Turning technological relatedness into industrial strategy: The productivity effects of Smart Specialisation in Europe

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Abstract

In this paper we evaluate the impact of Smart Specialisation policies on European regional economies. We propose a novel analytical framework that considers the policy prescription defined by the Entrepreneurial Discovery Process (EDP) in the identification of new growth opportunities and the role that technological relatedness plays in choosing the new industrial specialisation priorities. We then estimate the effects of the policy by using an IV estimation approach to address endogeneity problems. We apply it to an extensive dataset of 102 NUTS2 regions extracted from the European Commission Smart Specialisation Portal. The results reveal that Smart Specialisation strategies increased labour productivity as long as the priorities were 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 specialization? 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 specialization, 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 generalizable 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 place-specific characteristics of regions which cannot be completely designed and implemented from the top-down. The third European Union Cohesion Policy cycle (2014-2020) introduced the principle that in order to obtain policy support, each region had to develop and submit 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 policy is premised on the ex-ante identification of the economic strengths and potential of regions. The expansion of a region's growth opportunity set should target the creation 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 (EDP) (Foray, P. A. David, and B. H. Hall, 2011; Foray, Goddard, and Beldarrain, 2012). This process outlines a path of specialization or diversification guided by the decision to explore new production possibilities, which should be negotiated with a broad range of stakeholders, including firms, higher education institutions, research organizations, and independent innovators. Through EDP, regions assess their existing knowledge assets and explore in which complementary and more or less adjacent domains they should expand their innovation capabilities (P. David, Foray, and B. Hall, 2009). The EDP implies that Smart Specialisation rejects the idea of a 'one-size-fits-all" policy approach (Di Cataldo, Monastiriotis, and Rodríguez-Pose, 2022), with every region creating – at least in theory – an original and specific strategy, both in terms of areas and schemes of intervention. Regional strategies may differ greatly from each other in multiple aspects. In this work, we are going to focus on the mechanisms of choice of manufacturing specializations. We are going to refer to this specific decision as an 'industrial specialization decision' or 'industrial inclusion'. An evaluation of these strategies requires the development of an analytical framework that can bring together the selection and the impact sides of the policy.In this work we build such a framework linking together technological capabilities, regional selection of specializations and productivity. This approach can have general applicability in the evaluation of place-based innovation policies because it accounts for the ex-ante characteristics of regions and their role in conditioning the policy impact. Moreover, we make a novel empirical contribution by showing whether and how the Smart Specialisation policy has been beneficial in European regions in terms of labor productivity (but we anticipate that results hold if we consider alternative variables such as Gross value Added or hours worked). We show that regions that selected their specializations based on their relatedness with pre-existent technological capabilities outperformed regions that made similar choices irrespective of those capabilities.

The paper is organized 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 specialization decisions and their impact on regional performance. The paper concludes by discussing the implications of Smart Specialisation policies and their development.

Literature Review

Smart Specialisation can be considered as an explicit articulation of the idea of place-based innovation policy for the European area (Barca, 2009). Smart Specialisation was conceived as an innovation-enhancing policy that aimed to create self-sustaining, 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" to increase productivity (P. David, Foray, and B. Hall, 2009). As a policy, Smart Specialisation is intrinsically linked with the third cycle of European Cohesion Policies (2014-2020) and so it has been labelled 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). 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). However, it is important to stress that when S3 was implemented, our understanding of Smart Specialisation was significantly less articulated than it is now, to the degree that Smart Specialisation has also been defined as a "policy running ahead of theory" (Foray, P. A. David, and B. H. Hall, 2011). Smart specialisation policies have theoretical foundations that are rooted in evolutionary economic geography. Scholars interested in innovation have long argued that space and history matter in the production, diffusion and use of new knowledge (Dosi et al., 1988). It is well known that has both a tacit and codified component, and this makes knowledge bundles highly contextual to places and sensitive to proximity (or distance-related decay) (Feldman and Kogler, 2010). Tacit knowledge is particularly difficult to identify and measure, and is only transmittable through frequent and repeated social interactions. Because of the tacit nature of an important share of productive knowledge (Polanyi, 2012), economic agents absorb and share knowledge in specific local contexts. By doing 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 organizations (R. N. Freeman, 1987), and by adapting their institutional frameworks (R. R. Nelson, 1995). Out of a wealth of tacit interactions, codified knowledge also emerges in ways that can be also captured by specific quantitative indicators. Comparative advantages can be built on this knowledge by strengthening existing specializations or by entering new knowledge domains (Foray, P. A. David, and B. H. Hall, 2011).

The expansion into new domains is a process that entails different diversification choices in various possible directions. The literature on 'related diversification' stresses the idea that there are advantages in diversifying with a clear view of what sectors, technologies, skills, and outputs 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 specializations can evolve (Iacobucci and Guzzini, 2016).

The empirical literature has dedicated considerable attention to the concept of relatedness and its role in economic growth (Content and Frenken, 2016; Boschma, 2017). 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 et al., 2022), higher GDP growth rates (Saviotti and Frenken, 2008), increments in labor productivity (Boschma and Iammarino, 2009; Rocchetta, Ortega-Argilés, and Kogler, 2022), and stronger resilience after crises (Rocchetta and Mina, 2019; Rocchetta, Mina, et al., 2022). Moreover, related industrial structures are likely to follow trajectories that can increase relatedness even further, since high relatedness may lead to branching into new related - rather than unrelated - industries (Neffke, Henning, and Boschma, 2011; Neffke and Henning, 2013). This is because regions are more likely to acquire new specializations 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). Despite the emerging evidence on the effects and role of relatedness, it remains quite difficult to describe in practice what a 'related economy' might be, and relatively little attention has been given to the contexts and mechanisms through which related variety shapes regional economic growth (Bathelt and Storper, 2023). Smart Specialisation was firstly conceived as a new pathway for the development of relatedness-based industrial strategies (Foray, 2009; Foray, Goddard, and Beldarrain, 2012). This dominant approach has led the subsequent literature to interpret and analyze Smart Specialisation using the concepts of "related diversification" and "relatedness" (McCann and Ortega-Argilés, 2011; McCann and Ortega-Argilés, 2015). Despite this helped to frame Smart Specialisation in a well-defined literature, the most recent conceptualizations are calling in to doubt the dominant role of related diversification in regional development policies. In particular, they tend to emphasize the benefits of branching into more novel but less related domains (Giustolisi, Benner, and Trippl, 2023; Deegan, Broekel, and Fitjar, 2021; asheim, 2019). Indeed, wide evidence emerged on the ambivalent performance of excessively related economies (Rocchetta, Ortega-Argilés, and Kogler, 2022). While a minimum degree of proximity is desirable to enhance knowledge diffusion, excess proximity might lead to negative economic outlooks. Too much technological relatedness, indeed, negatively correlates with the ability of regions to adjust to emerging disruptive sectors (De Noni, Ganzaroli, and Pilotti, 2021) with the risks of lock-in (Boschma and Iammarino, 2009; Broekel and Boschma, 2012). However, by the time S3 strategies came out, related diversification was still unchallenged as the driving principle behind Smart Specialisation.

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 is to be spent. This process is described in the Smart Specialisation guidelines (Foray, Goddard, and Beldarrain, 2012) where a key role is played by the Entrepreneurial Discovery Process (EDP). Foray, P. A. David, and B. Hall (2009) conceptualized the EDP as a learning process that aims to identify research and innovation domains where a region has the potential to excel, and where entrepreneurial actors are likely to lead the exploration of new promising areas for future specialization. As a policy tool, the EDP is an evidence-based approach that pushes stakeholders to generate insights into the potential of new activities, thereby allowing for more effective targeting of research and innovation policy objectives (Perianez Forte and Wilson, 2021). An entrepreneurial discovery process may start with the identification of priorities for the region's S3 strategy and extend stakeholders' participation into policy implementation, while priorities are progressively refined and policies adapted over time (Foray, Eichler, and Keller, 2021). In general, priorities should be set for those sectors in which a regional economy has greater potential to gain new competitive advantages. By the relatedness principles, this is likely to be in related areas of activity (Balland et al., 2019). It is interesting that not all stakeholders may 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). Furthermore, and in practice, local stakeholders can make a variety of choices based on reasons that depart from principles of relatedness or unrelatedness. In this respect, 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), and it is possible that – even in the absence of vested interest – some regions select strategies, for example, by mimicking neighboring regions rather than following a well-structured EDP (Di Cataldo, Monastiriotis, and Rodríguez-Pose, 2022).

A recent thread of empirical studies has addressed the role of relatedness in a Smart Specialisation strategy framework. Rigby et al. (2022) employ a relatedness-complexity framework study Smart Specialisation effects on regional employment. Deegan, Broekel, and Fitjar (2021) show that the likelihood of including an economic domain (NACE sector) in the EDP is positively correlated to skills relatedness and the complexity of that sector. Marrocu et al. (2023) evaluated the specialization paths of regions, comparing policy decisions with regional comparative advantages and related diversification paths. Panori, Kakderi, and Dimitriadis (2022) attempt to identify the possible specialization decisions of 16 regions based on technological opportunities. All these analyses provide very interesting insights. However, as noted by Bathelt and Storper (2023), 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 address this gap in the literature, and we do so, first of all, by building an analytical framework that takes into account the mechanisms through which regions select the industries to be included as priorities in their Specialisation strategies. This framework explicitly links the industrial side of the policy with the regions' technological capabilities and advantages. Thanks to this approach, we can analyze how relatedness influence the choice of industries, and at a second stage we can then assess the effects of these choices on regional productivity. Because of the time window that is available, we will focus on the short and medium-term effects of the policy, but we will address the dynamic effect of the policy through time. Building on insights from both the related diversification and the Smart Specialisation literature, we now turn to the illustration of our empirical strategy.

Research strategy, Data and Methods

A key challenge in evaluating place-based innovation policies is identifying the mechanisms behind policy decisions. In the case of Smart Specialisation the decisions regarding the choice of the industrial priorities that are to be included as new specializations is made through the Entrepreneurial Discovery Process (EDP). The EDP consists of a continuous process of self-discovery that aims at identifying the domains with more favorable growth expectations. The principle of relatedness suggests that among the domains identified through the EDP, regions should choose the ones that are closer to the ones where innovators already operate. The intuition behind this principle is that a similar approach embeds fewer risks for the innovators (Balland et al., 2019). The type of related diversification process that the policy promotes depends on regional characteristics and is conditional of the portfolio of existing activities (Deegan, Solheim, et al., 2022). In evaluating the effectiveness of S3 policies we need to analyze how a relatedness-based approach can improve regional performances. To do that, we rely on three specific assumptions drawn from the design of Smart Specialisation and the EDP.

Firstly, we consider the distribution of technological capabilities in relation to their possible industrial applications. We conjecture that a match between the incumbent technological capabilities and the demand for skills (P. David, Foray, and B. Hall, 2009) has a positive impact on regional productivity. Indeed, a capabilities-matching approach is likely to lead to reallocating production factors where technological capabilities are stronger. In the short and medium run, we expect labor productivity to change as labor inputs and output adjust after policy implementation. The degree to which an industry is related to the region's productive context depends on the pool of technological capabilities it can deploy. Secondly, we need to isolate the effects of industrial inclusion in the region S3 strategy from the effects of those dynamics that make a sector more or less related. Thirdly, S3 strategies may or may not be fully aligned with the technological dynamics of the region. Technological relatedness is not the only possible rationale for the of selection of priorities. Some regions may make decisions based on criteria that deviate from purely economic considerations, maybe due to the power asymmetries between local stakeholders (e.g. workers may be under – or over–represented in the governance charged with strategic decisions) (Aranguren et al., 2019). In some cases, regions do not have adequate managerial support to implement a coherent and well-organized approach (Gianelle, Guzzo, and Mieszkowski, 2019). Nevertheless, when industries included in the policy are related to the region's technological core, we consider these choices to follow a relatedness-based EDP.

Our goal is to assess if S3 policies that follow a relatedness approach in the choice of priorities foster regional productivity growth. We use a two-stage estimation strategy to proxy the selection stage as the first stage and use the fitted values in the main regression for the second (evaluation) stage. Using an instrument for the selection of priorities represents an important advantage besides the identification of unbiased estimates. An IV approach, contrary to OLS generates estimates that are Local Average Treatment Effects (LATEs). This means that an IV will identify the effect of the treatment – i.e. whether a sector is included in the S3 strategies – for regions that chose the treatment *because* of the relatedness of the sector with technological capabilities of the region (our instrument). The estimator compares regions that specialized in sector k because k had high relatedness, with regions that did not specialize in k because the sector was not related. By using the different weighting scheme of the IV estimators with respect to the OLS, we can identify in an appropriate way the effects of a specialization choice that is made following a relatedness approach. While we are not able to observe the effects of specializations made following different rationales without employing a different instrument, the advantage of our approach is that it makes it possible to model the selection process based on an exogenous factor, and to use its variations to estimate the impact of specializations choices on regional productivity.

We collect data from the European Commission's portal on S3 policies '*S3 Platform*'.[1] Using the EyeRIS3, it is possible to scan the regions' RIS3 documents and their summary

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

sheets. For every region, the summary sheets report the structure of the strategy and related industrial specializations. Every strategy is divided into priorities and every priority captures a specific objective. The industrial specializations are those economic domains associated with any target.[2] For every priority, industrial specializations are identified by their NACE2 code Rev. 2. We collect S3 data on 102 NUTS2 regions.[3] The average number of priorities in the strategies we observe is 5.5. On average, every priority is associated with 4.6 industrial sectors. The focus of our analysis is on the manufacturing sectors (NACE1 code 'C'). Even though technological dynamics can affect also the service sector, both technology and productivity are measured more reliably for the manufacturing sectors, and the use of patents as proxies for technological capabilities is more appropriate for the study of manufacturing than for services (Boschma, 2017). Moreover, there is no established way to link technology classes with specific service sectors, whereas the literature provides greater details and precise indications for manufacturing (Eurostat, 2008; Panori, Kakderi, and Dimitriadis, 2022). We use the detailed information contained in patent documents to track technological capabilities at the regional level, and exploit co-occurences and complementarities across technology classes and industries to assess the impact of the policy

INSERT FIGURE 1

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[2]These data present important limitations. The most important one is that we cannot observe in any detail the extent to which a sector is included in the strategies, but we can only observe if the sector is present in at least one priority. We have no information on the size of the funds that were granted and in what specific way they were spent.

[3]The entire set of regions in the portal includes 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 the regions in Austria, Czechia, Germany, Denmark, Spain, France, Italy, Netherlands, Portugal and Romania.

In figure 1 we can observe the distributions of industrial sectors included in the regions' strategies. There are 23 NACE2 manufacturing sectors. The median number of specializations in our sample is 4. As we can see, among 102 regions only 22 present an S3 strategy with 6 or more industrial specializations. Four of them present 10 specializations, while 7 regions included no manufacturing specializations in their strategy. These are all included in the sample because dropping them would result in sample selection bias, which must be avoided. 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 involving a limited number of sectors. There are few exceptions, but most regions decided to specialize in fewer than 6 manufacturing sectors.

As we have already emphasised, S3 policies were designed when Smart Specialisation guidelines suggested to follow a relatedness approach to diversification in the pursuit of higher value-added economic activities. To this end, industrial inclusions did not target related technologies per se, but related industries. To estimate the effects of an industrial inclusion, we employ a standard Two-Ways Fixed Effect Difference-in-Difference (TWFE DiD) estimation. The equation of this standard model is reported in (1):

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

Y_{rt} is an outcome indicating regional productivity, X_{rt} captures regional characteristics, $D_r^{(k)}$ is a dummy taking value 1 if region r included sector k in its RIS3, while $Post_t$ is a dummy taking value 1 if the year is after 2013. The two-ways FE are represented by α_r and α_t. Notice that the inclusion of these fixed effects cancels out the estimation of the non-interacted parameters $D_r^{(k)}$ and $Post_t$. The *average* impact of the decision to specialize in sector k on labor productivity, then, is β^k. However, estimating this parameter is challenging. There are, indeed, two factors that can act as confounders in an empirical setting.

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

The first confounder in equation (2) is the *Interdependent Sectors* factor. This depends on how these strategies are built. Indeed, industrial specializations co-occur with different frequencies in priorities. The probability of having an industrial specialization in one priority is not independent from other industrial specializations. 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; because the same technological shocks simultaneously affect upstream and downstream activities; because some sectors might contribute to the same priority, affecting different aspects of one specialization objective; or, finally, because a specialization strategy reallocating competencies towards more productive sectors 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 specializations 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.[4] We chose this data-driven approach because the association we got from clustering had sound

[4]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.

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. specialization in some industrial areas is assumed to be independent of specialization in any other. In Figures 2 and 3 we can observe how the specializations in the broader industrial areas are distributed in the regions of our sample. Unsurprisingly, agro-food and components represent the most common specializations. The second and third most frequent specializations are in the automotive and health industries. The least common industrial areas are wood and paper industries.

INSERT TABLE 1

INSERT FIGURE 2

INSERT FIGURE 3

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 priority choices also based on these dynamics, so we cannot state that the choices made are random. In our empirical framework we solve this problem by instrumenting the inclusion decisions with the degree of relatedness of the sector. We build such relatedness index following 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. In light of this, some patent finds application in more than one industrial sector. Using patent data by inventors' location we catch how technological capabilities are distributed across regions and technological sectors. If a region produces a patent in a certain sector, it means that it hosts inventors (and organizations) endowed with technological capabilities in that sector. [5]

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. In other words, 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.[6]

INSERT TABLE 2

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

In the first stage of our model, we derive the likelihood that each region specializes in

[5] Naturally, there are limitations to this approach, and it is important to bear them in mind. First, patents do not capture the full extent of potentially relevant tacit and informal knowledge. Secondly, we exclude technological knowledge that has no industrial application, and do not observe complementary capabilities that may be important to take technologies to the market, such as managerial capabilities.

[6] Metals is not reported since no region chose it as a specialization area.

each sector following the relatedness principle. We want to test whether a sector with a greater degree of technological relatedness to the existing knowledge base of the region is more likely to be included in a RIS. we therefore formulate the following hypothesis:

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

In the second stage, we estimate the impact of these priority decisions on labor productivity growth. The literature leads us to expect that regions specializing 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 specializing in industries more related to their existing technological capabilities experience on average higher productivity gains.

Before the estimation, it is important to look at how the specialization decisions of each industrial inclusion correlate with some of the regional characteristics in 2013. When we do this, we can also detect whether some specializations are more likely to be adopted based on some specific regional characteristic. In table 3, we can see the correlation indices with three dimensions: labor productivity, GVA and share of employees in KIS. Specialization decisions are mostly uncorrelated with all of these dimensions, with a few exceptions. Agro-food industries are not chosen as an inclusion in regions with more service sector employees. This is plausible since there will be a weaker preference for agro-food specializations in urban areas. Wood and paper, and light industries' inclusions, instead, are more frequent in low-productivity regions.

INSERT TABLE 3

Our estimation strategy follows a 2SLS approach. In the first stage, we proxy the specialization decisions across seven industrial areas as reported in equation (3).[7]

[7]We discard Furniture from the analysis since it was chosen as an industrial specialization only by three

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

We include country-level fixed effects to account for national-level policy preferences and sector-level fixed effects to control for the remaining sector-dependent unobserved heterogeneity. 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.[8] The regressions we estimate in the second stages are described by equation (4).

$$\begin{aligned} \Delta log(Prod_{rt}) = \phi_r + \phi_t + \delta \widehat{SPE}_r^{(j)} \times Post_t + \\ + \gamma_1 log(Prod_{rt-1}) + \gamma_2 KIS_{rt} + \gamma_3 log(R\&Dpercap_{rt-1}) + u_{rt} \end{aligned} \tag{4}$$

For the regional controls and outcome variables, we extract data from Eurostat. We use data from 2009 to 2019. The treatment period is comprised between 2013 and 2019. The year 2013 is included because of the bottom-up design of the policy. As stakeholders took part in the decision-making process and influenced decisions, they could also anticipate policy decisions as these were being designed. In any case, results are robust to the exclusion of 2013 from the treatment period. The key dependent variable is labor productivity growth. Following recent literature (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 one-period lagged labour productivity level,

regions.

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

the investments in R&D per capita and the share of employees in the Knowledge Intensive Sector (KIS). R&D per capita is the sum of private and public R&D expenditure per capita purchasing power standard for the 2005 currencies values. KIS is, instead, the share of workers employed in medium-high or high knowledge-intensive sectors. These controls are needed also to observe the intensity of innovation inputs. In particular, R&D represents the intensity of innovation investments, while KIS represents the intensity of labor force employed in knowledge-related production. The inclusion of regional and year fixed effects makes the non-interacted regressors redundant. For this reason we focus on the parameter δ which catches the joint variation across the time dimension and the regions.

As we can see in table 4, the average labor productivity growth rate is 2.1% across all 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 Central and Eastern European Countries (CEEC) starting from a lower base relative to the others.

INSERT TABLE 4

Results

In table 5 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 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 supported. This implies that the likelihood of an industrial inclusion is higher for industrial areas closer to the existing knowledge base. In particular, *ceteris 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 specialization 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.

INSERT TABLE 5

In table 6 we test hypotheses H_2 in which we conjectured that regions that indicate their priorities following related diversification principles are the ones that experience higher productivity gains from implementing S3 policies. We can observe in the table the effect of different industrial inclusions on regional labor productivity growth. We report the OLS and IV estimates for three models. The first model is displayed in the first two columns. 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 obtain a clear picture of Smart Specialisation mechanisms and the effectiveness of our estimation strategy.

INSERT TABLE 6

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 labor productivity 0.9, 1.5, 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 labor 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 industry was included because of a relatedness approach or because of a different one. In this sense, OLS estimates capture the effect of a specialization *unconditional* to the relatedness of industries.

To test our second hypothesis we need to run the second stage of our estimation. Results from the IV estimates in table 6 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 labor 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.[9] S3 strategies were effective only when industrial inclusions were based on a relatedness approach (even though the policy prescriptions were less precise about the application of the relatedness principle than more recent presentations of S3). This is interesting also because every region could produce specific paths of specialization/diversification that might be unfit for other regions even in the presence of similar industrial structures, and strategies that proved effective did not need to include the same priorities for all regions (reflecting the "one-size-does-not-fit-all" feature of the policy).

[9] We are aware that these results do not represent a strictly causal estimation of specialization 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 labor productivity growth.

Due to data limitations, we are aware that we observe only a part of the mechanisms leveraged by Smart Specialisation. However, we can still observe their fit with existing capabilities and how industrial specialization decisions affect regional performances. These decisions propagate from the sectoral to the regional level due to channels that are not influenced by top-down characteristics of the policy. There are several channels at play. Firstly, we have a channel for efficient recombination of competencies. Indeed, the EDP can be seen as a dynamic way of unveiling regional potential to achieve new specializations. In this sense, the EDP can be useful to identify a different reallocation of labor inputs to produce a better match with technological capabilities. The inclusion of a related industry into the strategy implies that this reallocation can be achieved more efficiently and is consistent with Balland et al. (2019)'s relatedness-complexity framework. It suggests that specializing in related industries is less risky because of the similarities between capabilities. Furthermore, these similar capabilities can be employed in new, more productive areas, reallocating factors to achieve higher 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 (qualitative case studies could add more depth in addressing this particular aspect of the policy), they will spread faster in the industries included in strategies as long as these industries are closer to the core by the principle of relatedness. In this way these new routines are embedded in the regional production systems, propagating from the specialization targets. Finally, a signaling channel might also be at play. Inclusion decisions highlight which sectors can be suitable targets for investors. This is an important aspect of the EDP. Indeed, when an innovator enters a new sector, they signal to other potential entrants that that sector presents unexploited opportunities. This is the informational externality problem mentioned by Foray (2017). Since Smart Specialisation policies are designed to follow a bottom-up approach, investors and any agent involved in the innovation process are, at the same time, recipients and senders of signals about entrepreneurial opportunities. Because of all these mechanisms, we expect that in the short run labor productivity is the first productivity dimension where we can detect relevant improvements, as growth rates should accelerate through several channels.

Smart Specialisation effects over time

We can provide additional evidence to assess the timing of policy impact and whether the effects of Smart Specialisation due to relatedness increase or decrease over time. The empirical model we have estimated so far indicated that regions specializing in related sectors had higher productivity growth rates after 2013. Results of a Diff-in-Diff on productivity levels showed on average null effects. A Diff-in-Diff compares the average after 2013 with the average before 2013. If we want to appreciate the dynamic effects of the policy, we can use an event study design. This allows us to compare the average difference between specializing and non-specializing regions in year t, with the average difference in 2013:

$$log(Prod_{rt}) = \alpha + \sum_{\tau=2008}^{2019} \gamma_\tau I(t=\tau) + \sum_{\tau \neq 2013} \delta_\tau \widehat{SPE_r} \times I(t=\tau) + X_{rt}\beta + \phi_r + u_{rt} \qquad (5)$$

We report the estimate of δ_τ in figures 4 and 5. We show both IV (in red) and OLS estimates (in blue), because their difference shows how different the productivity dynamics are – again – when we take into account both the selection and treatment dimensions. The δ_τ parameters of the IV model represent the difference between the LATE in year τ and the LATE in 2013. We can see that this effect is growing larger over time. The difference increased over 25% for most specializations. Because of data limitations, we cannot investigate the cumulative effects of the policy beyond 2019 (and the Covid19 shock), but the evidence is compelling that relatedness-based S3 policies set regional economies on a steady growth trajectory, at least for the period we can observe.

INSERT FIGURE 4

INSERT FIGURE 5

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 specialization 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 7 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.

INSERT TABLE 7

Estimates in table 7 are mostly consistent with the findings in table 6. 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.

Effects across high and low-productivity regions

The effects we observe are estimated on a heterogeneous sample of regions. Regions differ in many respects, and in the aggregate these differences may also be reflected in labor productivity levels. It is interesting to test if Smart Specialisation inclusions have a different impact on productivity conditional on high- vs. low initial productivity levels. We can divide the regions in two subsamples based on their 2013 labor productivity. We then perform on the two groups of regions the same analysis whose results are shown in table 4 and compare the results shown in table 8.

INSERT TABLE 8

As we can see from this table, results are significant and stronger across all the specializations in low-productivity regions. In high-productivity regions, the signs are still positive, but effect sizes are lower, and in some cases also statistically weaker. These results show that Smart Specialisation policies have not only benefited those regions that arguably already had the broadest set of related diversification options (the relatively more advanced regions) but also – and to an even stronger degree – those that were lagging behind.

"Leave-one-country-out" models

INSERT TABLE 9

It is important to verify whether our main results are driven by regions concentrated in a few countries. We estimate the same models as in table 3 with 4 different subsets of data. We perform our analyzes excluding the regions of one country at a time. In table 9 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 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.

Alternative dependent variables

INSERT TABLE 10

In table 10 we report the estimates of the Smart Specialisation choices on the growth rates of GVA and hours worked as an additional robustness check. The returns of inclusions on GVA growth are statistically significant and positive for every specialization 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 labor 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 does not hold, instead, on average. Specializing in a sector without taking into account its relatedness has no effect even on hours worked and 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 in the labor productivity of complying regions. The use of these two alternative measures enriches our analyses, and provides a coherent picture of policy impact, but they cannot capture all the nuances of the complex process of regional development. Further research could focus on the more qualitative features of long-term processes and impacts.

Service-oriented and digital Smart Specialisation strategies

One limitation of our work is its focus on manufacturing rather than the service sectors and the lack of detailed information about specific investments in key areas such as digital technologies. There is, however, some scope to account at least partially for the service orientation and the digital content of regional strategies because we can look for indications of service and digital activities among the regional specialization choices. Professional services (NACE code "M72") appear in most of the regions in our sample as it is listed in at least one of their priorities. Unfortunately, due to data limitation, little can be said on how services are coupled with specific manufacturing sectors. The same problem arises with digital industries (NACE codes J62 and J63). Specializations in digital sectors are also common in RIS documents, but they are difficult to interpret and much less reliable for our estimation approach. Regions often included digital specializations 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 specialization 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 of these sectors. Nevertheless, professional services and digitalization might be important components of a region's strategy. We see that in the regions' priorities for S3, services are often listed in combination with other manufacturing sectors. This implies that both professional services and digitalization might be included as complements to manufacturing strategies rather than as sectors of specialization *per se*.

To control for the effect of services on labor productivity in the S3 policy framework, we run a robustness test exploiting the data on the complementarity between services and/or digital industry specializations and manufacturing sectors. We perform a text analysis on documents with the description of priorities. We can observe every priority associated with a manufacturing sector if words such as "ICT", "digital", "professional" and "service" appear in its description. This way, we can verify not only if region r included sector i in its strategy, but also if such a strategy has digital or service-oriented features. 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. We are aware that our approach cannot provide a full account of these dimensions of regional change, but the use of text analytic tools is very useful to alleviate concerns of counfounding effects due to digitalisation and service-orientation within a strategy.

Table 11 presents the estimation results for 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 confirmation that the channels we identified are effective regardless of the implementation of digital or professional services among the stated priorities. The triple interactions, moreover, estimate the effects of digitization or servitization 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 specialization decisions, especially for those regions that implemented their strategies following the principle of related diversification.

INSERT TABLE 11

Conclusions

In this paper, we have proposed a novel analytical framework for the evaluation of place-based policies and used it to assess the productivity effects of Smart Specialisation, taking into account the choices made in the selection of priorities. 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 manufacturing 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 reveal that Smart Specialisation had a significant impact on labor productivity growth when the principle of related diversification was followed. Results are positive across all the inclusion decisions.

Naturally, the paper also presents some limitations. For example, it does not provide a full account of the service sector. Moreover, it does not consider the Cohesion Policy framework, nor does it address the problem of remaining disparities among EU regions, which has been recognized 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 particular 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 favor or hinder the effectiveness of the policy. More generally, by focusing on a robust estimation of efficiency gains, we have not provided a complete picture of the long-term transformative potential of Smart Specialisation policies. Arguably only detailed case study evidence will be able to shed light on these nuanced and complex aspects of the regional development process.

However, our results bear important implications for the design of future 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. Our findings support the idea that related diversification has been a very effective approach to regional growth also in laggard regions. Moreover, the identification of sectors of specialization through related diversification benefits regional economies regardless of the specific industrial specializations they pursue. Moreover, this happens to be true even when considering different implementations, like when digital or service-oriented strategies are considered. One interesting aspect of further developments of Smart Specialisation is that they may depart from, or extend beyond, related diversification, for example by giving more prominence to mission-oriented principles (Mazzucato, 2013), such as climate mitigation. It is also possible that complementary policies, through different levels of the policy mix, might be able to address the limitations of relatedness-based Smart Specialisation. Smart Specialisation may work in combination with complementary policies. In order to foster unrelated, radical breakthroughs, one might consider the extension of innovation grants schemes as an effective policy tool in support of business innovation under a mission framework. The evidence in favor of this option is very strong both in the US and in Europe (Howell, 2017; Bloom, Van Reenen, and Williams, 2019; Santoleri et al., 2022). There is no reason to believe that Smart Specialisation and a large R&D grant (or similar) scheme are incompatible, except of course under tight budget constraints. To date the optimal balance of bottom-up and top-down approaches is unknown, and this makes it even more important to carefully evaluate the impact of specific policy measures. Only further research will be able to monitor the possible future benefits of regional development policies, and assess whether the productivity gains we have observed in association with related diversification are persistent through time over the long-term, or whether, how, and when these gains will decay, as technologies, industries, firms and institutions adapt and change over time.

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Appendix

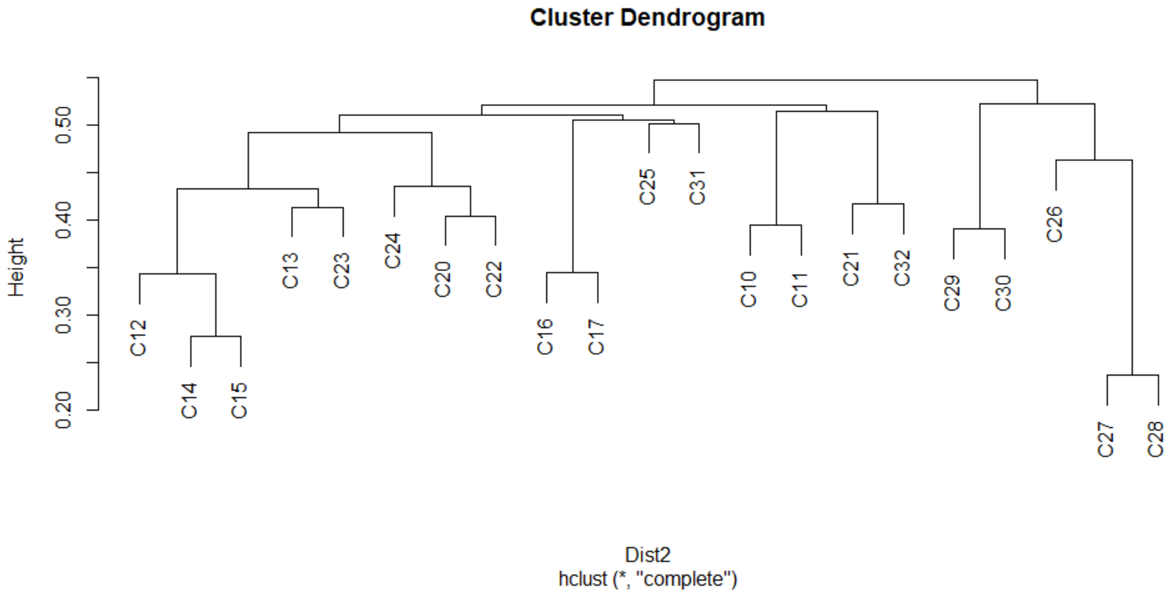
Hierarchical Clustering

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 specializations. 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:

$$d_{jk} = \frac{1 - \rho_{jk}}{2} \tag{6}$$

where ρ_{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 ?? we can observe the dendogram of our hierarchical clustering.



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 neighboring 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.

Tables

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**)[10]
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).

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

Table 3: Correlation between industrial inclusions with regional characteristics

	$log(Prod_{2013})$	$log(GVA_{2013})$	KIS_{2013}
Automotive	−0.139	0.033	0.045
Components	−0.063	0.103	−0.002
Agro-Food	−0.190	−0.277	−0.447
Light Ind.	−0.336	−0.083	−0.119
Materials	−0.056	−0.080	0.042
Health	0.024	−0.050	0.119
Wood and Paper	−0.345	−0.140	−0.214

This table reports the correlation indexes between specialization decisions with labour productivity (log), Gross Value Added (log), and the share of employees in medium-high and high Knowledge Intensive Sectors in 2013.

Table 4: 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 labor productivity (log), labor 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).

Table 5: Smart Specialisation decision rule across industrial areas

	Dependent variable:
	$\text{Specialization}_{jr}$
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.

Table 6: Effects of industrial choices on labor 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 labor 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).

Table 7: 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 labor 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.

Table 8: High vs. low productivity regions gains

	Dependent variable: $\Delta log(Prod_t)$	
	High Productivity Regions	Low Productivity Regions
Automotive	0.008	0.056^{**}
	(0.014)	(0.024)
Components	0.030	0.096^{***}
	(0.017)	(0.032)
Light Industries	0.022^{**}	0.099^{**}
	(0.011)	(0.041)
Agro-food	0.027^{*}	0.118^{***}
	(0.014)	(0.044)
Materials	0.029^{***}	0.099^{***}
	(0.010)	(0.030)
Health	0.017	0.095^{***}
	(0.010)	(0.032)
Wood & Paper	0.030^{***}	0.082^{***}
	(0.011)	(0.031)
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 labor productivity growth. We report the IV estimates across the subsample of regions whose productivity in 2008 was above the median (1) and below the median (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.

Table 9: Results from "leave-one-country-out" models

	Dependent variable: specialization$_{jr}$	
	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 specialization decisions ($specialization_{jr}$) 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.

Table 10: 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 11: Effects of digitization 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 labor productivity growth and the triple interaction with the dummy *Services*, i.e. if the priority features digitization or servitization 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.

Figure captions

Figure 1: Distribution of NACE2 specializations.

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

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

Figure 4: Effects of S3 specializations in automotive, components, light, and agro-food industries across years.

Figure 5: Effects of S3 specializations in materials, health, and wood and paper industries across years.

Figures

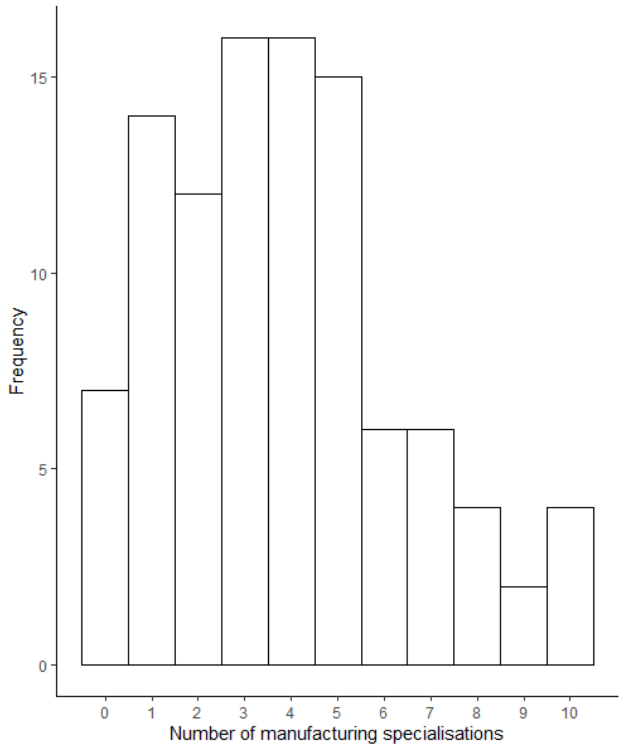
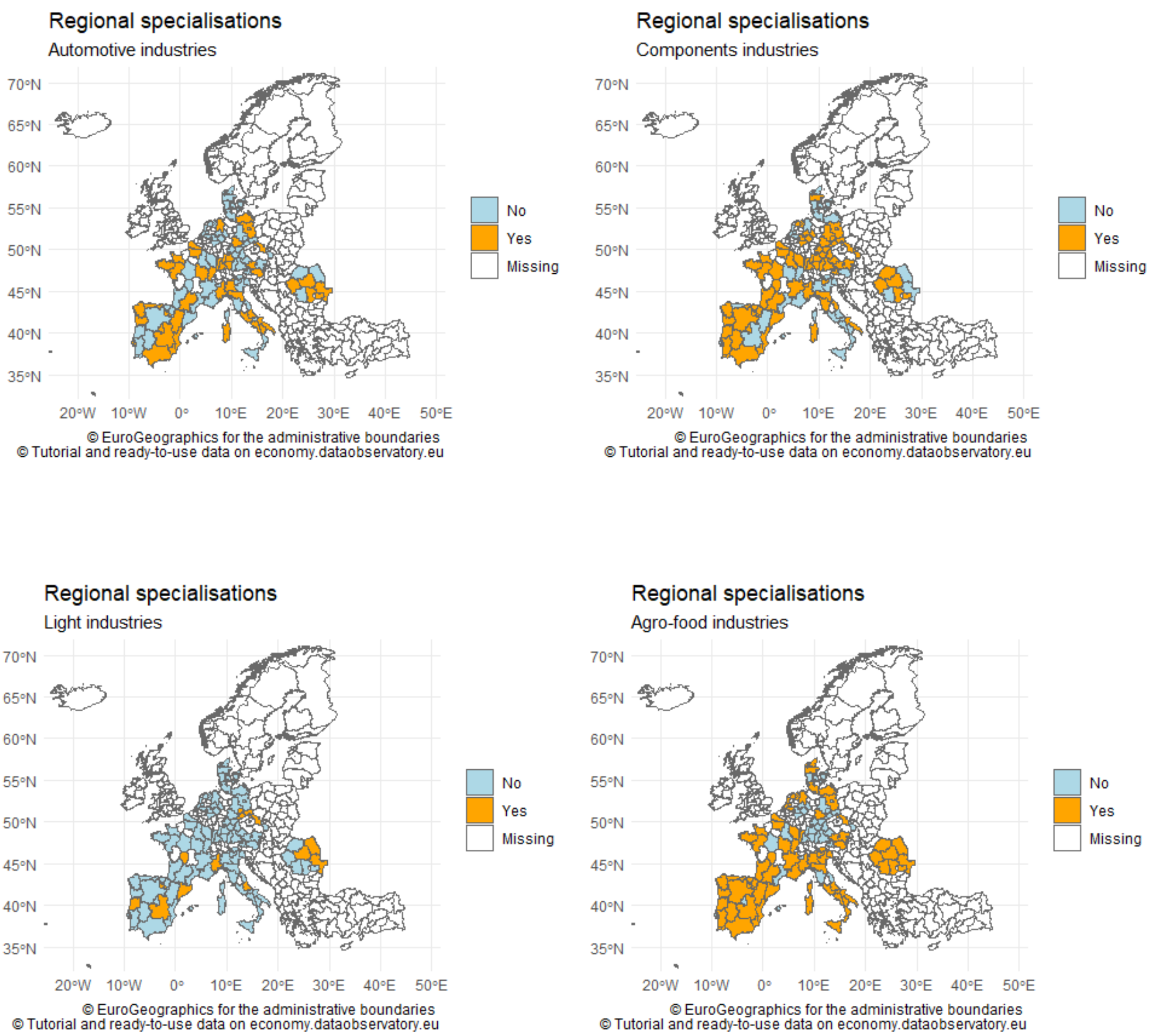


Figure 1

Figure 2


Regional specialisations
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35°N
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Yes
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Regional specialisations
Components industries
70°N
65°N
60°N
55°N
50°N
45°N
40°N
35°N
20°W 10°W 0° 10°E 20°E 30°E 40°E 50°E
No
Yes
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© EuroGeographics for the administrative boundaries
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Regional specialisations
Light industries
70°N
65°N
60°N
55°N
50°N
45°N
40°N
35°N
20°W 10°W 0° 10°E 20°E 30°E 40°E 50°E
No
Yes
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Regional specialisations
Agro-food industries
70°N
65°N
60°N
55°N
50°N
45°N
40°N
35°N
20°W 10°W 0° 10°E 20°E 30°E 40°E 50°E
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Yes
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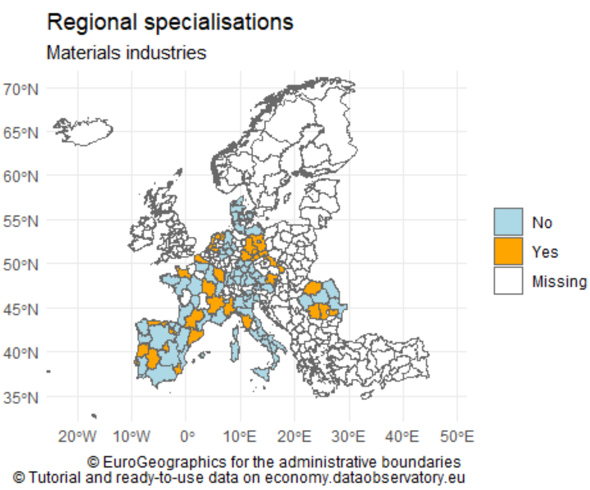
Figure 3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Materials industries
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0°
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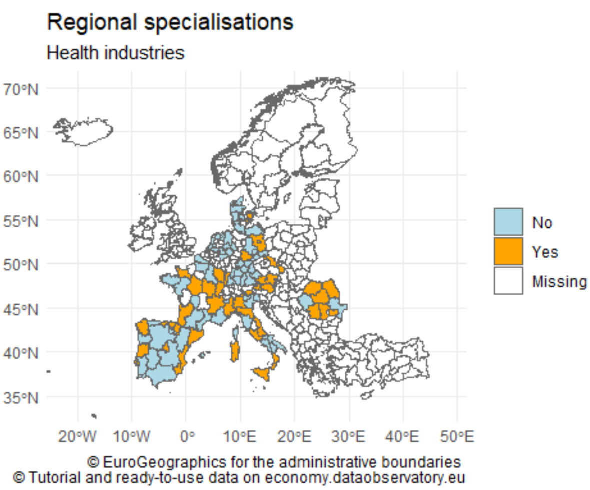
Regional specialisations
Health industries
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0°
10°E
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40°E
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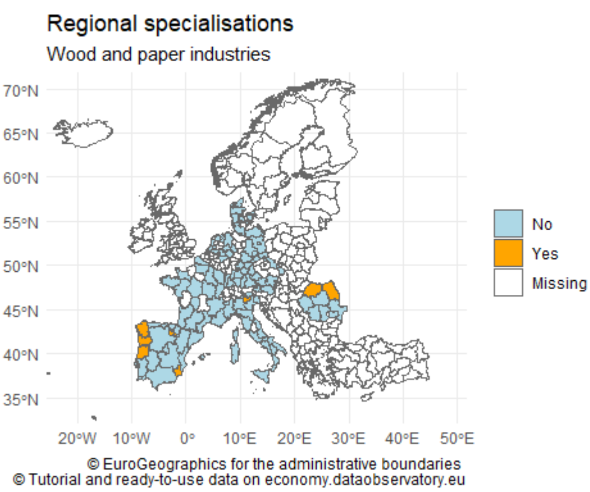
Regional specialisations
Wood and paper industries
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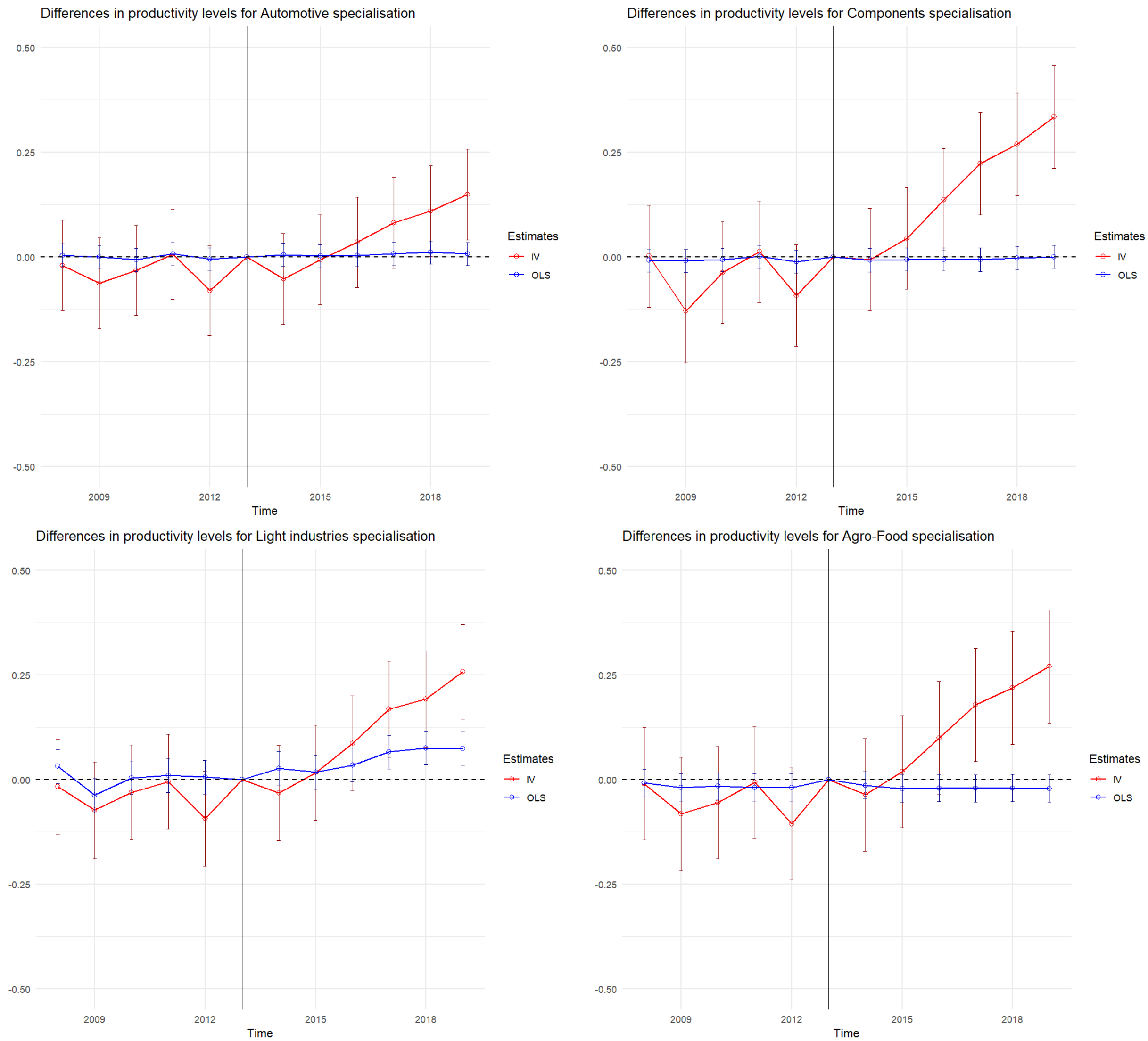
Figure 4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Differences in productivity levels for Components specialisation
Differences in productivity levels for Light industries specialisation
Differences in productivity levels for Agro-Food specialisation
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OLS
Time
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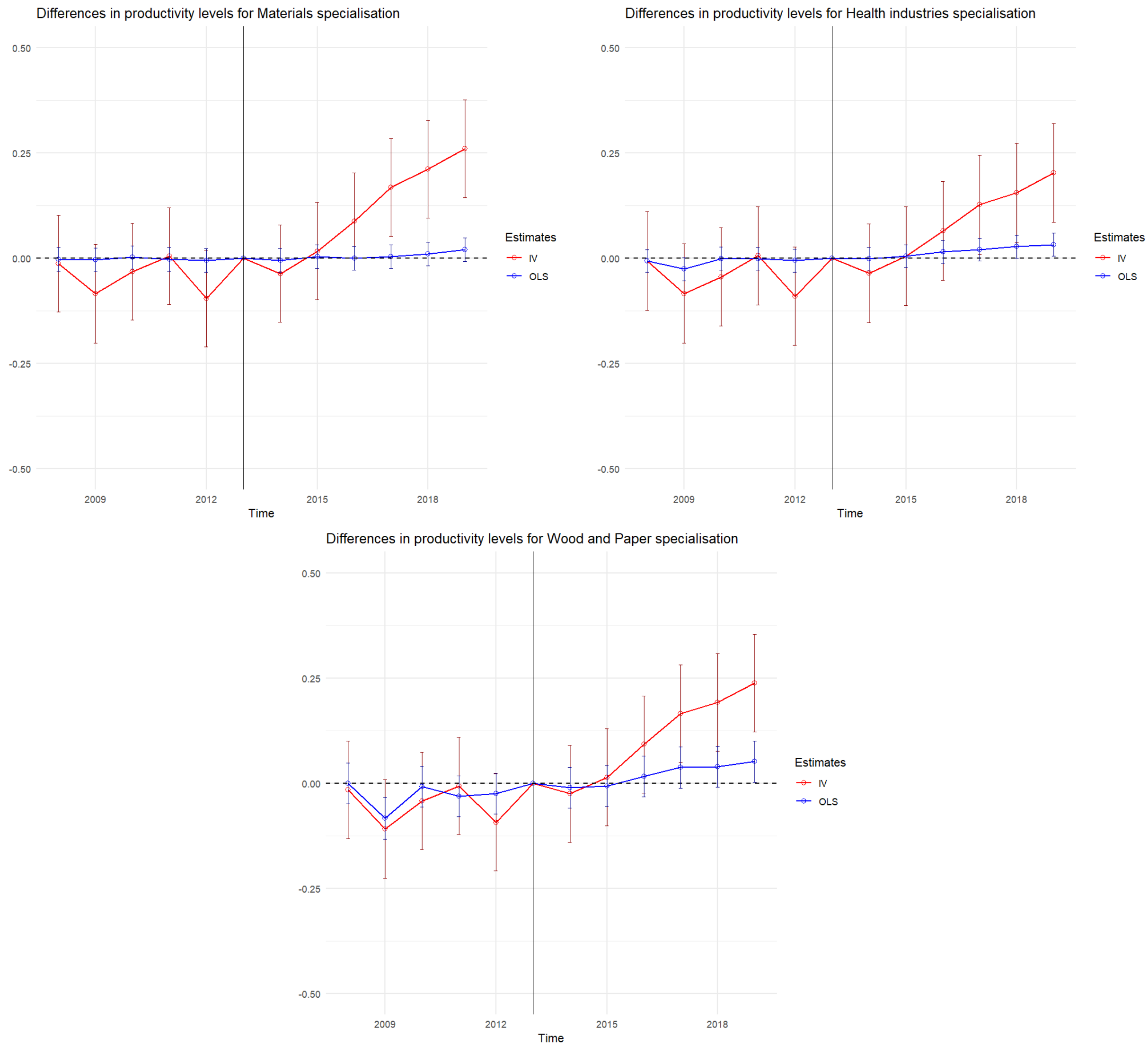
0.25
0.00
-0.25
-0.50
2009
2012
2015
2018

Figure 5



Differences in productivity levels for Materials specialisation
0.50
0.25
0.00
-0.25
-0.50
2009
2012
2015
2018
Time
Estimates
IV
OLS
Differences in productivity levels for Health industries specialisation
0.50
0.25
0.00
-0.25
-0.50
2009
2012
2015
2018
Time
Estimates
IV
OLS
Differences in productivity levels for Wood and Paper specialisation
0.50
0.25
0.00
-0.25
-0.50
2009
2012
2015
2018
Time
Estimates
IV
OLS