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Do EU regions benefit from smart specialization?

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Abstract

Smart specialization was conceived as a "bottom-up" framework to identify new growth paths connected to the existing knowledge cores of regions. Operationalization of smart specialization has proven difficult, though a recent "mapping" of technologies in terms of knowledge relatedness and complexity suggests a useful cost-benefit framework. We extend these ideas, locating EU cities in a smart specialization space and tracking their development of alternative technologies over the period 1981 to 2015. Panel models show employment growth and GDP growth are faster in cities that exhibit a logic of technological development consistent with the tenets of smart specialization.

Keywords

smart specialization; policy; complexity; technological relatedness; European Union

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Introduction

With growth derailed by the 2008 crisis, a continuing productivity gap with the USA, and with uneven prospects for many in southern and eastern Europe, the EU announced an ambitious development agenda in its Europe 2020 program built around smart, sustainable and inclusive growth (Foray et al., 2011; McCann and Ortega-Argiles, 2015). At the core of this development project is Smart Specialization (SS), a new vision of regional and national growth possibilities built around place-based capabilities. Envisaged as a 'bottom-up' initiative identifying local potentials for future development, SS seeks to renew and widen the knowledge and industrial base of regions, leveraging existing capabilities (Kroll, 2015).

While the European Commission has embraced the concept of SS, concerns have been raised with respect to operationalization of SS policy. Since its introduction, SS has been accused of being under-theorized (Foray et al., 2011; Boschma, 2014), lacking an empirical base (Morgan 2015; Unterlass et al., 2015; Iacobucci and Guzzini 2016; Santoalha 2016), being poorly implemented, and running the risk of not being effective in peripheral regions (McCann and Ortega-Argiles, 2015). Moreover, there is no consensus on what types of activities SS policy should target. Some scholars call for SS to promote radical change in regions to avoid lock-in (Grillitsch et al., 2018). Others advocate related diversification into more complex activities where such trajectories can be identified (Balland et al., 2019). While this debate is crucial for the development of effective SS policy, it is fair to say that discussion so far has remained rather speculative, as systematic empirical evidence is lacking. The objective of this paper is to contribute to this debate by providing empirical evidence of regional economic performance connected to the claims of smart specialization.

SS policy was introduced to the EU only in 2014 and thus it remains too early to investigate the impact of this ambitious framework. However, it is possible to look back in time, to examine the evolution of knowledge cores in European regions, and to assess whether or not regions that developed new technologies consistent with the SS approach out-performed those that did not. Following Balland et al. (2019), we argue that the objective of SS is to develop new activities that increase the complexity of a region's economy boosting competitive advantage and economic performance. As Balland et al. claim, cities and regions are more likely to be successful in developing new complex activities if those activities are closely related to existing strengths. This comes close to the spirit of SS policy which is about exploiting established capabilities in a region to diversify along new growth trajectories. In this paper, we examine whether European cities that followed a path of technological development consistent with SS policy out-performed cities that did not. Our analysis uses patent data for a set of 145 EU city-regions spanning the period 1981 to 2015. Results, from analysis of panel models, indicate that regions where technological development adhered more closely to the broad contours of our SS policy framework, entering more complex, related technology classes while jettisoning less related and less complex technologies, enjoyed faster employment growth and faster GDP growth than their competitors.

The paper is organized in four parts. Section 2 briefly reviews the literature around smart specialization and concepts such as relatedness and complexity used to operationalize the SS policy framework. Section 3 outlines the data employed in this study of technological evolution and economic performance in European cities. Section 4 presents findings concerning the link between SS and economic outcomes. Section 5 concludes, discussing the implications of our analysis for SS policy and its operationalization.

Smart Specialization in a relatedness and complexity policy framework

The recommendations of the *Knowledge for Growth Expert Group* commissioned by the EU to explore the trans-Atlantic productivity gap provided a technology-driven model of place-based policy (Foray et al., 2009). Their call for SS focused on building competitive advantage in research domains and sectors where regions possessed existing strengths, and leveraging those capabilities through diversification into related technologies and industrial sectors. At the core of SS policy, then, is a focus on knowledge production. For individual locations, the policy prescription is to identify those technological assets that comprise the region's knowledge core and then extend innovative capabilities along place-based trajectories that both reduce competitive overlap with competing regions while enhancing regional synergies. Selection of policy targets within the SS approach is viewed as a process of entrepreneurial discovery, of attempts to identify the key political-economic actors (inventors, firms, universities, governing institutions and the networks that link them) that would comprise a viable innovation system, alongside the domains of activity, the trajectories along which dynamic forms of competitive advantage would be developed (Asheim, 2014). In this sense, the concept of SS extends the earlier focus on learning regions and regional innovation systems in a more targeted or directed evolutionary frame (Morgan, 1997; Boschma, 2014).

Effective development of the SS model will require significant shifts in regional growth and innovation policy. Though not a concern in this paper, precisely how SS should be designed, implemented and assessed within the policy environment has generated considerable discussion (Nauwelaers et al., 2014; Rodriguez-Pose et al., 2014; Moodysson et al., 2015; Foray, 2016; McCann and Ortega-Argiles, 2016). There remains the crucial question of how the concept of SS might be operationalized. How do we identify the knowledge capabilities of regional economies, and how do we assess the trajectories of technological diversification that make most sense for regions to follow from an economic point of view?

There is a large body of literature showing that the knowledge capabilities of regions change over time (Hall and Preston, 1988; Kogler et al., 2013). The set of capabilities expands when new technologies enter the region and it contracts as established technologies are abandoned. The process of invention, of developing new technologies, is a resource-using activity and, as such, constrained by resources available to actors. The pace and direction of technological entry and exit in a region is shaped by expectations regarding the costs and returns to the exploration and exploitation of different kinds of ideas. Following Breschi et al. (2003), knowledge subsets that demand similar and complementary capabilities and skills for their use are referred to as being related. When knowledge components are dissimilar and tend not to be combined, they are considered to be unrelated. The cost of diversifying from one technology to another will be relatively low when the two technologies are related. As the relatedness between technologies declines, the costs of diversifying from one to the other increases, as there is less overlap between the required capabilities, and more resources must be used to understand the growing share of that which is novel. A similar reasoning holds for abandoning a technology. That is, the (opportunity) cost of exiting a technology is relatively low if capabilities are maintained in related technologies. However, that cost will rise steeply when there are few alternatives and when that technology is widely used in the development of many other ideas, especially those that are valuable (Pinheiro et al., 2018).

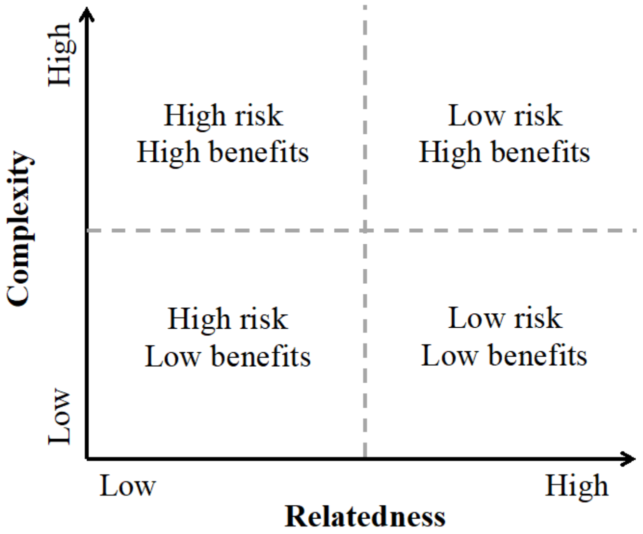
The importance of relatedness for innovation and economic development in regions has been highlighted by Boschma (2005) and Frenken et al. (2007). In early work, studies adopted a static view on relatedness, concentrating on the relationship between related variety and economic growth in a region. Later papers took a more dynamic approach to relatedness, shifting attention to the processes through which the industrial or technological structures of regions evolve (Neffke, 2009; Neffke et al., 2011). This work tended to confirm the theoretical ideas outlined above, finding persistent patterns of entry and exit of activities in regions over time, following the principle of relatedness (Hidalgo et al., 2018). Thus, the entry of new activities is enhanced by the degree of relatedness with existing activities in a region, and the exit of current activities is promoted when those activities are less related to the technological base of the regional economy (Boschma, 2017). With respect to knowledge dynamics in particular, regions are inclined to build new capabilities in technologies related to their existing strengths, and more likely to discard capabilities in technologies far from their knowledge core (Kogler et al., 2013; Boschma et al., 2015; Rigby, 2015).

The knowledge cores of regions vary not only in terms of technological composition but also in terms of value. Currently, there exist few direct measures of the returns to technologies, like forward citations or litigation (Trajtenberg, 1990; Harhoff et al., 2003; Ejermo, 2009). Following the concept of complexity introduced by Hidalgo and Hausmann (2009), Balland and Rigby (2017) define complex technologies as those which combine many knowledge components and which are produced in relatively few regions with broad sets of capabilities. These technologies are regarded as valuable because they generate relatively high rents and their tacit nature means that they are a persistent source of regional growth (Maskell and Malmberg, 1999). Less complex technologies, that can be produced by many regions, tend to have low value and only limited capacity to sustain competitive advantage.

Balland et al. (2019) developed a SS framework around these core ideas of relatedness and complexity. This framework rests upon a methodology to systematically identify new technological opportunities that complement and leverage the existing knowledge stocks of regions. These technological opportunities can be identified as those knowledge fields in which a region does not yet possess critical development capacity, that have a high degree of relatedness with the region's existing knowledge base and that would raise the value, or upgrade, the region's portfolio of knowledge assets. Their template for operationalizing SS policy is summarized in Figure 1.

For any region, it is possible to map technological fields in which the region does not possess a relative technological advantage at time *t*. These potential new technologies are located in Figure 1 according to their relatedness and their complexity relative to the existing knowledge core of the region. The four quadrants in Figure 1 highlight the cost-benefit tradeoff that undergirds SS policy. The policy-maker should consider developing those technologies that occupy the north-east quadrant, for these technologies promise above average returns (higher complexity) at relatively low risk (higher relatedness). Technologies in the south-west quadrant are poor choices for SS as they are far removed from the existing knowledge core of the region and characterized by relatively low (complexity) value. New technologies that are far from the region's knowledge core are risky in the sense that they are unrelated to the technological capabilities of the region. The north-west and south-east quadrants in Figure 1 represent risk-return profiles that are less straightforward to appraise. The high risk-high benefit quadrant might yield significant technological rents to a region, though the probability of sustained innovation in these unrelated technologies is low. Technologies that fall in the low risk-low benefit quadrant have a strong likelihood of successful development yet they present little value added to the region's economy.

Figure 1: The Smart Specialization Framework



Source: Balland et al. (2019)

While this SS framework highlights the role of relatedness in shaping regional development trajectories, a number of scholars have argued that SS policy should encourage regions to induce radical change in order to avoid lock-in (Frenken and Wanzenbock, 2018; Grillitsch et al., 2018). The concern here is that pushing a model of development around the concept of relatedness will narrow the base of regional economies making them less resilient over time. While there is little empirical evidence to date that supports such claims (Pinheiro et al., 2018), we reject these arguments for they assume that related development must narrow the set of capabilities that regions possess. This need not be the case. It is important to note that the relatedness between different activities is not static but shifts over time as new activities are developed and new recombinations of existing activities appear. These dynamics may broaden the knowledge core of regions that develop new technologies related to their existing stocks. In this paper, we contribute to these debates by analyzing whether regions that follow the logic of SS enjoy higher economic performance in the long-run.

Data and operationalization of the smart specialization framework

At its core, the SS initiative rests upon a framework to identify new technological opportunities that complement and extend the existing knowledge stocks of regions. These technological opportunities can be identified as those knowledge fields that satisfy three simple criteria. First, they should be technologies in which a region does not currently possess critical development capacity. Second, they should have a high degree of relatedness with the region's existing knowledge base. Third, their development should raise the value, or upgrade, the region's portfolio of knowledge assets. Balland et al. (2019) provide a template for operationalizing SS policy using patent data applied to EU regions. We combine patent data from the European Patent Office (EPO) and regional economic accounts from Cambridge Econometrics to analyze the technological evolution and economic performance of 145 EU cities spanning the years 1981-2015. The cities examined have generated at least 50 patents in each of the 5-year segments spanning the overall study period. These "cities" are defined by combining data from NUTS3 regions according to Eurostat (2019). In the analysis below we discuss construction of a smart specialization index, and its components, before exploring the relationship between that index and city performance.

Development of the SS framework demands identification of the knowledge core of regions and the value of different technology fields. Here we follow Kogler et al. (2013), Boschma et al. (2015), Rigby (2015) and Balland and Rigby (2017) who extend the product space arguments of Hidalgo and Hausmann (2007) into knowledge space. These efforts utilize patent data that are classified by technology field, by the timing and location of invention. The EPO places patents into at least one of 652 different technology classes in the Cooperative Patent Classification (CPC) system. By convention, inventions are dated using patent filing dates rather than grant dates to more precisely capture the time at which new knowledge is produced and to eliminate the bias associated with shifts in the time-lag of examination. The geography of invention is traced by the location of patent (co-)inventors. In the analysis that follows, we focus on patents generated by inventors across cities identified in EPO data. Individual patents are weighted from 0 to 1 according to the share of their co-inventors that are located within the EU. In similar fashion, patents are fractionally allocated to different technology fields according to the frequency of knowledge claims that they make within each CPC class. We recognize that patents are an imperfect measure of knowledge production, in part because not all new knowledge is patented, yet there is no clearly superior alternative (Griliches, 1990).

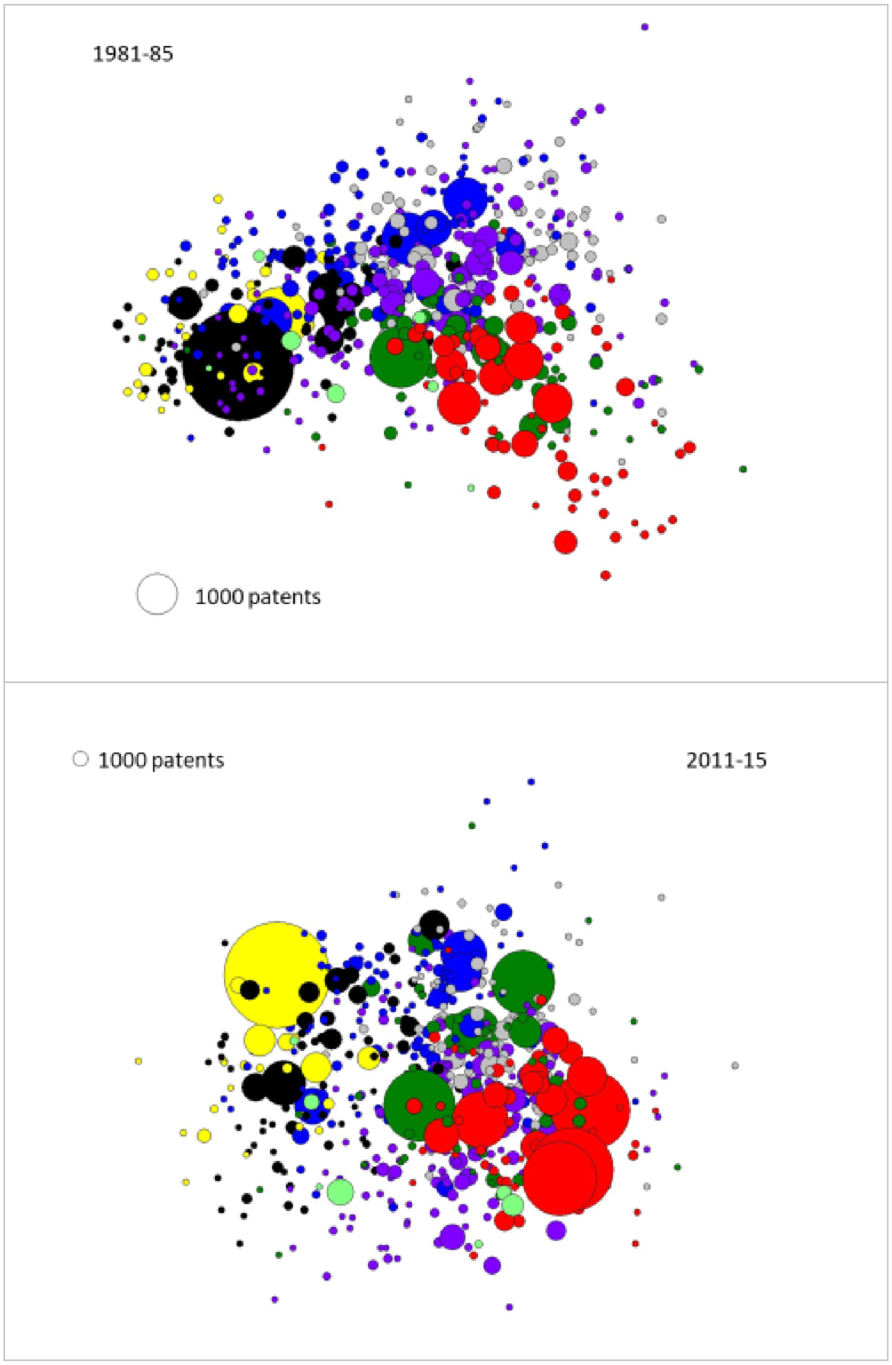
Measuring Technological Relatedness and Relatedness Density

To measure technological relatedness between CPC classes for a given time period, we count the weighted number of EU patents that contain a co-class pair, say i and j, and then standardize this count by the number of patents in total that record knowledge claims in CPC classes i and j. Relatedness (ϕ_{ij}^{t}) in period t is therefore a standardized measure of the frequency with which two technology classes appear on the same patents. High values of relatedness indicate that two technology classes are more frequently combined on patents than the average of such pairings. This suggests that there are significant technological complementarities between these classes. Low values of relatedness indicate that technology classes are relatively independent of one another.

The relatedness between technologies is readily visualized as a network in knowledge space. Figure 2 maps the relatedness between CPC technology classes for the periods 1981-1985 and 2011-15, a time span that brackets the study period. The colors in Figure 2 correspond to eight aggregate technology groupings recognized by Schmoch (2008). Classes with high relatedness values are located close to one another. Hence, we see individual technologies of different aggregate types (colors) clustering together in the knowledge space, capturing the cognitive proximity between those classes. The size of the nodes in Figure 2 illustrates the number of patents produced in each technology class. The nodes are scaled across the two time periods to illustrate the rapid growth in the pace of invention across the EU over the last 35 years.

Between 1981 and 1985, 59,823 patents were generated across the EU cities examined. Between 2011-15, 136,972 patents were developed over the same areas. These counts comprise approximately 66% and 40% of total EU patents for the two periods respectively, the remaining patents generated in other parts of the EU. (Note that while our study rests on a subset of EU patents overall, results from analysis across all NUTS2 regions reported in Appendix 3 are qualitatively the same as those we report below.) During the first period mapped in Figure 2, the three technology classes generating the most patents were C07D - Heterocyclic Compounds, C07C – Acyclic or Carbocyclic Compounds and G01N – Investigating or Analyzing Materials. For the 2011-15 period, most CPC patents were located in the following three classes A61K – Preparations for Medical, Dental or Toilet Purposes, H04L – Transmission of Digital Information and G06F – Electrical Digital Data Processing. The changes over time in the relative positions of the nodes in Figure 2 reflect technological discoveries that lead to different frequencies of combinations of technology classes on individual patents.

Figure 2: Technological Relatedness in the EU Knowledge Space



Notes : The eight aggregate CPC technology classes are electronics (red), instruments (green), chemicals (black), biotech (yellow), industrial process (blue), machinery & transport (purple), consumer goods (grey) and climate change technologies (light green).

While Figure 2 illustrates the relatedness between technology classes in the EU, it is also possible to measure the degree to which patents cluster in knowledge space around a particular technology field. This measure of clustering is referred to as the relatedness density of a technology, following Hidalgo et al. (2007). The relatedness density of technology class *i* in city *r* time *t* is found as the technological relatedness (ϕ_{ij}^{t}) of technology *i* to all other technologies *j* in which city *r* exhibits regional technological advantage (RTA), divided by the sum of the technological relatedness of technology *i* to all other technologies that are found in city *r* in period *t*

$$RELATEDNESS\ DENSITY_{i}^{rt} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}^{t} * RTA_{j}^{rt}}{\sum_{j \neq i} \phi_{ij}^{t}}$$

and where RTA is a binary variable that assumes the value 1 (0) when a city possesses a larger (smaller) share of patents in a particular technology than the reference region (the sum of all metropolitan areas considered in the EU) for a given period. More formally, city *r* has RTA in technology *i* at time *t* such that $RTA_{i}^{rt} = 1$ when

$$\frac{patents_{i}^{rt} / \sum_{i} patents_{i}^{rt}}{\sum_{r} patents_{i}^{rt} / \sum_{r} \sum_{i} patents_{i}^{rt}} > 1\ .$$

In the analysis that follows, revealed technological advantage, technological relatedness between patent classes and the relatedness density of all technology fields are constructed for each of our 145 cities for consecutive five-year periods running from 1981-85, …., to 2011-15.

Measuring Knowledge Complexity

Hidalgo and Hausmann (2009) outline a method for calculating the complexity of products and countries using trade data. Their complexity index reflects the difficulty of producing particular commodities as revealed through the spatial distribution of individual products and the combination of different product bundles in country export baskets. Balland and Rigby (2017) develop a measure of knowledge complexity for U.S. regions and technology classes using an eigenvector reformulation of the method of reflections outlined by Hidalgo and Hausmann (2009).

Here we follow the approach of Balland and Rigby (2017) and develop a bimodal network that connects cities to the technological fields in which they are most active. Note that we do this for *n=366* cities and *k=652* CPC technology classes that demarcate the U.S. city-system of technology production. Hence, we borrow complexity measures for the 652 CPC patent classes generated from U.S. rather than EU data. We do this simply because the method of reflections does not work well for EU regions. We believe that this is primarily due to the fact that EU regions are parts of different countries and so many of the more complex types of technologies that are found in few U.S. cities tend to be duplicated across cities and regions within the EU. This duplication lowers the complexity values of technologies that we understand to be more complex. That said, the correlation between the complexity values for CPC technology classes in the U.S. and EU systems is about 0.6. Using EU complexity data in the following analysis produces results that are qualitatively similar to those shown below. Table 1 reports the top ten technology fields in terms of complexity for the period 2011-15. The table shows complexity values indexed to the score of the most complex class.

Table 1: Top Technology Fields by Complexity, 2011-15

CPC Patent Class	Technology Field	Complexity (Indexed)
H04L	Transmission of digital information	100
H03M	Code conversion	96.7
H03K	Control of electronic oscillations	95.3
G06F	Electronic digital data processing	95.2
H01L	Semi-conductor devices	89.1
H03K	Pulse techniques	88.6
H04N	Pictorial communication	88.3
H01S	Devices using stimulated emissions	88.0
B81C	Manufacture of micro-structural devices	87.4
G05F	Systems for regulating electric/magnetic variables	84.4

Table 2 highlights the EU cities with the highest and lowest values of aggregate complexity in the period 2011-15. The complexity score for each city is built as a weighted average of the CPC technology class scores and the share of each city's patents in those classes. Scores for the initial period for each of the cities observed are also provided. A more comprehensive chart showing complexity values for all 145 cities over time is reported in Appendix 1. Rennes enjoys the highest complexity score for the period 2011-15 as a result of patent specialization in telecommunications sectors that score high in complexity. Reims, an older industrial city with little invention in new technology classes, has the lowest complexity score of the 145 EU cities in 2011-15. There is some stability in city complexity ranks over time: the correlation coefficient in city complexity scores between 1981-85 and 2011-15 is 0.44. Of the top 20 most complex cities in 2011-15, seven were in the top 20 in 1981-85: Edinburgh, Eindhoven, Grenoble, London, Nice, Rennes and Toulouse. Of the 20 least complex cities in 2011-15, nine have remained at the bottom of the complexity table since 1981-85: Aberdeen, Amiens, Bologna, Coventry, Iserlohn, Odense, Osnabruck, Reggio nell'Emelia and Reims. The average change in city rank by complexity across the entire study period was 33. Over the thirty-five years examined, Malmo recorded faster growth in technological complexity than any other city, and Ipswich recorded the fastest decline in complexity.

Table 2: Complexity Scores in EU Cities

Rank & City	Complexity Score		Rank & City	Complexity Score	
	1981-85	2011-15		1981-85	2011-15
1 Rennes	59.02	84.11	136 Bologna	44.95	44.61
2 Dublin	49.23	72.11	137 Ingolstadt	48.34	44.37
3 Stockholm	52.82	70.28	138 Bielefeld	49.38	44.15
4 Antwerp	55.70	70.25	139 Coventry	41.63	44.12
5 Grenoble	59.81	69.29	140 Osnabruck	44.72	43.61
6 Tampere	46.25	69.21	141 Rouen	48.98	41.60
7 Nice	59.38	68.08	142 Reggio n'E	41.32	41.29
8 Caen	50.70	67.45	143 Aberdeen	45.58	41.28
9 Helsinki	51.84	67.11	144 Amiens	43.22	39.67
10 Eindhoven	73.49	67.03	145 Reims	45.15	39.15

Notes: Reggio n'E is Reggio nell'Emilia.

Smart Specialization in EU City-Regions, 1981-2015

From the methods just discussed it is possible to identify all technology fields in which EU cities have RTA and those in which they do not have RTA, alongside measures of the knowledge complexity and the relatedness density of those technologies across the five-year time-periods examined. Using these variables, individual cities are mapped in the smart specialization framework of Figure 1 to highlight the relatedness density and complexity of the technology fields in which they gain and lose RTA between time periods. These patterns correspond to technological entry and technological exit.

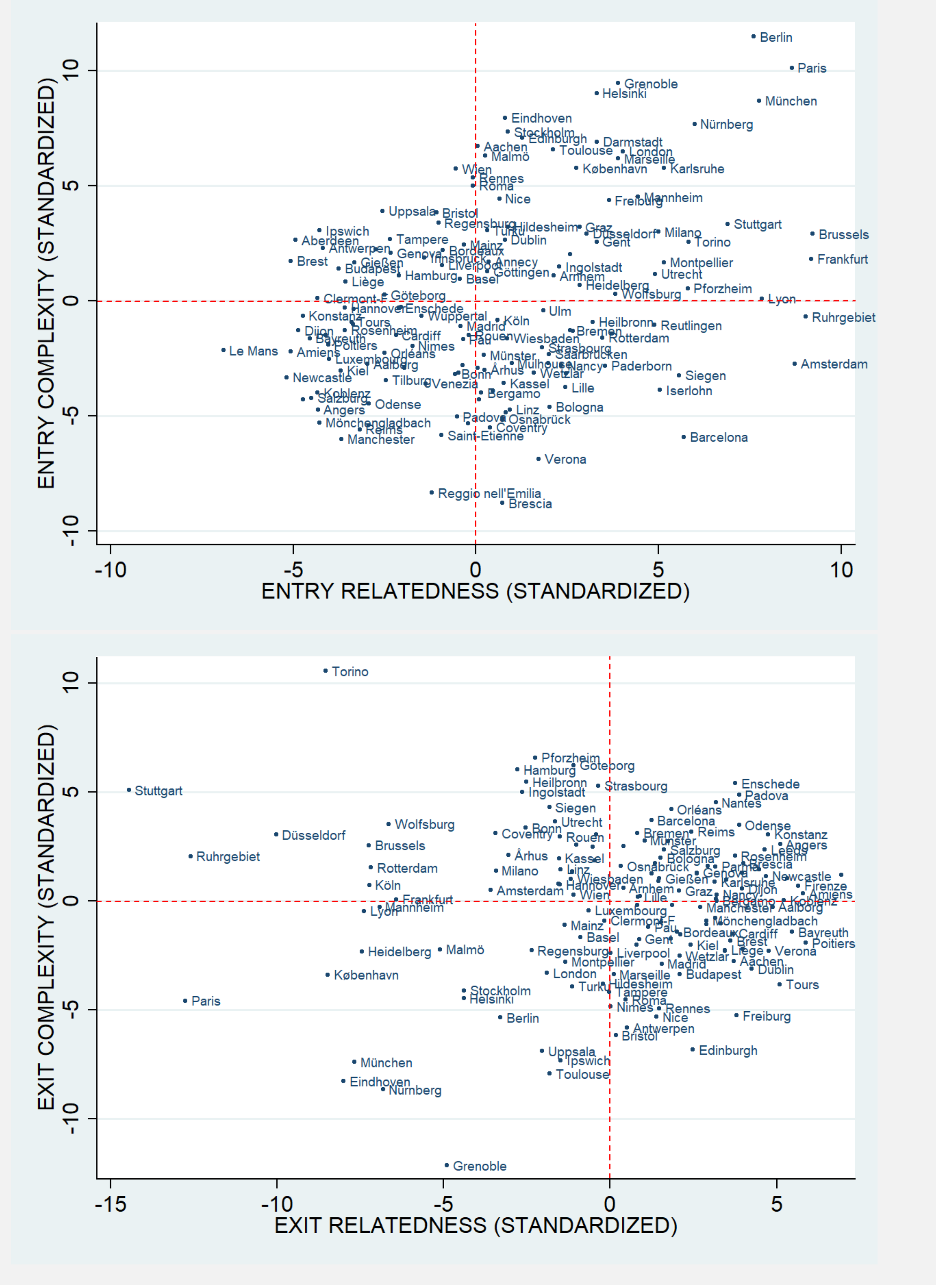
The coordinates of this mapping are developed in the following way. In the case of technological entry, all technology classes in which the RTA of a city takes the value 0 in period *t* are identified. These classes are candidates for technological entry (gaining RTA). The relatedness density and complexity scores of these potential entry classes are recorded. Next, the actual technological fields in which a city gains RTA between period *t* and period *t+1* are identified along with the relatedness density and complexity values of these fields. The mean relatedness density and complexity scores of the potential entry classes are then subtracted from the relatedness and complexity scores of the technology classes in which a city develops RTA. The result indicates whether a city builds RTA in technology classes that have relatedness density and complexity scores above or below the average of those classes in which it has not yet developed a competitive advantage (RTA).

Summing these deviations across time-periods generates an overall index of entry complexity and relatedness density values for each city between 1981-85 and 2011-15. We develop the same index for technological exit. Exit occurs when a city has RTA in time period t, but loses it by period t+1. Again we identify the technology classes in which cities lose RTA and calculate the sum of the complexity and relatedness density measures for those cities across technology classes and time periods, relative to the set of all technology classes in which RTA may be lost. Calculating the difference between the potential and realized relatedness density and complexity values for entry and exit controls for differences in knowledge cores between EU cities and yields measures that report how well cities exploit the potential to upgrade to technologies characterized by high relatedness density and high complexity, while also abandoning those technologies with low relatedness density scores and low complexity.

Figure 3 maps the results of this exercise for the EU cities examined, with the data on entry shown in the top panel and that for exit in the bottom panel. The relatedness density and complexity deviations in this figure are normalized. Note that a few cities (in the core of the spaces) are dropped from the panels to improve readability. Thinking back to Figure 1, it is advantageous to enter technology classes in the top-right quadrant, where relatedness density to the knowledge core of the city is high and where the average complexity value of the technology classes that are entered is also high. Entering technology classes in the bottom-left quadrant, where density and complexity values are low compared to those available, is not likely to improve city performance. In terms of technological exit (bottom panel of Figure 3), cities located in the lower-left quadrant, where complexity and relatedness density values are lower than the average of all technology classes in which RTA is established, should experience the largest gains in performance as they are shedding the least attractive technologies.

From Figure 3, it is clear that cities occupy quite different parts of the SS space both in terms of technological entry and technological exit. It is interesting that the most inventive cities, those that are generally regarded as the most dynamic parts of the EU, tend to concentrate in the top-right quadrant of the SS space in the case of entry. These cities, including Paris, Munich, Berlin, Grenoble, Helsinki and Nurenberg, are building RTA in the most complex technology fields available to them, and which are often closely related to their existing knowledge core. Other innovative cities such as Eindhoven, Stockholm, Aachen, Malmo, Vienna, Rennes, Rome and Nice are developing highly complex technologies, though these are less closely connected to their existing knowledge bases. Older industrial centers such as Amsterdam, Ruhrgebiet, Reutlingen, Siegen, Iserlohn and Barcelona are generating RTA in technologies that build upon their existing strengths, but these are often low complexity (low value) fields. A relatively large number of smaller cities are entering technology classes that are unrelated to their existing strengths: these are the metro areas with negative relatedness density values in the entry panel of Figure 3.

Figure 3: Smart Specialization in EU City-Regions by Entry and Exit, 1981-2015



These cities are split in terms of whether entry is in relatively high complexity classes (Uppsala, Bristol, Regensburg and Tampere) or in low complexity classes (Manchester, Munchengladbach, Reims, Angers, Koblenz, Salzburg and Oldenburg).

Shifting to the bottom panel of Figure 3 and the results for technological exit, only a small number of EU cities are exiting low complexity classes unrelated to their knowledge cores as SS policy would advocate. Again the cities in this group, those in the bottom-left quadrant of the exit panel are the EU's most high-tech centers – Paris, Munich, Eindhoven, Nurenberg, Grenoble and Copenhagen. A number of cities are abandoning technologies that generate above average complexity values and which are close to their existing capabilities. These are the cities in the top-right quadrant of the exit panel, highlighted by Enschede, Padova, Nantes, Odense and Konstanz. A few cities, notably Stuttgart and Torino, are exiting technology fields that, while relatively unrelated to their knowledge cores, exhibit above average complexity.

Note that while Figure 3 shows these results for the study period as a whole, Appendix 2 reports the relatedness density and complexity values for each city for the first and last time-periods, for both technological entry and exit. As might be expected, there is considerable movement of cities in the SS space over time, though quite some consistency in relative positions especially for larger cities.

Does smart specialization improve the economic performance of EU cities?

Do EU cities enjoy improved economic performance if they develop technology stocks in a manner consistent with SS? In other words, if cities enter and exit technological fields so that the relatedness density and complexity of their knowledge portfolios increase over time, will they outperform other cities where technology evolves in some other fashion? To help answer this question, a SS index is constructed. This index is found by summing the normalized values of relatedness density and complexity for entry (taken from Figure 3) and then subtracting from that sum the normalized values of relatedness density and complexity for exit. Cities that enter new technology fields that raise relatedness and complexity and which exit technological fields with lower than average relatedness and complexity will score highest on the smart specialization index. These are the cities in the top-right quadrant of the entry (top) panel in Figure 3 and in the lower-left quadrant of the exit (bottom) panel. Normalized values of both relatedness density and complexity are used so that these two variables have a reasonably similar weight in the resulting SS index.

In Table 3, EU cities are binned into five quintiles on the basis of their SS index calculated across all five-year periods between 1981-85 and 2011-15. Twenty-nine cities are located in each of the quintiles that are reported in descending order of smart specialization. Across cities in each quintile the average rate of employment growth and the average rate of GDP growth are reported. The table makes it very clear that, at least in cross section by quintile, cities scoring higher in terms of the SS index enjoy faster economic growth. There is a positive monotonic relationship between SS and employment growth across the quintiles and a near monotonic relationship for GDP growth.

Of course, within each of the quintiles there is considerable variation in growth rates of employment and GDP across cities.

Table 3: The Relationship between Smart Specialization and Economic Growth

Smart Specialization Quintiles (normalized)	Employment Rate of Growth	GDP Rate of Growth
1	0.30184	0.68426
2	0.29769	0.66836
3	0.25388	0.58820
4	0.21746	0.55201
5	0.19738	0.56507

Notes: GDP data are in constant 2005 euros. Simple growth rates for employment and GDP are measured between consecutive 5-year periods and then summed.

We now explore the relationship between SS and economic growth in panel form, seeking to push more clearly a policy-related claim that if cities adopt a SS approach to managing technology, on average they will enjoy improved economic performance. Two different dependent variables are used for this task, the rate of growth of employment and the rate of growth of GDP. Growth rates are preferred over levels to remove some of the influence of scale. They also fit better with the independent variables that comprise the SS indicators, for they are change variables. Arguably, employment and GDP are the most general and, perhaps, the most important indicators of economic performance.

The primary independent variables in the analysis are the SS index and its main components. All variables in the regression model, illustrated below, are measured within EU cities for each five-year time slice. Using a fixed effect panel format in our regression model focuses attention on temporal shifts in technology development within cities and allows removal of the influence of fixed city-specific influences on performance. Over the medium-length study period of 35 years or so, these fixed effects might incorporate urban variations in broad scale institutions/regional innovation systems/growth policy. The analysis incorporates a time-lag in that we examine entry and exit in regions between time periods *t* and *t+1* and then explore the variation in regional performance for time-period *t+1*. We add time fixed effects to the regression model to control for period-specific shocks that might impact urban growth. Employment or GDP in levels form for the base year of the growth period of each city is added to control for city-size, consistent with standard growth models.

Although careful search for a well-specified causal growth model is beyond the scope of this investigation, we offer a simple framework where changes in the SS index are seen as leading to subsequent shifts in economic performance within cities. Given the nature of economic data, we anticipate concerns with endogeneity, driven both by simultaneity bias (reverse causation) and by time-varying omitted variables. We use an instrumental variables approach to assess the exogeneity of our key independent variables. We do not have readily available instruments for our SS index and so we use 5-, 10- and 15-year lags of all independent variables as instruments.

Concerns with use of lagged variables as instruments are raised by Bellemare et al. (2016). The advantage of multiple instruments is that we can make use of over-identification possibilities to run Hansen's test of their exogeneity, in addition to the standard tests for weak instruments available through first-stage regression diagnostics. All regressions reported are robust to concerns with heteroscedasticity. The instrumental variables regressions are estimated with a generalized method of moments model.

Note that as our observations are spatial units we must think about spatial dependence in the data. In a simple test, Moran's I measures were constructed for employment growth and GDP growth across the spatial units for different periods. The analysis of spatial autocorrelation in these variables made use of city centroids and spatial weights based on inverse distances between all pairs of cities included in the analysis. Note that for most all periods the Moran I coefficient of spatial autocorrelation was insignificant for both dependent variables (the Moran coefficient turns significant in the final period for the employment growth variable). A more comprehensive test of spatial dependence in our data made use of spatial panel models. Tests of spatial lag and error effects in R using the package spml indicated no significant concerns with either form of spatial dependence. Results from spatial lag models are reported in Tables 4 and 5. In our non-spatial panel models, we entered spatial lags in final tests, none were significant, and the inclusion/exclusion of the spatial variables had no significant impact on the results reported.

The results of our analysis are displayed in Table 4 (where employment growth is the dependent variable) and in Table 5 (where GDP growth is the dependent variable). Overall, the results indicate a positive and significant link between metropolitan performance and the SS index, though there is some variation in findings across the different models presented. Estimated in fixed effects form this link is established at the city level. In Model 1, across Tables 4 and 5, the SS index is the key independent variable. The SS variable is positively and significantly related to employment growth in cities, but while positive, it is not significantly related to the growth of GDP. In Model 2, the two primary components of the SS index are separated to examine the differential impacts of relatedness density and complexity on urban performance. Both relatedness density and the complexity measures are positively related to rates of growth of employment and GDP, though only the complexity index is significant in these regressions. We have no clear theoretical expectation regarding the city scale measures in the regression models.

Models 3 and 4 in Tables 4 and 5 repeat the same analysis as Models 1 and 2, though they add a spatial lag of the dependent variable to confirm that spatial dependence is not a significant issue in the analysis presented. The spatial lag model was estimated with the R-package splm using inverse distance weights. With the spatial lag term included, the positive coefficient on the SS index in Model 3 of Table 5 becomes significant. Models 5 and 6 incorporate instrumental variables in an attempt to explore the influence of endogeneity in the data. The key instruments are one-, two- and three-period lagged values of our SS index (Model 5), the lagged values of the relatedness density and complexity measures (Model 6) and the city scale variable. First stage tests for Models 5 and 6 across both tables show that our instruments are identified and that they are not weak. Employing multiple lags allows use of Hansen tests that reveal our instrument sets are exogenous in all cases.

Table 4: EU city-region employment growth and smart specialization
(Dependent variable is employment growth)

Ind. Variables	Model 1	Model 2	Model 3 (spatial lag)	Model 4 (spatial lag)	Model 5 (IV)	Model 6 (IV)
Spatial lag			0.1746 (0.1743)	0.1805 (0.1735)		
Smart spec index	0.0319* (0.0179)		0.0016** (0.0008)		0.4655** (0.1986)	
EE relatedness		0.0120 (0.0260)		0.0003 (0.0012)		0.7226** (0.3374)
EE complexity		0.0504* (0.0259)		0.0027** (0.0011)		0.2339 (0.2006)
Lagged Employment	0.0003 (0.0005)	0.0003 (0.0005)	-3.21E-06 (5.52E-06)	-4.17E-06 (5.55E-06)	-0.0138* (0.0078)	-0.0120* (0.0068)
Time fixed effects	YES	YES	YES	YES	YES	YES
Observations	870	870	870	870	435	435
R^2 within	0.12	0.12				
KP LM-statistic					25.874***	31.401***
Cragg-Donald F					7.705***	4.444***
KP Wald F					3.409***	3.760**
Hansen J					3.456	4.844

Notes: The smart specialization measures (relatedness and complexity) are normalized. EE stands for entry and exit. Employment is added to control for city-size in Models 1, 3 and 5, while GDP is added to control for city-size in Models 2, 4 and 6. All standard errors are robust and reported in parentheses. * significant at 0.1, ** significant at 0.05, *** significant at 0.01. In the instrumental variable estimation of Model 5, KP is the Kleinbergen-Paap rk LM statistic testing for under-identification and KP Wald is the Wald rk F-statistic testing for weak identification. Note that these test-statistics assume heteroscedastic robust standard errors rather than errors that are i.i.d. The Hansen J-statistic is not significant, confirming that our instruments are exogenous. The spatial lag panel model was typically preferred over the spatial error panel model and so is reported in the table.

Using the instrumental variables approach in Model 5 shows that the smart SS index is positive in sign and a significant determinant of variations in employment growth and GDP growth. When we explore which of the two components of the index exerts the stronger impact on the dependent variable, the measure of relatedness density is most important in terms of understanding variations in the rate of growth of employment and the measure of complexity most important in terms of understanding differences in the rate of growth of GDP. The size of the coefficients is considerably higher in the instrumental variables estimates than the prior models, a consistent finding across much econometric literature While Models 5 and 6 are certainly not well-specified, the results indicate that the core independent variables are exogenous and thus it is reasonable to assume that in a less parsimonious model these results may persist.

Table 5: EU city-region GDP growth and smart specialization
(Dependent variable is GDP growth)

Ind. Variables	Model 1	Model 2	Model 3 (spatial lag)	Model 4 (spatial lag)	Model 5 (IV)	Model 6 (IV)
Spatial lag			-0.251 (0.2200)	-0.2484 (0.2195)		
Smart spec index	0.0308 (0.0196)		0.0022* (0.0011)		0.2333** (0.0927)	
EE relatedness		0.0084 (0.0302)		3.41E-04 (1.70E-03)		0.1910 (0.1419)
EE complexity		0.0512* (0.0269)		0.0038** (0.0016)		0.2621** (0.1202)
Lagged GDP	0.0035** (0.0016)	0.0032** (0.0015)	1.56E-05* (7.99E-06)	1.39E-05 (8.04E-06)	-0.0187 (0.0115)	-0.0188* (0.0112)
Time fixed effects	YES	YES	YES	YES	YES	YES
Observations	870	870	870	870	435	435
R^2 within	0.39	0.40				
KP LM-statistic					25.124***	33.022***
Cragg_Donald F					9.754***	4.894***
KP Wald F					6.612***	5.605***
Hansen J					5.592	8.146

Notes: See notes to Table 2.

Though the results are not shown here, if we add together the entry components of the SS index (entry_relatedness + entry_complexity) and if we add together the exit components (exit_relatedness + exit_complexity), these two composite variables are both significant in a specification similar to Model 6 with lagged values of these variables again serving as instruments. In these panel regressions explaining employment growth and GDP growth, the coefficients on the composite entry and exit variables have the correct sign and they are relatively similar in magnitude.

In one final note, Appendix 3 shows results of estimating the base panel models (Models 1 and 2 from Table 4 and Table 5) for 274 NUTS2 regions within the EU. The results are consistent with those shown above. In the case of NUTS2 regions then, SS and its components are relatively good predictors of employment growth and GDP growth over 5-year periods between 1981-85 and 2011-15. This finding suggests that our core results are not limited to the set of cities that we have examined.

Conclusion

Smart specialization represents an important new policy platform for EU regions. The program is ambitious, seeking to raise aggregate regional productivity across EU regions and to reduce inter-regional variations in economic performance. Whether the SS initiative can overcome well-known tradeoffs between efficiency and equity remains to be seen. Furthermore, whether the policy framework will work for all regions is an open question. At this time, the SS program is in early stages of operationalization and little is known about its likely impact. Yet, the importance and the size of the initiative call for attention. We argue that some sense of the possibilities of SS might be generated through exploration of historical data. We pursue this task by generating an index that maps how well EU cities have followed a technology development path that corresponds to the principles of SS outlined in Balland et al. (2019). The relationship between this index of SS and regional economic performance forms the analytical core of this paper.

The SS framework rests upon identification of the knowledge core of regions and a mapping of new technological trajectories for each region that build on existing capabilities. We demonstrate how to capture the knowledge profiles of EU regions and how to identify new knowledge possibilities that rest upon existing stocks of technology. Those possibilities can be ordered in terms of the costs and benefits of their development. The cost of knowledge development is linked to the relatedness of new technologies to the existing knowledge core of the region. When new technological alternatives are closely related to that core, the cost of their development is relatively low. Technology alternatives that are unrelated to a region's existing set of capabilities are risky to develop and thus pose higher costs. The benefits of developing different technologies depend upon the rents they generate. Those rents will tend to be greater for forms of knowledge that are more complex, those that are difficult to produce and to imitate.

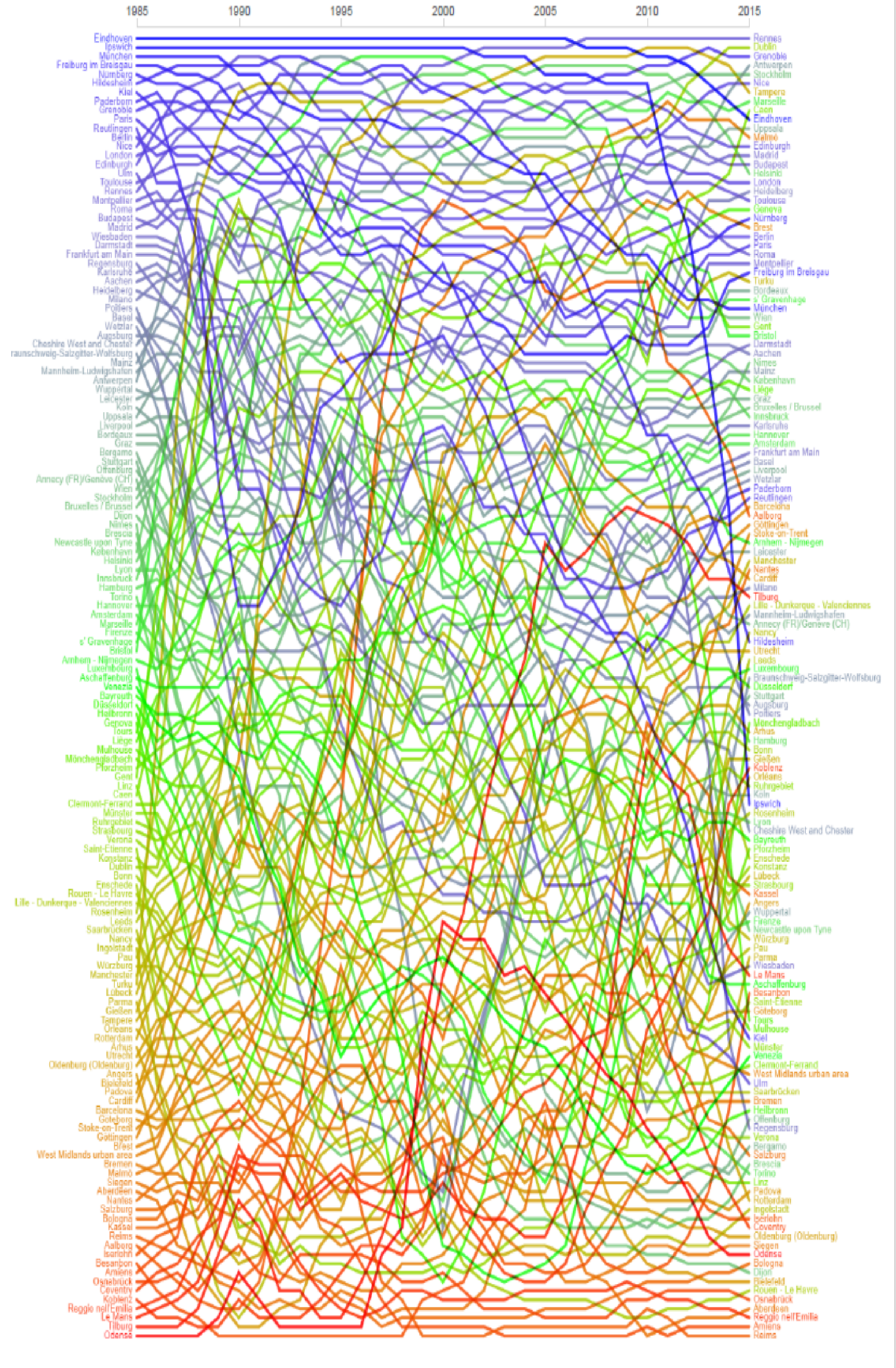
EU patent data, measures of employment growth and GDP growth at the city level are used to operationalize the arguments above. We map the knowledge cores of 145 EU cities for five-year periods spanning the period 1981 to 2015. For each city in each time-period, we examine patterns of technological entry and exit and use these to measure how closely changes in the knowledge stocks of the city correspond to a SS ideal. If cities develop (abandon) new technologies that are more (less) complex and more (less) related to their current knowledge profiles than the average of those technologies available to them (currently in use) they will score high on a SS index. The SS index, and its two core components of relatedness and complexity, are used as the primary independent variables in a series of fixed effect panel regressions that attempt to explain the variance in the economic performance of EU cities. Two separate dependent variables, employment growth and GDP growth, measure that performance. The panel regressions incorporate specific controls for spatial dependence and instrumental variables are developed to examine claims of the exogeneity of predictors.

The results show that EU cities following knowledge development trajectories that are closer to the SS ideal experience faster employment growth and faster GDP growth than cities that score lower on the SS index. When focusing on employment growth, the cost-component of the SS index, our measure of knowledge relatedness, is the most important driver of performance. When the target is GDP growth, the benefits-component of SS, knowledge complexity, exerted the strongest influence on performance. We are excited by these results that imply smart specialization policies that assist cities and regions to diversify their knowledge cores into related and more complex technological fields might well generate gains in economic performance.

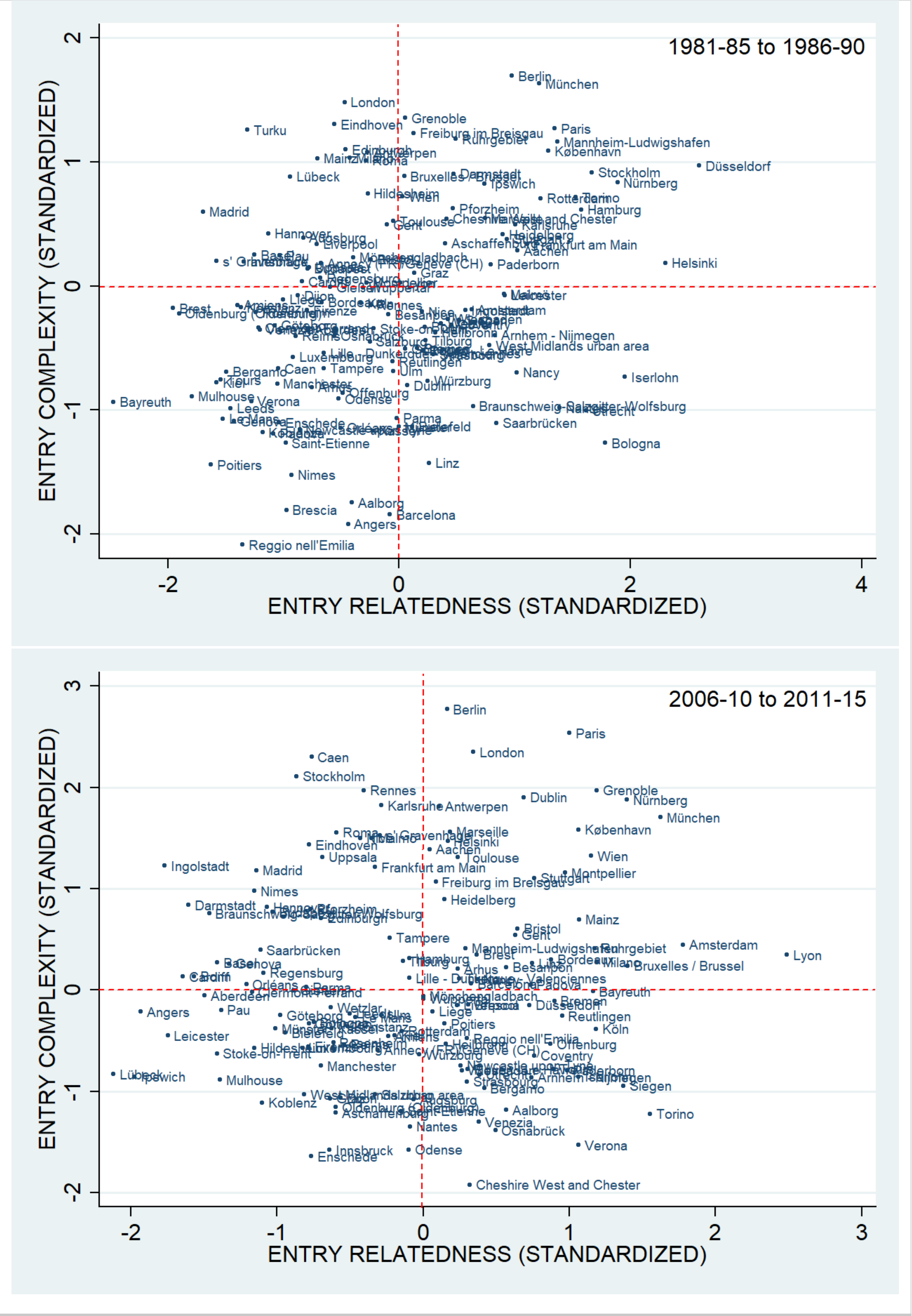
Still, some words of caution are necessary. Clearly, much more work is required to bolster our findings that remain preliminary. The results are robust to analysis at the NUTS2 regional level, across a broader set of 274 regions, but whether they will hold in a much more carefully developed causal model of economic performance remains to be seen. In addition, sub-setting regional accounts to explore how well smart specialization might work across smaller regions, those that are more or less specialized, those that are less innovative, and those that are more generally rendered "peripheral" in different ways, represent critical next steps.

Appendix 1: Complexity Scores for all EU cities 1981-85 to 2011-15

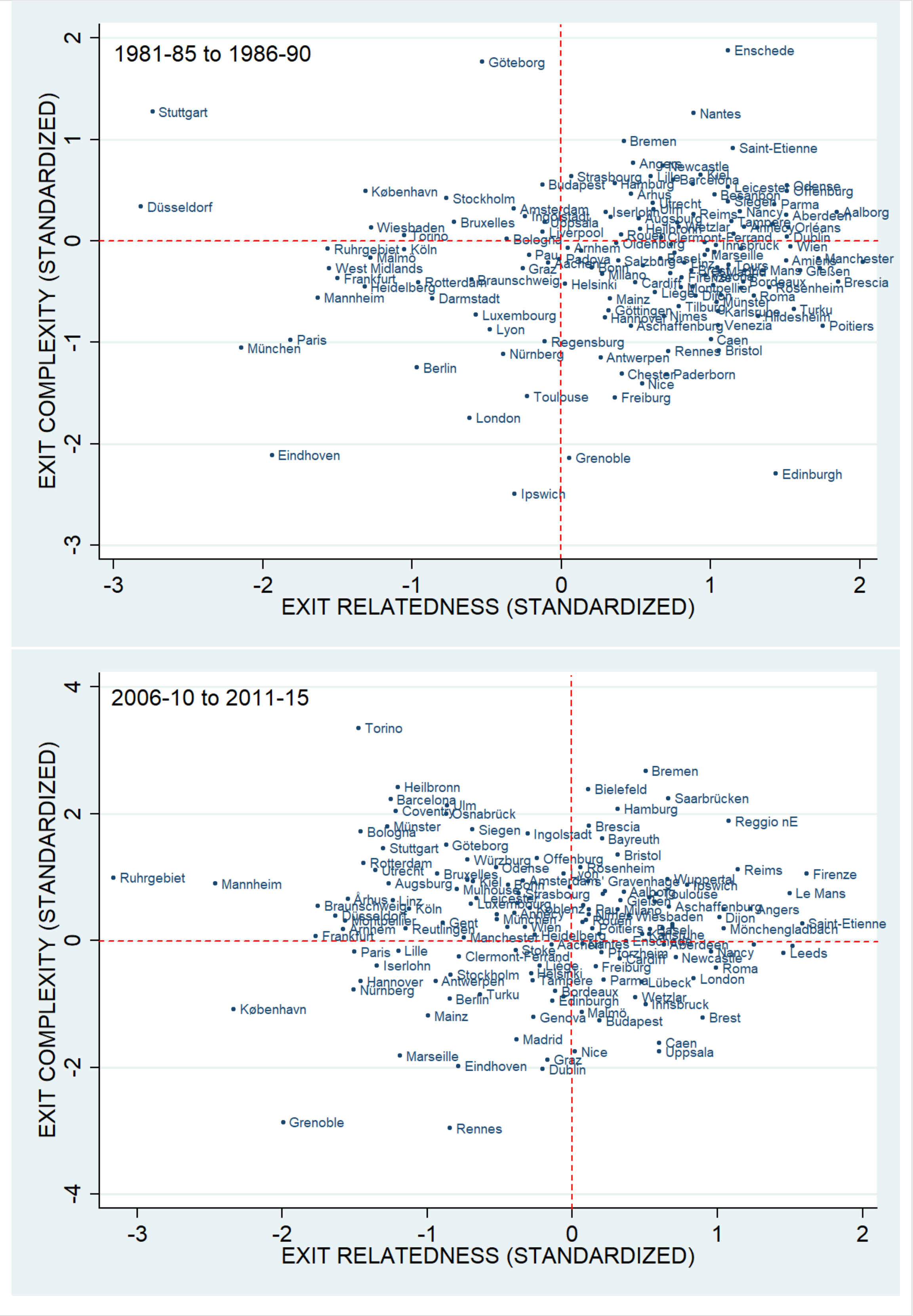
The blue lines in Figure A1 highlight those city-regions that begin the study period with relatively high technology complexity scores. The red lines denote regions where the initial technology complexity scores are relatively low, while the green and orange lines denote those locations with intermediate starting values of technological complexity. To help frame the figure, note that in the first-period 1981-85, the lowest city technology complexity score was recorded by Odense (38.4) and the highest score by Eindhoven (73.49). By 2011-15, the city with the lowest technology complexity score was Reims (39.15) and the city with the highest was Rennes (84.11).


1985
1990
1995
2000
2005
2010
2015
Eindhoven
Ipswich
München
Freiburg im Breisgau
Nürnberg
Hildesheim
Kiel
Paderborn
Grenoble
Paris
Reutlingen
Berlin
Nice
London
Edinburgh
Ulm
Toulouse
Rennes
Montpellier
Roma
Budapest
Madrid
Wiesbaden
Darmstadt
Frankfurt am Main
Regensburg
Karlsruhe
Aachen
Heidelberg
Milano
Poitiers
Basel
Wetzlar
Augsburg
Cheshire West and Chester
raunschweig-Salzgitter-Wolfsburg
Mainz
Mannheim-Ludwigshafen
Antwerpen
Wuppertal
Leicester
Koln
Uppsala
Liverpool
Bordeaux
Graz
Bergamo
Stuttgart
Offenburg
Annecy (FR)/Genève (CH)
Wien
Stockholm
Bruxelles / Brussel
Dijon
Nimes
Brescia
Newcastle upon Tyne
Kobenhavn
Helsinki
Lyon
Innsbruck
Hamburg
Torino
Hannover
Amsterdam
Marseille
Firenze
s' Gravenhage
Bristol
Arnhem - Nijmegen
Luxembourg
Aschaffenburg
Venezia
Bayreuth
Düsseldorf
Heilbronn
Genova
Tours
Liège
Mulhouse
Mönchengladbach
Pforzheim
Gent
Linz
Caen
Clermont-Ferrand
Münster
Ruhrgebiet
Strasbourg
Verona
Saint-Etienne
Konstanz
Dublin
Bonn
Enschede
Rouen - Le Havre
Lille - Dunkerque - Valenciennes
Rosenheim
Leeds
Saarbrücken
Nancy
Ingolstadt
Pau
Würzburg
Manchester
Turku
Lübeck
Parma
Gießen
Tampere
Orleans
Rotterdam
Arhus
Utrecht
Oldenburg (Oldenburg)
Angers
Bielefeld
Padova
Cardiff
Barcelona
Göteborg
Stoke-on-Trent
Göttingen
Brest
West Midlands urban area
Bremen
Malmö
Siegen
Aberdeen
Nantes
Salzburg
Bologna
Kassel
Reims
Aalborg
Iserlohn
Besanþon
Amiens
Osnabrück
Coventry
Koblenz
Reggio nell'Emilia
Le Mans
Tilburg
Odense
Rennes
Dublin
Grenoble
Antwerpen
Stockholm
Nice
Tampere
Marseille
Caen
Eindhoven
Uppsala
Malmö
Edinburgh
Madrid
Budapest
Helsinki
London
Heidelberg
Toulouse
Genova
Nürnberg
Brest
Berlin
Paris
Roma
Montpellier
Freiburg im Breisgau
Turku
Bordeaux
s' Gravenhage
München
Wien
Gent
Bristol
Darmstadt
Aachen
Nimes
Mainz
Kobenhavn
Liège
Graz
Bruxelles / Brussel
Innsbruck
Karlsruhe
Hannover
Amsterdam
Frankfurt am Main
Basel
Liverpool
Wetzlar
Paderborn
Reutlingen
Barcelona
Aalborg
Göttingen
Stoke-on-Trent
Arnhem - Nijmegen
Leicester
Manchester
Nantes
Cardiff
Milano
Tilburg
Lille - Dunkerque - Valenciennes
Mannheim-Ludwigshafen
Annecy (FR)/Genève (CH)
Nancy
Hildesheim
Utrecht
Leeds
Luxembourg
Braunschweig-Salzgitter-Wolfsburg
Düsseldorf
Stuttgart
Augsburg
Poitiers
Mönchengladbach
Arhus
Hamburg
Bonn
Gießen
Koblenz
Orléans
Ruhrgebiet
Koln
Ipswich
Rosenheim
Lyon
Cheshire West and Chester
Bayreuth
Pforzheim
Enschede
Konstanz
Lübeck
Strasbourg
Kassel
Angers
Wuppertal
Firenze
Newcastle upon Tyne
Würzburg
Pau
Parma
Wiesbaden
Le Mans
Aschaffenburg
Besanþon
Saint-Etienne
Göteborg
Tours
Mulhouse
Kiel
Münster
Venezia
Clermont-Ferrand
West Midlands urban area
Ulm
Saarbrücken
Bremen
Heilbronn
Offenburg
Regensburg
Verona
Bergamo
Salzburg
Brescia
Torino
Linz
Padova
Rotterdam
Ingolstadt
Iserlohn
Coventry
Oldenburg (Oldenburg)
Siegen
Odense
Bologna
Dijon
Bielefeld
Rouen - Le Havre
Osnabrück
Aberdeen
Reggio nell'Emilia
Amiens
Reims

Appendix 2 Figure A1: Scatterplot of Entry Relatedness and Entry Complexity



Appendix 2 Figure A2: Scatterplot of Exit Relatedness and Exit Complexity



Appendix 3: EU NUTS2-region employment growth and GDP growth and smart specialization

	Dependent Variable is employment growth		**Dependent Variable is GDP growth**	
Independent Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Smart spec index	0.0655*** (0.0216)		0.0390*** (0.0143)	
EE relatedness		0.0887** (0.0372)		0.0201 (0.0134)
EE complexity		0.0512** (0.0211)		0.0336** (0.0143)
Employment or GDP in levels	-0.0043*** (0.0004)	-0.0043*** (0.0004)	-0.0040*** (0.0003)	-0.0039*** (0.0003)
Time fixed effects	YES	YES	YES	YES
Observations R^2 within	1334 0.56	1334 0.57	1318 0.50	1318 0.52

Note: All models estimated with robust standard errors

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