An Evolutionary Approach to Regional Development Traps in European Regions

Pierre-Alex Balland and Ron Boschma

Papers in Evolutionary Economic Geography

24.20

Utrecht University Human Geography and Planning

An Evolutionary Approach to Regional Development Traps in European Regions

Pierre-Alex Balland and Ron Boschma

10 July 2024

Abstract

This paper proposes an evolutionary take on regional development traps. Our definition of regional traps centers around the structural inability of regions to develop new complex activities. We distinguish between several different traps. Using industry data, we follow European regions over time and provide evidence on which regions in the EU are trapped, and what kinds of traps they have fallen into. Our econometric analysis shows that being trapped has a negative impact on employment and wage growth in regions. We also find evidence that our development trap indicator explains well whether regions are stuck in a regional development trap, as defined by Iammarino et al. (2020).

Introduction

Despite unprecedented technological progress and global connectivity, some regions in Europe and the United States seem stuck. Stuck in the past and unable to gain from current economic developments while other regions seem to take-it-all. This leads to growing spatial inequalities and a persistent perception of unfairness, resulting in populist votes and polarization (Rodríguez-Pose et al. 2023).

Iammarino et al. (2020) introduced the trap concept to the regional level in Europe. In their seminal contribution, regions are trapped when showing persistent low levels of economic growth (Diemer et al. 2022). This study paid, however, little attention to the role of history and path dependencies in assessing the development prospects of regions. There is also little recognition that regions may end up in different types of traps. An evolutionary approach to regional development traps might offer such a dynamic perspective, as it accounts for self-reinforcing dynamics that make regions follow specific trajectories that might enhance but also limit their capacity to develop new activities (Arthur 1990, 1994; Boschma 1997; Rigby and Essletzbichler 1997; Boschma and Lambooy 1999). However, an evolutionary approach to regional development traps is still yet underdeveloped.

This paper makes a first attempt to develop an evolutionary concept of regional traps. It accounts for the persistent weak ability of regions to develop new activities and upgrade their economies. We build on the relatedness/complexity framework (Balland et al. 2019; Pinheiro et al. 2022; Rigby et al., 2022) to develop a typology of regional traps. We distinguish between three ideal types of regional traps, based on the average complexity of activities in a region and their average relatedness density. We also shed light on the possible links between regional development traps, as defined by Iammarino et al. (2020) and our evolutionary typology of regional traps (Balland et al. 2019).

Using industry data, we follow European regions over time and provide evidence on which regions in the EU are trapped, and what kinds of traps they have fallen into. Our definition of regional traps centers around the structural inability of regions to develop new complex activities. We also explore how different types of traps are linked to economic performance such as employment and wage growth, and we investigate whether they correlate with regional development traps, as identified by Iammarino et al. (2020). These insights are useful for policy discussions about regional traps, what to do about them, how to escape from them, and how to avoid them in the first place. This is especially relevant for Smart Specialization policy in places that are trapped or run the risk of falling into a trap.

This paper is structured as follows. We briefly discuss the literature on traps, such as the middle-income trap. Then, we propose an evolutionary take on regional traps and present a typology. We present the data and explain how regional traps are empirically identified. We present a map of the different types of traps in Europe. We investigate whether this has economic implications for regions. Finally, we briefly discuss some possible implications for further research and policy, in particular Smart Specialization policy.

Regional traps

The 'trap' concept is anything but new. The poverty trap literature is huge and long-standing (e.g. Redding 1996; Azariadis and Stachurski 2005; Barrett and Swallow 2006), and so is the literature on the middle-income trap (Gill and Kharas, 2007, 2015; Kharas and Kohli, 2011; Cai 2012; Im and Rosenblatt 2013; Lee 2013; Eichengreen, Park and Shin 2012, 2014; Doner and Schneider 2016; Glawe and Wagner 2016; Ye and Robertson 2016; Vivarelli 2016; Agénor 2017; Bresser-Pereira et al. 2020). Whereas the poverty trap literature refers to countries with very low-income levels that show little to no growth, the middle-income trap describes the situation of emerging countries that managed to develop rapidly but are unable to grow further. Due to the rise of labor and other costs, they get stuck in two ways: it is hard for them to compete with low-income countries in labor-intensive, mature industries, while they lack strong capabilities to develop knowledge-intensive industries and compete with more advanced countries.

The reason why middle-income traps exist has been attributed to inadequate infrastructure, low quality of human capital, poor institutions, limited access to financial resources, among other factors (Lee 2013; Agénor 2017). Scholars have also mentioned the importance of institutional reforms to escape the middle-income trap. Doner and Schneider (2016) refer to the poor ability of countries that are stuck to implement institutional change and pursue effective public intervention. Aghion and Bircan (2017) followed a similar argument, focusing on institutional structures that promote or block the development of new growth paths. This literature adopts an evolutionary approach in which the middle-income trap is associated with path dependencies of trajectories and institutional inertia.

Fuest et al. (2024) proposed the concept of 'middle tech trap' to describe the current technological state-of-affairs of the European Union with respect to the US and China. OECD et al. (2019) have stretched the concept of traps when looking at development opportunities in Latin American and Caribbean countries. They refer to four different development traps this group of countries are caught in: a productivity gap, a social vulnerability trap, an institutional trap, and an environmental trap. They present them as vicious cycles that limit the capacity of countries to move to higher levels of development, especially with regard to inclusive and sustainable growth.

However, few comparative studies exist that have identified regional traps at the sub-national level[1]. Iammarino et al. (2020) examined so-called development traps in Europe in regions based on prolonged low growth rates in Gross Regional Product per capita, productivity and employment. These concern low-income regions that experienced sustained growth but got stuck at some point in time, as well as old industrial regions that

[1] The club convergence literature identified distinct groups of regions, each of which have their own dynamics (Quah 1997), but they lack an evolutionary perspective.

once belonged to the most prosperous regions in Europe but which have been losing manufacturing activities for decades, due to offshoring and outsourcing, among other reasons. Iammarino et al. (2020) found that factors that increased the risk of regions falling into a development trap included lower shares of manufacturing, higher shares of non-market services, higher dependency ratios, and lower quality of government, rather than factors like innovation capacity and human capital. An interesting recent study on development traps in Turkish regions (Çınar 2023a,b) suggests that regions with related variety and complex productive structures have a lower risk of falling into such traps[2].

The Iammarino et al. (2020) study generated key insights on regional traps but focused little attention on the role of history and path dependency to identify them. It takes a snapshot of the economic state of affairs that regions are in, using conventional growth indicators, but with little focus on their future development prospects (Diemer et al. 2022). Moreover, their development trap concept does not differentiate between types of traps, which might be crucial to consider, as regions follow specific trajectories. Evolutionary approaches account for circular, self-reinforcing dynamics that make regions follow distinct trajectories (Arthur 1990, 1994; Boschma 1997; Rigby and Essletzbichler 1997; Storper 1997; Boschma and Lambooy 1999a; Martin and Sunley 2006) that may enhance but can also limit their capacity to develop new growth paths.

A rather old but relevant literature focused on the notion of lock-in (David 1985; Arthur 1990, 1994). In economic geography, lock-in has been associated almost exclusively with the lack of adaptability of old industrial regions (Grabher 1993; Boschma and Lambooy

[2] The European Commission (2023) has also proposed the notion of 'talent development trap'. Regions are considered to be caught in such a trap when they are subject to persistent decline in their working-age population, low numbers of high-educated people, and structural outflows of talent.

1999b; Martin and Sunley 2006; Pike et al. 2009; Hassink 2007, 2010; Evenhuis 2017). Drawing inspiration from evolutionary economics and network science, this body of literature highlighted different forms of lock-in, such as cognitive, economic and institutional lock-in (Grabher 1993) that make old industrial regions trapped in a process of structural economic decline. Lee and Malerba (2017) shed light on the concept of lock-in by focusing on the inability of incumbent leaders to respond to changes in technology, demand, and institutions. Moreover, the economies of regions may be subject to institutional lock-in and fail to adapt, because of a weak ability to implement institutional change (Boschma and Lambooy 1999b).

More recently, evolutionary scholars have argued that diversification opportunities of regions depend on local capabilities (Hidalgo et al. 2007; Neffke et al. 2011; Kogler et al. 2013; Boschma et al. 2015; Rigby 2015; Petralia et al. 2017; Alshami et al. 2018; Balland et al. 2019, 2020; Hartmann et al. 2020, 2021). Over time, regions accumulate an unique set of capabilities that are embodied in people, institutions and the activities they employ. This set of local capabilities conditions which new growth trajectories are more likely to develop in a region (Neffke et al. 2011; Boschma 2017). This also implies that diversification opportunities differ widely across regions.

Pinheiro et al. (2022) used such an evolutionary framework to identify the diversification potentials of regions of varying income levels. They found that low-income regions have diversification potentials primarily in low-complex activities, which contrasts with high-income regions that have such opportunities primarily in high-complex activities. Pinheiro et al. (2022) suggested that regions may be trapped in a ‘low complex’ economy because they lack the ability to diversify into high-complex activities. They also observed a category of medium-complex regions that lack good options in either complex or non-complex activities. While these latter regions may have escaped a low-complexity trap (i.e. their opportunity space is not anymore in low-complex activities only), they still have a hard time to move in complex activities, as required capabilities may be lacking.

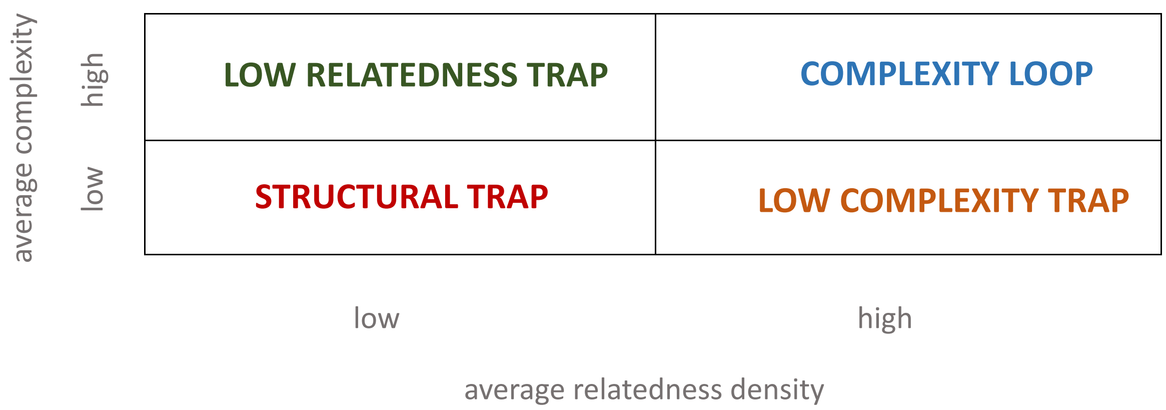
Toward an evolutionary conceptualization of regional traps

Balland et al. (2019) proposed a framework building on the notions of relatedness and complexity to determine whether regions have opportunities to diversify into complex activities, and if so, in which complex activities. Relatedness refers to the costs of developing a new activity. The more related the local capabilities are to the capabilities that are required to develop a new activity, the less risky and costly to develop it. Complexity refers to the potential economic benefits of diversification. Complex activities combine many capabilities which makes it hard for regions to develop them. This implies that the economic benefits of complex activities will be higher, because few regions can master and produce them (Hidalgo and Hausmann 2009; Balland and Rigby 2017). Bachtrögler-Unger et al. (2023) have used this framework to identify which regions in Europe are best placed to develop Twin Transition technologies.

The Balland et al. (2019) framework is useful to demonstrate that regions have different sets of diversification opportunities available to them. Major urban agglomerations tend to show a positive relationship between relatedness and complexity: they have opportunities to develop complex activities, and few opportunities to move into low-complex activities (Pinheiro et al. 2022). Old industrial regions show a different opportunity space. Some old industrial regions are stuck in a low-complexity trap: there is a negative relationship between relatedness and complexity, which means they have opportunities to move into low-complex but not in high-complex activities (Balland et al. 2019). Other old industrial regions show a diversification opportunity space that is neither close to complex nor to non-complex activities (Pinheiro et al. 2022). Their opportunity space is not anymore in simple activities only, but they still miss relevant capabilities to move into more complex activities. Less developed regions have again different opportunity sets. They might lack low-hanging fruits altogether, which makes it very hard to move into anything new. Or their opportunity set is limited primarily to some low complex activities such as tourism and agriculture, which implies strong competition with many other regions. In all these cases, they seem to be trapped in a 'low complexity' state.

Because regions follow distinct paths, it is crucial to differentiate between different types of traps. In this paper, we define and identify three ideal types of regional traps, based on the average complexity of activities present in the region, and their average relatedness density to any activity. The average complexity denotes the complexity level of the current economic structure of a region. The average relatedness density refers to the ability of a region to adapt and diversify: the higher, the more opportunities to develop activities. Such conceptualization also enables us to determine how much each region is actually trapped, as that depends on the scores of regions on both indicators. In the end, regions will be trapped to a greater, or to a lesser extent. The three regional traps are depicted in Figure 2.

Figure 2. A typology of regional traps



The ‘structural trap’ is the worst trap regions can end up in. It involves regions that combine a low average relatedness density with a low average complexity. They are stuck, having an economy of low complexity, with a lack of real diversification opportunities, and therefore they are likely to stagnate. This contrasts with regions that combine high average levels of relatedness and complexity. These regions are in a ‘complexity loop’, having complex structures and a strong ability to adapt. This is very different from regions in a ‘low relatedness’ trap: this is a special category of regions that combine high average complexity with a low average relatedness density. They are stuck in a ‘low relatedness’ trap, as their past success in complex activities does not enhance their ability to move into something new. They have succeeded to move in some complex activities but these have remained isolated from other local activities: their capabilities do not allow them to move into other complex activities, nor into low-complex activities. This makes them vulnerable and less resilient. The ‘low complexity trap’ refers to regions that have high average relatedness density combined with a low average complexity. They have diversification opportunities, but most likely in low complex activities, in line with Pinheiro et al. (2022).

Data and methods

In order to determine development traps, Iammarino et al. (2020) measured the relative economic performance of regions over time. They account for three measures simultaneously: GDP per capita, productivity, and employment to population ratio. Their trap indicator measures if a region’s growth is persistently lower with respect to the European average, the average of the country that the region belongs to, and the region’s own past performance. They also measure the length of the regional traps which is captured by the number of years a region scores low on the majority of growth comparisons.

Instead of looking at economic growth, we focus on the opportunities that regions have (or not) to move into new (complex) activities, as this will have implications for their future growth and development. We mainly use industry data to determine which regions in Europe are trapped, in what kind of traps they are stuck, and which regions have managed to escape such traps. The advantage of using industry data is that industry activity is not biased towards high-income regions, as patent data are (Pinheiro et al. 2022). This allows us to identify traps in every type of region, including low-income regions.

We measure industrial relatedness and complexity in 214 NUTS-2 European regions using employment data from Eurostat, which is compiled by the *Structural Business Statistics* (SBS). The SBS provides disaggregated NACE codes (level 1, 2 and 3) but some sectors are entirely missing, such as the financial and the agricultural sector, and the overall coverage is only 58.9%. To account for such limitations in the SBS, we also use the Annual Regional Database of the European Commission (ARDECO) which provides employment data by NUTS2-regions and NACE code, which is produced by the Joint Research Centre & DG for Regional and Urban Policy. The ARDECO dataset is comprehensive but industry codes are more aggregated. We combine both datasets, and when relevant, we subtract the SBS employment count from the ARDECO employment count (K-N residual for instance).

Because of its historical legacy, the NACE classification in SBS provides too much detailed classification for low-complex sectors such as manufacturing. Therefore, we re-aggregated some categories to be consistent with the overall level of aggregation in SBS. We focus on employment numbers among 33 industry classes (2-digit NACE, Rev. 2). Regions span all EU-27 countries. Numerous changes in NUTS-2 boundaries have been accounted for, plus missing years have been extrapolated. Regions have also been matched with the regional classification used in Iammarino et al. (2020), to make our findings comparable with their study[3].

As explained before, we identify regional traps by measuring the Average Relatedness Density to any industry and Average Complexity of existing industries in a region. We follow Hidalgo et al. (2007) and calculate Average Relatedness Density in three steps. The first step is to measure the relatedness between industries. Relatedness between industries is captured by the cosine normalized co-occurrences of industries in the same regions. The second step is to measure a Relatedness Density measure which estimates the relatedness of an industry to the overall region's portfolio of industries. The third step is to measure the Average Relatedness Density to all industries for a given region.

We use the eigenvector reformulation of the Method of Reflection to assess the Average Complexity of industries in a region (Hidalgo and Hausmann 2009; Balland et al. 2022). This method considers the diversity of activities in a region and how many other regions can produce these activities. This captures the idea that many regions can produce simple goods and services, but only a few regions can engage in complex industries that require capabilities from a wide range of industries. Using the matrix of Revealed Comparative Advantages M_{ij}, we compute the Economic Complexity of all industries. We calculate an Average Economic Complexity index (ECI), defined as the average complexity of all industries in which a region has Revealed Comparative Advantage, and calculated as the eigenvalue:

[3] There are missing values for some regions such as Central Hungary (Budapest) and Mazowieckie (Warsaw) due to changes in the NUTS2 classification.

$$\mathrm{CI}_i = \sum_j \frac{M_{ij}}{U_j D_i} \sum\nolimits_c M_{ij}\ \mathrm{ECI}_i \quad (1)$$

where D_i stands for the diversity of a region, i.e., the number of industries in a region.

Figure A.1 in Appendix 1 presents the complexity rankings of industries. The most complex ones turn out to be in service industries, such as Motion Picture & Television Production, Computer Programming, Telecommunications, Head Office & Management Consultancy Activities, and Finance & Insurance. The least complex industries can be found in Agriculture, Forestry & Fishing, Mining & Quarrying, and Basic Manufacturing.

Complexity loops and structural traps in Europe

Figure 3 presents a map of regional traps in Europe. The 4 colors represent the 4 types of regions of our typology proposed in Figure 2. These are based on the Average Complexity and Relatedness Density (RD) scores of all European regions in terms of rankings[4] over the period 2011-2019[5]. The regions colored in blue are in a 'complexity loop' (both indicators above the mean), the regions colored in green are in a 'low relatedness trap' (average complexity above, but RD below the mean), the orange colored regions concern the ones in a 'low complexity trap' (average complexity below the mean, but average RD above the mean), and the red colored are in a 'structural trap' (both indicators below the mean). The figure suggests that the majority of regions is trapped in one way or another. However, one should bear in mind that the two variables are continuous rather than binary. For a region, it is not just a matter of being trapped or not, but being trapped to a greater or lesser extent. This is shown in Figure A2.1 in Appendix 1.

[4] The scores of regions in terms of absolute values are presented in Figure A2.2 in Appendix 2

[5] The figures on Regional Traps in Europe in the case of technologies can be found in Figures A3.1 and A3.2 in Appendix 3.

Figure 3. Map of regional traps in Europe (rankings)

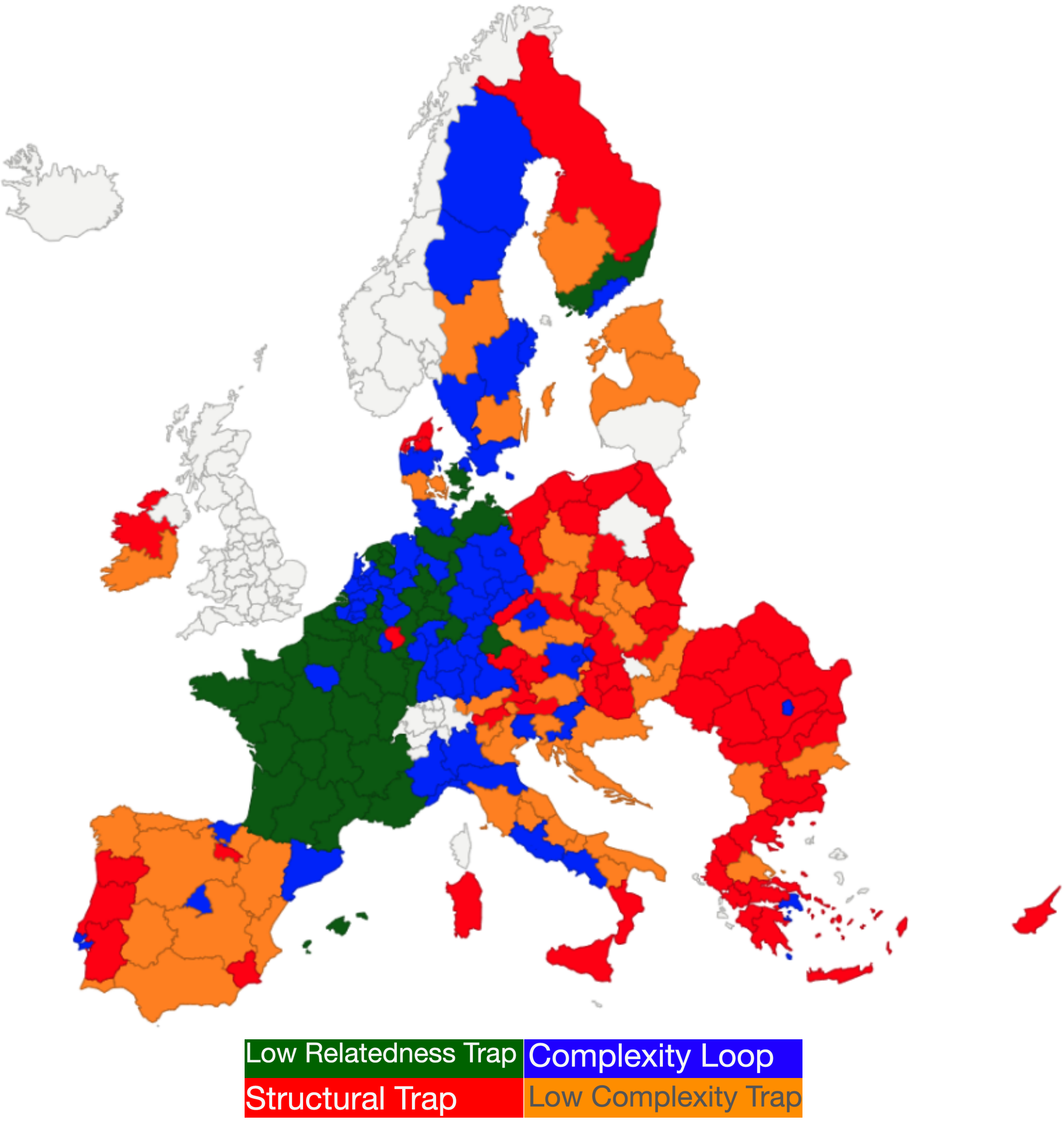


Figure 3 shows that more developed regions often find themselves in a 'complexity loop'. This includes almost all capital regions like Stockholm, Ile de France, Madrid, Vienna, Bratislava, Amsterdam, Helsinki, Rome, Berlin, Lisboa, Copenhagen, Bucharest, Ljubljana, Athens and Brussels. Many regions in Germany (including Eastern Germany) are in a 'complexity loop', but also some regions in the Netherlands (in the major urban areas), Belgium (part of Flanders), Italy (Piemonte, Lombardy, Emilia-Romagna), Sweden (in the North and South West), Spain (Basque country, Catalonia) and Denmark. The Paris region is the only French region in a complexity loop.

Many less developed regions in Eastern Europe in Romania, Bulgaria, Hungary, Slovakia, Poland and Greece are stuck in a 'structural trap'. But this also applies to some regions in Portugal, the South of Italy, and Austria. This is very different from regions that have fallen in a 'low relatedness trap'. None of those are located in Eastern and Southern Europe. Most of them can be found in more peripheral parts of some West-European countries such as France, the Netherlands, Germany and Belgium. These regions have a very limited set of opportunities to move in high- and low-complex industries. Regions that are caught in a 'low complexity trap' are often found in Eastern Europe, like Zagreb (Croatia), Yugozapaden (Bulgaria) and Wielkopolskie (Poland). Also many regions in Spain and Italy appear to find themselves in a 'low complexity trap'. However, most of these regions do not show extreme absolute values, as Figure A2.2 in Appendix 2 shows.

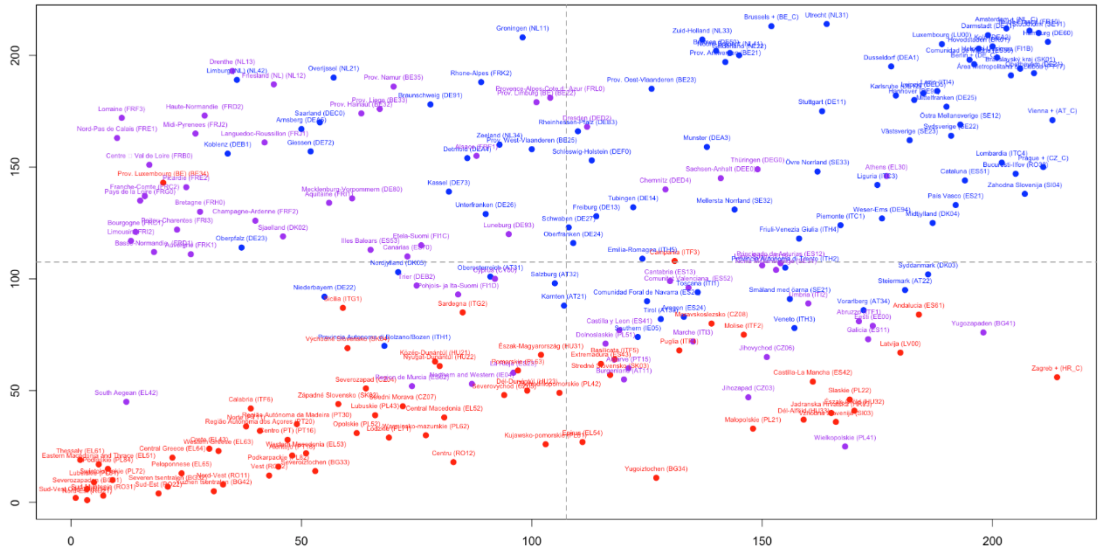
Figure 4 presents the scores of all regions on Average Complexity and Average Relatedness Density (in terms of rankings[6]), and indicates which of these regions concern more developed regions (with a GDP per capita over 90% of the EU average), transition regions (between 75% and 90%), and less developed regions (below 75%)[7]. Almost all more developed regions (colored blue) show a relatively higher average complexity: they

[6] The same figure based on values is shown in Appendix 4.

[7] Appendix 5 shows the distribution of regional traps across Northern, Eastern and Southern Europe. Almost all regions in Northern Europe are in a complexity loop, or in a low relatedness density trap. This is in contrast to regions in Eastern Europe that are almost all caught in a structural trap, or in a low complexity trap. The exceptions in Eastern Europe are 4 capital regions (Bratislava, Prague, Bucharest and Ljubljana) that find themselves in a complexity loop. Southern Europe is similar to Eastern Europe in two ways: most regions are stuck in a structural trap or in a low complexity trap, and there are no regions in both parts of Europe that are stuck in a low relatedness density trap. Southern Europe is still different from Eastern Europe, because the former has much more regions in a complexity loop, most notably capital regions like Lisboa, Madrid, Rome and Athens, but also regions like Lombardy, Catalonia, Basque Country, Liguria and Piemonte.

find themselves either in a complexity loop or in a low relatedness trap. All less developed regions (colored red) have relatively lower average complexity levels, and are either stuck in a structural trap or a low complexity trap. The transition regions (colored purple) show a more diverse pattern: they can be found in all 4 quadrants of Figure 4, but especially in a low relatedness density trap, and a low complexity trap.

Figure 4. Regional traps across more developed, transition, and less developed regions



We also added a dynamic analysis and explored whether regions trapped in 2011 were still being trapped in 2019, which regions managed to escape a trap, and which regions fell into a trap. In Table 1, a trap transition matrix is presented[8]. What strikes the eye first is a lot of stability in the period 2011-2019. The overwhelming majority of regions remains in the same group: this applies to 77% of the regions in a 'complexity loop' and in a 'low relatedness trap', and 63% of regions in a 'structural trap'. As expected, moving from a 'complexity loop' to a 'structural trap' and *vice versa* is very rare. This happened only to 1 region and 2 regions (Oberosterreich and Salzburg) respectively. A total of 12 regions

[8] A similar trap transition matrix for technologies can be found in Table A5.1 in Appendix 5.

managed to escape from a trap and moved into a complexity loop. Five of them moved out of a low relatedness trap (increasing their Average Relatedness Density), and five of them moved out of a low complexity trap (increasing their Average Complexity). A total of 19 regions succeeded in moving from a 'structural trap' into a 'low complexity trap', meaning they managed to increase their Average Relatedness Density while their Average Complexity remained below the median[9]. These are located in Eastern Europe, such as Poland, Hungary, Romania, Slovenia and Czech Republic, but also in countries like Finland, Spain, Denmark, Ireland and Portugal.

Table 1. Traps transition matrix 2011-2019

2019

2011

	Complexity loop	Low relatedness trap	Low complexity trap	Structural trap	Total
Complexity loop	**46 (77%)**	12 (20%)	1 (2%)	1 (2%)	60
Low relatedness trap	5 (11%)	**36 (77%)**	1 (2%)	5 (11%)	47
Low complexity trap	5 (11%)	0 (0%)	**33 (70%)**	9 (19%)	47
Structural trap	2 (3%)	1 (2%)	19 (32%)	**38 (63%)**	60
Total	58	49	54	53	214

Regional traps and economic performance

Can we find a relationship between traps and economic prosperity in regions? That is, do trapped regions grow less on average? We look at employment and wage growth in regions. We did not use GDP data, as in some EU regions (like in Ireland) GDP is significantly inflated by non-resident multinational enterprises. We position each region in

[9] A similar Structural trap dynamics for technologies can be found in Figure A6.1 in Appendix 6.

one of four quadrants in terms of its employment and wage growth dynamics relative to all the other regions (above or below the median) in the period 2011-2019. The employment data comes from the ARDECO database.

Table 2 shows in which of those 4 quadrants each of the 4 types of regions is positioned in terms of its labor market dynamics from 2011 to 2019[10]. First, as expected, regions in a 'complexity loop' show the highest relative performance, as compared to regions that are trapped: the majority of these regions (52%) showed higher relative growth in both employment and wages (E+W+), while they form the relative smallest group (17%) in the category of regions with growth rates below the median in both employment and wages (E-W-). Examples are Athens, Basque Country, Catalonia and Ovre Norrland. The vast majority of regions in a 'complexity loop' (77%) has experienced above average employment growth: outstanding regions are Prague, Bratislava, Stuttgart, Oberbayern and Hamburg. Second, we cannot conclude that regions stuck in 'structural traps' show the worst performance. While they score the lowest on employment growth (only 33% of them showed relative employment growth E+), they score the highest on relative wage growth (61% of them showed wage growth above the median W+). Many of the latter group concern regions with low initial wage levels in Eastern Europe, most notably from Bulgaria, Romania and Poland. The share of regions in a 'structural trap' (28%) is actually lower in the worst performance category (E-W-) than regions in 'low relatedness traps' and 'low complexity traps' (43 and 45% respectively), while they show similar performances compared to these regions in the best performance category E+W+ (23%

[10] A similar table on the relationship between labor market dynamics and types of regional traps can be found for technologies in Table A6.1 in Appendix 6 and for industries and technologies combined in Table A7.1 in Appendix 7.

versus 26 and 23%). Third, each of the three types of regional traps shows peculiar features. The largest group of regions in a ‘structural trap’ (38%) experienced relative employment decline in combination with relative wage growth (E-W+). This is different from regions in a ‘low complexity trap’ and a ‘low relatedness trap’ that show the highest shares in the worst economic performance category (E-W-). Examples of the former are Epirus (Greece) and some Spanish regions (like Asturias, Castilla-La Mancha, Castilla Y Leon). Examples from the latter group are dominated by French regions like Picardie, Lorraine and Haute-Normandie. These two groups of regions show remarkable differences too: regions in a ‘low relatedness trap’ score better on relative employment growth (E+) than on wage growth (W+), in contrast to regions in a ‘low complexity trap’ of which the majority scores below the median of employment growth (64%) and wage growth (58%).

Table 2. Relationship labor market dynamics and types of regional traps

	E+W+	E+W-	E-W+	E-W-
Complexity loop	52%	25%	7%	17%
Low relatedness trap	26%	26%	6%	43%
Low complexity trap	23%	13%	19%	45%
Structural trap	23%	10%	38%	28%

We also regressed regional employment and wage growth 2011-2019 on Average Relatedness Density and Average Complexity, while controlling for other variables. We estimated a baseline model with 6 dependent variables: employment growth (values and ranks), wage growth (values and ranks), and a combined indicator of employment and wage growth (values rescaled and ranks), as shown in Figure 5. We included control variables: level of employment in 2011; level of wages in 2011; share of Research and Development expenditures in total GDP; share of Gross Value Added in manufacturing;

share of population with Higher Education; Quality of Government (EQI) (Rodríguez-Pose and Castaldo 2015; Rodríguez-Pose and Muštra 2022).

Figure 5. Baseline employment and wage growth model

	Dependent variable:					
	Employment Growth	Employment Growth (Rank)	Wage Growth	Wage Growth (Rank)	Both (Rescaled)	Both (Rank
	(1)	(2)	(3)	(4)	(5)	(6)
EMPlevel	-0.104	3.444	5.591***	15.139***	4.252**	18.583**
	(0.577)	(5.557)	(1.556)	(4.381)	(1.848)	(8.044)
WAGElevel	0.124**	0.888*	-1.272***	-4.136***	-0.774***	-3.248***
	(0.055)	(0.527)	(0.148)	(0.415)	(0.175)	(0.763)
GERD_PCT_GDP	1.480***	15.609***	1.383	8.632**	3.955**	24.241***
	(0.515)	(4.963)	(1.389)	(3.913)	(1.650)	(7.185)
GVA_IND_SHARE	-0.026	-0.217	0.359**	1.477***	0.236	1.260
	(0.058)	(0.557)	(0.156)	(0.439)	(0.185)	(0.806)
SHARE_HIGH_EDUC	-0.100	-1.176*	0.235	-0.169	-0.006	-1.344
	(0.068)	(0.650)	(0.182)	(0.513)	(0.216)	(0.941)
EQI	0.230	6.508	5.392***	32.709***	4.738**	39.216***
	(0.697)	(6.712)	(1.879)	(5.292)	(2.232)	(9.715)
Constant	0.381	68.764	3.025	86.557**	72.685***	155.321**
	(4.606)	(44.352)	(12.416)	(34.969)	(14.748)	(64.203)
Observations	214	214	214	214	214	214
R^2	0.173	0.183	0.429	0.492	0.179	0.240
Adjusted R^2	0.149	0.160	0.413	0.478	0.156	0.218
Residual Std. Error (df = 207)	5.895	56.761	15.890	44.753	18.875	82.166

F Statistic (df = 6; 207)	7.202***	7.747***	25.971***	33.461***	7.537***	10.916***
Note:						*p**p***p<0.01

Models 1 and 2 in Figure 5 show that only R&D expenditures and initial wage levels show a positive and significant relationship with regional employment growth. Models 3 and 4 show that employment level, gross value added in manufacturing, and quality of government have a positive and significant relationship with regional wage growth, while wage level shows a negative correlation: the lower initial wage level, the higher the relative wage growth. Models 5 and 6 show that employment level, R&D expenditures and quality of government have a positive and significant relationship with a combined indicator of employment and wage growth, while wage level has a negative relationship.

Figure 6 adds our main variable of interest REL+COMP. It stands for a combined continuous indicator of Average Relatedness Density and Average Complexity, either rescaled or in terms of rankings[11]. In models 3, 6 and 9, we take a combined indicator of REL+COMP which includes both industry and patent data. In 8 of the 9 models, the variable REL+COMP is positive and significant: the higher the Average Relatedness Density and Average Complexity of a region is, the higher the relative employment and wage growth of the region. The variable also adds explanatory power to the overall model, as illustrated by the significant increase of the R-squared in models 1 (from 0.17 to 0.31) and 6 (from 0.24 to 0.31). This finding is even stronger when we only include the EU-15 countries (old member states). For the EU-13 countries (new member states since 2004), we found a strong relationship on employment but not on wage growth (see Figures A9.1 and A9.2 in Appendix 9). Models 1 and 2 show R&D expenditure is again positive and

[11] A similar extended econometric model for technologies can be found in Figure A7.2 in Appendix 7.

significant but initial wage level is not anymore, while higher education has turned significant, showing a negative relationship with regional employment growth. The same control variables are significant in Models 3 and 4. In Models 5 and 6, the employment level is not significant anymore, while in Model 6 higher education turns into a significant (negative) coefficient[12].

Figure 6. Extended employment and wage growth model

	Employ. Growth (1)	Employ. Growth (rank) (2)	Employ. Growth (rank) (3)	Wage Growth (4)	Wage Growth (rank) (5)	Wage Growth (rank) (6)	Emp and Wage Growth (rescaled) (7)	Emp and Wage Growth (rank) (8)	Emp and Wage Growth (rank) (9)
EMPlevel	-0.927*	-4.978	-4.609	5.543***	11.936***	12.204***	2.627	6.958	7.595
	(0.546)	(5.548)	(5.698)	(1.606)	(4.565)	(4.636)	(1.848)	(8.074)	(8.286)
WAGElevel	0.055	0.220	0.719	-1.276***	-4.390***	-4.198***	-0.910***	-4.171***	-3.479***
	(0.051)	(0.519)	(0.509)	(0.151)	(0.427)	(0.414)	(0.174)	(0.755)	(0.741)
GERD_PCT_GDP	0.901*	10.139**	9.644*	1.350	6.551	6.457	2.812*	16.690**	16.101**
	(0.482)	(4.842)	(4.995)	(1.419)	(3.983)	(4.065)	(1.633)	(7.045)	(7.264)
GVA_IND_SHARE	0.006	-0.088	0.092	0.361**	1.526***	1.589***	0.300*	1.438*	1.681**
	(0.053)	(0.529)	(0.542)	(0.157)	(0.435)	(0.441)	(0.181)	(0.770)	(0.788)
SHARE_HIGH_EDUC	-0.208***	-2.042***	-1.997***	0.228	-0.498	-0.468	-0.219	-2.540***	-2.465**
	(0.064)	(0.642)	(0.657)	(0.189)	(0.528)	(0.535)	(0.218)	(0.935)	(0.956)
EQI	0.105	6.771	8.837	5.385***	32.809***	33.558***	4.491**	39.580***	42.394***
	(0.640)	(6.369)	(6.490)	(1.884)	(5.240)	(5.281)	(2.169)	(9.269)	(9.438)
IND REL + COMP (RS)	0.195***			0.011			0.386***		
	(0.031)			(0.091)			(0.105)		
IND REL + COMP (RANK)		0.439***			0.167**			0.606***	
		(0.090)			(0.074)			(0.131)	
IND REL + COMP + TECH REL + COMP (RANK)			0.348***			0.127*			0.475***
			(0.084)			(0.069)			(0.123)
Constant	-1.364	124.468***	112.025**	2.924	107.743***	102.326***	69.241***	232.210***	214.352***
	(4.237)	(43.608)	(43.995)	(12.472)	(35.877)	(35.797)	(14.354)	(63.457)	(63.979)
Observations	214	214	214	214	214	214	214	214	214
R^2	0.306	0.268	0.246	0.430	0.505	0.501	0.230	0.312	0.292
Adjusted R^2	0.283	0.243	0.220	0.410	0.488	0.484	0.203	0.289	0.268

[12] We also regressed regional GDP and productivity growth 2011-2019 on Average Relatedness Density and Average Complexity. Appendix A10 shows that REL+COMP has a positive coefficient, but it is almost never significant.

Residual Std. Error (df = 206)	5.411	53.866	54.682	15.928	44.316	44.493	18.331	78.384	79.521
F Statistic (df = 7; 206)	12.985***	10.780***	9.589***	22.157***	29.976***	29.504***	8.770***	13.347***	12.132***
Note:								*p**p***p<0.01	

Finally, we examined the degree of overlap between the regional development trap (Iammarino et al. 2020) based on persistent slow economic growth and our three ideal types of regional traps for the period 2011-2019. Iammarino et al. (2020) calculated two regional development trap indicators, based on three performance measures: GDP per capita, productivity, and employment to population ratio. Both trap indicators measure if a region's growth is lower than that of the EU, of the country that the region belongs to, or of the region itself during the previous five years. The first indicator (DT1) counts how many of the nine growth comparisons a region scores lower than the three benchmarks. The second indicator (DT2) counts how much lower the growth of a region is compared to the EU, the country and its own past performance. We calculated whether our REL+COMP indicator predicts well the extent to which regions are in a development trap or not (DT1 and DT2) (average of 2011-2019), controlling for other variables.

In Figure 7, Models 1 and 4 include the absolute values of DT1 and DT2, while models 2, 3, 5 and 6 take the rankings of regions with respect to DT1 and DT2. What is interesting to see is that the coefficient of our REL+COMP indicator is always negative and significant, meaning that the higher the REL+COMP indicator is (i.e. the lower the extent to which is region is stuck in any of our three traps), the less likely regions are also caught in a Development Trap. As far as the control variables are concerned, the variable GDP level is positive and significant (already rich regions tend to grow more slowly). The variables GVA Industry Share and Higher Education are negative and significant, meaning the higher the share of GVA in industry and the higher the education level, the less a region is stuck in a Development Trap. The variables Employment levels and Quality of Government are not significant.

Figure 7. Extended model: development and regional traps

	Dependent variable:					
	DT1 (1)	DT1 – rank (2)	DT1 – rank (3)	DT2 (4)	DT2 – rank (5)	DT2 – rank (6)
EMPlevel	0.013	6.916	7.317	-0.048	-0.792	-0.811
	(0.011)	(5.647)	(5.680)	(0.045)	(5.407)	(5.455)
GDPlevel	0.00001***	0.003***	0.003***	0.00002***	0.003***	0.003***
	(0.00000)	(0.001)	(0.001)	(0.00000)	(0.001)	(0.001)
GERD_PCT_GDP	-0.020**	-10.100**	-8.791*	-0.001	-3.707	-2.482
	(0.010)	(4.936)	(5.024)	(0.040)	(4.726)	(4.825)
GVA_IND_SHARE	-0.005***	-2.312***	-2.411***	-0.022***	-2.851***	-2.949***
	(0.001)	(0.498)	(0.501)	(0.004)	(0.477)	(0.481)
SHARE_HIGH_EDUC	-0.003**	-1.689**	-1.643**	-0.014***	-1.491**	-1.485**
	(0.001)	(0.651)	(0.655)	(0.005)	(0.624)	(0.629)
EQI	0.011	2.578	1.684	0.032	-8.757	-9.543
	(0.012)	(6.074)	(6.115)	(0.049)	(5.816)	(5.874)
IND REL + COMP (RS)	-0.002***			-0.010***		
	(0.001)			(0.003)		
IND REL + COMP (RANK)		-0.248**			-0.286***	
		(0.101)			(0.097)	
IND REL + COMP + TECH REL + COMP (RANK)			-0.217**			-0.229***
			(0.086)			(0.083)
Constant	0.660***	122.915***	126.710***	1.088***	165.916***	173.217***
	(0.078)	(42.347)	(41.736)	(0.326)	(40.543)	(40.088)
Observations	214	214	214	214	214	214

R^2	0.250	0.250	0.251	0.271	0.313	0.309
Adjusted R^2	0.224	0.224	0.225	0.246	0.289	0.286
Residual Std. Error (df = 206)	0.106	54.515	54.471	0.444	52.193	52.320
F Statistic (df = 7; 206)	9.787***	9.788***	9.852***	10.940***	13.393***	13.187***
Note:	*p**p***p<0.01					

Policy implications

Being trapped or not, and in what kind of trap, has important policy implications. The basic meaning of our evolutionary trap concept is that regions have either few opportunities to diversify (this applies to regions caught in a 'structural trap' or a 'low relatedness trap'), or regions have opportunities only in low-complex but not in high-complex activities (this applies to regions in a 'low complexity trap'). What policy actions might be needed to assist regions to escape from such regional traps? And what policy interventions are required to avoid that regions will get trapped in the future?

No matter what circumstances, it is crucial that policy takes as point of departure the capabilities that are available to a region. These capabilities should provide directionality to policy, as they condition which opportunities are more realistic to develop, and which societal challenges are more feasible to be taken up (Alshamsi et al. 2018; Balland et al. 2019; Marrocu et al. 2022; Pinheiro et al. 2022; Rigby et al. 2022). Identifying such opportunity sets in regions can assist policy makers to improve their priority-setting, as is required in Smart Specialization policy (Foray 2015). Although regions stuck in a 'low relatedness trap' might have little opportunities because of missing relevant capabilities, empirical analysis at the level of technologies and industries may still reveal that these regions have some low hanging fruits that could be targeted (Boschma 2024).

For regions in a 'low complexity trap', there might be at least three policy options. One option is to ensure that local opportunities for developing low-complex activities are seized. This is, for instance, the case for many green technologies in less developed regions which tend to have capabilities to develop renewable activities (Van den Berge et al. 2020; Bachtrögler-Unger et al. 2023). Such policy should tackle bottlenecks that prevent regions to exploit these low-hanging opportunities, such as lack of finance, low education, poor research infrastructure, a weak entrepreneurial culture, and low quality of institutional governance (Cortinovis et al. 2017). However, such policy action would not assist such regions to escape from their 'low complexity trap'. Probably the best policy option would be to develop the few complex activities that are related to local activities that could lift the overall complexity of their regional economies. Even regions in a 'low complexity trap' might have some opportunities in more complex activities that could be targeted. However, when opportunities in low-complex activities are rare or non-existing, a third option might become feasible, which is breaking out of the low-complexity trap. The only way out of this trap might be to make a sort of jump (Boschma 2024).

When low-hanging fruits are largely lacking in a region, as is often the case for regions caught in a 'structural trap', targeting activities that are far removed from the regional knowledge base might be a good second-best option. However, developing some completely new and complex involves a high-risk strategy, as local capabilities are weak and not of immediate relevance, and it may require strong institutional capacities in regions to make such high-risk policy work. First of all, it means that policy intervention should invest massively and in a concerted manner in capabilities in education, research, companies and institutions. Second, it should promote connections with other regions that studies have shown to promote unrelated diversification (Zhu et al. 2017; Boschma 2024).

Balland and Boschma (2011) showed that less developed regions tend to diversify less, unless they link to other regions that give access to complementary capabilities. Other policy actions could target the inflow of external (multinational) firms (Neffke et al. 2018; Cortinovis et al. 2020) and (return) migrants (Caviggioli et al. 2020; Miguelez and Morrison 2022) and the establishment of new research collaborations (Uhlbach et al. 2022) which have proven successful in developing new growth paths in regions. These policy actions could contribute to regions moving up the complexity ladder. However, such a policy is not without risks, as it may create cathedrals in the desert, with no significant spillovers to local activities, as local firms and people may lack the appropriate absorptive capacity and skills, and formal and informal institutions tend to be weak.

What is crucial is to support institutional agents that tackle regional traps and to ensure that the vested interests of powerful incumbents that represent such traps will not frustrate this transformation process. This might apply especially to old industrial regions that once belonged to the most prosperous regions (Hassink 2010) but are now stuck in a 'low complexity' or 'low relatedness trap'. What institutional agents do is building legitimacy, mobilizing resources, promoting collective action, and creating new institutions that are essential for regions to adapt and diversify (Sotarauta and Pulkkinen 2011). This should be taken up in Smart Specialization policy that aims to promote the active engagement and participation of local stakeholders (Foray 2015; Sotarauta 2018).

And how about regions that are not caught in a trap, but instead find themselves in a 'complexity loop', which means they have relevant capabilities to move in complex activities? They are likely to be subject to a range of market, system and transformational failures (Schot and Steinmueller 2018) that prevent such regions from exploiting their opportunities. They compete at the global level, and need assistance to stay at the frontier.

Strong policy intervention is needed to tackle bottlenecks to ensure local opportunities are actually activated, such as weak university-industry linkages, labor market mismatches, a lack of venture capital, poor laws and regulations, and weak research collaboration.

Conclusions

This article proposes an evolutionary perspective on regional traps. Our trap notion accounts for self-reinforcing dynamics that make regions follow specific trajectories that may favour their ability to develop new growth and complex paths (regions in a complexity loop) or that limit their capacity to do so, as captured by our regional trap indicator. A distinction was made between different ideal types of regional traps, as regions have different histories and follow distinct paths that are embodied in the complexity levels of their techno-economic structures and their opportunity set that is available to them in order to adapt and diversify. We proposed three ideal types of regional traps: regions that are stuck in a structural trap, a low complexity trap, or a low relatedness trap, depending on the average complexity of their industries and their average relatedness density.

A key finding was that more developed regions are often in a 'complexity loop'. They have complex structures and a strong ability to adapt, like many capital regions in Europe. Instead, many less developed regions in Eastern Europe find themselves caught in a 'structural trap', meaning their economies consist of low-complex activities with little opportunities to adapt and diversify. Regions that have fallen in a 'low relatedness trap' are mainly located in peripheral parts in Western Europe: these regions have a limited set of opportunities to move in both high- and low-complex industries. Regions that are stuck in a 'low complexity trap' are often situated in Eastern Europe. Their low-complex economies provide diversification opportunities but primarily in low-complex activities.

We also find that most regions remained caught in the same trap during the period 2011-2019. Only 12 regions managed to escape from a trap and moved into a ‘complexity loop’. We also found a group of 19 regions in a wide range of countries but especially from Eastern European countries (like Poland, Hungary and Romania) that succeeded to move from a ‘structural trap’ to a ‘low complexity trap’, meaning they managed to increase their Average Related Density while their Average Complexity remained below the median.

We also examined the economic performance of regions that were trapped in terms of their relative employment and wage growth. First, as expected, regions in a ‘complexity loop’ show the highest relative performance, as compared to regions that are trapped. Second, many regions in a ‘structural trap’ experienced relative low employment growth but high average wage growth. Many of those concerned regions in Eastern Europe with low initial wage levels. Third, almost half of the regions in a ‘low complexity trap’ and ‘low relatedness trap’ witnessed a relative low employment and wage growth rate. Still, regions in a ‘low relatedness trap’ scored better om relative employment than on wage growth, in contrast to regions in a ‘low complexity trap’ of which the majority scored below the median of employment and wage growth in Europe. Fourth, our econometric analyses showed that the higher the combined indicator of average relatedness density and complexity in a region is, the higher its relative employment and wage growth in the period 2011-2019. This variable also added considerable explanatory power to the overall model. Finally, we examined the overlap between the regional development trap (Iammarino et al. 2020) based on persistent slow economic growth and the three ideal types of regional traps. The econometric analysis showed the lower the extent to which a region was caught in the three traps, the lower the extent to which a region found itself in a development trap.

These insights on regional traps have policy implications, such as what to do about each type of trap, how to escape from them, and how to avoid them in the future. In short, we argued policy should promote the exploitation of opportunities where low-hanging fruits exist. We also argued that a number of policy options are available in regions that are in a 'low complexity', 'low relatedness trap' or 'structural trap'. This requires identification of these traps, and rethinking of how policy practices can avoid and overcome them.

Needless to say is that our analyses on regional traps also call for further research.

First, our findings showed that many regions seem to be trapped, but it is better to speak in terms of intensity of traps: regions are trapped to a greater or lesser extent. This is also what our analyses show: many regions remain caught, but some regions also manage to escape from their trap. For instance, the majority of regions in a 'structural trap' remained stuck, but some of them managed to improve in terms of an increase in their average relatedness density, though they remained stuck in a low complexity state. However, the analysis did not shed light on what factors might be held responsible for remaining trapped or not. We leave this crucial question for future research. A more in-depth analysis of successful cases might also throw important light on this outstanding issue.

Second, there is potential to account for inter-regional linkages when defining regional traps. Regions that lack relevant capabilities to diversify may also lack the ability to exploit complementarities in other regions. Balland and Boschma (2021) showed that linkages giving access to capabilities in other regions that complement existing capabilities of regions are important for their ability to adapt and diversify. Bachtrögler-Unger et al. (2023) found there is substantial untapped potential in inter-regional collaboration when it comes to twin transition technologies. This study showed that inter-regional collaborations in Europe take place mainly within national borders, while relevant complementary capabilities are mainly found outside their own countries and thus require international linkages. This would imply that regions can also be trapped in an inward-looking state.

Third, evolutionary approaches have also attached importance to the role of institutions (Aghion and Bircan 2017; Cortinovis et al. 2017). Doner and Schneider (2016) argue it is difficult for countries to escape a middle-income trap because of a poor capacity to pursue effective public actions and implement institutional change. Future research should incorporate the role of institutions and institutional entrepreneurship (Garud et al. 2002; Battilana et al. 2009; Sotarauta and Pulkkinen 2011) more explicitly in the definition of regional traps. Institutional agents might be crucial to tackle traps: they build legitimacy, mobilize resources, promote collective action, and create new institutions that are essential to develop new activities successfully. This could be one of the factors that could explain why some regions have managed to escape a trap, while other regions remained stuck.

References

Arthur, W. B. (1994). *Increasing returns and path dependence in the economy*: University of Michigan Press.

Agénor, P.-R. (2017) Caught in the middle? The economics of middle-income traps, *Journal of Economic Surveys*, 31(3), 771–791.

Aghion, P. and Bircan, C. (2017) The Middle-Income Trap from a Schumpeterian Perspective. In *EBRD Working Paper No. 205* (No. 205). https://doi.org/10.2139/ssrn.3119146

Alshamsi, A., Pinheiro, F. L., & Hidalgo, C. A. (2018) Optimal diversification strategies in the networks of related products and of related research areas. *Nature Communications,* 9 (1), 1328.

Arthur W. B. (1990) Silicon Valley locational clusters: when do increasing returns imply monopoly? *Mathematical Social Sciences* 19 (3), 235–251.

Arthur, W. B. (1994) *Increasing Returns and Path Dependence in the Economy*. Ann Arbor: University of Michigan Press.

Azariadis, C. and Stachurski, J. (2005) Poverty Traps. In P. Aghion and S. N. Durlauf (Eds.), *Handbook of Economic Growth* (Vol. 1, pp. 295–384). https://doi.org/10.1016/S1574-0684(05)01005-1

Bachtrögler-Unger, J., P.A. Balland, R. Boschma and T. Schwab (2023) Technological capabilities and the twin transition in Europe. Opportunities for regional collaboration and economic cohesion, report, Bertelsmann Stiftung, Berlin, 82 pp.

Balland, P.A. and R. Boschma (2021) Complementary inter-regional linkages and Smart Specialisation. An empirical study on European regions, *Regional Studies* 55 (6), 1059-1070.

Balland, P.A., R. Boschma, J. Crespo and D. Rigby (2019) Smart specialization policy in the EU: Relatedness, knowledge complexity and regional diversification, *Regional Studies* 53 (9), 1252-1268.

Balland, P.A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N. and Rigby, D. (2022) The new paradigm of economic complexity, *Research Policy* 51 (3), 1-11.

Balland, P.A., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., and Hidalgo, C. (2020) Complex Economic Activities Concentrate in Large Cities, *Nature Human Behavior* 4, 248–254.

Balland, P.A. and D. Rigby (2017) The geography of complex knowledge, *Economic Geography* 93 (1), 1-23.

Barrett, C. B. and Swallow, B. M. (2006). Fractal poverty traps. *World Development*, 34(1), 1–15.

Battilana, J., Leca, B. and Boxenbaum, E. (2009) How actors change institutions: Towards a theory of institutional entrepreneurship. *Academy of Management Annals* 3, 65–107.

Benhabib, J., Perla, J. and Tonetti, C. (2014) Catch-up and fall-back through innovation and imitation. *Journal of Economic Growth*, *19*(1), 1–35.

Boschma, R. A. (1997) New industries and windows of locational opportunity. A long-term analysis of Belgium. *Erdkunde* 51, 12–22.

Boschma, R. (2017) Relatedness as driver behind regional diversification: a research agenda, *Regional Studies* 51 (3), 351-364.

Boschma, R. (2024) Designing Smart Specialization Policy: relatedness, unrelatedness, or what? in: M. Anderson, C. Karlsson and S. Wixe (eds.) *Handbook of Spatial Diversity and Business Economics*, Oxford: Oxford University Press, forthcoming.

Boschma, R.A. and J.G. Lambooy (1999a) Evolutionary economics and economic geography, *Journal of Evolutionary Economics* 9, 411– 429.

Boschma R. and Lambooy J. (1999b) The prospects of an adjustment policy based on collective learning in old industrial regions, *Geojournal* 49, 391–399.

Bresser-Pereira, L.C. , Araújo, E.C. and Perez, S.C. (2020) An alternative to the middle-income trap. *Structural Change and Economic Dynamics* 52, 294–312.

Cai, F. (2012) There a “Middle-income Trap”? Theories, Experiences and Relevance to China. *China & World Economy* 20 (1), 49–61.

Caviggioli, F., P. Jensen and G. Scellato (2020) Highly skilled migrants and technological diversification in the US and Europe. *Technological Forecasting and Social Change* 154, 119951.

Çınar, İ.T. (2023a) Regional development trap in Turkey: Can relatedness find a way out? *Papers in Regional Science*, 102(4), 817–850.

Çınar, İ.T. (2023b) Regional development trap and economic complexity in Turkey: Evidence from provincial data, *Regional Science. Policy and Practice* 15 (9), 2224-2253.

Cortinovis, N., R. Crescenzi and F. van Oort (2020) Multinational enterprises, industrial relatedness and employment in European regions, *Journal of Economic Geography* 20, 1165–1205.

Cortinovis, N., J. Xiao, R. Boschma and F. van Oort (2017) Quality of government and social capital as drivers of regional diversification in Europe, *Journal of Economic Geography* 17 (6), 1179–1208.

David, P. A. (1985) Clio and the Economics of QWERTY, *American Economic Review* 75, 332-337.

Diemer, A., S. Iammarino, A. Rodríguez-Pose and M. Storper (2022) The regional development trap in Europe, *Economic Geography* 98 (5,) 487-509.

Doner, R. F. and Schneider, B. R. (2016) The Middle-Income Trap: More Politics than Economics. *World Politics* 68 (4), 608–644.

Eichengreen, B., Park, D. and Shin, K. (2012) When Fast-Growing Economies Slow Down: International Evidence and Implications for China. *Asian Economic Papers*, *11*(1), 42–87.

Eichengreen, B., Park, D. and Shin, K. (2014) Growth slowdowns redux. *Japan and the World Economy*, *32*, 65–84.

European Commission (2023) Harnessing talent in Europe's region, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, Strasbourg, 17 Januari 2023, 22pp.

Evenhuis, E. (2017) Institutional change in cities and regions: a path dependency approach *Cambridge Journal of Regions, Economy and Society* 10 (3), 509–526.

Foray, D. (2015) *Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy*. London: Routledge.

Fuest, C., D. Gros, P.L. Mengel, G. Presidente and J. Tirole (2024) EU Innovation Policy, How to escape the middle technology trap, Report by the European Policy Analysis Group.

Garud, R., S. Jain and A. Kumaraswamy (2002) Institutional entrepreneurship in the sponsorship of common technological standards: The case of Sun Microsystems and Java, *Academy of Management Journal* 45 (1), 196–214.

Gill, I. S. and Kharas, H. (2007) *An East Asian renaissance: ideas for economic growth*. Washington, DC: The World Bank.

Gill, I. S. and Kharas, H. (2015) The Middle-Income Trap Turns Ten. In *Policy Research Working Papers*. https://doi.org/doi:10.1596/1813-9450-740393

Glawe, L. and Wagner, H. (2016) The Middle-Income Trap: Definitions, Theories and Countries Concerned—A Literature Survey. *Comparative Economic Studies*, *58*(4), 507–538.

Grabher G. (1993) The weakness of strong ties: the lock-in of regional development in the Ruhr area, in Grabher G. (Ed.) *The Embedded Firm*, pp. 255–277. Routledge, London.

Hartmann, D., Bezerra, M., Lodolo, B., & Pinheiro, F. L. (2020) International trade, development traps, and the core-periphery structure of income inequality. *EconomiA, 21*(2), 255-278.

Hartmann, D., Zagato, L., Gala, P., & Pinheiro, F. L. (2021) Why did some countries catch-up, while others got stuck in the middle? Stages of productive sophistication and smart industrial policies. *Structural Change and Economic Dynamics, 58*, 1-13.

Hassink, R. (2007) The strength of weak lock-ins: the renewal of the Westmünsterland textile industry, *Environment and Planning A* 39, 1147-1165

Hassink, R. (2010) Locked in decline? On the role of regional lock-ins in old industrial areas. In R. Boschma and R. Martin (Eds.), *The Handbook of Evolutionary Economic Geography*. Cheltenham, UK: Edward Elgar Publishing, pp. 450-468.

Hidalgo, C. and R. Hausmann (2009) The building blocks of economic complexity. *Proceedings of the National Academy of Sciences* 106, 10570–10575.

Hidalgo, C.A., Klinger, B., Barabasi, A.L. and Hausmann, R. (2007) The product space and its consequences for economic growth, *Science* 317, 482–487.

Iammarino, S. A. Rodríguez-Pose, M. Storper and A. Diemer (2020) Falling into the middle-income trap? A study on the risks for EU regions to be caught in a middle-income trap, Final Report, European Commission DG Regional and Urban Policy, Brussels.

Im, F. G., and Rosenblatt, D. (2013) Middle-Income Traps: A Conceptual and Empirical Survey. In *Policy Research Working Papers*. https://doi.org/doi:10.1596/1813-9450-6594

Kharas, H. and Kohli, H. (2011) What Is the Middle Income Trap, Why do Countries Fall into It, and How Can It Be Avoided? *Global Journal of Emerging Market Economies* 3 (3), 281–289.

Kogler, D. F., Rigby, D. L. and Tucker, I. (2013) Mapping knowledge space and technological relatedness in US cities. *European Planning Studies* 21 (9), 1374–1391.

Lee, K. (2013) *Schumpeterian Analysis of Economic Catch-up: Knowledge, Path-Creation, and the Middle-Income Trap*. Cambridge: Cambridge University Press.

Lee, K. and Lim, C. (2001). Technological regimes, catching-up and leapfrogging: findings from the Korean industries. *Research Policy, 30*(3), 459-483.

Lee, K and F. Malerba (2017) Catch-up cycles and changes in industrial leadership:Windows of opportunity and responses of firms and countries in the evolution of sectoral systems, *Research Policy* 46 (2), 338-351.

Marrocu, E., R. Paci, D. Rigby and S. Usai (2022) Evaluating the implementation of Smart Specialisation policy, *Regional Studies* 57 (1), 112-128.

Martin, R. and Sunley P. (2006) Path dependence and regional economic evolution, Journal of Economic Geography 6, 395–437.

Miguelez, E. and A. Morrison (2022) Migrant inventors as agents of technological change, *Journal of Technology Transfer*, forthcoming.

Neffke F., M. Henning and R. Boschma (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions, *Economic Geography* 87 (3), 237–265.

Neffke, F., M. Hartog, R. Boschma and M. Henning (2018) Agents of structural change. The role of firms and entrepreneurs in regional diversification, *Economic Geography* 94 (1), 23-48.

OECD, et al. (2019) "The "new" development traps" in Latin American Economic Outlook 2019: Development in Transition, OECD Publishing, Paris, pp. 95-121.

Petralia, S., Balland, P.A., Morrison, A. (2017) Climbing the ladder of technological development. *Research Policy* 46, 956–969.

Pike A, Birch K, Cumbers A, MacKinnon D, McMaster R. (2009) A Geographical Political Economy of Evolution in Economic Geography. *Economic Geography* 85 (2), 175-182.

Pinheiro, F.L., P.A. Balland, R. Boschma and D. Hartmann (2022) The dark side of the geography of innovation: Relatedness, complexity, and regional inequality in Europe, *Regional Studies*, forthcoming.

Quah, D. T. (1997) Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. *Journal of Economic Growth*, 2(1), 27–59.

Redding, S. J. (1996) The Low-Skill, Low-Quality Trap: Strategic Complementarities between Human Capital and R&D. *The Economic Journal*, 106(435), 458–470.

Rigby, D. L., Essletzbichler, J. (1997) Evolution, process variety, and regional trajectories of technological change in US manufacturing. *Economic Geography* 73 (3), 269–284.

Rigby, D.L., C. Roesler, D. Kogler, R. Boschma and P.A. Balland (2022) Do EU regions benefit from Smart Specialisation principles?, *Regional Studies* 56 (12), 2058-2073.

Rodríguez-Pose, A. and M. Di Cataldo (2015) Quality of government and innovative performance in the regions of Europe. *Journal of Economic Geography* 15 (4), 673−706.

Rodríguez-Pose, A., L. Dijkstra and H. Poelman (2023) The geography of EU discontent and the regional development traps, European Commission, DG Regional and Urban Policy, WO 03/2023, Brussels.

Rodríguez-Pose, A. and V. Muštra (2022) The economic returns of decentralisation: Government quality and the role of space, *Environment and Planning A*, 54(8), 1604-1622.

Schot J. and W.E. Steinmueller (2018) Three frames for innovation policy: R&D, systems of innovation and transformative change, *Research Policy* 47 (9), 1554–1567.

Sotarauta, M. (2018) Smart specialization and place leadership: Dreaming about shared visions, falling into policy traps? *Regional Studies, Regional Science* 5, 190–203.

Sotarauta, M. and Pulkkinen, R. (2011) Institutional entrepreneurship for knowledge regions: In search of a fresh set of questions for regional innovation studies, *Environment and Planning C* 29, 96–112.

Storper, M. (1997) The regional world: territorial development in a global economy, Guilford Press.

Uhlbach, W.H., P.A. Balland and T. Scherngell (2022) Public R&D funding and new regional specialisations: The contingent role of technological relatedness, *Industry and Innovation* 29 (4), 511-532.

Van den Berge, M., A. Weterings and F. Alkemade (2020) Do existing regional specialisations stimulate or hinder diversification into cleantech? *Environmental Innovation and Societal Transitions* 35, 185-201

Vivarelli, M. (2016) The middle income trap: a way out based on technological and structural change. *Economic Change and Restructuring*, 49 (2), 159–193.

Ye, L. and Robertson, P. E. (2016) On the Existence of a Middle-Income Trap. *Economic Record*, 92(297), 173–189.

Zhu, S., He, C., and Zhou, Y. (2017) How to jump further and catch up? Path-breaking in an uneven industry space. *Journal of Economic Geography* 17 (3), 521–545.

Appendix

A1. Ranking of complexity of industries

NACE	NACE name	complexity
J59	Motion picture, video and television programme production, sound recording and music publishing activities	0.320
J62	Computer programming, consultancy and related activities	0.301
N7	Administrative and support service activities	0.269
J61	Telecommunications	0.268
M70	Activities of head office, management consultancy activities	0.266
K-N residual	Financial, insurance and other service activities	0.253
M73	Advertising and marketing research	0.246
M72	Scientific research and development	0.240
J58	Publishing activities	0.203
M71	Architectural and engineering activities, technical testing and analysis	0.146
N81	Services to buildings and landscape activities	0.124
J60	Programming and broadcasting activities	0.095
O-U residual	Public administration, education, health and arts	0.049
N82	Office administrative, office support and other business support activities	0.048
M69	Legal and accounting activities	0.034

J63	Information service activities	0.029
L68	Real estate activities	0.022
H	Transporting and storage	0.002
M75	Veterinary activities	0.002
M74	Other professional, scientific and technical activities	-0.012
C2C	Manufacturing of machinery and transport	-0.045
I55	Accommodation	-0.051
G45	Wholesale and retail trade	-0.056
C28	Manufacturing of electrical, electronic and computers	-0.059
I56	Food and beverage service activities	-0.071
G, I, J residual	Miscellaneous services	-0.091
F	Construction	-0.094
C1C	Manufacturing of chemicals and metals	-0.106
N80	Security and investigation activities	-0.187
E	Electricity, gas, water collection, sewerage and waste	-0.211
C1A	Basic manufacturing	-0.231
B	Mining and quarrying	-0.346
A	Agriculture, forestry and fishing	-0.357

A2. Regional traps in Europe

Figure A2.1 Regional traps in Europe (rankings)

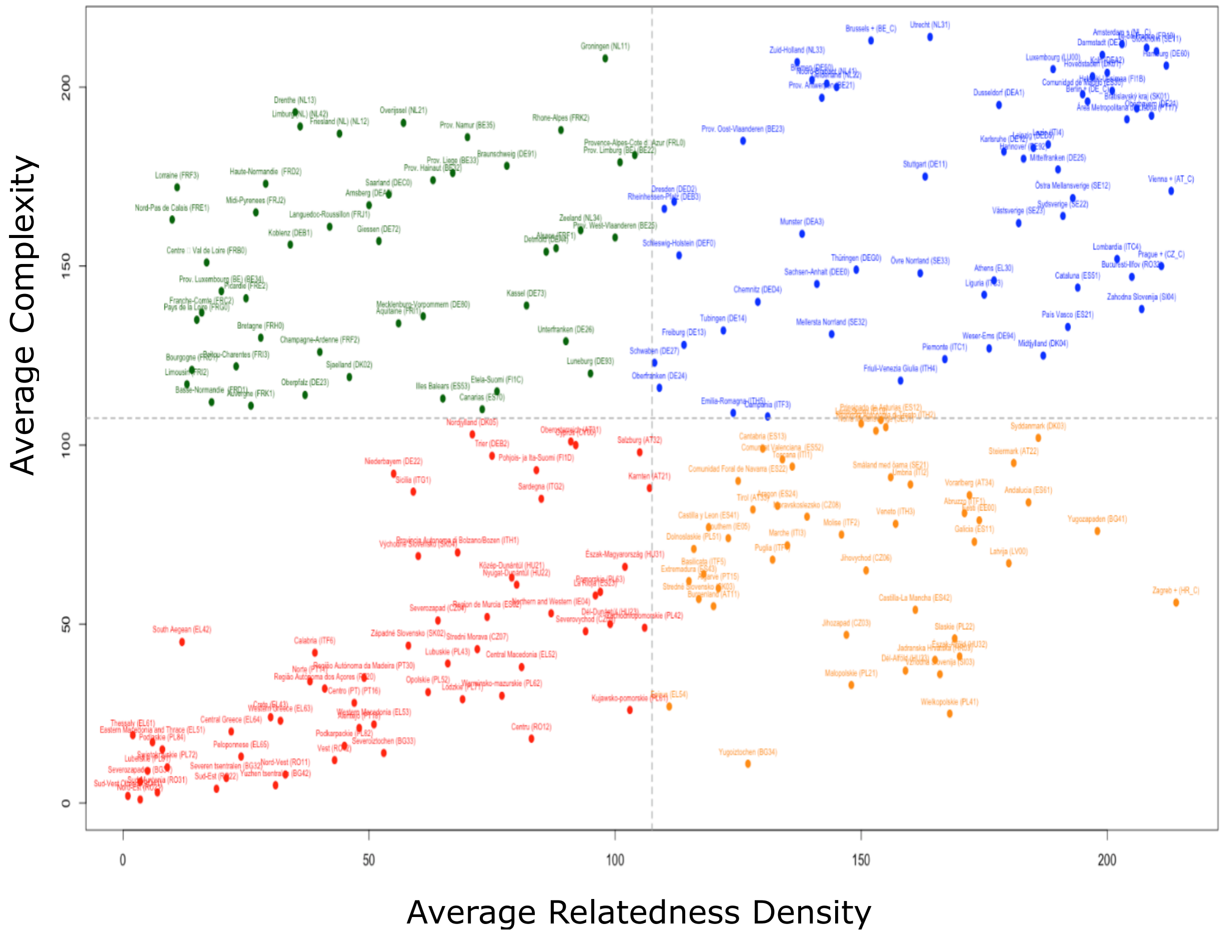
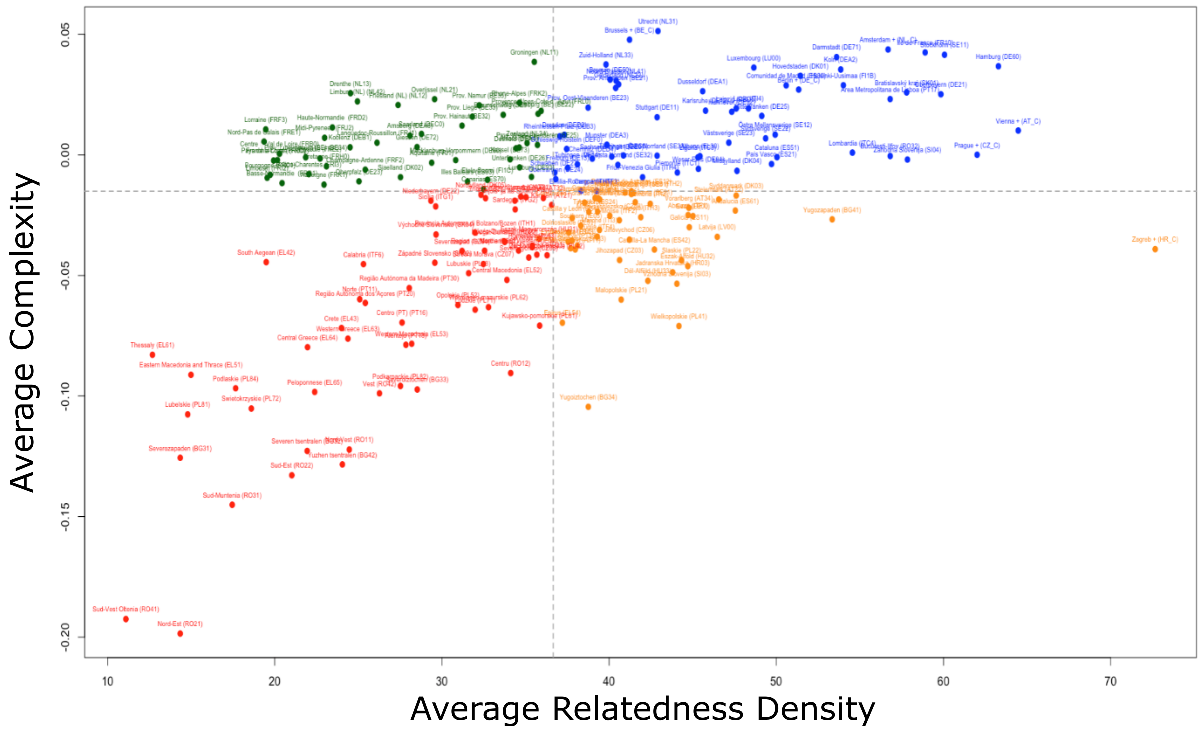


Figure A2.2 Regional traps in Europe (values)



A3. Patent analysis

Next to the industry data analysis, we did similar analyses on technologies based on patent data by 33 technology classes for the 214 NUTS2-regions in Europe. Data were taken from the REGPAT dataset (August 2023 version, OECD). Figure A3.1 presents the Average Complexity and Relatedness Density scores in terms of rankings of all regions over the period 2011-2019. Figure A3.2 presents these scores of regions in absolute values.

Figure A3.1 Regional traps in Europe (technologies) (rankings)

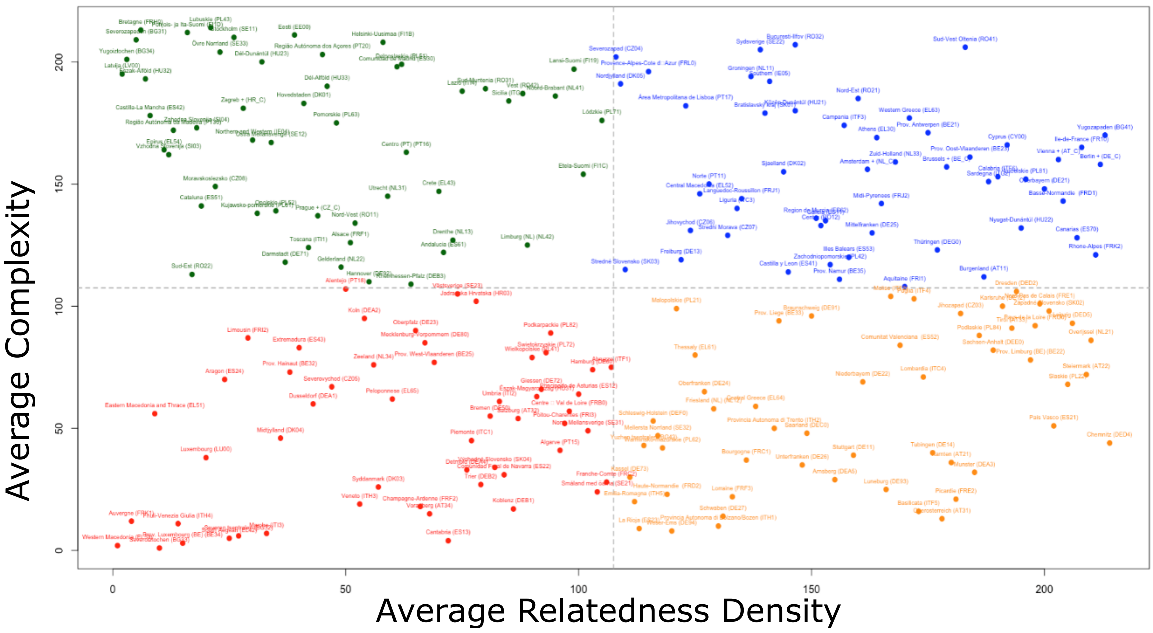
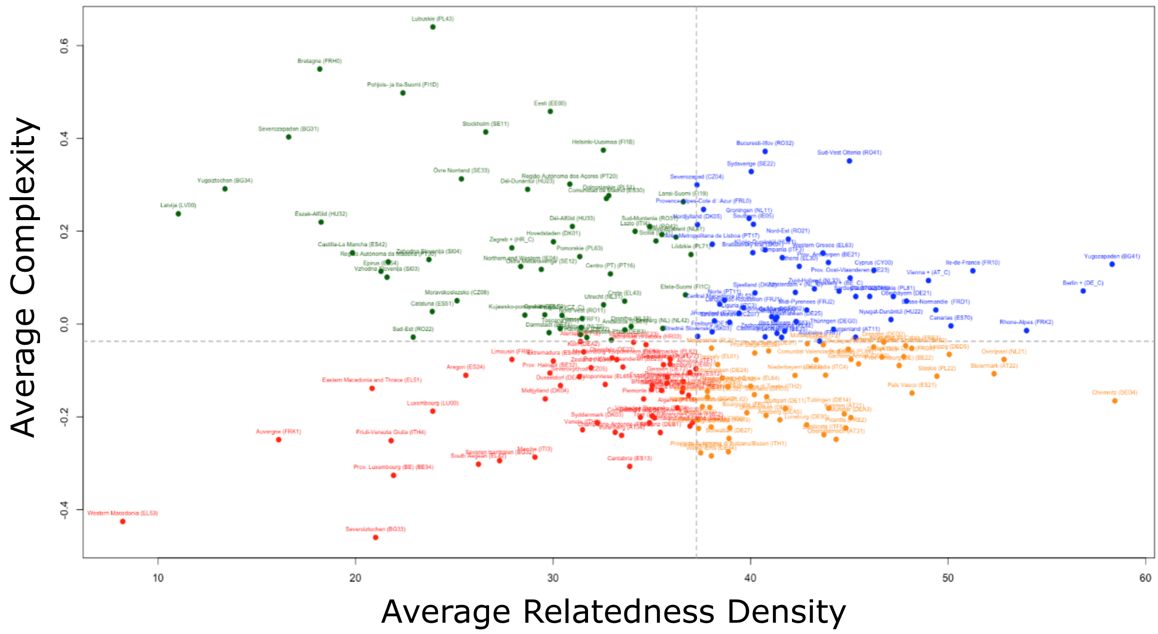
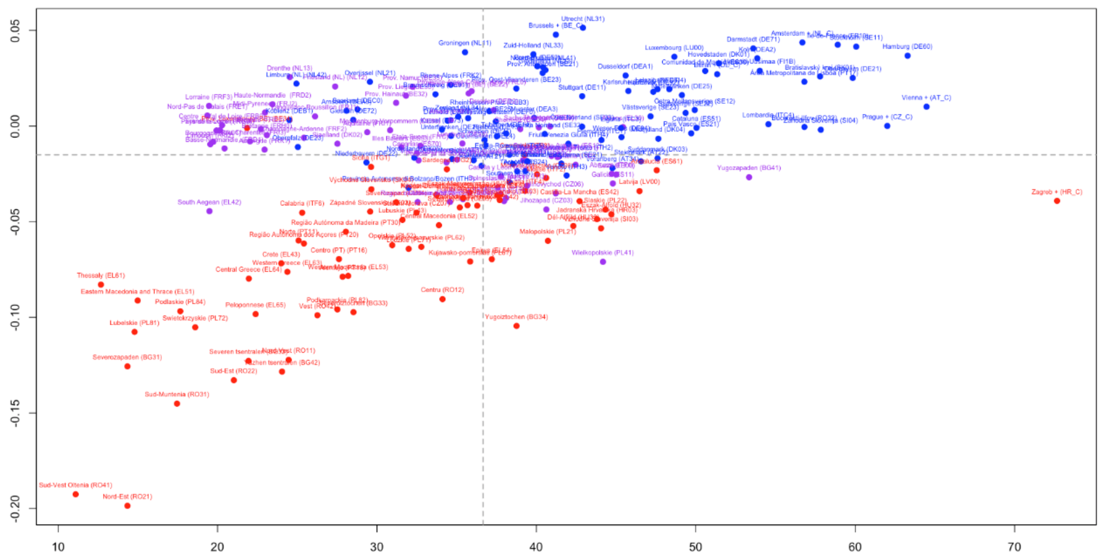


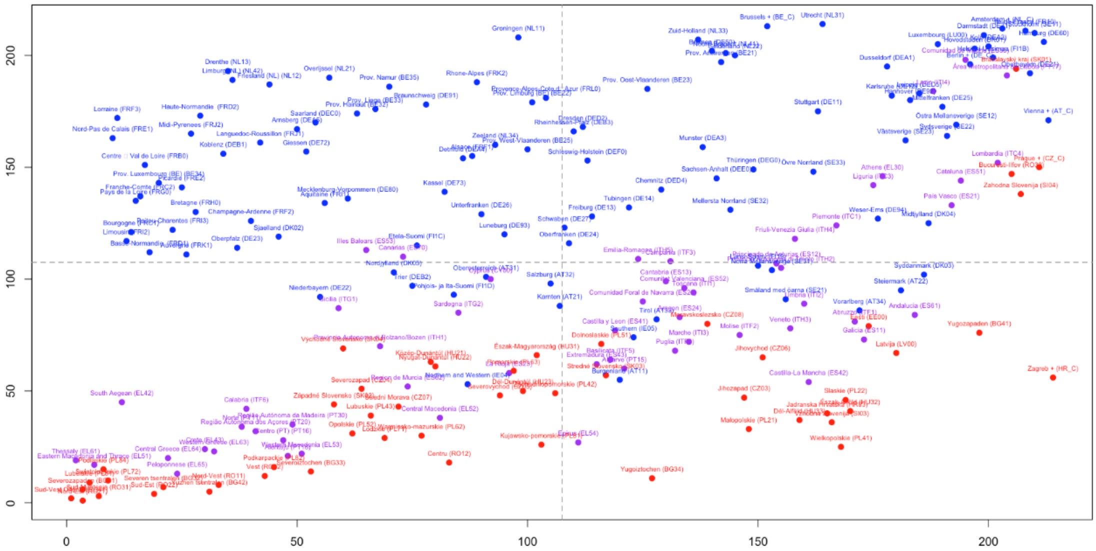
Figure A3.2 Regional traps in Europe (technologies) (values)



A4. Regional traps across more developed (blue), transition (purple) and less developed regions (red) (in values)



A5. Regional traps across regions in Northern (blue), Eastern (red) and Southern Europe (purple) (rankings)



A6. Traps transition matrix technologies

Table A6.1 Traps transition matrix 2011-2019 (technologies)

2011 \ 2019	Complexity loop	Low relatedness trap	Low complexity trap	Structural trap	Total
Complexity loop	**22 (41%)**	16 (30%)	11 (20%)	5 (9%)	60
Low relatedness trap	14 (26%)	**26 (49%)**	5 (9%)	8 (15%)	47
Low complexity trap	10 (19%)	2 (4%)	**26 (49%)**	15 (28%)	47
Structural trap	3 (6%)	10 (19%)	18 (33%)	**23 (43%)**	60
Total	49	54	60	51	214

A7. Regional traps and labor market dynamics for technologies

Table A7.1 Relationship labor market dynamics and types of regional traps (technologies)

	E+W+	E+W-	E-W+	E-W-
Complexity loop	33%	24%	17%	26%
Low relatedness trap	23%	25%	25%	28%

Low complexity trap	42%	13%	19%	26%
Structural trap	30%	11%	13%	46%

Figure A7.2 Extended econometric model (technologies)

Technology - Employment and Wage Growth Models

	Dependent variable:					
	Employment Growth	Employment Growth (Rank)	Wage Growth	Wage Growth (Rank)	Both (Rescaled)	Both (Rank)
	(1)	(2)	(3)	(4)	(5)	(6)
emplevel	-0.091	2.814	5.346***	14.254***	4.082**	17.068**
	(0.599)	(5.688)	(1.613)	(4.478)	(1.917)	(8.224)
wagelevel	0.123**	0.927*	-1.256***	-4.082***	-0.763***	-3.155***
	(0.056)	(0.533)	(0.150)	(0.419)	(0.179)	(0.770)
GERD_PCT_GDP	1.487***	15.126***	1.253	7.952**	3.865**	23.077***
	(0.523)	(5.053)	(1.409)	(3.978)	(1.675)	(7.305)
GVA_IND_SHARE	-0.027	-0.179	0.372**	1.529***	0.245	1.350*
	(0.059)	(0.562)	(0.158)	(0.442)	(0.187)	(0.813)
SHARE_HIGH_EDUC	-0.099	-1.237*	0.218	-0.255	-0.018	-1.493
	(0.069)	(0.662)	(0.185)	(0.521)	(0.219)	(0.956)
EQI	0.229	6.939	5.405***	33.315***	4.747**	40.255***
	(0.699)	(6.771)	(1.882)	(5.330)	(2.237)	(9.789)
REL + COMP (RS)	-0.003		0.048		0.033	
	(0.030)		(0.082)		(0.097)	
REL + COMP (Rank)		0.037		0.052		0.090
		(0.069)		(0.055)		(0.100)
Constant	0.465	69.132	1.478	87.074**	71.615***	156.205**
	(4.719)	(44.433)	(12.711)	(34.980)	(15.107)	(64.242)
Observations	214	214	214	214	214	214
R^2	0.173	0.185	0.430	0.495	0.180	0.243
Adjusted R^2	0.145	0.157	0.411	0.477	0.152	0.218
Residual Std. Error (df = 206)	5.909	56.859	15.915	44.761	18.915	82.206
F Statistic (df = 7; 206)	6.145***	6.659***	22.240***	28.802***	6.450***	9.462***
Note:						*p**p***p<0.01

A8. Patent and industry analysis combined

Table A8.1 Relationship labor market dynamics and types of regional traps (industries and technologies combined)

	E+W+	E+W-	E-W+	E-W-
Complexity loop	58%	21%	5%	16%
Low relatedness trap	0%	60%	0%	40%
Low complexity trap	30%	20%	20%	30%
Structural trap	29%	0%	36%	36%

A9. Extended employment and wage growth model (EU-15 and EU-13)

Figure A9.1 Extended employment and wage growth model (EU-15)

	Dependent variable:								
	Emp Growth (1)	Emp Growth (rank) (2)	Emp Growth (rank) (3)	Wage Growth (4)	Wage Growth (rank) (5)	Wage Growth (rank) (6)	Emp and Wage Growth (rescaled) (7)	Emp and Wage Growth (rank) (8)	Emp and Wage Growth (rank) (9)
Employment level	-0.878^{*}	-1.611	-1.109	2.476^{***}	7.948^{**}	7.397^{**}	1.560	6.337	6.287
	(0.506)	(4.195)	(4.239)	(0.829)	(3.588)	(3.583)	(1.839)	(5.930)	(5.956)
Wage level	0.319^{***}	2.430^{***}	2.725^{***}	-0.147	-0.461	-0.350	0.577^{**}	1.969^{***}	2.375^{***}
	(0.064)	(0.533)	(0.519)	(0.105)	(0.456)	(0.439)	(0.234)	(0.754)	(0.730)
GERD_PCT_GDP	0.895^{**}	8.079^{**}	7.200^{**}	0.608	5.892^{**}	4.902	3.176^{**}	13.972^{***}	12.102^{**}
	(0.401)	(3.444)	(3.579)	(0.656)	(2.946)	(3.025)	(1.455)	(4.869)	(5.029)
GVA_IND_SHARE	-0.060	-0.545	-0.376	0.065	0.359	0.493	-0.052	-0.186	0.117
	(0.051)	(0.431)	(0.445)	(0.084)	(0.369)	(0.376)	(0.186)	(0.610)	(0.625)
SHARE_HIGH_EDUC	-0.284^{***}	-2.322^{***}	-2.418^{***}	-0.639^{***}	-2.207^{***}	-2.314^{***}	-1.686^{***}	-4.529^{***}	-4.732^{***}
	(0.060)	(0.512)	(0.524)	(0.098)	(0.438)	(0.443)	(0.218)	(0.723)	(0.736)
EQI	0.426	7.721	9.438^{*}	10.281^{***}	40.236^{***}	41.132^{***}	16.711^{***}	47.957^{***}	50.570^{***}
	(0.571)	(4.826)	(4.843)	(0.935)	(4.128)	(4.093)	(2.074)	(6.823)	(6.804)
IND REL + COMP (RS)	0.121^{***}			0.208^{***}			0.621^{***}		
	(0.028)			(0.046)			(0.103)		
IND REL + COMP (RANK)		0.290^{***}			0.143^{*}			0.433^{***}	
		(0.090)			(0.077)			(0.128)	
IND REL + COMP + TECH REL + COMP (RANK)			0.256^{***}			0.170^{**}			0.427^{***}
			(0.091)			(0.077)			(0.128)
Constant	-2.182	36.338	24.940	-1.761	57.416^{**}	56.223^{**}	68.245^{***}	93.754^{**}	81.162^{*}
	(3.757)	(33.005)	(32.463)	(6.151)	(28.235)	(27.436)	(13.640)	(46.663)	(45.610)
Observations	161	161	161	161	161	161	161	161	161
R^2	0.444	0.390	0.381	0.641	0.554	0.558	0.658	0.557	0.556

Adjusted R^2	0.418	0.362	0.352	0.625	0.533	0.538	0.642	0.537	0.535
Residual Std. Error (df = 153)	4.368	37.238	37.515	7.151	31.856	31.705	15.857	52.647	52.708
F Statistic (df = 7; 153)	17.421^{***}	13.970^{***}	13.443^{***}	39.104^{***}	27.098^{***}	27.564^{***}	42.035^{***}	27.463^{***}	27.350^{***}
Note:									*p**p***p<0.01

Figure A9.2 Extended employment and wage growth model (EU-13)

	Dependent variable:								
	Emp Growth (1)	Emp Growth (rank) (2)	Emp Growth (rank) (3)	Wage Growth (4)	Wage Growth (rank) (5)	Wage Growth (rank) (6)	Emp and Wage Growth (rescaled) (7)	Emp and Wage Growth (rank) (8)	Emp and Wage Growth (rank) (9)
Employment level	-2.998	-6.422	-7.856^{*}	9.385^{*}	9.665^{***}	9.807^{***}	3.122	3.242	1.951
	(2.334)	(4.402)	(4.669)	(5.392)	(3.508)	(3.546)	(8.114)	(5.649)	(5.866)
Wage level	-0.463	-1.004	-0.848	-3.630^{***}	-2.176^{***}	-2.178^{***}	-4.896^{***}	-3.180^{***}	-3.026^{***}
	(0.358)	(0.685)	(0.719)	(0.827)	(0.546)	(0.546)	(1.245)	(0.879)	(0.903)
GERD_PCT_GDP	2.116	5.516	8.587	6.588	1.217	1.007	11.785	6.733	9.593
	(2.915)	(5.445)	(5.569)	(6.732)	(4.339)	(4.230)	(10.131)	(6.987)	(6.997)
GVA_IND_SHARE	-0.251	-0.524	-0.583	0.247	0.263	0.269	-0.309	-0.262	-0.314
	(0.199)	(0.374)	(0.395)	(0.459)	(0.298)	(0.300)	(0.691)	(0.480)	(0.496)
SHARE_HIGH_EDUC	-0.511^{*}	-0.974^{*}	-0.867^{*}	1.248^{**}	0.971^{**}	0.969^{**}	0.159	-0.003	0.101
	(0.262)	(0.492)	(0.515)	(0.605)	(0.392)	(0.391)	(0.911)	(0.631)	(0.647)
EQI	1.363	3.611	4.309	-9.141	-3.589	-3.674	-6.581	0.022	0.635
	(2.360)	(4.461)	(4.720)	(5.451)	(3.554)	(3.585)	(8.203)	(5.724)	(5.930)
IND REL + COMP (RS)	0.246^{***}			-0.046			0.510^{**}		
	(0.070)			(0.161)			(0.242)		
IND REL + COMP (RANK)		0.720^{***}			-0.057			0.664^{***}	

		(0.191)			(0.152)			(0.245)	
IND REL + COMP + TECH REL + COMP (RANK)			0.522^{***}			-0.048			0.474^{**}
			(0.176)			(0.133)			(0.221)
Constant	29.651	95.624^{**}	106.312^{**}	-21.424	-41.853	-43.049	97.788	53.771	63.263
	(19.894)	(37.752)	(40.323)	(45.952)	(30.082)	(30.626)	(69.149)	(48.442)	(50.659)
Observations	53	53	53	53	53	53	53	53	53
R^2	0.307	0.351	0.285	0.602	0.588	0.588	0.393	0.331	0.294
Adjusted R^2	0.199	0.250	0.174	0.540	0.524	0.524	0.298	0.227	0.184
Residual Std. Error (df = 45)	7.086	13.376	14.035	16.369	10.659	10.660	24.632	17.164	17.632
F Statistic (df = 7; 45)	2.846^{**}	3.473^{***}	2.566^{**}	9.731^{***}	9.167^{***}	9.164^{***}	4.155^{***}	3.178^{***}	2.674^{**}
Note:									*p**p***p<0.01

A10. Extended econometric model: GDP and Productivity Growth

	Dependent variable:							
	GDP Growth (1)	GDP Growth (2)	GDP Growth (rank) (3)	GDP Growth (rank) (4)	Productivity Growth (5)	Productivity Growth (6)	Productivity Growth (rank) (7)	Productivity Growth (rank) (8)
GDP level	-0.0005^{***}	-0.0005^{***}	-0.003^{***}	-0.003^{***}				
	(0.0001)	(0.0001)	(0.001)	(0.001)				
Productivity level					-0.402^{***}	-0.381^{***}	-3.389^{***}	-3.323^{***}
					(0.101)	(0.109)	(0.492)	(0.457)
GERD_PCT_GDP	-0.422	-0.473	4.877	3.652	0.682	0.790	11.917^{***}	11.365^{**}
	(1.086)	(1.103)	(4.551)	(4.665)	(0.984)	(1.007)	(4.516)	(4.616)

GVA_IND_SHARE	0.734***	0.737***	2.348***	2.421***	0.489***	0.484***	1.850***	1.884***
	(0.115)	(0.116)	(0.472)	(0.474)	(0.107)	(0.108)	(0.474)	(0.476)
SHARE_HIGH_EDUC	0.555***	0.543***	1.103*	1.017	0.331**	0.351**	0.597	0.555
	(0.145)	(0.151)	(0.617)	(0.618)	(0.133)	(0.139)	(0.616)	(0.618)
EQI	-2.670*	-2.619*	5.135	6.073	-0.093	-0.202	17.696***	18.172***
	(1.370)	(1.385)	(5.678)	(5.725)	(1.421)	(1.439)	(6.426)	(6.476)
IND REL + COMP (RS)		0.022				-0.036		
		(0.078)				(0.069)		
IND REL + COMP (RANK)			0.132				0.070	
			(0.091)				(0.087)	
IND REL + COMP + TECH REL + COMP (RANK)				0.139*				0.075
				(0.076)				(0.076)
Constant	0.978	0.343	92.123***	88.867***	8.947	9.905*	138.509***	136.807***
	(5.555)	(5.992)	(22.793)	(22.603)	(5.549)	(5.859)	(24.776)	(24.565)
Observations	214	214	214	214	214	214	214	214
R^2	0.324	0.325	0.324	0.328	0.235	0.236	0.327	0.328
Adjusted R^2	0.308	0.305	0.305	0.309	0.217	0.214	0.308	0.309
Residual Std. Error	12.654 (df = 208)	12.682 (df = 207)	51.635 (df = 207)	51.486 (df = 207)	11.635 (df = 208)	11.656 (df = 207)	51.514 (df = 207)	51.475 (df = 207)
F Statistic	19.969*** (df = 5; 208)	16.581*** (df = 6; 207)	16.551*** (df = 6; 207)	16.848*** (df = 6; 207)	12.808*** (df = 5; 208)	10.680*** (df = 6; 207)	16.791*** (df = 6; 207)	16.870*** (df = 6; 207)
Note:								*p**p***p<0.01