully aligned with Smart Specialisation principles, and some regions might make decisions based on criteria that deviate from purely economic considerations, or these considerations might be significantly influenced by power asymmetries between local stakeholders (e.g. workers may be under – or over-represented in the governance charged with strategic decisions), as suggested by Aranguren et al. (2019).

Our goal is to assess if Smart Specialisation policies, and by implication related diversification choices, foster regional productivity in the EU. To do so, we collect data from the European Commission's portal on S3 policies '*S3 Platform*'.[3] Using the EyeRIS3, it is possible to scan the regions' RIS3 documents and their summary sheets. More specifically, the summary sheets report the structure of the strategy and related industrial specialisations. Every strategy is divided into priorities and every priority is centred around a specific objective. The industrial specialisations are the economic domains associated with any priority target.[4] For every priority, industrial specialisations are identified by their NACE2 code Rev. 2. We collect S3 data on 102 NUTS2 regions.[5] The average number of priorities in the strategies is 5.5. On average, every priority is associated with 4.6 industrial sectors. We restrict our analysis to the manufacturing sectors (NACE1 code 'C'). Even though technological dynamics can affect also the service sector, the development of new technologies and the use of patents, which are going to measure, involves manufacturing activities more

[3] https://s3platform.jrc.ec.europa.eu/ (European Commission, 2013)

[4] These data present important limitations for the analysis of Smart Specialisation policies. The biggest one is that we cannot observe how and to which extent a sector is included in the strategies. We observe only if the sector is reported in at least one priority. We cannot establish if these decisions are implemented, how many European funds were granted, and if and how they were spent.

[5] The entire set of regions in the portal is 196 units. However, because of several incomplete time series for complementary data we need for estimation purposes, 94 units had to be dropped. Our final sample includes regions in Austria, Czechia, Germany, Denmark, Spain, France, Italy, Netherlands, Portugal and Romania.

than services (Boschma, 2017). Moreover, there is no established way to link technology classes with specific service sectors, whereas the literature provides much greater details for manufacturing sectors (Eurostat, 2008; Panori, Kakderi, and Dimitriadis, 2022).

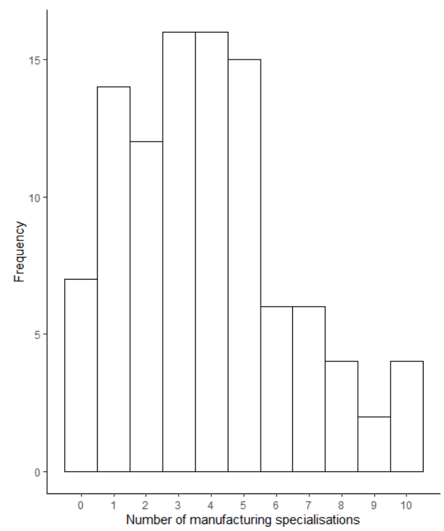



**Figure 1:** Distribution of NACE2 specialisations

In figure 1 we can observe the distributions of numbers of industrial sectors included in the strategy by the regions. There are 23 NACE2 manufacturing sectors. The median number of specialisations in our sample is 4. As we can see, over 102 regions only 22 present an S3 strategy with 6 or more industrial specialisations. Four of them present 10 specialisations, while 7 regions included no manufacturing specialisations in their strategy. This is not surprising, since many regions focused on the services industries in their RIS documents. We decided to include them in the sample as well, even if their strategies might be unaligned to Smart Specialisation dynamics we aim to analyse. We believe, indeed, that dropping them would result in a selection bias since these are all highly productive regions. The most frequent manufacturing NACE2 sectors are food industries (C10) with 75 occurrences, electrical equipment (C27) with 53 occurrences, and machinery industries (C28) appearing in 44 strategies. This underlines that regions create targeted strategies that involve a limited number of industrial sectors. There are few exceptions, but most of regions decided to specialise in less than 6 manufacturing sectors.

Smart Specialisation policies suggest that diversification should follow the principle of relatedness. They should also capture latent growth opportunities and improve productivity by targeting higher value-added sectors. Moreover, policy decisions do not target related technologies, but industries. Assume a basic (empirical) model for policy evaluation as described in equation (1):

$$Y_{rt} = \alpha_r + \sum_k \beta_k D_{rt}^{(k)} + X_{rt}\gamma + u_{rt} \tag{1}$$

$Y_{rt}$ is an outcome indicating regional economic performances, $X_{rt}$ captures regional characteristics, while $D_{rt}^{(k)}$ represents all the industrial specialisations. Let $D_{rt}^{(k)}$ be equal to 1 if the region $r$ included sector $k$ in its RIS3 and the year is after 2013, and 0 otherwise. The impact on labour productivity of the decision to specialise in sector $k$, then, is *on average* $\beta^k$. However, estimating this parameter is challenging. There are, indeed, two factors that can act as confounders in this empirical setting.

$$\begin{aligned}
\hat{\beta}_k &= E[Y_{rt}|D_{rt}^{(k)} = 1, X_{rt} = x] - E[Y_{rt}|D_{rt}^{(k)} = 0, X_{rt} = x] \\
\hat{\beta}_k &= \beta_k + \sum_{j \neq k} \beta_j \underbrace{\Big[E[D_{rt}^{(j)}|D_{rt}^{(k)} = 1] - E[D_{rt}^{(j)}|D_{rt}^{(k)} = 0]\Big]}_{\textit{Interdependent Sectors}} + \\
&\quad + \underbrace{E[u_{rt}|D_{rt}^{(k)} = 1] - E[u_{rt}|D_{rt}^{(k)} = 0]}_{\textit{EDP Dynamics}}
\end{aligned} \tag{2}$$

The first confounder in equation (2) is the *Interdependent Sectors* factor. This depends on how these strategies are built. Indeed, industrial specialisations co-occur with different frequencies in priorities. The probability of having an industrial specialisation in one priority is not independent from other industrial specialisations. Indeed, some sectors are more complementary than others and they tend to be more frequently associated when a priority aims at a particular target. This might be because sectors are in different parts of the same value chain. The same technological shocks simultaneously affect upstream and downstream activities. Also, some sectors might contribute to the same priority, affecting different aspects of the specialisation objective. Finally, a specialisation strategy may induce the reallocation of competencies towards more productive sectors. This may affect similar industrial sectors even if these are not the main focus of the policy. For all these reasons, we cannot assume that industrial specialisations are independent, but we can assume that this dependency is stronger among some sectors and weaker among others. For this reason, we aggregate NACE2 industries into industrial areas to reduce this *Interdependent Sector* bias. Thereby, we obtain 9 clusters from the original 20 NACE2 manufacturing sectors.[6] We chose this data-driven approach because the association we got from clustering had sound theoretical validity. The hierarchical clustering algorithm we used is described in detail in the Appendix. The composition of industrial groups allows us to perform our empirical analysis without losing information. In table 1 we report the aggregation in industrial areas we are going to use in our analysis. Specialisation in some industrial areas is assumed to be independent from specialisation in any other. In Figures 2 and 3 we can observe how the specialisations in the broader industrial areas are distributed in the regions of our sample. Unsurprisingly, agro-food and components represent the most common specialisations. The second and third most frequent specialisations are in the automotive and health industries. The least common industrial area are wood and paper industries.

The second confounder in (2) comes from the EDP process itself. EDP defines how technology evolution will affect policy decisions. However, some sectors could be experiencing dynamics that may transform them into core regional activities, regardless of whether they were included in Smart Specialisation Strategies or not. Indeed, regions make industrial priorities choices also based on these dynamics, so we cannot assume that the choices made are random. However, what we can assume is that the probability of an industrial area being included in RIS3 depends on its relatedness to the regional "core". For this reason, in

[6] The NACE2 sectors for manufacture are 23, but 'Printing and reproduction of recorded media' (C18), 'Manufacture of coke and refined petroleum products' (C19), and 'Manufacture of fabricated metal products, except machinery and equipment' (C25) did not appear in any region's RIS3.

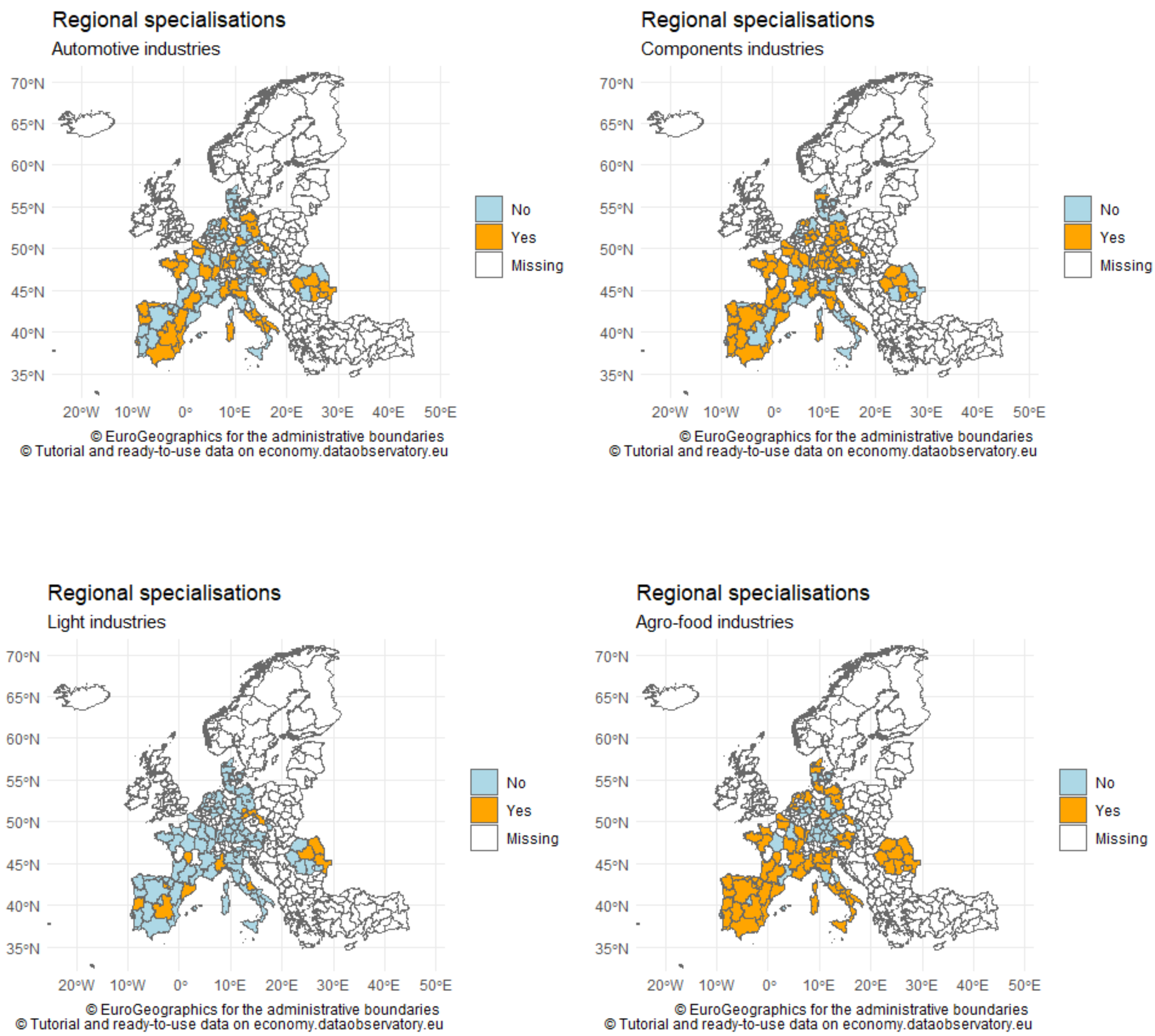
**Table 1:** Data-driven clustered sectors

| Industrial Area | NACE2 sectors associated |
|---|---|
| **Agro-food** | Manufacture of food products (**C10**) |
| | Manufacture of beverages (**C11**) |
| **Light Industries** | Manufacture of textiles (**C13**) |
| | Manufacture of wearing apparel (**C14**) |
| | Manufacture of leather and related products (**C15**) |
| | Manufacture of other non-metallic mineral products (**C23**) |
| **Wood and Paper** | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials (**C16**) |
| | Manufacture of paper and paper products (**C17**) |
| **Materials** | Manufacture of chemicals and chemical products (**C20**) |
| | Manufacture of rubber and plastic products (**C22**) |
| | Manufacture of basic metals (**C24**) |
| **Health** | Manufacture of basic pharmaceutical products, and pharmaceutical preparations (**C21**) |
| | Other manufacturing (**C32**)[7] |
| **Metals** | Manufacture of basic metals (**C25**) |
| **Components** | Manufacture of computer, electronic and optical products (**C26**) |
| | Manufacture of electrical equipment (**C27**) |
| | Manufacture of machinery and equipment n.e.c. (**C28**) |
| **Automotive** | Manufacture of motor vehicles, trailers and semi-trailers (**C29**) |
| | Manufacture of other transport equipment (**C30**) |
| **Furniture** | Manufacture of furniture (**C31**) |

[6] Most of the other manufacturing activities are 'Manufacture of medical and dental instruments and supplies (C32.5).

the first step, we derive the likelihood that each region specialises in each sector following the relatedness principle. According to it (P. David, Foray, and B. Hall, 2009; McCann and Ortega-Argilés, 2015), regions should build their strategies diversifying in the related industries with better opportunities. This represents the selection stage of our Smart Specialisation analytical model. We adopt this approach by exploiting the finding of Deegan, Broekel, and Fitjar (2021). Indeed, they show that an industrial specialisation is correlated with the skill-relatedness of that sector. This leads us to formulate the following hypothesis:

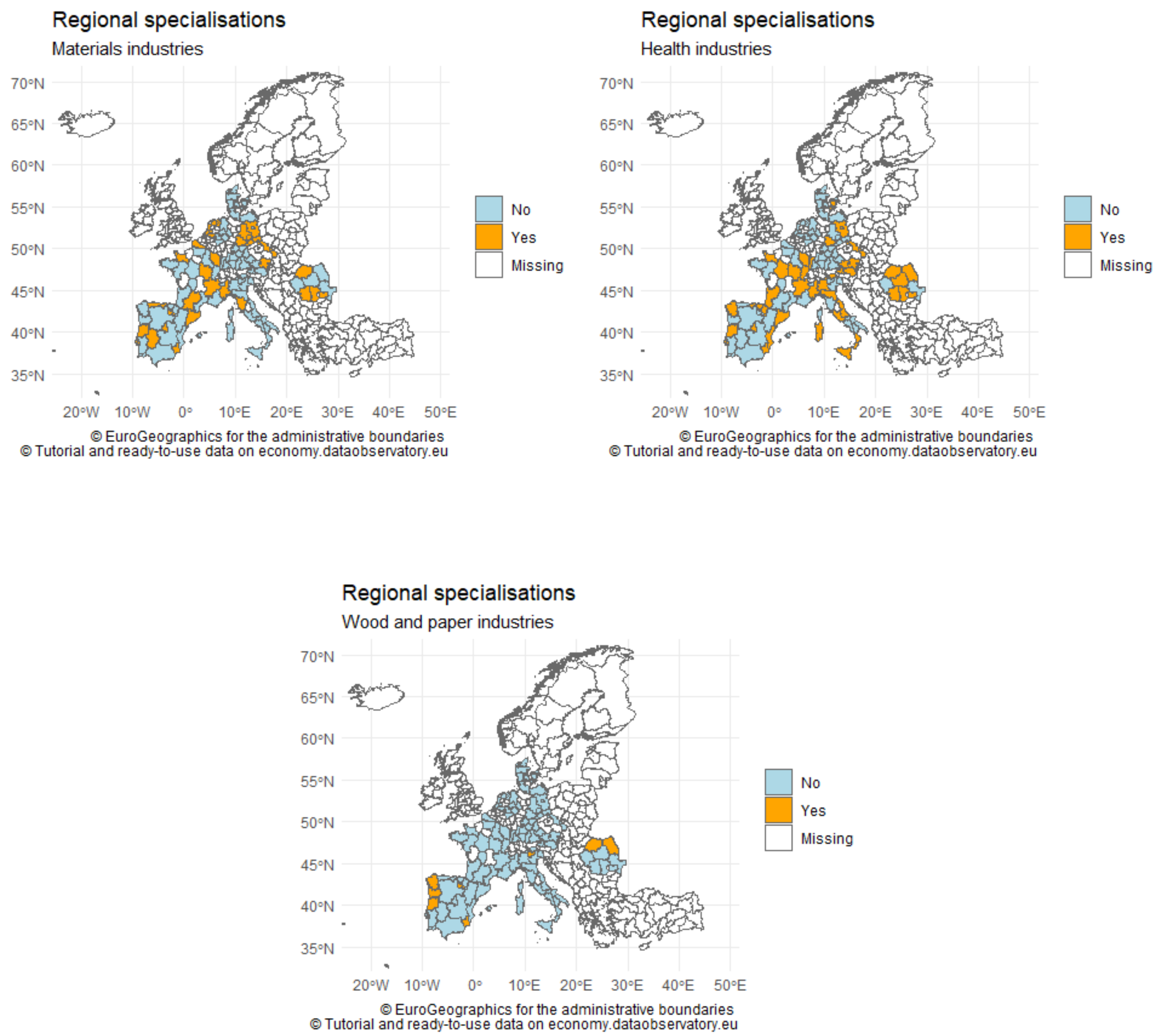
**Figure 2:** Distributions of the specialisations across automotive, components, light, and agro-food industries.




***H1: Industrial areas that are more technologically related to the regional industrial core are more likely to be included in an S3 strategy.***

In the second step, we estimate the impact of these decisions on labour productivity growth. This represents the evaluation stage of our analytical model. The method allows us to measure the impact of Smart Specialisation strategies conditional on the extent to

**Figure 3:** Distributions of the specialisations across materials, health, and wood and paper industries.




which regions followed the policy principles. The literature leads us to expect that regions specialising in industries with technological capabilities that are more related to existing knowledge bases will generate higher productivity gains. We therefore propose the following hypothesis:

***H2: Regions that specialise in industries that are more related to their existing***

***technological capabilities are more likely to experience higher productivity gains.***

To test these hypotheses, we employ an IV approach to proxy the selection stage as the first stage and use the fitted values in the evaluation stage. The advantage of this approach is that it makes it possible to model this process based on exogenous factors and to use their variations to observe the impact on labour productivity. We use as instrument the *Technological Relatedness in Production* (TRP) index. We build this index using the Relatedness Density approach (Boschma and Iammarino, 2009; Balland et al., 2019) and the patent class-industry conversion tables from Eurostat (2008). We follow the same conversion approach as Panori, Kakderi, and Dimitriadis (2022). This variable captures how related an industrial area is to the rest of the regional knowledge base. To compute this variable, we derive a rule that associates to every IPC code the corresponding NACE2 code in which it finds an industrial application. It must be noted that a single patent can be associated with more than one IPC code. This means that the same patent can find application in more than one industrial sector. Using the relatedness approach, we can exploit the co-occurrences of different industrial tags in the same patent to define how close two industrial areas are in the regional knowledge base. If the industrial area $j$ in region $r$ is particularly related to all the others, it will be "dense" in relatedness. This means that such an industry is well-connected in the regional knowledge space, sharing technological capabilities with other branches of the industrial structure. The Smart Specialisation literature often singled out the role of related density as an indicator of proximity to the regional "core". For this reason, we argue that, from an entrepreneurial discovery perspective, a related industry is also an industry in which it is easier for the region to acquire a competitive advantage. In table 2, we can observe how the TRP is distributed across industrial areas.[8]

As we can see, TRP is indexed between 0 and 1 across regions, separately for every sector. Agro-food, furniture, and wood and paper present the most right-skewed distributions. This

[8]Metals is not reported since no region chose it as a specialisation area.

**Table 2:** Instrument variables summary statistics

| Statistic | N | Mean | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Automotive | 102 | 0.561 | 0.000 | 0.186 | 0.689 | 0.885 | 1.000 |
| Components | 102 | 0.285 | 0.000 | 0.120 | 0.273 | 0.440 | 0.987 |
| Food | 102 | 0.369 | 0.000 | 0.000 | 0.333 | 0.625 | 1.000 |
| Furniture | 102 | 0.304 | 0.000 | 0.000 | 0.273 | 0.500 | 1.000 |
| Light | 102 | 0.431 | 0.000 | 0.222 | 0.456 | 0.639 | 1.000 |
| Materials | 102 | 0.382 | 0.000 | 0.212 | 0.349 | 0.515 | 1.000 |
| Health | 102 | 0.385 | 0.000 | 0.172 | 0.309 | 0.556 | 1.000 |
| WoodPaper | 102 | 0.281 | 0.000 | 0.000 | 0.097 | 0.500 | 1.000 |

is not surprising, since they are all low technology-intensive sectors.

Our estimation strategy consists of a 2SLS approach. In the first step, we proxy the specialisation decisions across seven industrial areas.[9] In the second step, we estimate the effects of the different industrial choices on labour productivity growth. The equation in (3) describes the regression model we use for the first stages.

$$SPE_{jr}^{(2013)} = \alpha + \beta TRP_{jr} + \varphi_c + \varphi_j + u_{jr} \tag{3}$$

We include country-level fixed effects to adjust for national-level policy preferences and sector-level fixed effects to control for sectors included with more frequency. We use the fitted values for the different $SPE_{jr}^{(2013)}$ in the second stage. We estimate seven different regressions, to avoid multicollinearity between treatment variables.[10] The regressions we estimate in the second stages are described by equation (4).

[9] We discard Furniture from the analysis since it was chosen as an industrial specialisation are only by three regions.

[10] Instruments and fitted values are highly correlated, making it difficult to consistently estimate a regression with all the industrial specialisations at the same time.

$$\Delta log(Prod_{rt}) = \phi_c + \delta_1^j \widehat{SPE}_r^{(j)} + \delta_2 Post_t + \delta_3 \widehat{SPE}_r^{(j)} \times Post_t + \\ + \gamma_1 log(Prod_{rt-1}) + \gamma_2 KIS_{rt} + \gamma_3 log(R\&Dpercap_{rt-1}) + \theta_t + u_{rt} \tag{4}$$

For the regional controls and the outcome variable, we extract data from Eurostat. We use data from 2009 to 2019. We use as treatment period the time window between 2013 and 2019. The reason for including the year 2013 is the bottom-up design of the policy as stakeholders could take part in decision-making process and influence decisions. They could also anticipate policy decisions as these were being designed. If we exclude 2013 and run the analyses using 2014-2019 as the treatment period, results remain stable. We use labour productivity as the dependent variable. Following prior art (Rocchetta, Ortega-Argilés, and Kogler, 2022) we measure it by dividing the Gross Value Added in each region by the number of hours worked per full-time equivalent unit. As controls we employ the variables R&D per capita and KIS. The first is the sum of private and public R&D expenditure per capita purchasing power standard for the 2005 currencies values. The variable KIS is, instead, the share of workers employed in medium-high or high knowledge-intensive sectors. These controls are needed to observe the intensity of innovation inputs. In particular, R&D represents the intensity of innovation investments, while KIS represents the intensity of labour force employed in knowledge-related production. For this reason, they help us to control a suspected source of endogeneity which is the intensity of innovative activities in the regions.

As we can see, the average labour productivity growth rate is 2.1% across all the samples. Its distribution is quite concentrated between the first and third quartiles with few outliers. In particular, the negative outliers are concentrated during the years of debt crisis in the countries that were most affected by it. Extreme outliers above 15% are mostly regions in the Central and Eastern European Countries (CEEC) starting from a lower base relative to the others.

**Table 3:** Summary statistics of the regional variables

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Δlog(Prod) | 1,224 | 0.021 | 0.029 | −0.111 | 0.006 | 0.031 | 0.197 |
| log(Prod) | 1,224 | 3.438 | 0.493 | 1.461 | 3.342 | 3.724 | 4.285 |
| KIS | 1,176 | 3.104 | 1.677 | 0.600 | 1.900 | 3.800 | 10.300 |
| R&D per capita | 1,224 | 380.171 | 345.054 | 6.000 | 162.975 | 500.825 | 2,089.300 |

This table reports the summary statistics for labour productivity (log), labour productivity growth, the share of employees in medium-high and high Knowledge Intensive Sectors, and total R&D expenditure per capita purchasing power standard at 2005 (log).

# Results

In table 4 we test the first hypothesis $H_1$. We have conjectured that industries that are more related to existing technological capabilities are more likely to be included in the S3 strategies. To test it, we need to evaluate the coefficient of the instrument TRP in the first stage. Since the TRP exhibits a positive and significant coefficient, our first hypothesis is validated. This implies that the likelihood of an industrial inclusion is higher for industrial areas closer to the existing knowledge base. In particular, *coeteris paribus* a sector completely unrelated to the core of a regional knowledge space is nearly 15% less likely to be included than a perfectly related sector. This is consistent with the idea that Smart Specialisation builds on the principle of related diversification. Our instrument is, thus, correlated with the specialisation decisions. Since this is the first stage of our strategy we are also interested in that this is not a weak instrument. We perform an F test on the difference between 16.671 and 10. The critical value for $F_{17,696;0.005}$ is 1.97 and we can reject the null hypothesis that the instrument is weak, and we move on to the second stage.

In table 5 we test hypotheses $H_2$ in which we conjectured that regions that indicate their priorities following a related diversification principles are the ones that experience higher productivity gains from implementing S3 policies. We can observe in the table the effect of the different industrial inclusions on regional labour productivity growth. We report the OLS and IV estimates for three models. The first model is displayed in the first two columns.

**Table 4:** Smart Specialisation decision rule across industrial areas

| | *Dependent variable:* |
|---|---|
| | Specialisation$_{jr}$ |
| Constant | 0.301$^{***}$ |
| | (0.086) |
| TRP$_{jr}$ | 0.163$^{***}$ |
| | (0.054) |
| Country Fixed Effects | ✓ |
| Industries Fixed Effects | ✓ |
| Observations | 714 |
| $R^2$ | 0.289 |
| Adjusted $R^2$ | 0.272 |
| Residual Std. Error | 0.418 (df = 696) |
| F Statistic | 16.671$^{***}$ (df = 17; 696) |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

This table reports the estimates coefficients for the TRP of each industrial group and the relative growth of their employment share on the decision of including the industrial group in the S3 strategy. Country and industrial cluster fixed effects are added. Bootstrapped standard errors in parentheses.

The coefficients we show are simple Diff-in-Diff estimates. In the second two columns, we control for NUTS2 and year-fixed effects. In the final two columns, we add regional controls, such as lagged productivity levels, the share of workers employed in medium-high and high Knowledge Intensive Sectors (KIS) and R&D expenditure per capita. We present both OLS and IV because their comparison makes it easier to give a plain explanation of Smart Specialisation mechanisms. In the Appendix, we report the tables with results for each separate estimation.

OLS estimates in the first model are mostly non-significant. Only light industries, health, and wood and paper indicate a positive effect. This means that, on average, regions that included these sectors in their strategies experienced growth in labour productivity 0.9, 1.5,

**Table 5:** Effects of industrial choices on labour productivity

| | *Dependent variable:* $\Delta log(Prod_t)$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | |
| | OLS | IV | OLS | IV | OLS | IV |
| Automotive | 0.002 | 0.035*** | 0.002 | 0.035* | 0.001 | 0.038** |
| | (0.003) | (0.013) | (0.004) | (0.019) | (0.004) | (0.017) |
| Components | 0.001 | 0.061*** | 0.001 | 0.061** | 0.001 | 0.065*** |
| | (0.003) | (0.016) | (0.004) | (0.019) | (0.004) | (0.024) |
| Light Industries | 0.009* | 0.060*** | 0.009 | 0.063** | 0.008 | 0.049** |
| | (0.005) | (0.014) | (0.007) | (0.026) | (0.006) | (0.027) |
| Agro-food | 0.002 | 0.066*** | 0.002 | 0.066** | 0.002 | 0.067*** |
| | (0.004) | (0.017) | (0.003) | (0.027) | (0.004) | (0.025) |
| Materials | 0.004 | 0.061*** | 0.004 | 0.061*** | 0.005 | 0.063*** |
| | (0.003) | (0.014) | (0.005) | (0.023) | (0.005) | (0.021) |
| Health | 0.007** | 0.049*** | 0.007 | 0.049** | 0.006 | 0.051*** |
| | (0.003) | (0.015) | (0.004) | (0.021) | (0.004) | (0.020) |
| Wood & Paper | 0.015** | 0.054*** | 0.015 | 0.054** | 0.017 | 0.056*** |
| | (0.006) | (0.015) | (0.014) | (0.023) | (0.014) | (0.021) |
| Regional FE | | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | ✓ | ✓ | ✓ | ✓ |
| Regional Controls | | | | | ✓ | ✓ |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the coefficients of the interaction $SPE_r^{(j)} \times Post2013_t$ across all the choices of industrial inclusion on labour productivity growth. We report OLS and IV separately for each set of estimations. Every row represents the coefficients from a separate regression. In column (1) we display the estimates from the simple Difference-in-Difference models. In column (2) we add regional fixed effects (NUTS2 regions) and year fixed effects. In column (3) we add regional controls. Additional controls are $log(Productivity_{t-1})$, $KIS_t$, $log(R\&Dpercapita_t)$. Standard errors in parentheses in column (1). Clustered standard errors at the regional level in parentheses in columns (2) and (3).

and 0.6 percentage points respectively higher than the regions that did not include them. OLS estimates, however, become completely non-significant when fixed effects are added. This implies that Smart Specialisation strategies had a null average effect across regions. OLS represents the average statistical difference in regional labour productivity growth rates between regions that included industry $k$ in their strategy and regions that did not. These average differences are Average Treatment Effects (ATEs). These differences however cannot establish if the industrial inclusion is a good fit given the regional structure. We can only see if the region included it or not. In this sense, OLS estimates capture the effect of a specialisation *unconditional* to the regional ex-ante trajectories.

To test our second hypothesis we need to run the second stage of our estimation. IV estimates, by construction, allow us to detect a different parameter from ATE, since they are Local Average Treatment Effects (LATEs). These estimates isolate the effects of the policy when the degree of technological relatedness of the industrial sector is high. This comes from a different weighting scheme of IV estimators concerning OLS. The parameter IV estimates represent the exogenous variations of the instrument on the outcome variable (reduced form). Each variation of the instrument receives a different weight based on how much the fitted value and the endogenous values correlate in the first stage. These weights are higher if the specialisation $k$ in region $r$ (endogenous value) was done according to the related diversification principle (corresponding fitted value). A specialisation decision in a region where the industry has no strict technological links with the industrial base will receive a lower weight than a region where the industry is more related. The IV estimate then will be a weighted average of the S3 effects for those units whose specialisations followed Foray, P. A. David, and B. Hall (2009)'s principles more closely. For this reason, we argue that the IV estimator is a good way to identify the effects of industrial specialisations conditional on the technological relatedness channel.

Results from the IV estimates in table 5 reveal that Smart Specialisation has been very effective for regions that included sectors according to related diversification principles. As we can see, IV estimates are consistent across all three models. All choices made following regions' technological diversification trajectory show an increase in labour productivity growth rates between 3.8% and 6.7%. The industrial area with the highest expected growth are components industries, agro-food industries, and materials. Automotive and light industries, instead, are the one showing the smallest effect on productivity growth acceleration. Regions following relatedness in the definition of the strategy report positive effects from these inclusions. It is worthy highlighting that all industries can have a positive effect on regional productivity growth. These results confirm our second hypothesis.[11] S3 strategies were effective only when the industrial inclusion was based on a relatedness principle. It is necessary, nonetheless, to stress that such prescriptions were very vague at the time of the S3 strategies design in 2013. This means that most of the regions defined their policies without a theory underpinning them. Our analysis, thus, relies on an evaluation of the EDP process in the light of ex-post theoretical categories. Furthermore, EDP is a process through which agents interact and learn from others to define the policy. This implies that EDP can hardly be analysed according to 'correct-or-wrong' categories. The uniqueness of every region can produce specific paths of specialisation/diversification that might be unfit for regions with a similar industrial structure. Our analytical framework, however, allows us to exploit specifically the variations of technological dynamics of the industrial structure and to compare them with the policy decisions.

Due to data limitations, we are aware that we observe only a part of the mechanisms leveraged by Smart Specialisation. More specifically, we can see only if a sector is included or not in the regional strategies. However, we can still observe how industrial specialisation decisions affect regional performances. These decisions propagate from the sectoral to the regional level due to channels that are not influenced by the characteristics of the policy.

[11] We are aware that these results do not represent a strictly causal estimation of specialisation decisions. However, our identification strategy allows us to exploit the exogenous variations coming from the regional characteristics that help defining the EDP. The reduced form, then, represents the effects of relatedness of across industries on labour productivity growth.

There are several channels at play. Firstly, we have a channel for efficient recombination of competencies. Indeed, EDP can be seen as a dynamic of unveiling regional potentialities of achieving new specialisations. A 'correct' EDP will point out a different reallocation of technical and technological competencies towards more complex but related productions. The inclusion of the right industry into the strategy implies that this reallocation can be achieved with less effort. Indeed, the relatedness-complexity framework (Balland et al., 2019) suggests that specialising in related industries is less risky because of the similarities between capabilities. Furthermore, these similar capabilities can be employed in new, more complex, and thus more productive, areas, boosting overall regional productivity. Secondly, especially in laggard regions (Kroll, 2015), Smart Specialisation had the effect of strengthening good practices and new routines. While we cannot observe which and how these routines were implemented, they will spread faster in the industries included in the RIS documents as long as these industries are closer to the core in a relatedness sense. In this way these new routines are embedded in the regional innovation systems, propagating from the specialisation industries. Finally, we think of a signalling channel. Inclusion decisions, indeed, highlight which sectors a region wants to prioritise. This prioritisation is by itself an important aspect of the policy itself. Since Smart Specialisation policies (should) follow a bottom-up approach, investors and agents of the innovation process are, at the same time, signalling and being signalled about the potentialities in the regional economies. We can think about this in different ways. One way is that EDP for private agents consists (also) of an exchange of signals and information about the industries' potential. Firms involved in EDP might update their expectations and allocate investments based on policy decisions. If the industries flagged in the EDP are technologically related to the regional industrial base and they showed good economic performances, these investments have been more effective and generated stronger productivity gains. Another way is to think about this, even though this is less likely, is to envisage a signal towards external investors who do not participate in the EDP, since a possible external investor could perceive the inclusion of an industry as a signal of its economic performances or the availability of related capabilities in the region.

# Robustness checks

## Weighted Least Squares

As a robustness check on the estimation method, we use a Weighted Least Squares approach. We weigh observations using the share of employment for each industrial choice. The idea is that regions with a higher share of employees working in $j$ will be more impacted by its inclusion in the S3 strategy. For this reason, it would be misleading to weigh every region in the same way. Since the share of employment is expected to grow with the specialisation decision, we use the value in 2013 to conduct our analysis. The choice of 2013 as a reference year depends on the fact that the Great Recession in 2008-2009 and the European debt crisis in 2011-2012 can undermine the weights due to uneven impacts across industrial sectors. Moreover, we cannot choose a year that follows the industrial inclusion because of the risk of endogenous weights. Table 6 reports estimates from the baseline model with NUTS2 and year-fixed effects and regional controls. The first column shows Weighted Least Squares estimates. In the second column, the coefficients represent the results of the Weighted Instrumental Variable regressions.

Estimates in table 6 are mostly consistent with the findings in table 5. Only the health industries lose a great part of their effect in the IV specification. In any case, results in the weighted regressions are robust with our baseline results in table 4. In the Appendix, we report tables containing the results for each separate estimation.

## "Leave-one-country-out" models

We then investigate if our main results are driven by a few regions, possibly concentrated in a few countries. We estimate the same models as in table 3 with 4 different subsets of data. We perform our analyses excluding the regions of one country at a time. In table 7

**Table 6:** Weighted Least Squares estimates

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | WLS | WIV |
| Automotive | 0.0001 | 0.076*** |
| | (0.004) | (0.017) |
| Components | 0.005 | 0.056*** |
| | (0.003) | (0.014) |
| Light Industries | 0.010* | 0.123*** |
| | (0.005) | (0.018) |
| Agro-food | -0.001 | 0.049*** |
| | (0.005) | (0.017) |
| Materials | 0.004 | 0.053*** |
| | (0.004) | (0.015) |
| Health | 0.004 | 0.027* |
| | (0.003) | (0.014) |
| Wood & Paper | 0.022*** | 0.082*** |
| | (0.005) | (0.016) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Regional Controls | ✓ | ✓ |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the coefficients of the interaction $SPE_r^{(j)} \times Post2013_t$ across all the industrial choices on labour productivity growth. We report Weighted Least Squares estimates (1) and Weighted Instrumental Variable estimates (2) for the model. We use weights computed on the share of employment by cluster in 2013. We control for NUTS2 fixed effects and year fixed effects. Additional controls are $log(Productivity_{t-1})$, $KIS_t$, $R\&Dpercapita_t$. Clustered standard errors at the NUTS2 regional level in parentheses.

we show the results from the first stages. As we can see in the first column, the $TRP_{jr}$ is consistent with our baseline results across all different sub-samples. There are no significant changes between the models. The role of technological relatedness, indeed, shows a discrete

**Table 7:** Results from "leave-one-country-out" models

| | *Dependent variable: $Specialisation_{jr}$* | |
|---|---|---|
| | $TRP_{jr}$ | F-test |
| W/o Austria | 0.162*** | 15.319*** |
| | (0.060) | (df = 15; 642) |
| W/o Czechia | 0.139*** | 16.397*** |
| | (0.058) | (df = 15; 677) |
| W/o Germany | 0.193*** | 16.448*** |
| | (0.059) | (df = 15; 621) |
| W/o Denmark | 0.157*** | 15.402*** |
| | (0.060) | (df = 15; 663) |
| W/o Spain | 0.142** | 13.726*** |
| | (0.062) | (df = 15; 579) |
| W/o France | 0.149** | 12.895*** |
| | (0.065) | (df = 15; 572) |
| W/o Italy | 0.169*** | 14.106*** |
| | (0.065) | (df = 15; 558) |
| W/o Netherlands | 0.176*** | 15.650*** |
| | (0.060) | (df = 15; 635) |
| W/o Portugal | 0.159*** | 16.433*** |
| | (0.058) | (df = 15; 649) |
| W/o Romania | 0.173*** | 16.047*** |
| | (0.059) | (df = 15; 649) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the coefficients of the Related Density ($TRP_{jr}$ in column 1) on the specialisation decisions ($Specialisation_{jr}$) using different "leave-one-country-out" subsets. For every row regions from a country are removed from the estimation. Country and industries' fixed effects are added to the models. In column 2 F-tests are reported for every model. Standard errors in parentheses in columns 1. Degrees of freedom for the F-statistics in parentheses in column 3.

degree of variation in decision processes across countries when they are individually taken out.

In column 3 we report the results of the models F-statistics. These values are all very high and statistically greater than 10, i.e. in every specification the condition for not having weak instruments is satisfied. For this reason, we could use these "leave-one-country-out" models to estimate the second stages as well. Estimates of the "leave-one-country-out" second stages remain robust with the IV estimates in the baseline models. The Appendix contains the results of second-stage estimations.

## Alternative dependent variables

In table 8 we report the estimates of the Smart Specialisation choices on GVA and hours worked growth rates as an additional robustness check. We used these two variables to compute our measure of labour productivity. The returns of inclusions on GVA growth are statistically significant and positive for every specialisation in the IV estimation. OLS models produce a statistically significant effect only for agro-food, wood and paper, and light industries. All the IV coefficients of the growth of hours worked are positive. These results are fully consistent with the findings we have discussed for labour productivity. These estimates help us to understand the main component of productivity growth. Smart Specialisation choices bolstered productivity by increasing regional production without negative effects on occupation. When decisions were made according to the relatedness principles, the growth of hours worked even accelerated with respect to the previous period. This is not true, instead, on average. Specialising in a sector without taking into account its relatedness has no effect even on occupation, not just on productivity. This table highlights that the direct (positive) effect on GVA growth rate has offset the indirect (negative) effect on hours worked in all industries, generating an overall increment of the labour productivity for complying regions.

**Table 8:** Effects of industrial choices on GVA and hours worked growth rates

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | $\Delta log(GVA_{rt})$ | | $\Delta log(HoursWorked_{rt})$ | |
| | OLS | IV | OLS | IV |
| Automotive | 0.007 | 0.121*** | 0.003 | 0.045*** |
| | (0.006) | (0.024) | (0.004) | (0.016) |
| Components | 0.004 | 0.171*** | 0.002 | 0.055*** |
| | (0.006) | (0.031) | (0.004) | (0.016) |
| Light Industries | 0.022** | 0.140*** | 0.008 | 0.034** |
| | (0.011) | (0.028) | (0.006) | (0.015) |
| Agro-food | 0.009* | 0.157*** | 0.004 | 0.041** |
| | (0.005) | (0.035) | (0.004) | (0.017) |
| Materials | 0.009 | 0.155*** | 0.0003 | 0.046*** |
| | (0.006) | (0.031) | (0.004) | (0.016) |
| Health | 0.009 | 0.139*** | 0.001 | 0.048*** |
| | (0.006) | (0.029) | (0.004) | (0.016) |
| Wood & Paper | 0.033** | 0.141*** | 0.012 | 0.045*** |
| | (0.014) | (0.028) | (0.007) | (0.017) |
| Regional FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Regional Controls | ✓ | ✓ | ✓ | ✓ |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the coefficients of the interaction $SPE_r^{(j)} \times Post2013_t$ across all the industrial inclusions on GVA and hours worked growth rates. We report OLS and IV separately for each set of estimations. Every row represents the coefficients from a separate regression. In the first two columns we report the results for GVA growth rates. In the last two columns we report the results for hours worked growth rates. NUTS2 and year fixed effects are added along with regional controls. Regional controls are $log(Productivity_{t-1})$, $KIS_t$, $log(R\&Dpercapita_t)$. Clustered standard errors at the regional level in parentheses.

**Table 9:** Effects of digitisation and servitisation

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | Professional Services | Digital Services |
| Automotive | 0.043** | 0.044** |
| | (0.017) | (0.018) |
| Automotive×Services | 0.006 | -0.014 |
| | (0.008) | (0.010) |
| Components | 0.072*** | 0.074*** |
| | (0.025) | (0.025) |
| Components×Services | 0.017*** | -0.002 |
| | (0.006) | (0.007) |
| Light Industries | 0.074** | 0.078*** |
| | (0.029) | (0.030) |
| Light Industries ×Services | 0.045 | -0.056 |
| | (0.027) | (0.040) |
| Agro-food | 0.070*** | 0.070*** |
| | (0.026) | (0.026) |
| Agro-food×Services | -0.009 | -0.008 |
| | (0.006) | (0.006) |
| Materials | 0.066*** | 0.070*** |
| | (0.022) | (0.022) |
| Materials×Services | 0.018 | -0.023 |
| | (0.031) | (0.018) |
| Health | 0.050*** | 0.057*** |
| | (0.019) | (0.021) |
| Health×Services | 0.048 | -0.003 |
| | (0.066) | (0.011) |
| Wood & Paper | 0.059** | 0.062*** |
| | (0.023) | (0.025) |
| Wood & Paper×Services | 0.042 | -0.033 |
| | (0.031) | (0.045) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Regional Controls | ✓ | ✓ |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the coefficients of the interaction $SPE_r^{(j)} \times Post2013_t$ across all the industrial choices on labour productivity growth and the triple interaction with the dummy *Services*, i.e. if the priority features digitisation or servitisation characteristics. We report the triple interaction with digital services dummy in column (1) and with professional services in column (2). We control for NUTS2 fixed effects and year fixed effects. Additional controls are $log(Productivity_{t-1})$, $KIS_t$, $R\&Dpercapita_t$. Clustered standard errors at the NUTS2 regional level in parentheses.

## Service-oriented and digital Smart Specialisation strategies

Due to data limitation problems, we do not include services industries in our analyses. However, professional services (NACE code "M72") are important components of S3 strategies, since they frequently appear on RIS documents. Despite that, there is no description of how these services are implemented in the strategies, nor whether and how they are coupled with specific manufacturing sectors. Furthermore, the greatest part of the regions in our sample identified M72 as a priority, making the sample very unbalanced and virtually uninformative. Finally, and most importantly, services are hard to include in a related technological diversification setting. Related technological diversification is computed using patent data. Patents, however, capture only a part of innovation activities that are often linked to manufacturing industries. Services, on the other hand, rely mostly on non-patentable innovations, such as organisational innovations or financial innovations. Digital industries (J62 and J63) present the same issues. Specialisations in digital sectors are very common in RIS documents. However, they are difficult to interpret and less reliable for our relatedness approach. Regions often included digital specialisations to highlight the adoption or the increment of digital processes in their production. This makes it hard to define if their inclusion in a strategy is actually aiming at developing an industrial specialisation in digital industries. Also, even if there are technological classes that find a direct application in J62 and J63 (Eurostat, 2008), patentable innovations in digital services represent a minor part of the entire innovation activities undergoing in these sectors. However, is important to take into account both professional and digital industries. To do that we see that in the regions' priorities for S3, services are often listed in combination with with other manufacturing sectors. This implies that both professional and digital services might be included as complements to manufacturing strategies rather than as sectors of specialisation per se. To control for the effect of services on labour productivity in the S3 policy framework, we run a robustness test exploiting the data on the complementary aspects between services and/or digital industries specialisation with manufacturing sectors. To do that we execute a text analysis on documents with priorities' descriptions. Through this analysis, we can observe every priority with a manufacturing sector if words such as "ICT", "digital", "professional" and "service" appear in its description. In this way, we can control not only if region $r$ included sector $i$ in its strategy, but also if such a strategy features digital or service-oriented characteristics. We can thus distinguish manufacturing strategies that presented digital and service-oriented aspects from those that did not. In order to evaluate if the effects we observed in the main estimations are led by the implementation of digital or service-oriented strategies, we run our main estimations on the group of regions that indicated priorities coupled with, respectively, professional service and digital services.

Table 9 presents the estimation results of the effects of digital and professional services when these are coupled with manufacturing strategies. As we can see, the simple interaction terms (reported in the table with the name of the sector) present coefficients that are very similar and consistent with the estimates presented in table 4. We interpret this as a confirmation that the channels we identified are effective regardless of the implementation of digital or professional services among stated priorities. The triple interactions, moreover, estimate the effects of digitisation or servitisation processes when implemented in the strategies. While digital-oriented strategy has no statistically significant effect for any sector, service-oriented strategies seem to be slightly more effective in components industries. In general, however, these features do not alter the effect of specialisation decisions, especially for those regions that implemented their strategies following the principle of related diversification.

## Conclusions

In this paper, we have proposed a novel analytical framework for the evaluation of place-based policies and use it to assess the productivity effects of Smart Specialisation, taking into account the choices made in local economies and their implementation. We conjectured that the regions that choose their priorities following the technological diversification principles are the ones that can obtain higher gains in terms of productivity. We test this hypothesis by running a 2SLS on a database that combines information on regions' S3 strategies and their technological and industrial structure. To include in our analytical framework the degree of related diversification in S3 strategies (P. David, Foray, and B. Hall, 2009; McCann and Ortega-Argilés, 2015), we instrument the industrial policy decisions with the Technological Relatedness in Production (TRP). This original index connects the regions' technological base to their industrial composition. Our estimations uncover that Smart Specialisation has a significant impact on labour productivity growth when the theoretical principle of related diversification is followed. Results are positive across industrial specialisations of choice.

Naturally, the paper also presents some limitations. For example, it relies on patents, thus underestimating knowledge processes in domains that are not appropriable via formal intellectual property rights. Moreover, we do not consider the Cohesion Policy framework and do not address the problem of remaining disparities among EU regions, which has been recognised as a significant challenge in the context of EU regional innovation policy (see for example McCann and Ortega-Argilés (2013)). We have not considered the effects of technological or industrial cooperation between regions. This has been shown to produce benefits for cooperating regions from the viewpoint of diversification (Santoalha, 2019), and this aspect could provide an interesting avenue for further development from an evaluation perspective. Finally, we have not integrated institutional dynamics (Iacobucci, 2014), but further in-depth case studies of policy implementation could shed complementary light on specific governance mechanisms that might favour or hinder the effectiveness of the policy.

All in all, however, our results bear important implications for the design of future regional economies' place-based development policies. The framework we propose can also be adopted to better identify the channels through which regional characteristics affect the policy itself. The findings generally support the idea that related diversification has been a prominent and effective approach to regional growth. The main policy implication we draw is that regions can achieve sustained growth regardless of the industrial path they pursue, as long as they adhere to a consistent application of the policy. When the Entrepreneurial Discovery Process direct the strategies towards related sectors, regions have proved that they can overcome the risk of lock-in and stimulate growth, even though each of them may choose to prioritise different areas of specialisation. Indeed, we explicitly investigate the phenomenon of relatedness within the context of S3 strategies. In particular, we have shown that strategies that targeted related diversification and high-growth principles are consistent with the "high-road policy" theorised in the relatedness-complexity framework by Balland et al. (2019).[12] This result is not straightforward, given the ongoing debate on whether industrial policy should focus on more disruptive activities (De Noni, Ganzaroli, and Pilotti, 2021), also to pursue higher societal goals (Mazzucato, 2013). Our results suggest that policies targeting complex emergent sectors as possible 'game-changers' must be integrated into the technological and industrial contexts of countries and regions, or they may fail to produce any competitive advantage. Moreover, only further research will be able to monitor the possible future benefits of related diversification strategies, and assess whether the productivity gains we have observed are persistent through time, or whether there are limits that might generate decreasing benefits, as technologies, firms, industries and institutions adapt and change over time.

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[12]The term "high-road policy" refers to a Smart Specialisation strategy that targets high-complexity, high-relatedness sectors of technological specialisation.

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# Appendix

## Hierarchical Clustering

To aggregate sectors we rely on a data-driven approach. In particular, we use an algorithm of hierarchical clustering to build clusters of observations given a certain distance among the industrial specialisations. We indexed the correlation measure of the industrial inclusions in the same priorities to build a proximity measure. More specifically, we compute the distance between sectors $j$ and $k$ as:

$$d_{jk} = \frac{1 - \rho_{jk}}{2} \tag{5}$$

where $\rho_{jk}$ is the Pearson-correlation index for the co-occurrences of $j$ and $k$ in the same priority. In particular, $d_{jk}$ will be 1 if $j$ and $k$ appear in every priority only combined, while it will be 0 if $j$ never appears in a priority if $k$ is included and vice-versa. We have 20 sectors over 22 because 'Printing and reproduction of recorded media' (C18) and 'Manufacture of coke and refined petroleum products' (C19) never appear.

The algorithm of hierarchical clustering is an unsupervised reiterative method. It starts by sorting all the distances between the pairs of NACE2 sectors. Then it associates the two closest NACE2 sectors in one cluster. After that, it sorts all the units considering the cluster as one single unity and proceeds to match closest sectors in another cluster. Since each cluster counts as one unit, the new distances are computed between the units and the centroids of the clusters. This algorithm is called hierarchical because it associates two units at a time, starting from the closest ones up to the most distant. The easiest way to represent this process is a graph called dendrogram, due to its similarities to a tree. The dendrogram presents as many associations as several units minus one. This is because, in the last step, all units are clustered in one unique group. In Figure 4 we can observe the dendogram of our hierarchical clustering.

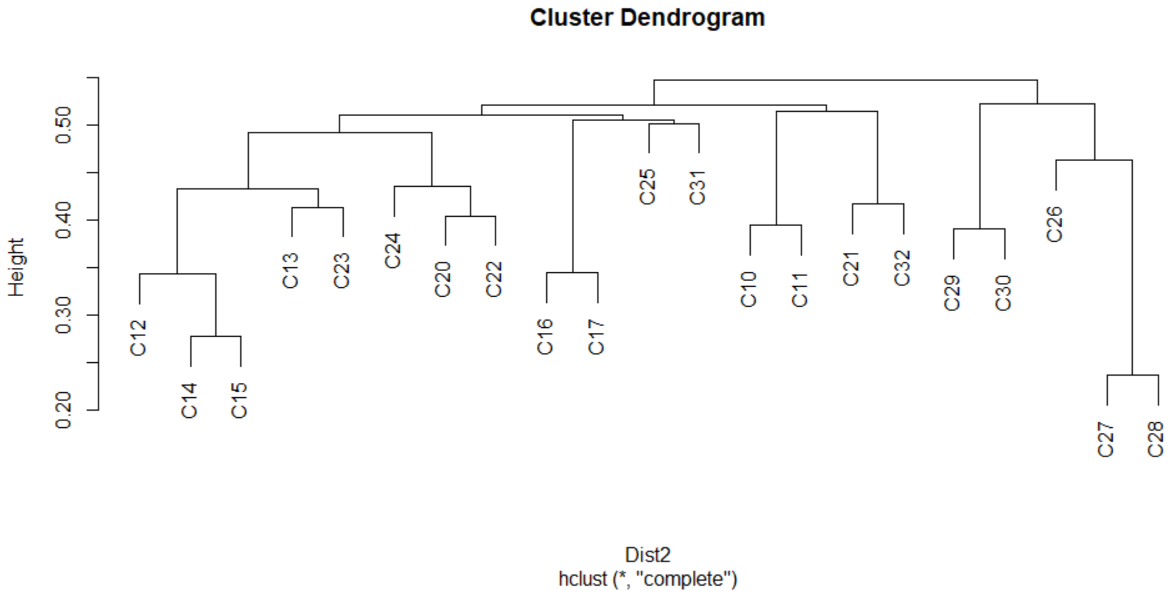


**Figure 4:** Dendogram of industries

The algorithm is completely unsupervised and defines only how close the are units. The decision on how many groups is convenient to aggregate the observations does not depend on any parameter of the group. To define the number of groups we are going to employ we need to cut the tree, based on clustering validation. To do that we observe the silhouette values of the clustering. The silhouette value is a measure of how similar an object is to its cluster (cohesion) compared to other clusters (separation). The silhouette ranges from -1 to +1, where a high value indicates that the object is well-matched to its cluster and poorly matched to neighbouring clusters. If most objects have a high value, then the clustering configuration is appropriate. If many points have a low or negative value, then the clustering configuration may have too many or too few clusters. Specifically, we perform the silhouette for any value between 1 and 21. These values correspond to the number of clusters we aim to aggregate our units by proceeding hierarchically along the dendrogram. The lowest is the number of cuts, the higher is the probability that a cluster is too wide and catches a negative silhouette value for at least one unit. We proceed until we find the minimum number of cuts with all silhouette widths greater than zero. The number of clusters that we got from the silhouette analysis is 9. Intuitively this can be represented as a line that cuts the dendrogram intersecting only nine of its branches. What is on the same "branch" under that line is going to be aggregated in the same cluster for our subsequent analysis.

We are aware of the limits of unsupervised methods, however, the aggregation this algorithm proposed is reasonable also from a theoretical perspective. We decided, then, to use these clusters for our analysis because they presented a straightforward economic interpretation of our results.

## OLS and IV estimates

**Table 10:** Automotive ATE and LATE

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.026 | 0.029 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.002 | 0.0002 |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.020 | 0.021 |
| | (0.014) | (0.013) |
| Automotive$\times Post_t$ | 0.001 | 0.038** |
| | (0.004) | (0.017) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.305 | 0.311 |
| Adjusted $R^2$ | 0.232 | 0.239 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 11:** Components ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.027 | 0.029 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.002 | $-0.0002$ |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.020 | 0.022 |
| | (0.014) | (0.014) |
| Components$\times Post_t$ | 0.001 | 0.065*** |
| | (0.004) | (0.024) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.305 | 0.318 |
| Adjusted $R^2$ | 0.232 | 0.247 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 12:** Agro-food ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.027 | 0.029 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.002 | $-0.0003$ |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.020 | 0.021 |
| | (0.014) | (0.013) |
| Agro-food$\times Post_t$ | 0.002 | 0.067*** |
| | (0.004) | (0.025) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.305 | 0.317 |
| Adjusted $R^2$ | 0.232 | 0.246 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 13:** Light Industries ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.027 | 0.030 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.002 | $-0.001$ |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.020 | 0.022 |
| | (0.014) | (0.013) |
| Light Industries$\times Post_t$ | 0.008 | $0.063^{**}$ |
| | (0.006) | (0.027) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.307 | 0.320 |
| Adjusted $R^2$ | 0.235 | 0.249 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

**Table 14:** Materials ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.027 | 0.030 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.002 | $-0.0005$ |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.021 | 0.021 |
| | (0.014) | (0.013) |
| Materials$\times Post_t$ | 0.005 | 0.063*** |
| | (0.005) | (0.021) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.306 | 0.319 |
| Adjusted $R^2$ | 0.234 | 0.248 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 15:** Wood & paper ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| log($Prod_{t-1}$) | 0.028 | 0.029 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.001 | 0.0002 |
| | (0.002) | (0.002) |
| log($R\&D_{t-1}$) | 0.022 | 0.021 |
| | (0.013) | (0.013) |
| Wood & Paper×$Post_t$ | 0.017 | 0.056*** |
| | (0.014) | (0.021) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.311 | 0.316 |
| Adjusted $R^2$ | 0.239 | 0.245 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 16:** Health ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | OLS | IV |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.027 | 0.029 |
| | (0.018) | (0.018) |
| $KIS_{t-1}$ | 0.001 | $-0.00003$ |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | 0.020 | 0.021 |
| | (0.014) | (0.014) |
| Health$\times Post_t$ | 0.006 | $0.051^{***}$ |
| | (0.004) | (0.020) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.307 | 0.314 |
| Adjusted $R^2$ | 0.234 | 0.242 |
| Residual Std. Error (df = 1063) | 0.025 | 0.025 |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

# Weighted Least Squares approach

**Table 17:** Automotive ATE and LATE

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | $0.042^{***}$ | $0.040^{***}$ |
| | (0.012) | (0.012) |
| $KIS_{t-1}$ | 0.00004 | $0.006^{*}$ |
| | (0.003) | (0.003) |
| $\log(R\&D_{t-1})$ | $-0.002$ | $-0.002$ |
| | (0.004) | (0.004) |
| Automotive$\times Post_t$ | $0.076^{***}$ | 0.0001 |
| | (0.017) | (0.004) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.335 | 0.320 |
| Adjusted $R^2$ | 0.263 | 0.246 |
| Residual Std. Error (df = 853) | 0.004 | 0.004 |
| F Statistic (df = 93; 853) | $4.631^{***}$ | $4.314^{***}$ |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

**Table 18:** Components ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.039*** | 0.033*** |
| | (0.010) | (0.010) |
| $KIS_{t-1}$ | −0.002 | 0.0004 |
| | (0.002) | (0.002) |
| $\log(R\&D_{t-1})$ | −0.001 | −0.0004 |
| | (0.003) | (0.004) |
| Components×$Post_t$ | 0.056*** | 0.005 |
| | (0.014) | (0.003) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.308 | 0.296 |
| Adjusted $R^2$ | 0.232 | 0.219 |
| Residual Std. Error (df = 864) | 0.003 | 0.003 |
| F Statistic (df = 94; 864) | 4.087*** | 3.864*** |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 19:** Agro-food ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.018 | 0.016 |
| | (0.011) | (0.011) |
| $KIS_{t-1}$ | 0.0004 | 0.002 |
| | (0.003) | (0.003) |
| $\log(R\&D_{t-1})$ | 0.002 | 0.002 |
| | (0.004) | (0.004) |
| Agro-food$\times Post_t$ | $0.049^{***}$ | $-0.001$ |
| | (0.017) | (0.005) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.289 | 0.282 |
| Adjusted $R^2$ | 0.211 | 0.204 |
| Residual Std. Error (df = 853) | 0.003 | 0.003 |
| F Statistic (df = 93; 853) | $3.722^{***}$ | $3.601^{***}$ |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

**Table 20:** Light industries ATE and LATE

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | $0.048^{***}$ | $0.049^{***}$ |
| | (0.011) | (0.011) |
| $KIS_{t-1}$ | 0.0004 | $0.007^{**}$ |
| | (0.003) | (0.003) |
| Light Industries$\times Post_t$ | $0.123^{***}$ | $0.010^{*}$ |
| | (0.018) | (0.005) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.370 | 0.338 |
| Adjusted $R^2$ | 0.302 | 0.266 |
| Residual Std. Error (df = 864) | 0.003 | 0.004 |
| F Statistic (df = 94; 864) | $5.409^{***}$ | $4.684^{***}$ |
| *Note:* | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

**Table 21:** Materials ATE and LATE

| | *Dependent variable:* $\Delta log(Prod_t)$ | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | $0.022^{**}$ | $0.020^{*}$ |
| | (0.011) | (0.011) |
| $KIS_{t-1}$ | $-0.001$ | 0.001 |
| | (0.003) | (0.003) |
| $\log(R\&D_{t-1})$ | 0.003 | 0.002 |
| | (0.004) | (0.004) |
| Materials$\times Post_t$ | $0.053^{***}$ | 0.004 |
| | (0.015) | (0.004) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.306 | 0.297 |
| Adjusted $R^2$ | 0.230 | 0.221 |
| Residual Std. Error (df = 864) | 0.003 | 0.003 |
| F Statistic (df = 94; 864) | $4.050^{***}$ | $3.890^{***}$ |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

**Table 22:** Health ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | WIV | |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.010 | 0.010 |
| | (0.011) | (0.011) |
| $KIS_{t-1}$ | −0.002 | −0.001 |
| | (0.003) | (0.003) |
| $\log(R\&D_{t-1})$ | 0.006 | 0.005 |
| | (0.003) | (0.004) |
| Health×$Post_t$ | 0.027* | 0.004 |
| | (0.014) | (0.003) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.284 | 0.282 |
| Adjusted $R^2$ | 0.206 | 0.204 |
| Residual Std. Error (df = 864) | 0.003 | 0.003 |
| F Statistic (df = 94; 864) | 3.645*** | 3.612*** |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 23:** Wood & paper ATE and LATE

| | *Dependent variable: $\Delta log(Prod_t)$* | |
|---|---|---|
| | WIV | WLS |
| | (1) | (2) |
| $\log(Prod_{t-1})$ | 0.031*** | 0.031*** |
| | (0.010) | (0.011) |
| $KIS_{t-1}$ | −0.0001 | 0.001 |
| | (0.003) | (0.003) |
| $\log(R\&D_{t-1})$ | 0.003 | 0.003 |
| | (0.004) | (0.004) |
| Wood & Paper$\times Post_t$ | 0.082*** | 0.022*** |
| | (0.016) | (0.005) |
| Regional FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Observations | 1,175 | 1,175 |
| $R^2$ | 0.324 | 0.316 |
| Adjusted $R^2$ | 0.251 | 0.241 |
| Residual Std. Error (df = 864) | 0.003 | 0.003 |
| F Statistic (df = 94; 864) | 4.415*** | 4.243*** |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

# Leave-one-out models

**Table 24:** Leave Austria Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.022 | 0.0004 | | | | | | | | | | | | |
| | (0.014) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.055$^{***}$ | 0.001 | | | | | | | | | | |
| | | | (0.021) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | −0.0003 | −0.001 | | | | | | | | |
| | | | | | (0.016) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.038$^{*}$ | 0.010 | | | | | | |
| | | | | | | | (0.023) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.034$^{*}$ | 0.003 | | | | |
| | | | | | | | | | (0.018) | (0.004) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.039$^{*}$ | 0.018 | | |
| | | | | | | | | | | | (0.022) | (0.014) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.038$^{**}$ | 0.006 |
| | | | | | | | | | | | | | (0.017) | (0.004) |
| Observations | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 |
| $R^2$ | 0.283 | 0.280 | 0.295 | 0.280 | 0.280 | 0.280 | 0.294 | 0.284 | 0.286 | 0.281 | 0.288 | 0.290 | 0.288 | 0.283 |
| Adjusted $R^2$ | 0.207 | 0.204 | 0.221 | 0.204 | 0.203 | 0.204 | 0.219 | 0.208 | 0.211 | 0.204 | 0.213 | 0.214 | 0.212 | 0.207 |
| Residual Std. Error (df = 971) | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

**Table 25:** Leave Czechia Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.041$^{***}$ | 0.001 | | | | | | | | | | | | |
| | (0.015) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.083$^{***}$ | 0.001 | | | | | | | | | | |
| | | | (0.024) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.008 | 0.001 | | | | | | | | |
| | | | | | (0.016) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.051$^{**}$ | 0.008 | | | | | | |
| | | | | | | | (0.022) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.055$^{***}$ | 0.005 | | | | |
| | | | | | | | | | (0.020) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.051$^{**}$ | 0.016 | | |
| | | | | | | | | | | | (0.022) | (0.015) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.051$^{***}$ | 0.005 |
| | | | | | | | | | | | | | (0.018) | (0.004) |
| Observations | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 | 1,139 |
| $R^2$ | 0.314 | 0.304 | 0.323 | 0.304 | 0.304 | 0.304 | 0.323 | 0.306 | 0.316 | 0.306 | 0.313 | 0.310 | 0.314 | 0.306 |
| Adjusted $R^2$ | 0.242 | 0.231 | 0.252 | 0.231 | 0.231 | 0.231 | 0.252 | 0.233 | 0.244 | 0.233 | 0.241 | 0.238 | 0.242 | 0.233 |
| Residual Std. Error (df = 1030) | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

**Table 26:** Leave Germany Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.039$^{***}$ | 0.001 | | | | | | | | | | | | |
| | (0.013) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.066$^{***}$ | 0.0003 | | | | | | | | | | |
| | | | (0.024) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.022 | 0.005 | | | | | | | | |
| | | | | | (0.018) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.060$^{***}$ | 0.009 | | | | | | |
| | | | | | | | (0.022) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.055$^{***}$ | 0.005 | | | | |
| | | | | | | | | | 0.019) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.052$^{***}$ | 0.017 | | |
| | | | | | | | | | | | (0.019) | (0.014) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.053$^{***}$ | 0.006 |
| | | | | | | | | | | | | | (0.016) | (0.005) |
| Observations | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 | 1,043 |
| $R^2$ | 0.315 | 0.306 | 0.319 | 0.306 | 0.308 | 0.307 | 0.328 | 0.308 | 0.318 | 0.307 | 0.316 | 0.312 | 0.316 | 0.308 |
| Adjusted $R^2$ | 0.242 | 0.232 | 0.247 | 0.232 | 0.234 | 0.233 | 0.257 | 0.235 | 0.246 | 0.234 | 0.244 | 0.239 | 0.244 | 0.235 |
| Residual Std. Error (df = 942) | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

**Table 27:** Leave Denmark Out

| | *Dependent variable:* $\Delta log(Prod_t)$ | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.045*** | 0.0003 | | | | | | | | | | | | |
| | (0.017) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.056*** | −0.0002 | | | | | | | | | | |
| | | | (0.020) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | −0.0003 | 0.001 | | | | | | | | |
| | | | | | (0.015) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.056** | 0.008 | | | | | | |
| | | | | | | | (0.024) | (0.006) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.054** | 0.004 | | | | |
| | | | | | | | | | (0.023) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.056** | 0.016 | | |
| | | | | | | | | | | | (0.025) | (0.014) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.058*** | 0.005 |
| | | | | | | | | | | | | | (0.020) | (0.004) |
| Observations | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 | 1,115 |
| $R^2$ | 0.324 | 0.316 | 0.327 | 0.316 | 0.316 | 0.316 | 0.334 | 0.318 | 0.325 | 0.317 | 0.324 | 0.322 | 0.324 | 0.318 |
| Adjusted $R^2$ | 0.253 | 0.244 | 0.256 | 0.244 | 0.244 | 0.244 | 0.264 | 0.246 | 0.254 | 0.246 | 0.253 | 0.251 | 0.253 | 0.246 |
| Residual Std. Error (df = 1008) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 28:** Leave Spain Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive×$Post_t$ | 0.064*** | 0.003 | | | | | | | | | | | | |
| | (0.014) | (0.005) | | | | | | | | | | | | |
| Components×$Post_t$ | | | 0.068*** | 0.004 | | | | | | | | | | |
| | | | (0.021) | (0.004) | | | | | | | | | | |
| Agro-food×$Post_t$ | | | | | 0.059*** | 0.004 | | | | | | | | |
| | | | | | (0.022) | (0.004) | | | | | | | | |
| Light Industries×$Post_t$ | | | | | | | 0.067*** | 0.013* | | | | | | |
| | | | | | | | (0.020) | (0.007) | | | | | | |
| Materials×$Post_t$ | | | | | | | | | 0.085*** | 0.006 | | | | |
| | | | | | | | | | (0.022) | (0.005) | | | | |
| Wood & Paper×$Post_t$ | | | | | | | | | | | 0.081*** | 0.028 | | |
| | | | | | | | | | | | (0.022) | (0.020) | | |
| Health×$Post_t$ | | | | | | | | | | | | | 0.068*** | 0.007 |
| | | | | | | | | | | | | | (0.017) | (0.005) |
| Observations | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 | 971 |
| $R^2$ | 0.354 | 0.332 | 0.349 | 0.333 | 0.343 | 0.333 | 0.363 | 0.336 | 0.356 | 0.334 | 0.353 | 0.343 | 0.349 | 0.335 |
| Adjusted $R^2$ | 0.285 | 0.261 | 0.279 | 0.262 | 0.273 | 0.261 | 0.295 | 0.265 | 0.287 | 0.263 | 0.284 | 0.273 | 0.279 | 0.264 |
| Residual Std. Error (df = 876) | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 | 0.026 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 29:** Leave France Out

| | *Dependent variable:* $\Delta log(Prod_t)$ | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.039*** | 0.001 | | | | | | | | | | | | |
| | (0.014) | (0.005) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.055*** | −0.0003 | | | | | | | | | | |
| | | | (0.016) | (0.005) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.004 | 0.002 | | | | | | | | |
| | | | | | (0.013) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.047** | 0.009 | | | | | | |
| | | | | | | | (0.019) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.044** | 0.006 | | | | |
| | | | | | | | | | (0.017) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.047** | 0.018 | | |
| | | | | | | | | | | | (0.022) | (0.014) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.052** | 0.006 |
| | | | | | | | | | | | | | (0.022) | (0.005) |
| Observations | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 | 959 |
| $R^2$ | 0.308 | 0.299 | 0.311 | 0.299 | 0.299 | 0.299 | 0.317 | 0.301 | 0.307 | 0.301 | 0.307 | 0.306 | 0.307 | 0.301 |
| Adjusted $R^2$ | 0.234 | 0.223 | 0.237 | 0.223 | 0.223 | 0.223 | 0.243 | 0.226 | 0.233 | 0.225 | 0.232 | 0.231 | 0.232 | 0.226 |
| Residual Std. Error (df = 865) | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 30:** Leave Italy Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.037*** | 0.002 | | | | | | | | | | | | |
| | (0.013) | (0.005) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.049** | −0.002 | | | | | | | | | | |
| | | | (0.023) | (0.005) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.009 | 0.004 | | | | | | | | |
| | | | | | (0.015) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.051** | 0.009 | | | | | | |
| | | | | | | | (0.021) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.041** | 0.003 | | | | |
| | | | | | | | | | (0.018) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.039** | 0.018 | | |
| | | | | | | | | | | | (0.019) | (0.017) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.041*** | 0.009* |
| | | | | | | | | | | | | | (0.014) | (0.005) |
| Observations | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 | 947 |
| $R^2$ | 0.323 | 0.316 | 0.323 | 0.316 | 0.316 | 0.316 | 0.335 | 0.318 | 0.322 | 0.316 | 0.321 | 0.322 | 0.322 | 0.320 |
| Adjusted $R^2$ | 0.250 | 0.242 | 0.250 | 0.242 | 0.242 | 0.243 | 0.263 | 0.244 | 0.249 | 0.242 | 0.248 | 0.249 | 0.249 | 0.247 |
| Residual Std. Error (df = 854) | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.026 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 | 0.027 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

**Table 31:** Leave Netherlands Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.037*** | 0.0002 | | | | | | | | | | | | |
| | (0.012) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.050*** | 0.003 | | | | | | | | | | |
| | | | (0.017) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.007 | 0.003 | | | | | | | | |
| | | | | | (0.016) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.051** | 0.008 | | | | | | |
| | | | | | | | (0.021) | (0.006) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.048*** | 0.008 | | | | |
| | | | | | | | | | (0.018) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.048** | 0.017 | | |
| | | | | | | | | | | | (0.019) | (0.015) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.048*** | 0.005 |
| | | | | | | | | | | | | | (0.015) | (0.004) |
| Observations | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 | 1,067 |
| $R^2$ | 0.314 | 0.306 | 0.315 | 0.306 | 0.306 | 0.306 | 0.324 | 0.308 | 0.316 | 0.309 | 0.315 | 0.312 | 0.315 | 0.307 |
| Adjusted $R^2$ | 0.242 | 0.232 | 0.243 | 0.233 | 0.232 | 0.233 | 0.253 | 0.234 | 0.244 | 0.236 | 0.242 | 0.239 | 0.242 | 0.234 |
| Residual Std. Error (df = 964) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| *Note:* | | | | | | | | | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 32:** Leave Portugal Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.038*** | 0.001 | | | | | | | | | | | | |
| | (0.013) | (0.004) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.055*** | 0.001 | | | | | | | | | | |
| | | | (0.018) | (0.004) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | 0.006 | 0.003 | | | | | | | | |
| | | | | | (0.015) | (0.004) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | 0.053** | 0.009 | | | | | | |
| | | | | | | | (0.021) | (0.007) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.046*** | 0.005 | | | | |
| | | | | | | | | | (0.017) | (0.005) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.047** | 0.023 | | |
| | | | | | | | | | | | (0.019) | (0.019) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.047*** | 0.006 |
| | | | | | | | | | | | | | (0.015) | (0.005) |
| Observations | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 | 1,127 |
| $R^2$ | 0.320 | 0.311 | 0.322 | 0.311 | 0.311 | 0.311 | 0.331 | 0.313 | 0.320 | 0.313 | 0.319 | 0.320 | 0.320 | 0.313 |
| Adjusted $R^2$ | 0.249 | 0.239 | 0.251 | 0.239 | 0.239 | 0.239 | 0.260 | 0.241 | 0.249 | 0.240 | 0.248 | 0.249 | 0.248 | 0.241 |
| Residual Std. Error (df = 1019) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

**Table 33:** Leave Romania Out

| | *Dependent variable: $\Delta log(Prod_t)$* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Automotive$\times Post_t$ | 0.0002 | 0.003 | | | | | | | | | | | | |
| | (0.009) | (0.002) | | | | | | | | | | | | |
| Components$\times Post_t$ | | | 0.028$^{**}$ | 0.0004 | | | | | | | | | | |
| | | | (0.013) | (0.002) | | | | | | | | | | |
| Agro-food$\times Post_t$ | | | | | −0.023$^{**}$ | −0.004 | | | | | | | | |
| | | | | | (0.009) | (0.003) | | | | | | | | |
| Light Industries$\times Post_t$ | | | | | | | −0.005 | 0.001 | | | | | | |
| | | | | | | | (0.008) | (0.004) | | | | | | |
| Materials$\times Post_t$ | | | | | | | | | 0.004 | 0.002 | | | | |
| | | | | | | | | | (0.009) | (0.003) | | | | |
| Wood & Paper$\times Post_t$ | | | | | | | | | | | 0.003 | −0.002 | | |
| | | | | | | | | | | | (0.009) | (0.003) | | |
| Health$\times Post_t$ | | | | | | | | | | | | | 0.009 | 0.001 |
| | | | | | | | | | | | | | (0.009) | (0.002) |
| Observations | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 | 1,075 |
| $R^2$ | 0.260 | 0.260 | 0.265 | 0.260 | 0.264 | 0.261 | 0.260 | 0.260 | 0.260 | 0.260 | 0.260 | 0.260 | 0.260 | 0.260 |
| Adjusted $R^2$ | 0.181 | 0.182 | 0.187 | 0.181 | 0.186 | 0.183 | 0.181 | 0.181 | 0.181 | 0.181 | 0.181 | 0.181 | 0.182 | 0.181 |
| Residual Std. Error (df = 971) | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01