Celtic tree of life

The two-way significance of relatedness

An analysis of the regional determinants of resilience in Great Britain's financial services sector during recovery of the 2008-2014 Great Recession

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Abstract (English)

Research on regional resilience has attracted much interest by scholars in the past decade – in particular economic geographers. Where much attention has been paid to notions in evolutionary thinking in the field of economic geography such as industrial relatedness and clustering of economic activity, the current body of literature is still rather limited when relating these ideas to resilience. In particular, the latter concept is of relevance considering past, current and future economic crises such as the recent Great Recession that started in the US housing market and transcended into the rest of the (developed) world causing economic but also social disrupture. Interestingly, many studies and policy endeavors have focused on coping with crises' impact and the factors that are most decisive (i.e. supportive or detrimental) in mitigating negative effects. However, perhaps even more interesting is instead to examine periods of recovery and growth in itself. In this regard, there is a promising development of including evolutionary ideas into the field. Growth paths and (regional) ability to reinvent and adapt to economic change are of particular importance. This thesis has sought to find out what factors are most important regarding (un)employment recovery after the Great Recession from an evolutionary and structural economic viewpoint by exploiting an Ordinary Least Squares regression method and calculating two indices for both industry concentration and (un)related variety. The main results tell that industry concentration and 'related variety' are closely related and individually positively contribute to growth. Furthermore, when these variables are statistically combined, there is an interesting trade-off visible that demonstrates how related variety in conjunction with industry concentration (also interpreted as specialization) impacts regional resilience. Essentially, there is an intersection at 65% related variety and 35% unrelated variety where industry concentration as being either low or high is more or less beneficial to (un)employment recovery. Below the intersection, high concentration is more beneficial, and after that low to no concentration is. Interpretation arrives at the notion of negative regional 'lock-in' and the stages of economic development the regions (371 Local Authority Districts) find themselves in. Concluding, there have been produced spatial results with use of GIS that show that the regions with generally high related variety and low concentration perform best. NUTS-1 region London is the most pronounced example of this, and Scotland most negatively affects resilience.

Abstract (Dutch)

Onderzoek naar regionale veerkracht heeft veel aandacht getrokken onder wetenschappers in het afgelopen decennium. Waar veel aandacht geschonken is aan begrippen in evolutionaire benaderingen in het werkveld van de economische geografie zoals industriële gerelateerdheid en ruimtelijke concentratie van economische activiteit, is de huidige stand in de literatuur nog relatief onbeproefd wanneer deze concepten aan regionale veerkracht worden gerelateerd. In het bijzonder is het laatste begrip relevant denkend aan verleden, huidige en toekomstige economische crises zoals de recente Financiële Crisis die begon in de huizenmarkt van de VS en oversloeg naar de rest van de (ontwikkelde) wereld en zorgde voor economische maar ook sociale disruptie. Interessant genoeg hebben veel studies en beleidsvraagstukken de focus gehad op het omgaan met de impact van economische crises en de factoren die daarin het meest belangrijk zijn (zowel positief als negatief van invloed) en in het verzachten van de effecten. Wellicht nog interessanter is om juist te kijken naar perioden van groei en herstel als zodanig. In dit verband is er een veelbelovende ontwikkeling gaande die ideeën uit de evolutionaire benadering inbrengt. Groeipaden en (regionale) mogelijkheden tot heruitvinden en aanpassen aan economische verandering zijn hierbij in het bijzonder van belang. Deze scriptie heeft getracht om te onderzoeken welke factoren het meest belangrijk zijn voor werkgelegenheidsherstel na de Financiële Crisis vanuit een evolutionair en structureel economisch perspectief door een kleinste kwadraten regressiemethode toe te passen en door het berekenen van

twee indices voor zowel sectorale concentratie en (on)gerelateerde variëteit. De belangrijkste resultaten laten zien dat sectorale concentratie en gerelateerde variëteit dicht met elkaar in verband staan en individueel gezien positief bijdragen aan groei. Verder, wanneer deze indices statistisch met elkaar gecombineerd worden is er een interessante wisselwerking zichtbaar welke laat zien hoe gerelateerde variëteit in samenspel met sectorale concentratie (ook te interpreteren als specialisatie) invloed uitoefent op de regionale veerkracht. In essentie is er een kruispunt van 65% gerelateerde variëteit dat raakt aan 35% ongerelateerde variëteit waarbij sectorale concentratie als zijnde laag of hoog meer of minder bijdraagt aan werkgelegenheidsherstel. Onder het kruispunt is hoge concentratie voordeliger en na de kruising is lage concentratie voordeliger. De interpretatie raakt aan het begrip ‘lock-in’ en stadia van economische ontwikkeling waarin de regio’s (371 Lokale Autoriteitsdistricten) zich bevinden. Concluderend zijn er ruimtelijke resultaten met behulp van Geografische Informatie Systemen gegenereerd welke laten zien dat regio’s met in het algemeen hoge gerelateerde variëteit en lage sectorale concentratie het beste presteren. NUTS-1 regio Londen is het meest vooraanstaande voorbeeld hiervan, en Schotland heeft de meest negatieve invloed op de economische veerkracht.

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Quite a few people deserve words of recognition in supporting and contributing to the process of writing this master’s thesis. First of all, my supervisor Dimitris Ballas has been utmost supportive, critical and inspiring regarding the end product but also the entire journey that started somewhere in February 2021. He encouraged me to be creative and find others to help and has most importantly been positive and enthusiastic. The end-presentation at the Graduate Research Day last January has been a rewarding, confronting and also encouraging experience that marked a point where I found confidence about my work. Further, Tasos Kitsos (Aston University, UK) who is particularly specialized in regional resilience in his home country has supported me in the writing process and was always readily and kindly available for interesting discussions concerning methods, theory and more fundamental scientific practices. Moreover, we together came to the idea of constructing the interaction term of related variety and industry concentration that lead to the two-by-two matrix in section 4.5 below. I am thankful for his input and look forward to collaborate with him in this field of study in the future. Two of Dimitris’ PhD students were also very willing to help out and advise me. In particular, Alvertos Konstantinis took time for me and offered the opportunity to practice my final presentation just as Tasos did and also a dear friend of mine Sander Morsman who just graduated from his master’s in econometrics at the Erasmus School of Economics. Sander and I furthermore held discussions about the models I use benefitting from his vast experience in his field. I always have appreciated interdisciplinary work and collaboration throughout my studies and intend to continue doing so. The second PhD-student I would like to thank is Thanasis Ziogas who advised me on some statistical matters without hesitation. Lastly, there are several people in a more personal sphere that supported me. I want to thank Nanette V. and Shirly for their help with planning the final presentation and giving me confidence. I also want to pay gratitude to Nanette L. who I have known for more than two years now and who has strengthened my critical thinking and made combining studies with my personal life more organic and in balance. Finally, Natascha, who I have not known for a very long time, is the most open, kind and sincere woman I encountered so far and who shares with me a certain matter of philosophy, and has soothed high levels of tension right before the Graduate Research Day in our meaningful discussions and with her tips on how to relieve stress and affirm that I can do it.

Of course, any mistakes or misinterpretations found in this thesis are attributable to the author alone.

1. From economic crisis to windows of opportunity

1.1 Introduction

The most recent and systemic financial crisis that started in the US housing market and transcended into Europe by 2008 – the Great Recession – is and has been subject of study in many research papers, books, documentaries and the like. This economic crisis appeals to the imagination so strongly as the peoples of Europe experienced dramatic cuts in their spending power and governments enacted the so-called 'austerity policies' that have been harmful to national economies (Clark et al., 2018). In the US, Gross Domestic Product (GDP) fell with 4.3 percent from 'peak to trough' between 2007-2009 (Weinberg, 2013), and in the UK with 5.2 percent in roughly the same period (Reuters, 2014). Perhaps more importantly, economic downturn resulted in vast employment losses across countries. Martin (2012) argues in his study on the UK that employment figures are more telling with respect to economic change resulting from crises because they capture labour market dynamics and reveal how different industries (and regions) react to such circumstances.

While crisis *impact* is an important perspective to take lessons from (see Kitsos, 2020, and Martin, 2012; 2016), there is another aspect to economic shocks; namely the period of *recovery* wherein new growth paths are to be found and taken by economic agents within and across the regions they act in (Boschma, 2015).

Regarding the financial crisis, its impact *and* recovery, the UK is an interesting case as London functions as the financial headquarters of the country itself but also Europe and beyond. This culturally and economically unique island-nation has a long history of overseas expansion and industrial developments that changed the (developed) world for good. What at this moment in time cannot be left out of the discussion regarding the UK's present and future economic developmental paths is the decision on Brexit. Yet, in this thesis, the analyses' time frame runs up to 2019 to omit 'COVID' which would have introduced large fluctuations in business cycles and therefore data. The worldwide but also regional socioeconomic circumstances resulting from COVID-measures are furthermore conceptually very different from studying the Great Recession. Besides further limitations regarding data that reach not farther than 2021, the study does not take Brexit empirically under consideration. However, studying the financial crisis in a British context so chronologically close to this event, the outcomes of this thesis might serve as input or inspiration for further ways of inquiry – moreover because Brexit touches on the financial sector which is outlined extensively by Whyman & Petrescu (2020). Having said this with regard to Brexit, the further contents of this section (and thesis) will focus on the Great Recession.

Regional differentiations of coping with the financial crisis are of great interest to scholars like Martin (2012; 2016), Boschma (2015) and also more recently Kitsos (2018; 2020). The idea is that – obviously – different regional contexts with their particular economic, social and geographical characteristics are first confronted with an economic shock, and, importantly, react to the latter in their own way. The current thesis takes employment figures as its core developmental indicator regarding the financial crisis and recovery. As employment is not an isolated pool of labour that can be drawn from on demand and be disconnected from socio-economic characteristics like human capital and demographic peculiarities for instance, these factors and more are studied in detail from this chapter onwards and are present in the analyses.

Further, following Boschma (2015), Frenken et al. (2007) and Kitsos (2020), it becomes clear that particular (regional) industrial structures or compositions are, again, to differing extents important with regard to dealing with economic downturn *and* growth. The latter can be interpreted as regional *resilience*, a concept that has attracted much attention in the last decade or so by many scholars in evolutionary thinking and taken over by policy-makers in the EU amongst others (McCann, 2015). It is particularly this concept – regional resilience – that is subject of study in this thesis. Bristow and Healy (2020) in this light use notions of 'bouncing back' and/or 'bouncing forward'. Martin (2012) laid the foundation for these ideas by demonstrating visually a so-called 'plucking model' that shows options of how regions may react to crises. Figure 1 below depicts a region's possible growth path – in this case a path that returns to its former pace and volume. Of course, there are the possibilities of regions not bouncing back and even decline in terms of employment and/or output. On the other hand, there are regions that bounce forward and even exceed their former growth trajectories. Following Boschma (2015), this could indicate that the region found new growth paths, for instance in *related* economic activities that attract employment and induce further industrial branching and development.

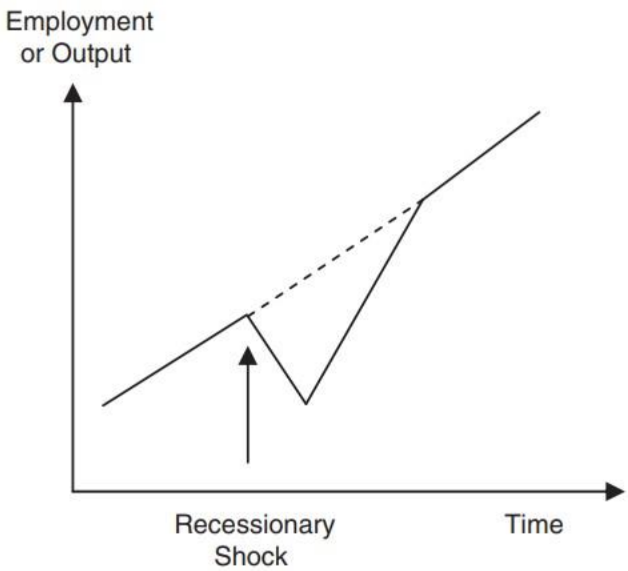


Figure 1: "Impact of a recessionary shock on a region's growth path: region returns to pre-shock growth trend" (Martin, 2012, p. 6)

In this study, it is however not the aim to track economic development all the way from pre-recession up to recovery. Instead, as chapter 4 extensively dives into, the dependent variables representing regional resilience subtract employment in the crisis period from employment in the recovery period. When the result is (more) positive, resilience/recovery is greater.

In order to give a further flavor of the methodology that is used, the mentioned phenomena of industry relatedness but also industry concentration are briefly considered. Industry concentration is also an indicator of specialization and relates to concepts of (negative) 'lock-in' and basically the stages the particular regions find themselves along the lines of industrial development. Industry relatedness captures inter/intra-industry linkages which says something about economic complexity and also 'learning processes' regions and their constituent agents find themselves in. These concepts are discussed in more detail (also in relation to the aims of this thesis) in the theoretical framework (chapter 3) as well as in section 5.6. Two indices capturing industry relatedness and concentration are calculated and the outcomes are fed into the regression models that are formulated in chapter 4 as well.

Using these indices and combining them statistically gives novel insight into regional economic performance in a more comprehensive way where everything comes together, as many studies to date are investigating 'impact' on the one hand referring to resilience as stated above, and on the other hand (un)related variety, specialization-diversification and/or industry concentration are not integrally studied in conjunction with each other – also regarding resilience. In this light, Boschma (2015) asks for insight into the (combined) contributions of (un)related variety with regard to resilience. This precise straw is captured by the decomposable entropy index of diversification (see section 4.3.1) that consists of SIC2007-based industry structures resulting in usable values per Local Authority District (LAD). Moreover, as data up to 2019 (in fact up to 2021 for most variables) are now available, a more comprehensive and more meaningful account can be made regarding recovery of the financial crisis. For instance, Faggian et al. (2018) produced an interesting study on resilience following Martin (2012) and Martin and Sunley (2015) with amongst others a focus on recovery, yet in the Italian national context. Their time-frame is however more limited – also due to their definition of the crisis period. Both Faggian et al. (2018) and Kitsos (2020) stress the importance for disaggregated regional/local analyses when studying resilience, and by borrowing theory and methods from both studies, this thesis contributes to the field by 1. introducing a unique set of (interaction) variables including industry relatedness and concentration, 2. considering a more spread-out and up-to-date time-frame capturing the entire crisis and recovery up and until 2019 and 3. by potentially providing leads that may connect the ability to recover with coping with future economic shocks like Brexit and COVID as the latter two will put Great Britain's resilience to the test as well. In fact, economic crises do not seem to stay absent after this, as the current war in Ukraine distorts national economies in rapid pace looking at for instance fuel and gas prices. In other words, being prepared and/or having clear notions of how regional economic structures contribute to or weaken economic development and growth may facilitate policymakers with useful tools.

In order to systematically study the above-discussed phenomena with both a sound theoretical basis and societal relevance in how regions react and respond to economic crises – the Great Recession in this thesis – the following research question has been formulated.

What is the influence of (un)related variety and industrial concentration on resilience of Great Britain's regions after the 2008-2014 Great Recession?

Sub-questions:

1. What is the sectoral composition of Great Britain's Local Authority Districts in terms of (un)related variety and industrial concentration?

2. Which elements in and related to the sectoral composition contribute to or reduce (un)employment recovery/growth with respect to the Great Recession?

3. Which Local Authority Districts in Great Britain are most resilient and what spatial patterns can be identified?

In the following chapter (2), a brief country profile is sketched in order to provide background knowledge and statistics that will be drawn from throughout the thesis. Data are presented for the United Kingdom and not only Great Britain. This is the case as the country profile does not directly serve as empirical input for any of the analyses and because including Northern Ireland gives a more complete picture[1]. Next, chapter 3 outlines the theoretical framework leading to the conceptual model which gives structure to the concepts under consideration and provides the reader with a state of the art literature review pertaining to the relevant concepts. Following the latter, chapter 4 introduces the data and units of analysis. In this chapter, the three main approaches are outlined starting with the overarching approach of measuring resilience. The two indices – Herfindahl-Hirschmann Index and an Entropy index of diversification – that are individually part of the methodology as well are elaborated

[1] Reasons for excluding Northern Ireland from the models are given in section 4.1.

on in detail in the following subsections. These indices furthermore serve as input for the main regression analysis. Chapter 5 dives into the results. This quite comprehensive chapter gives summary statistics, but more importantly it seeks to clarify and discuss the relationships that are found by regression, spatial analysis with GIS and by exploring some particular relationships in more detail visually. Finally, chapter 6 concludes and tries to answer the research question posed above.

Figure 2: Administrative map of the United Kingdom (source: WorldAtlas, 2021)

2. Country profile

This chapter will concisely report relevant industrial and human capital-based outlooks for the UK as well as statistics pertaining tot the labour market. The main aim is to provide a picture of the country and its core socio-economic structures that are important background knowledge for further analyses.

2.1 Sectoral structure and exports

The United Kingdom showed a GDP of 3,246.54 million international dollars in 2019 and $48,603.04 GDP per capita in Purchasing Power Parity (PPP) in the same year (International Monetary Fund, 2021). There were relatively large quarterly fluctuations in 2020 mostly due to restrictions imposed by governments related to the corona-virus with the highest figures in Q2 and Q3 (-19.5 and +16.4 per cent respectively) – yet with promising future prospects according to IMF – representing 'real GDP' (Office for National Statistics, 2021a, p. 5). This measure reflects GDP corrected for inflation which may be more realistic than nominal GDP in terms of fluctuations related to production (Investopedia, 2021).

To provide more detailed information concerning the national economy, the sectoral division is interesting as this reflects how the country earns its money. An important note is however that there is considerable regional variation in economic activity and thus the way local/regional economies are structured. The OECD (2020b, p. 7) notes that in 2019 there was a division between 'Agriculture, forestry and fishing', 'Industry including construction' and 'Services' of respectively 0.7, 19.5 and 79.8 per cent. This confirms the general picture of the advanced Western economies that have experienced shifts in economic activity towards services and also known as 'knowledge economies'. Moreover, the latter number representing services is significantly higher than the OECD average of 70.5 per cent.

When digging somewhat deeper into the services profile of the UK but this time related to exports, figure 3 depicts an interesting division between goods and two types of services. It can be seen that services play an important role in export (to the EU27 in this case), and when looking at export in general, Office for National Statistics (2019c, p. 14) reports that "exports of oil and financial services were the main contributors of the rising value of total exports in 2018". 2019 however shows different contributors to service exports with an increase of £7.2 billion to £317.7 billion with 'Financial Services' contracting by over £3 billion. The reason for this could lie in financial service providers leaving the UK in the light of Brexit (mostly to the EU27), yet this can re-evaluated in later periods to obtain a clearer picture and also trade deals with third countries play an important future role here according to Institute for Government (2020). Moreover, export of services to non-EU countries in 2019 increased with £8.8 billion to £194.0 billion – mainly to the US and Asia – while services exports with regard to EU-countries "decreased slightly over the year to £123.7 billion" (Office for National Statistics, 2020, p. 8). It is interesting to look at more future prospects, which will covered in section 2.4 that however can be found in Appendix I.

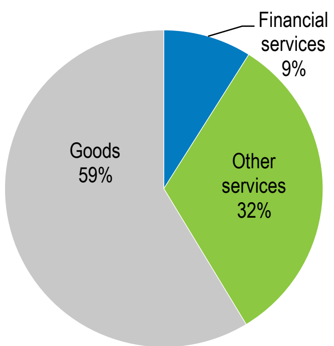


Figure 3: Export-division of goods and services to the EU27 in 2018 (source: OECD, 2020, p. 10)

2.2 Human capital

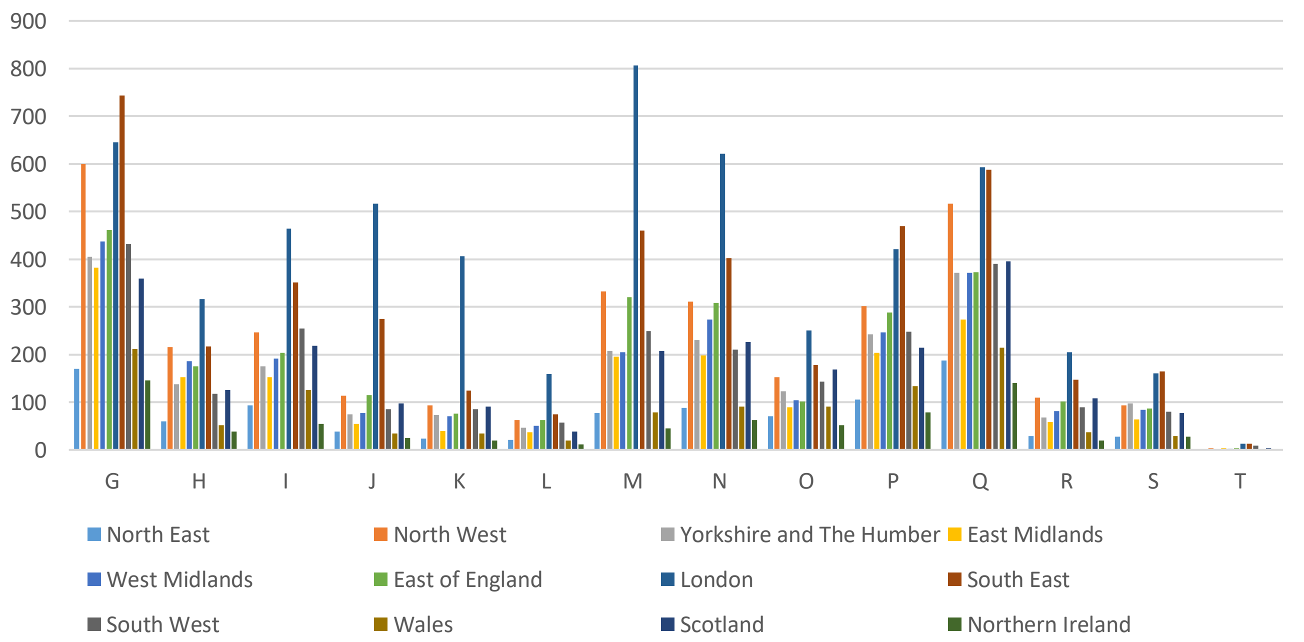
Related to the UK's sectoral composition and also its international position and competitiveness, human capital is regarded as a very important *resource* the country brings forth, for instance through top-class universities as the most prominent being Oxford and Cambridge.

The OECD (2020c) reports that 'middle-skill workers' are declining in the UK and beyond in relative terms. However, in absolute numbers these types of jobs are in general not vanishing. The reason for the shift in shares of occupation types lies in the large increases in both low- and high skilled jobs (OECD, 2020c, p. 222). Questions then raise what exactly is behind these developments which may be answered rather easily, yet the consequences for labour market performance and also *competitiveness* are more complex. It is namely important whether such changes are structural, and, if they are, how workers and their employers are affected from differing dimensions such as related to labour market institutions (Boeri & Van Ours, 2013).

More pertinent in this section however are questions related to the functioning of human capital and its embeddedness in the sectoral structure. This indicates to what extent national but also regional territories are characterized by certain occupational groups and/or divisions. The empirical analysis in chapter 5 however deals with less aggregated data. In figure 4 below, several industries in the service sector will be compared across NUTS1-regions in the UK with data available from Office for National Statistics (2021b).

Looking at figure 4, it immediately stands out that London and South East contribute largely to almost all services sectors. Also region North West does, yet not very pronounced in 'Information & communication' and 'Financial & insurance activities', of which the latter is obviously mostly characteristic for London and also to a (much) lesser extent – but second in rank – for South East. More details about the particular economic activities and deliberations about sectoral accounts will be provided in chapters 4 and 5 in order to give more insight into the distinct industrial profile accompanied by more specific data on amongst others human capital, regional specialization, entrepreneurial activity and so on. The following section goes beyond human capital and dives into the labour market related to the UK's unique socio-economic characteristics.

Figure 4: Sectoral employment division of services by NUTS1-regions in December 2019 (thousands; seasonally adjusted)



*See sectoral descriptions below:

G	= Wholesale & retail trade; repair of motor vehicles and motorcycles
H	= Transport & storage
I	= Accommodation & food service activities
J	= Information & communication
K	= Financial & insurance activities
L	= Real estate activities
M	= Professional scientific & technical activities
N	= Administrative & support service activities
O	= Public admin & defence; compulsory social security[2]
P	= Education
Q	= Human health & social work activities
R	= Arts, entertainment & recreation
S	= Other service activities
T	= People employed by households, etc

2.3 Labour market outlook

Before turning to the extensive and more technical resilience discussions in section 3.1, it is appropriate to sketch the current situation with regard to the British labour market. Known is that the UK historically has an economic profile that can be identified as mostly liberal, advocating free trade and letting 'the market' prevail – more similar to the US and the Anglo-Saxon model (de Pater, 2004, p. 158). This stands in contrast to many countries on the European mainland that are highly developed welfare states with amongst others high unemployment benefits, e.g. the Scandinavian countries but also The Netherlands (Boeri & van Ours, 2013), that are moreover characterized by a large role for government intervention and public spending (yet acknowledging the neoliberal and decentralizing tendencies since approximately the 1980's, for instance in The Netherlands).

Table 1 below gives an overview of labour supply for the United Kingdom in 2019 which is the most recent year available. Interesting to see is the relatively low unemployment rate (3.7%) which however has been claimed to hide workers that are for amongst others health, age, *skills* and wider (labour) mobility-related issues unable to find appropriate jobs yet are willing to work (Beatty & Fothergill, 2002). There are regional components related to these issues, as for instance the latter authors mention industrial decline in the North West region of England, but there are also more recent phenomena discussed in British newspapers and also study reports (for instance, see Beatty et al., 2017 for an extensive research paper on regional differences of hidden unemployment).[3]

What can be argued based on the above observations concerning the labour market is that there will (of course) be socio-economic and thus regional differentiations with regard to the effects and prospects related to the Financial Crisis. The extent to what this phenomenon brings distress and eventually also opportunity is up to debate and can be interpreted from different angles. The perspective of policy-makers might be that is it wise to thoroughly analyze the costs and benefits for the country as a whole, and how local/regional issues regarding the labor market can be mitigated. It can also be argued that there are more fundamental labor market and socio-economic issues in the UK that are structural in nature and which may be influenced in some way by economic disrupture. The question then raises if more impactful changes should be avoided at all cost because there will always be localities suffering from them. The other perspective or answer to this might be that the UK and its regions and more in general its socio-economic resources and strengths are there to intelligently channel towards destinations that require them.

[2] "This series is not exclusively a public sector series as it includes some private sector jobs" (Office for National Statistics, 2021b).

[3] Appendix II shows a map with "Estimated hidden unemployment on incapacity benefits, by district, November 2016" (Beatty et al., 2017, p. 11).

Population of working age (16-64)	42 million
Active population/Labour force	34 million; participation rate: 81.4%
Inactive population	7.8 million
Employed	32.7 million; employment rate: 78.4%
Unemployed	1.3 million; unemployment rate: 3.7%
Real unemployment[4]	2.28 million; unemployment rate: 5.7% (2017)
Part-time	Total: 23.1%; males: 11.2%; females: 36.1%
Involuntary part-time	Total: 11.8%; males: 19.1%; females: 9.2%
Full time	Total: 76.9%
Self-employment	Self-employment rate: 15.6%[5]

Table 1[6]: Labour supply overview of the United Kingdom in 2019 (Sources: OECD, 2021; OECD.Stat, 2020a-c; Office for National Statistics, 2021c)

It is interesting to end here with self-employment, or, more generic, entrepreneurial activity. As the UK has been historically a trading nation with far-reaching ambitions overseas, it is not hard to imagine that this trend will continue in the decades to come. However, the question then is according to what terms and conditions and with whom. Implications of Brexit are there when it comes to trade and doing business cross-border as trade agreements change and of course the relationship with the EU will be reconsidered this way. In the next section that is found in Appendix I, trade deals with third countries and also their implications along with future prospects will be considered. The continuation of the country profile in Appendix I is however not an integral part of the thesis (anymore) and only serves as input for further inquiry when for instance the study is repeated in 3-5 years regarding data.

2.4 Conclusions

This chapter has outlined ways in which the UK is an economically distinct country in the sense that the sectoral structure and related export and skill profiles share a common focal point. The highly competitive and service-based economy can be regarded as a strength that has nevertheless several flaws (think of hidden unemployment). However, building on what the country has to offer in these terms, the most interesting question is what post-crisis periods will bring and have brought forth regarding the national economy but also regional socio-economic structures.

From a more theoretical perspective considering human capital and economic development with regard to the above, the dynamics in the 'skill-biased' labour market are a factor that will probably have structural consequences when it comes to technological progress (Reijnders & de Vries, 2018). Embeddedness (proximity) of skills in the sectoral structure – referring to technological specialization and relatedness and thus *resilience* – are likely important factors impacting the UK considering its economic performance which also includes future *growth paths* and recovery. How these concepts and several others that were not mentioned explicitly here relate to each other will be discussed in the next chapter, which outlines the theoretical framework and tries to integrate these core ideas.

[4] Unemployment measured taking into account different employee-characteristics that arguably give a better (regional) representation of default unemployment (see text under table 1 and Beatty et al., 2017, pp. 9-12).

[5] "Self-employment is defined as the employment of employers, workers who work for themselves, members of producers' co-operatives, and unpaid family workers" (OECD, 2021).

[6] Most of the data presented in this table were also used for an assignment of the course 'Regional Labor Market Analysis' (GEMRAMA) that was taken in semester 2a (2021) at Groningen University. Credits are hereby also attributed to M. Bieleman with whom I collaborated in this course.

3. Theoretical Framework

In this section an attempt is made to establish the theoretical foundations on which to build further the rationale of inquiry as briefly elaborated on in section 1. First, attention is paid to a notion of 'resilience' that aligns with employment and the related industrial structure (Fingleton et al., 2012; Martin, 2012) in a way that captures dynamic economic development (Bristow & Healy, 2020). This with regard to the interplay between specialization-diversification and industrial relatedness that is (now) well-known in debates in evolutionary economic geography (Boschma & Frenken, 2010; Frenken et al., 2007). Further, these ideas are prevalent in the light of recent industrial policy called 'smart specialization' (McCann, 2015) which draws attention in many countries and their regions in order to strengthen and foster economic development (Pike et al., 2016). The aim of this chapter is not to design any form of guidelines for industrial policy, but rather to embed the 'umbrella concept' of regional resilience in evolutionary thinking and to get to a firm conceptual framework that allows for interpretation of regional recovery after economic crises and thereby identifying the essential elements that underpin this process.

3.1 Regional resilience

What came forth out of the country profile is that the UK's service sector is important in both sectoral (employment) division and exports. Martin (2012) argues that this broad sector – but especially 'finance insurance and business services' – proved to be most resilient in and after economic crises, and specifies that the UK's South East region (NUTS1) is performing better compared to North East. With regard to the recent 2008 economic crisis, Martin states that the regional differences in response were less pronounced and also declines in employment were less than in output. However, outside the core regions there is a greater dependency on the public sector as described in later sections, which in the light of the controversial austerity policies will have implications for economic development (Clark et al., 2018).

Considering economic crises, there are interesting and fundamental questions of where and to what extent there is actually being experienced a *shock*, and in which way(s). With regard to regional resilience, how the UK's national government and other concerned entities will set out their future developmental path is dependent on how the latter is interpreted (Whyman & Petrescu, 2020). To this end, the work of Bristow and Healy (2020) on regional economic resilience is referred to quite often as they established a comprehensive starting point of how to engage with this concept. They distinguish four definitions that however are not mutually exclusive and leave room for the researcher's own interpretation. Resilience is according to them also a buzzword that is increasingly used by economic geographers, policy makers and the like. Yet, in the case of large-scale economic crises like the Great Recession, it sheds light on how the situation may unfold taking account of socio-economic indicators like employment and industrial structures affecting adaptation. The definition used in this thesis relates to "resilience as 'positive adaptability' in anticipation of, or in response to, shocks". Importantly, the latter's interpretation of this definition is "[the] capacity of a system to maintain core performances despite shocks by adapting its structure, functions and organization. Idea of 'bounce forward'" (Bristow and Healy, 2020, p. 13). A shock can be interpreted as a relatively large external – but also internal – change in economic circumstances that is not necessarily negative in nature which initial intuition would suggest. It can also be seen as an 'opportunity' to test and restructure the economic context of regions insofar they adapt to the latter and grow out stronger, i.e. more *resilient*.

3.1.1 Adaptation and economic development

The above-mentioned idea of 'bounce forward' will be deepened out further in this and the next subsections following essentially the definition by Bristow and Healy (2020). 'Adaptation' is referred to by the latter as a more short term and ongoing process of gradually changing one's interplay with the economic environment and reflects a (regional) system's ability to sustain itself. 'Adaptability' is depicted by a more strategic and long-term decision process characterized by innovative action and anticipation towards new growth paths including a broad spectrum of resources that may be already available or are created, for instance in an interplay with institutions and important actors. The second term – adaptability – is most relevant in the approach of this thesis as it aligns with the medium or long-term processes of recovery after crisis over a period of 12 years in total (more on this in chapter 4). Adaptation nevertheless deserves attention with respect to the path-dependent economic dynamics which are discussed in the next section(s).

Interesting in the face of economic development when taking the example of Japan and other south-east Asian countries like South Korea in the 20th century is the so-called Asian miracle which features more often in this thesis (Nelson & Pack, 1999). It is argued by the latter that not simply because of (human) capital accumulation economic growth and development is spurred, but by a *learning process* of proactively and eagerly exploiting new technologies and thereby increasing productivity whilst incorporating them into economic structures and business practices. With regard to an already industrially and economically developed nation as the UK, this principle may be interpreted differently. However, the precedent of the Asian Miracle that lead to massive productivity increases and new socio-economic standards in those countries are exemplary for vital and rapid economic development under the right institutional and economic conditions (see section 3.1.2) that are importantly influenced by government, businesses and knowledge institutes (Nelson & Pack, 1999).

New and existing growth paths in this case are important units of analysis which is reflected in work by Neffke et al. (2011) on industry relatedness (see section 3.2 below) and also Boschma (2015) who extends the rationale to resilience in particular. The latter argues that economic development is characterized by path-dependent and dynamic processes of techno-industrial change that operate by certain mechanisms. The most important of these refer to industrial relatedness dynamics including (supporting) networks and institutions. Boschma further argues that "resilient regions are capable of overcoming a trade-off between adaptation and adaptability", of which the latter have been defined above. It can be said that adaptation may in some situations hamper adaptability – referring to uncertain and undetermined stadia of adapting to new growth paths – which in turn depends on the industrial structure but also the functioning of institutions (pp. 736-737).

3.1.2 Institutions and industrial dynamics

The economic role of institutions[7] is a large topic of debate when it comes to government intervention in markets. In recent decades, the place of institutions in shaping socio-economic development has regained acknowledgement by economic geographers. Important in this respect are both formal and informal rules and regulations that are argued to contribute to and revolve around growth paths in countries and regions (Gertler, 2018). Boschma and Frenken (2009) yet argue that 'territorial institutions' are *orthogonal* to organizational *routines* that accrue to businesses and essentially also to employees that carry them over when they change jobs or create new businesses. The latter state that businesses are characterized by a variety of organizational routines and moreover vary in their capability of setting the circumstances to their benefit regardless of the territorial institutions in situ.

[7] Institutions per se are not included empirically in the analyses. Rather, this short subsection functions as important context that is related to the other concepts. Routines however *are* to an extent captured in the analysis.

However, regarding growth (paths) as mentioned in section 3.1.1 above, institutions can facilitate – in combination with other engaged actors/entities and entrepreneurial activity – the learning processes firms and workers experience in order to gain efficiency and stimulate innovation (Nelson & Pack, 1999). Institutions so to say are the enabling or restraining socioeconomic tissue which can be argued to originate from the individual and firm level but also on a macro scale concerning (industrial) policy. This means that even in a less regulated UK under conservative government, "the rules of the game" are embodied in the economy and its transactions both widely and deeply (Gertler, 2010).

Boschma and Frenken (2009, p. 154) further argue that institutional change is important to "enable the emergence of new industries and the revival of mature industries". This is an interesting idea as crises can be argued to both induce and require institutional change in order to adapt to new and also more efficient economic circumstances. From the perspective of evolutionary economic geography, 'path dependency' and also *creative destruction* are concepts that capture dynamic economic change which leads to uneven outcomes (Boschma & Martin, 2007). These outcomes are reflected in the industrial structure and accompanying institutional frameworks that both affect labour markets and their functioning as well.

3.1.3 Labour market indicators

Relevant labour market indicators with respect to resilience that are also related to the country profile (chapter 2) include employment figures which however do not need further and detailed elaboration on top of what is provided in section 2.3, summarized in table 1. An exception is self-employment, but this indicator is covered in the next section (Entrepreneurial activity). Employment regarded from the perspective of economic development is represented by individuals that bear a certain accumulation of human capital. Further, this human capital can be broken down into shares of people living and working in agglomerations and/or regions of different sizes from a geographical perspective. Moreover, it is interesting to divide groups according to their demographic characteristics as Kitsos (2020) has done embodied by certain age groups. The latter are particularly related to labour market dynamics and vary across every country and region in distribution and size (Boeri & Van Ours, 2013). When related to the sectoral structure and degree of urbanization amongst others (see section 3.3.1), human capital which is in general concentrated in urban centers with much economic activity, for instance in proximity of clusters, can be representative of routines and the distribution and/or accumulation of knowledge in space.

In this regard, knowledge spillovers ingrained in their local economic context are an important subject of research. They may foster economic growth (Audretsch & Feldman, 2004), and perhaps also resilience as the functioning of the labour market both depends on these linkages and shapes their existence – for instance through observational learning, collaboration networks and informal contacts that are moreover bounded by the so-called *tacitness* of knowledge, meaning the extent to which knowledge can be made overt and can be transmitted to others and which in turn is bound in space (Breschi & Lissoni, 2001; Breschi & Lissoni, 2009).

Indicators referring to education and training relate to economic development in the sense that employers invest in their employees by means of 'on-the-job training', and also individuals invest in themselves – adding to human capital – when future income prospects are positive (Boeri & van Ours, 2013, p. 234). Labour market developments regarding investment in education and training can for instance be tracked by looking at income and education levels, but also with respect to both government and organizational policy. Interestingly, looking at educational data on self-employment, it can be observed that in the UK most entrepreneurs have higher levels of schooling (the highest increase is in the group with a degree or equivalent), and a decreasing share has little or no qualification (Office for National Statistics, 2018). Entrepreneurial activity and its role with respect to resilience in response to crises will be examined in the next section.

3.1.4 Entrepreneurial activity

In line with resilience-thinking and evolutionary perspectives that are prevalent in section 3.2, entrepreneurship can be approached in a way that captures the notion's innovation-inspired and environment-adaptive nature. For instance, Bosma and Sternberg (2014) claim that urban areas in particular are characterized by 'opportunity-motivated entrepreneurial activity' and that economic diversity and also growth are essential elements of this innovative climate pertaining to multiple cities in twelve European countries. The study covers nine urban areas in the UK of which London is the largest at NUTS-1 level. 'Perceived opportunities' show a correlation of -0.49 at the 0.05 significance level with variable 'specialization-diversity' (p. 1025), which (initially) points at a 'diversification premium'. There is other literature that stresses the interplay of firm (co-)location and competition and relates this to (national) competitiveness and value creation (Porter, 2000, 2008). Regarding firm survival rates and phenomena of co-location of firms in space, the latter refers back to the above-mentioned concept of 'creative destruction' that goes back to Schumpeter's work (1942), and has also attracted scientific attention more recently (Andersson & Klepper, 2013; Morrison & Boschma, 2019).

The above arguments lead to discussions featuring industry and also cluster lifecycles as discussed by Crespo (2011) who argues that *dynamic* regional economic circumstances, technological changes and the adaptive capabilities of the firms residing in these clusters shape their economic potential and survivability. This aligns almost perfectly with the discussion above concerning 'adaptation and economic development' (section 3.1.1), yet with a focus on the firm-level. Essentially, the definition holds when zooming in and out yet needs a sound interpretation that can be found in evolutionary thinking. It is for instance an interesting question how entrepreneurship from an evolutionary perspective leads to spatial-economic uneven outcomes and to what extent entrepreneurship per se contributes to resilience (Bristow & Healy, 2020). Notions of *path dependency* are in this regard of importance and give rise to deliberations about regional capabilities that are 'inherited' from the past and the particular entrepreneurial behaviors and routines that characterize those (Boschma et al., 2002a).

Entrepreneurship from an evolutionary perspective embodies both incremental and radical innovations – this also depends on the definition that is used – that moreover can induce and are affected by technological shifts and changes of paradigms. This is a more dynamic representation of firm behavior in time and space which also refers to the death and birth of enterprises. Considering this notion of creative destruction and entrepreneurship, Bristow and Healy (2020, p. 202) further argue that in case of the UK 'entrepreneurial dynamism' in general has a positive impact on 'recovery performance'. This could be an interesting straw for policy and for instance the emerging field of research on entrepreneurial ecosystems (Spigel, 2017).

Looking back at the discussed phenomena of (negative) lock-in and also taking a look forward to the discussion on relatedness in section 3.2, Aldrich et al. (2020, p. 74) mention the importance of variety in knowledge and network ties when considering actors in the working field. In this light, actors, i.e. employees, entrepreneurs, scholars but also firms and institutions, can be characterized by their levels of 'proximity' in regional and organizational economic structures. Industrial concentration in this light is a well-known phenomenon that has drawn and still draws attention from many scholars and policy makers. These ends will be discussed in the next section, which combines and builds on insights derived from the current and previous sections in this chapter and then bridges into the second part of this theoretical framework.

3.1.5 Proximity and industrial concentration

Industrial concentration is characterized by differing levels of competition and cooperation across space between firms and the knowledge ties that connect them. Porter (2000) amongst others stresses the importance of local competition – what has been mentioned above – in stimulating innovation and economic performance of regions. Following Porter but also many other scholars (e.g. Bjørn Asheim, Philip Cooke and Ron Martin) that study the functioning of clusters in the light of regional development, it is important to note that this concept is not without controversy in terms of definition and conceptual usage in policy (Martin & Sunley, 2003). It is therefore not the aim of this section to eulogize clusters or give a complete account of their mechanics. Instead, the interplay of several spatial-economic characteristics that come with industry concentration are interpreted with regard to 'proximity' which comes in different shapes and forms.

What comes forth out of recent work by economic geographers is that dynamic (knowledge) networks are largely affected by different kinds of *proximity* (Balland et al., 2015a; 2016). For instance, based on the seminal work of Boschma (2005), the latter authors argue that there is a certain trade-off relating to proximity and economic performance of actors. This refers back to the discussion in section 3.1.4 about entrepreneurial activity in the sense that co-location of firms both creates competition and also might spur innovative cooperation. Moreover, this discussion can be related to phenomena of *lock-in* which also account for (interconnected) nodes in knowledge networks. Put more simply, too much/many innate relationships in business locations and networks may reinforce the same old routines and practices which can be counterproductive. Examples of this were found in the German Ruhr-area, and what Hassink (2010, p. 453) further argues is that "regional lock-ins are embedded in varying national and supra- national institutional contexts". The latter is mentioned as these phenomena are or were also present in the case of the UK considering the old industrial areas in the North West of England amongst others. Such lock-ins are not always free of political and societal attachment to certain areas and also industrial structures (Hassink, 2010), and might also be linked to accompanying job losses (also referring to section 2.3). There is thus an institutional and social component to this as well – e.g. trade unions and also attachment of employees to certain regions and their socio-economic structures.

With regard to the latter, Cooke et al. (2005) argue that in the case of the UK 'social capital' is a decisive element in the light of regional and firm performance. They further stress the importance of such capital with respect to innovation: "innovative firms tend to make greater use of collaboration and information exchange, be involved in higher trust relationships, and make greater use of non-local networks" (p. 1074). There is an important role of individual firms that perform well in this respect, that according to the latter reside mostly in the stronger regions. In paragraph 3.2.1, this idea is accompanied by the particular notion of so-called 'gatekeepers of knowledge' that also are of importance regarding clusters. Looking in foresight to sections 3.2 and 3.3.1, stronger regions that thrive on the basis of agglomeration economies and also supportive institutions as argued above are according to Cooke et al. self-reinforcing structures that stimulate and are built upon synergy between all relevant actors involved.

Coming back to Germany on the European mainland, Breitenecker et al. (2017) stress the importance of taking into account regional heterogeneity when studying entrepreneurial activity. This then translates into the acknowledgement of 'regional embeddedness of entrepreneurship' and thus industrial concentration as well, and, as they argue, too high of an aggregation level studying these phenomena leads to misinterpreting the spatial and socio-economic situation at hand thereby affecting policy as well. This is an important insight to take into account in further steps in the analyses, i.e. the methodology (chapter 4), although data-availability of course limits the researcher to an extent.

Boschma et al. (2002b, p. 28) (empirically) found an inverted u-shape in the relationship between embeddedness and innovative performance. They confirm the balance as being a bedrock for firms' and more general economic viability. In the light of resilience, the above claim 'adaptive capacity' depends on this relationship, which importantly includes combinations of connections both proximate – more than the spatial notion alone – and distant when talking about networks. Considering industrial concentration with respect to proximity, it can similarly be argued – as exemplified above with the idea of (negative) lock-in – that there is likely a (dynamic) optimal distribution of connections that allow for both flexibility and focus. Boschma (2015) in regard to regional resilience speaks of ideally having 'loosely coupled networks'.

The next section dives into these ideas, yet networks per se are no units of analysis (see chapter 4). Rather, (regional) industrial structures are conceptually explored, and a bridge is attempted to be established between the notions accompanying industrial concentration and proximity examined above and industrial relatedness from an evolutionary perspective.

3.2 Techno-industrial relatedness and diversification

As described above very briefly, techno-industrial relatedness is a notion that captures recent areas of scientific discussions, especially related to resilience and (new) growth paths (Boschma, 2015; Pike et al., 2010). Specialization on the other hand – this idea however is intertwined with the former as becomes clear in the following sections – is lately associated with regional tendencies of (technological) *lock-in*, in particular with respect to knowledge networks and how these function in spatial economic clusters. This in turn relates to resilience, and, also, a lack of it (Crespo et al., 2014). Specialization is not argued upon in this thesis as being a negative spatial economic phenomenon – on the contrary. Industrial specialization has brought large amounts of economic growth and prosperity – especially in the industrial epochs of the UK (Martin et al., 2016, p. 581), yet under the right economic and also institutional circumstances as argued above. Particularly interesting is the interplay between the two ideas – specialization and relatedness – and the effects on resilience and the socio-economic context that *enables* growth and development, here in the light of crisis-recovery and future growth paths.

3.2.1 Related variety: an evolutionary perspective

In this thesis, related variety, a concept thoroughly explored by Dutch evolutionary economic geographers like Ron Boschma and also Koen Frenken, is assumed to play a significant role in the face of the 2008 financial crisis. And, more broadly, in the literature with regard to resilience of UK regions and the country as a whole after economic crises, the notion is regarded important for economic development and recovery/reorientation as well (Bristow & Healy, 2020; Martin et al., 2016).

Boschma and Iammarino (2009) empirically tested the influence of techno-industrial relatedness in Italy, and found regional effects of economic growth. This particularly has been related to "extraregional knowledge sparking intersectoral learning across regions" (p. 289). *Complementarity* of economic activities according to them is key and this refers back to the discussions in sections 3.1.1 and 3.1.2 about learning processes that can also be related to organizational routines and their embeddedness in the regional context. The question raises how resilience and a 'bounce forward' are achieved and how they connect to innovative economic activities. Complementarities and/or synergy between actors in and within regional territories and their connections beyond (think of knowledge networks), are important indicators which are however difficult to capture (Breschi & Lissoni, 2009).

In the following sub-sections, attention will be paid to these aspects more in-depth, also with regard to *tacitness* of knowledge and how this influences regional and also organizational economic performance. Techno-industrial relatedness in this respect is largely intertwined with and related to knowledge flows and interdependencies and/or complementarities between actors, e.g. firms and workers, on certain spatial scales (referring to proximity again) (Eriksson, 2011; Asheim et al., 2011). This is why the notion of 'knowledge flows' comes up quite often in this sub-section as well.

Frenken et al. (2007) connect related variety to so-called 'Jacobs externalities' (i.e. value derived from economic diversity), and argue that these with regard to employment are growth-enhancing. Yet, productivity growth has according to them more to do with "traditional determinants including investments and research and development expenditures" (p. 685). Furthermore, is it argued that productivity growth can most easily be achieved through fostering and developing manufacturing/production activities that also lead to "unconditional labor productivity convergence" (Rodrik, 2016, p. 3). This productivity growth then also depends on talent- and resource-absorbing entrepreneurship (Nelson & Pack, 1999), referring to section 3.1.4. As the UK is already a mature and developed industrial country with relatively high wages, the question comes up *how* these economic activities may still foster productivity and thus economic growth. Perhaps there is a role for techno-industrial relatedness in this respect, and thereby finding new niches is relevant in discussions regarding 'smart specialization'.

It can be argued that techno-industrial relatedness or related variety and its knowledge-transmitting mechanisms to be more precise, induce complementarities of knowledge as stated above, and thus are accompanied by and/or reflected in learning processes that may enhance productivity (see section 3.2.2). Moreover, countries like China and also to a lesser extent former UK colony India demonstrate that high growth in the service sector is possible (Bosworth & Collins, 2008). Here, in rather economic discussions that are not dealt with in detail in this paper, referring to value added can be pertinent. Arguably, The West is in general characterized by high value-added economic activities yet shows moderate figures of economic growth with however variations across countries, for instance depending on their general economic model which has been discussed in sections 2.3 and 3.1.3.

Coming back to R&D investments, these are largely attributable to bigger companies with sufficient resources available to them, and of course these investments are based on organizational intelligence, routines and related to built-up knowledge networks – for instance with key roles for 'gatekeepers of knowledge'. The latter are embodied by leader firms that are found to actively and strategically appropriate knowledge obtained from external and often extra-regional *related* sources and partners. How this particular knowledge is then disseminated across space is more complicated and reserved mostly for relationally proximate actors and firms (Morrison, 2008). The latter can be linked back to the earlier mentioned processes of lock-in as well and raises questions about which particular economic activities are important for wider economic development and how this is engendered (see section 3.2.3). What bridges into the following section are the actual (skilled) individuals but also companies that are embedded in wider socio-economic and industrial structures and how they function in a way that contributes to regions' and country's competitiveness. However, before that, the notion of 'unrelated variety' will be briefly touched upon.

3.2.2 Unrelated variety

Having discussed the concept of related variety, its counterpart, unrelated variety, also deserves some elaboration. As the name gives away, *unrelated* variety refers to economic activity of firms in (initially) industries that are technologically more distant from each other and do not necessarily share knowledge links in the area in which they are present. Referring to Frenken et al. (2007), unrelated variety is in terms of industrial structure linked to notions of 'portfolio', meaning that 'risk' – thinking of lock-in – is spread amongst more branches of economic activity. This is particularly of interest when thinking of resilience. Kitsos (2020) for instance has analyzed this phenomenon with regard to the 2008 financial crisis (but found no significant effect). The idea is however that unemployment is avoided to an extent when an economic shock hits the region of interest.

Bishop (2019) goes even further and claims that – underpinned by his empirics – unrelated variety leads to economic growth by itself as more radical innovations emerge because technologically more distant industries cross-over and break from the prevailing paradigms. Importantly, Bishop's analysis allows for interregional affiliations in entrepreneurship. His study furthermore concentrates on Great Britain and also with regard to the 2008 financial crises and recovery.

Boschma (2015) finally sheds light on determinants of resilience including (un)related variety and pays attention not only to recovery but also to growth paths after economic shocks. Basically, he asks for more scientific attention to growth after economic downturn from an evolutionary perspective.

Thereby, Boschma states that there is a need for understanding contributions of both related and unrelated variety and their contribution to regional economic compositions with respect to future paths of development. Webber et al. (2018) also point at this caveat in knowledge; particularly the relationship between resilience and growth. Because of this, the focus of resilience may be shifted from regions experiencing and enduring economic downturn to recovery focused on regional capabilities of finding new paths through adaptation. Clearly, (un)related variety plays a role in this respect, yet other related and supporting regional characteristics are of importance when (statistically) explaining growth and recovery.

3.2.3 Skills and competitiveness

The country profile (chapter 2) deals with the presence of skilled labour in the UK. Skills are a crucial building block for any country and economy that wants to thrive, and they simultaneously shape the patterns of economic development, specialization and thus also competitiveness in regional but also (inter)national perspectives. Of course, what has been demonstrated above is that no single element in the economy operates on its own, and should be interpreted as a composition of (ideally) reinforcing elements.

It can be argued that economic geography plays an important theoretical and empirical role in research on regional competitiveness (Huggins & Thompson, 2017). Skills in this light are embedded in regional socio-economic structures and/or 'innovation systems'. According to the latter, education but also upgrading of technological capabilities of firms, and, broader, regions or countries is crucial to foster economic growth and development. Regarding competitiveness, Huggins and Thompson stress a continuous process of 'catching up' and operating at technological frontiers. This of course relates to the particular knowledge and skills that are present and prevalent in the UK or Great Britain in this case, and the question is whether the related economic activities are functioning at these frontiers.

Knowledge is in the literature often regarded as either 'codified' or 'tacit' (De Bruin & Ferrante, 2011; Johnson et al., 2002; Rallet & Torre, 2019), and individuals, firms and regions are to differing extents able to exploit and appropriate (new) knowledge. The latter is reflected in their *absorptive capacity*, which also is intertwined with learning processes as discussed above, and shapes their paths regarding economic development and competitiveness in the sense that availability and appropriation of knowledge embodies entrepreneurial opportunity and innovation, which is moreover spatially bound as demonstrated below (De Bruin & Ferrante, 2011).

There are many angles and dimensions from which these aspects related to knowledge can be approached, yet what in this thesis is most relevant is the 'economic geography of innovation' that dives into spatial patterns of innovation and co-location of firms and human capital (Rallet & Torre, 2019, p. 427). The latter argue, just as Breschi and Lissoni (2009), that skilled workers are to a certain extent *bound in space*. In other words, geographical proximity matters, and it is according to Rallet and Torre precisely this *tacit* knowledge that characterizes the professional (and social) trails and ties these individuals 'mark in space'. The earlier mentioned mechanisms of knowledge transfer (section 3.2.1) are according to the latter still underdeveloped in terms of scientific analysis, or, at least, scholars are still unable to obtain the complete picture in which innovation in time and space is captured.

It is further interesting to consider the digital revolution and increasingly advanced communication technologies that perhaps counterintuitively do not seem to replace but rather complement real-life and face-to-face (business) contact. Attracting, retaining and fostering economic activity characterized by complex knowledge (Balland et al., 2019) is what most likely will contribute to local, regional or even national competitiveness.

What stands out regarding the introduction and country profile is that the UK has a couple of core-regions and also sectors based on output, export and skills amongst others, that have moreover demonstrated *resilience* after multiple economic crises (Martin, 2012; 2016). In the light of the Great

Recession, it is interesting to investigate whether these same regions and sectors are most important with regard to overall resilience by adding ideas concerning related variety and (in conjunction with) industrial concentration.

3.2.4 Growth paths

Intuitively, identifying growth paths means that regions or countries diversify into new economic activities that ideally are related to existing ones (Boschma, 2015), and, as the concept says, realize economic growth. Pike et al. (2016) in their book on 'local and regional development' stress that growth should be socio-economically inclusive, which means that 'resources' situated in the region under consideration are tapped and developed to the best possible extent. A counterargument to this could be that this hampers economic efficiency and perhaps even wastes resources in the sense that less viable elements are included which do not engender growth whilst others do. In the case of the UK this interpretation makes sense as the economic structure is more inclined toward efficiency and letting market forces prevail.

In the light of this chapter, there have been defined a spectrum of elements that contribute to growth paths which moreover fit into the evolutionary rationale in economic geography with the notion of *path dependency* at its core. What can be said here is that growth paths are *a priori* difficult to determine (as stated before), but economic activities that are promising in the light of industry relatedness and innovation *can* be identified and perhaps also be fostered when directing policy – both government and industry-induced. An example of this is found in the Dutch city of Eindhoven which has transformed itself from a declining and traditional industrial area into a vital high-tech cluster generating spin-offs that performs at the forefront of technology and contributes largely to the regional and national economy. In this respect there has been adopted a certain policy model that draws from industry, government and university – the so-called 'Triple-Helix' (Fernandez-Maldonado & Romein, 2010). This policy rationale will not be discussed here, yet it touches on the actors or parties mentioned in this chapter that in turn relate to the *resources* contributing the regional development.

Grillitsch and Sotarauta (2018) in the light of path-dependent regional growth paths also adopt a holistic view on growth – including (innovative) entrepreneurship – and moreover refer to agency and related *perceived* opportunities in time and space. The interesting observation by them is that, as has been demonstrated above in a slightly different way, regions with "similar structural preconditions" (p. 12) have different outcomes when talking about growth. Webber et al. (2018) in this regard claim that exactly the differences in 'coping' with economic developments, either positive or negative, define these growth paths. Empirically speaking, regions with large employment shares in 'resilient sectors' – i.e. not very sensitive to demand fluctuations – which would be financial services amongst others in the UK and South-East England, experience "more stable growth rates and be more resilient to economic downturns" which thus has an important evolutionary component (p. 2).

In the next section, a schematic synthesis is drawn from this and the previous chapter. As will be made clear below, not all concepts and ideas are empirically included, yet a firm framework is adopted that sheds light on regional resilience from an evolutionary perspective centered on Great Britain following a clear narrative.

3.4 Conceptual model

Figure 5 depicts the most important relationships that are examined in the current theoretical framework. Sections 3.1 and 3.2 together laid the foundation for both a pertinent interpretation of regional resilience and also the related socioeconomic elements of which industry relatedness and concentration form the core ideas that are under consideration throughout the thesis. Bearing the study's aims in mind, it can be tempting to look for an 'optimal' composition of the constituent elements in the conceptual model in order to arrive at growth paths and also a *bounce forward* would be ideal but is not realistic for every region. These discussions are however reserved for chapter 5.

The outer left box containing 'pre-existing conditions' also features elements that are presented in the country profile (and in extension the two sections in Appendix I). The bold concepts – 'techno-industrial relatedness', 'concentration' and 'resilience' – constitute what is considered the most important relationship in this thesis as stated above. Growth paths leading to a bounce forward represent possible outcomes that are embodied by the notions in the fifth and somewhat larger box to the right. Importantly, the boxes and the connections between them are to differing extents reciprocal and/or reflect synergy. This will be examined further throughout the thesis.

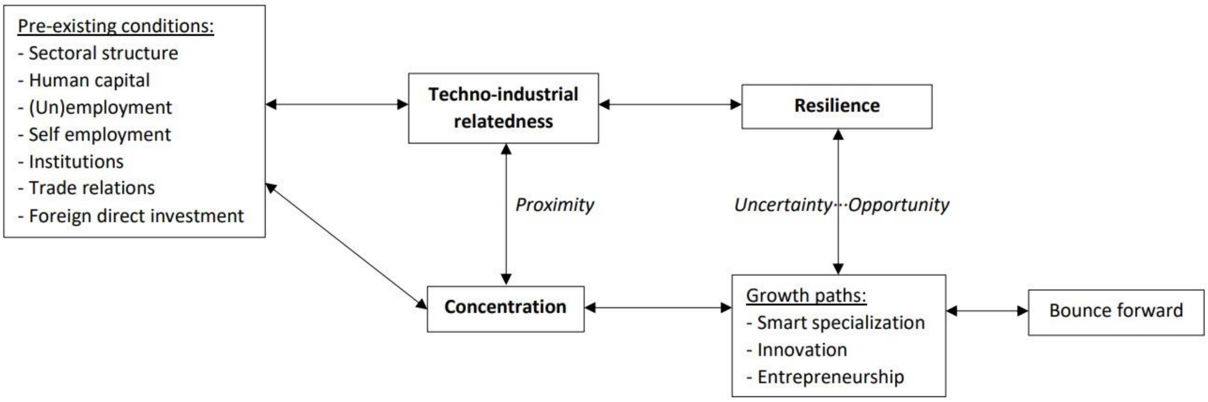


Figure 5: Conceptual model (Source: own elaboration)

Important to acknowledge is that not every element and/or concept discussed in this chapter and depicted in the conceptual model is (directly) usable with regard to the empirical models discussed in the next chapter. However, in essence, the theory that is covered and put into perspective above is a reflection of what is the most important narrative that overarches and epitomizes what would ideally be studied in detail. What actually *is* studied in detail depends also on the data that are available (see section 4.1), and on some creativity in what to do with these data.

Related to the main variables of interest – techno-industrial relatedness (including industrial variety), industry concentration and of course resilience – are certain notions of human capital and entrepreneurial activity that have also been extensively discussed above as these elements are regarded crucial in regional economic growth and development. Regarding growth paths, these are implicitly analyzed by calculating the dependent variables and observing which regions are most resilient – i.e. which ones have recovered most in terms of employment. Innovation and entrepreneurial activity contribute (assumed) quite heavily to this process. However, the focus in this thesis and also the theoretical framework is on industrial structures and their properties. Thus, the variables that will be operationalized in the following section besides the core variables are more thought of as supportive to the narrative and also oftentimes as *fixed effects* as several do not change in time rapidly.

Furthermore, smart specialization in the fifth box in the conceptual model above does not integrally feature in the empirics either. However, in the concluding section there is some attention paid to interesting perspectives in this respect.

Leading into the next section and in particular referring to subsection 4.5, economic *complexity* is what is sought to capture in this thesis. Techno-industrial relatedness, industry concentration and the control variables that will be covered in chapter 4 are set-up to approach this notion to the best possible extent yet within the limits of the time and resources this project is characterized by. As will be made clear, these concepts in conjunction with each other shed new light on what we already know.

4. Methodology and operationalization

This chapter outlines the quantitative methods that are employed in order to answer the research questions. Firstly, the data and units of analysis are described in section 4.1, and after that the three approaches this thesis takes are elaborated on in detail. Basically, there is an overarching regression analysis that captures measures of resilience in its dependent variables employment-recovery and unemployment-recovery. These variables are then put on the left hand side of the equation that includes a list of controls and also – and that leads to the second and third approach – explanatory variables of (un)related variety and industry concentration that are the main variables of interest. In order to obtain the latter variables and values, two indices are calculated for every region and they are also depicted in the appendices in maps produced in ArcGIS Pro.

4.1 Data and units of analysis

Regarding the regions mentioned above, these form the units of analysis. In particular, 371 so-called 'Local Authority Districts' (LADs), which are local administrative units, are used throughout the analyses. There has been made a choice to utilize the UK's LAD division of the year 2019 because all data in this thesis runs up to this year which ensures to the best possible extent consistency throughout the research project.[8] Furthermore, regarding variables 'firm birth rates' and 'firm death rates', there have been performed some harmonization steps to make the old LAD divisions match the ones in 2019. In particular, data for several LADs that were in different boundaries according to the 2015-division have been merged into the 2019-division. The details of these modifications are shown in appendix III. It is also important to note that the 11 LADs that pertain the Northern Ireland have been left out of any of the analyses. The reason is that data for multiple variables are not available from the main source of nomis - Official Labour Market Statistics; a data "service provided by the Office for National Statistics, ONS" (nomis, 2022, para. 1). Omitting Northern Ireland is a flaw in the research approach, yet it can be argued that the region constitutes only a small part of the UK and is (at least culturally) more distant to Great Britain.

The dataset itself that has been put together as said mainly originates from the UK's national statistics bureau (Office for National Statistics). The latter source provides rather rich data by gathering data through population surveys. The samples they draw are large enough to cover every region – even at the LAD-level. Importantly, the statistics bureau collects employment data by means of its Labour Force Survey which is its largest household survey that however (logically) bears some uncertainty in the results which is discussed briefly in the following section (4.1.1) (Office for National Statistics, 2021f).

With respect to the units of analysis, Kitsos (2020) argues that LADs approximate local labour markets to the best extent when working with regional data in the UK. According to the latter, this property the data is characterized by is appropriate when studying (regional) resilience, which is also confirmed by Faggian (2018, p. 397). Moreover, even at this fine-grained level of spatial-economic analysis, the explanatory variables still represent relatively large numbers of individuals with however several exceptions that are discussed in the following section. There is much variability (and commonality) between the LADs in size and characteristics, but the relatively large number of 371 ensures generalizability in the view of the author and others that have done research in this area – even more so as these regions (of course) belong to the same country they are situated in. The smaller regions can furthermore be aggregated into larger ones such as the NUTS-1 regions including the whole

[8] A full list of these LADs and their subdivisions under larger regions is provided on the website of NOMIS - Official Labour Market Statistics and/or can be requested from the author.

of Wales and Scotland which Kitsos has also done in his study and which can be interpreted as regional fixed effects.

4.1.1 Missing data

With respect to missing data, there are several reasons for this considering the dataset that is used. First of all, the data are *not* missing at random due to the good coverage of the surveys. However, there are good reasons for this, of which there is one of the risk of 'disclosiveness' when samples are too small. Unemployment figures are a good example of this which are figures based on model estimations and for instance omit the Isles of Scilly which lack data registrations in other variables as well and have only 2000 inhabitants (see the nomis Annual Population Survey which can be retrieved from Office for National Statistics (2022) that is in the list of references below). Another omission is the City of London. Of course there are also the above-discussed 'structural changes' in LAD divisions between 2015-2019 that result in missing data as well for multiple years regarding firm birth- and death rates. This has been dealt with to the best possible extent. Essentially, missing values which range from about 1-10 cases out of 371 are ignored by the models.

4.2 Approach I: Measuring resilience

Kitsos (2020) performs a regression analysis for the UK regarding resilience based on socio-economic indicators with respect to the Great Recession. He presents a theoretical framework named "The Determinants of Resilience", consisting of: 'pre-existing conditions'[9], 'industrial structure', 'specialization and diversity', 'human capital' and 'agglomeration economies' (p. 193), from which he derives variables that are analyzed with respect to 'employment impact' in the form of a multiple linear regression analysis.[10] 'Employment impact', or, 'employment recovery' in the current thesis as a dependent variable suggests that the aspects just described are related to employment changes and also in terms of *defining* resilience, this variable in itself aligns with the 'evolutionary nature' of the theoretical framework above (see section 3.1), and also referring to the mentioned work of Martin (2012) and Fingleton et al. (2012). Essentially, employment figures are better representations of economic development and change at the local geographical scale compared to mere growth figures, and further relate to other socio-economic and spatial indicators (Kitsos, p. 192) that have been mentioned in the latter's work and also in chapters 2 and 3 above.

The counter-relationship in Kitsos' (2020) approach to measuring resilience is between the independent variables and 'unemployment impact'. Just as the earlier mentioned employment impact, the variable represents the average (un)employment rate of a LAD in the crisis period in conjunction with either the minimum/maximum rate in the preceding period (p. 193). Along with these two variables, 'FTE impact' (full-time equivalent) and 'JSA impact' (job seekers allowance) are also used by the latter as they as they capture the flexibility in the UK's labour market – especially important with regard to economic crises, which moreover resonates with the analyses in the country profile. However, in order to maintain focus and keep the analyses manageable in the scope of this project, only models estimating resilience regarding (un)employment figures are included.

On the basis of the current theoretical chapter and following amongst others Faggian et al. (2018), more and/or other variables can be derived – yet the challenge lies within the time frame. Regarding data availability with respect to many used variables and the choice to avoid the period affected by Covid-19 in the analyses, only models up to 2019 will be fitted, and so the rationale for the methodology has to be tailored to this limitation. This does not mean that measuring regional

[9] See also Chapter 2 (Country Profile) of this thesis.

[10] The particular chapter written by Kitsos (2020) which is based on his earlier work – Kitsos (2018) and Kitsos and Bishop (2018) – is referred to often in this section as the work functions as the basis of this part of the analysis: measuring resilience by means of regression.

resilience this way cannot be extrapolated in any sense with regard to future crises and economic shocks such as resulting from Covid-19 and perhaps also Brexit. However, the aim of the thesis is to learn from and reflect on recovery from the most recent *financial crisis* and the mechanisms that underlie this process – amongst others because of the UK's economic structures as described above and as there is rich data (now) available. Furthermore, there are a couple of sound studies in this field already (see for instance Martin et al. (2016)), however not including the most recent data and with different perspectives that may overlap or can be individually 'gathered' from across such studies throughout the last decade.

The approach taken in this thesis assumes that departing from the situation that is pre-recovery – 'pre-existing conditions' as Kitsos (2020) defines them, however in his research project pre-*crisis* – are, also according to the latter, of great importance when facing an economic change that puts the regions' resilience to the test. The current analysis itself however is limited to – except for the dependent variables and the average of firm birth/death rates over 2015-2019 – including the effects of covariates for the year 2019. Doing a panel analysis instead with all of the available data from 2008-2019 would also be a possibility and would potentially yield even more interesting results with a time dimension included, also referring to Faggian et al. (2018) who point at the research gap related to analyzing long/short inter-period resilience and the effects they have on each other. Yet, again (as also a rather extensive spatial analysis is included), this idea will be reserved for future research which is discussed in the concluding section.

The focus on evolutionary economic concepts furthermore stems from the idea that economic change is rather incremental and path-dependent (Boschma et al., 2002) – yet often not predictable (!) – and related to adaptation and adaptability as mentioned in the theoretical framework above. Incremental changes are assumed here to lie within industrial and socio-economic developments such as sectoral contractions and growth, but also population changes and changes pertaining to the labour market which is essential in this thesis. As these changes – reflected by the chosen set of explanatory variables – are *mostly* characterized by a rather slow pace and/or constant in time, the choice for a cross-sectional regression model is pertinent. However, (un)employment-related recovery but also firm births (or in conjunction with one another), can take on rapid pace and therefore this is reflected in the dependent variables that are outlined in table 3 in the next section.

As follows from the research question presented in chapter 1, two of the most important factors regarding resilience are assumed to be techno-industrial relatedness and industrial concentration on a regional level. To this end, in section 4.3.1, a so-called 'entropy measure of diversification' (Jacqemin & Berry, 1979) is elaborated on that initially serves as an explanatory variable in the regression analysis. Section 4.4.1 deals with the Herfindahl-Hirschmann Index (following Brezina et al., 2016) that is as a next step also combined with the former index. Below, in section 4.2.1, an overview of the dependent variables and a summary of the explanatory variables is presented along with the econometric model that is used.

4.2.1 Econometric model and operationalization

In order to measure the relationships as broadly explained above, the following basic econometric specification (1) – a multiple linear regression model adapted from Kitsos (2020, p. 197) – will be used in the analysis. 'Recovery' with regard to the financial crisis in this equation means that the LADs under consideration are to differing extents capable of growth and renewal after this economic shock. This implies that employment recovery which has been described above is related to the regions' and thus the country's economic performance when facing crises. The particular variables that are analyzed below dig into this relationship.

$$Recovery = a + \beta_i X_i + \varepsilon \tag{1}$$

The dependent variables representing 'Recovery' in model (1) are given in table 3 below, which is adapted from Kitsos (2020, p. 193) as well and provides the mathematical expressions. The entire list of independent variables with descriptions is presented in Appendix IV. As the adverse employment effects of the Great Recession had rippled out by 2015 – looking at UK unemployment rates obtained from ONS by Lea (2018, p. 3) and following Kitsos – the time span for measuring resilience runs from 2008 to 2014 (crisis) and from 2015 to 2019 (recovery) which means 12 years in total. The dependent variables under consideration are particularly powerful as they allow for interregional variations in employment figures by using a 'peak-to-trough' method that considers minimum-maximum values in this time span. Kitsos argues that this method deals with "differential temporal aspects… as well as increased uncertainty and noise in survey data for lower geographical levels" (p. 192).

Regarding the employment rates presented in table 3, this peak to trough method is exploited, yet this time looking at average *maximum* employment rates and *minimum* unemployment rates instead of the lowest figures each year for 'employment impact' and maximum rates for 'unemployment impact'. These choices were made because the rates demonstrate the capabilities of the LADs in recovering, which also says something about adaptation and adaptability (see section 3.1.1). Picking precisely three maximum/minimum employment respectively unemployment rates in expressions Xi was decided on rather arbitrarily. It can be argued that three out of five (un)employment rates allow for incorporating enough variation for every LAD whilst not being too selective or arbitrary when instead only one or two rates would be picked that would lead to a possibly too bright picture. When using four instead of three (un)employment rates, the main variables of interest (industry concentration and relatedness) turn out somewhat more statistically significant yet the overall model's explaining power (R^2) becomes somewhat weaker with some changes to other coefficients as well. In order to adhere to the peak to trough principle, three years out of five are worked with.

Table 3: Dependent variables representing 'Recovery' (Source: adapted from Kitsos, 2020, p. 193)

Measure	**Mathematical expression**	**Xj**	**Xi**	**Resilience is greater when variable is…**
EMPrecovery	Xi-Xj	Average employment rate of a LAD for 2008-2014	Average of the three maximum employment rates of a LAD for 2015-2019	(More) positive
UNEMPrecovery	Xj-Xi	Average unemployment rate of a LAD for 2008-2014	Average of the three minimum unemployment rates of a LAD for 2015-2019	(More) positive

With regard to the explanatory variables represented by X_i in formula (1) above, as said, UK nomis-data is used. These data along with the units of analysis are elaborated on in section 4.1 above. Initially following Kitsos' (2020) regression analysis regarding the UK during and before the financial crisis, a basis of several explanatory variables will be extracted from the dataset that has been compiled but includes also newly added variables and/or modifications in time and space (e.g. regional dummies and the main variables of interest that feature in the interaction terms as well). These are presented below in equations (2) and (3); their descriptions are given in Appendix IV and in section 5.1 (table 5) the descriptive statistics are provided.

Importantly, the operationalization of the concepts dealt with in the theoretical framework leading to the conceptual model is rather close to the work of Kitsos (2020) as stated above, yet the particular angle in this thesis of analyzing industrial relatedness and concentration and thereby adhering to *evolutionary* thinking, variables are selected on a basis of contributions to resilience in both a regional/spatial and a temporal dimension. The latter however only counts for the two variables of firm birth and death rates and the two dependent variables (as mentioned above). The other covariates include the starting point after which the (selected) recovery period commences – (un)employment rate in 2014 – following Kitsos who picked the year of 2007 before the crisis commenced. The self-employment rate has been chosen to represent entrepreneurial activity (see section 3.1.4) yet this is a rather broad and encompassing variable as will be discussed in the results section. Next to firm birth and death rates it is motivated here to resemble innovative activity as well, yet patent data for instance would have been preferable to track innovation more precisely in time and space. Nevertheless, including this variable is considered important as/and it also correlates with the main variables of interest (see table 6 below).

With respect to education and training activities, there has been made a distinction between three types, namely 'on-the-job training', having a degree (or not) and having the highest level of National Vocational Qualifications (NVQs), all regarding the working age population. As elaborated on in the theoretical framework (see sections 3.1.3 and 3.2.3), on-the-job training is regarded as workers acquiring more *tacit* knowledge and know-how in their particular job. As this is assumed to be of great importance to industrial dynamics – i.e. industrial relatedness, concentration and growth in the mentioned 'learning processes' regions undergo – the variable is analyzed quite thoroughly in the results chapter.

The other three variables are to test for possible impact of high-level education either obtained in a more 'general' way like in knowledge institutes as universities resulting in a degree (or not), and to test for the effect of presumably more job-related education in the form of NVQs. The highest levels of qualifications are chosen as the sector(s) under consideration are expected to benefit most from these. Finally, having no degree (or qualification) at all is quite the opposite and is included as a control. See also section 3.1.3 for elaboration on differences in education levels (related to entrepreneurial activity).

The variables that are most obviously in line with the perspective of this thesis – X_7, X_8, X_9 and X_{10} – are discussed in the following three sections within this chapter. What can briefly be said here is that these explanatory variables are, especially (the share of) industry relatedness, adding to the literature with respect to resilience. Furthermore, comparing precisely the shares of related and unrelated variety in conjunction with industry concentration (in the UK) has to the author's knowledge not yet been studied at this level of detail and in this particular set-up.

To conclude, population density is expected to impact resilience as this is a proxy for urbanization that was highly significant in the work of Kitsos (2020) as well and referring to the theoretical framework above. Age groups are also taken over – however different categories – from the latter. Especially the (younger) working age population is expected to contribute to resilience and for instance easier job-finding processes that also correlate with the main variables of interest, e.g. relatedness. The regional dummies in fact resemble fixed effects and control for larger (NUTS-1) regions in Great Britain that are assumed to experience either positive or negative effects with respect to resilience. More precise, regions such as London (the obvious) probably outperform other regions, and Scotland may fall behind for several reasons. These discussions are held in chapter 5.

Below, equations (2) and (3) respectively represent EMPrecovery and UNEMPrecovery:

$$Y_i = a + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_{13} X_{13i} + \beta_{14} X_{7i} X_{9i} + \beta_{15} X_{7i} X_{10i} + \varepsilon \qquad (2)$$

$$Y_i = a + \beta_1 X_{1i} + \beta_2 X_{2i} + \ \ldots + \beta_{13} X_{13i} + \beta_{14} X_{7i} X_{9i} + \beta_{15} X_{7i} X_{10i} + \varepsilon \qquad (3)$$

i = 1, …, 371; where i denotes the number of the 'Local Authority District' (LAD).

X_1 = (Un)employment rate 2014 (LAD-level)
X_2 = Firm birth rates/firm death rates (average 2015-2019) (LAD-level)
X_3 = Self-employment rate (LAD-level)
X_4 = On-the-job training (LAD-level)
X_5 = Education level (having a degree/NVQ4+) (LAD-level)
X_6 = Having no degree/qualification (LAD-level)
X_7 = Industry concentration (Herfindahl-Hirschmann Index) (LAD-level)
X_8 = Unrelated variety ('Across' Entropy Index of diversification) (LAD-level)
X_9 = Related variety ('Within' Entropy Index of diversification) (LAD-level)
X_7X_9 = 'Relatedness within concentration' (LAD-level)
X_{10} = Share of (un)related variety to total variety (share Within/Total) (LAD-level)
X_7X_{10} = 'Share relatedness within concentration' (LAD-level)
X_{11} = Population density (log) (LAD-level)
X_{12} = Age groups (16-24, 25-49, 50-64) (LAD-level)
X_{13} = Regional dummies (London, South East, South West, East, North East, North West, Scotland) (Aggregated LADs)

4.3 Approach II: Measuring relatedness and diversification

In order to measure techno-industrial relatedness, there are several indices at the researcher's disposal that can be placed into three categories: categorical, SIC based and input based (Nocker et al., 2016, p. 200). According to the latter, the first category is rather subjective and hard to reproduce as it depends on the researcher's decisions of which industries to include and thus how related they are, and the third category consistently struggles with data availability regarding sales, R&D and so on. The second approach is not perfect either as it "wrongly assumes same distance between all 2-digit industries" (p. 200), yet it has been and is widely used and is relatively easy to calculate and replicate (Jacqemin & Berry, 1979; Palepu, 1985). Moreover, Palepu (1985, p. 244) argues that although SIC based measures have limitations, the classification system itself is well accepted, and the novel methodology (at that time) used by him lead to similar results as were obtained by his predecessors in diversification and relatedness research which indicates robustness across methods (Palepu, 1985, p. 250). Several decades later, the insights still validate theory and methods by prominent economic geographers – e.g. Ron Boschma, Philip McCann, Koen Frenken and also Pierre-Alexandre Balland who feature in the theoretical chapter of this thesis as well. This makes the current rationale and proposed method particularly interesting[11] – even more so as Kitsos (2020, p. 203), referring to Frenken et al. (2007) who study (un)related variety making use of similar indices, points at a possibly important role for industry relatedness/related variety with regard to resilience (in the UK), in addition to merely diversification, yet requires further examination to deepen the understandings.

[11] More sophisticated indices may add more value to the literature by – if possible – correcting for different dimensions of proximity. For instance, Bryce and Winter (2009) developed a 'A General Interindustry Relatedness Index' which "captures the knowledge relatedness structure underlying the U.S. manufacturing economy in the ways that firms actually combine resources to create value" (p. 1582). It would be interesting to incorporate the latter into employment-related empirics and thereby extending pure sectoral accounts of relatedness.

4.3.1 Entropy measure of diversification

Jacquemin and Berry (1979) discuss the often used 'Herfindahl Index' in comparison to 'the entropy (inverse) measure of industry concentration' (adjusted to industry diversification later in their paper – see J&B, 1979, pp. 360-361) and conclude that the first is inadequate in any direct decomposition of "additive elements which define the contribution of diversification at each level of… [the] aggregation to the total" (p. 361) – i.e. the distinction between 2- and 4-digit industry classes with regard to product groups in the paper of Jacquemin and Berry. This means that the Herfindahl Index is inferior in that respect compared to the Entropy Index, and, in addition, Palepu (1985) stresses the empirically tested importance of 'related diversification' which is captured by the latter index, yet with regard to firms' *performance* in the mentioned papers of both the latter and the former. The relevance of relatedness in diversification has also been confirmed in more recent work (e.g. Frenken et al., 2007) as discussed in section 3.2.1 above (theoretical framework), and is embodied by 'related variety'. The index is moreover picked up by Nocker et al. (2016) as an established measure of *relatedness*, who, just as Jacquemin and Berry, mention the distinction and relation between 2- and 4-digit SIC[12] industry classes.

Basically, in order to obtain an index of 'related diversification' (E_W), the latter state that the degree of 'unrelated diversification' – the index of the *across group* at the 2-digit level (E_A) – should be subtracted from the value of 'total diversification' (p. 200). Related diversification as a measure is derived because an 'extraction' is performed which takes the different shares of employment (in this thesis) across 4-digit industry groups but *within* the same 2-digit group(s), compared to the shares of employment in 4-digit industry groups that are present *across* different 2-digit industry groups (Jacquemin & Berry, 1979; Palepu, 1985). This will be demonstrated below. The mathematical specification that relates to 'total diversification' is the following:

$$E_T = \sum_{i=1}^{n} P_i \ln 1/\, P_i \tag{4}$$

"…where P_i is the share of either the *i*th firm (in the case of industry concentration) or the *i*th industry (in the case of industry diversification within the firm)" (Jacqemin & Berry, 1979, p. 360). In this thesis, P_i stands for employment shares of eighteen industries at the 4-digit level pertaining to broad industrial group 'K' (Financial and Insurance businesses). This broad category is the sum of these 18 industries or the three 2-digit categories (64, 65 and 66)[13].

Measuring the 4-digit *within* 2-digit Entropy Index is done by using the following equation[14] which however is for verification exercises as this sub-index is derived by subtracting E_A from E_T as explained above:

$$E_W = \sum_{i \in s} \frac{P_i}{P_s} \ln \frac{P_s}{P_i} \tag{5}$$

Further, "diversification at the 2-digit level – *across* 2-digit industry groups – may be written as" (p. 361):

$$E_A = \sum_{s=1}^{n} P_s \ln 1/\, P_s \tag{6}$$

[12] SIC is an abbreviation for 'standard industrial classification'.

[13] See Appendix V for the full list of 2- and 4-digit industries belonging to group K.

[14] For more details in deriving this equation from the preceding "general formula", see Jacqemin and Berry (1979, pp. 361-362).

The latter index (E_A) captures to an extent (at least conceptually) similar elements that the index in section 4.4.1 measures, as it considers diversification across industrial groups which resembles the earlier-mentioned ‘portfolio effects’. Different however is that it lacks the direct component of industry concentration in space. This will be elaborated on below and in the next section.

Regarding the latter equation(s), P_s relates to “a given 2-digit industry group (s), [for which] the proportion of the firm's total sales or production[15] within that 2-digit industry is given by” (p. 361):

$$P_s = \sum_{i \in s} P_i \tag{7}$$

Having laid out some of the formulae that are used in the current thesis, it is further important to note that techno-industrial relatedness measured this way “captures only the technological dimension of a firm’s activities” (Nocker et al., 2016, p. 200). Referring to the theoretical framework (chapter 3), relatedness is entwined amongst others with notions of *proximity* and also economic variety and specialization. The latter two concepts are expanded on in the next section and constitute another important variable in the analysis (see section 4.2 and appendix IV). Proximity however as has been mentioned can take at least five dimensions. The geographical dimension will be covered in the following section, and it is known that the latter impacts amongst others social and thus economic activity in space – i.e. bounds it – however in conjunction with the other dimensions (Boschma, 2005). It is interesting to derive and combine insights from the two measures of proximity in an empirical sense (see section 4.5).

4.4 Approach III: Measuring concentration

In addition to the diversification/relatedness index elaborated on above – and in particular the *within* entropy index – there are several approaches to rather easily assess industry concentration (could also be interpreted as a proxy for *specialization* and/or *variety*) by region, of which the first ‘broad perspective’ “… is to measure the extent to which a given national industry is evenly distributed spatially across the national urban system”, and the second “…to take a given region and to consider the relative contribution of each industry to the regional industrial structure” (McCann, 2001, p. 81).

4.4.1 Herfindahl-Hirschmann Index

In the perspective of this thesis, the most straightforward approach of measuring industry concentration as exercised by Kitsos (2020) and as explained by Brezina et al. (2016) is calculating the Herfindahl-Hirschmann index. The central idea is that industry (or product) shares distributed over certain units like firms or regions can be summed and squared so that a single measure of industry concentration ranging from zero to one is obtained for easy interpretation (more on this below).

Referring to McCann’s (2001) elaboration in conceptual terms, the index that will be used in this paper mostly aligns with the second approach. However, empirically speaking, the index that he adopted from Black and Henderson (1999, p. 324) – which is related to the first approach according to McCann – partly corresponds to the index used that is used in the current thesis. The difference is that the element of deviation from national employment is left out for the sake of simplicity, and obtaining the HHI-measures as such suffices for the analyses with regard to industrial concentration per LAD.

It is further interesting to infer industry concentration across regions by mapping the HHIs per LAD in GIS-software (see Appendix VIII/Section 5), besides statistical measures and by considering the concentration-thresholds that are explained below. For instance, properly visualizing the values

[15] In the current thesis it refers to the regions’ employment shares in a certain industry where *i* is an element of *s* in mathematical terms.

potentially makes visible ‘pockets’ of concentrated or dispersed economic activity in the UK. A next step would be to extend the GIS-analysis and employ clustering algorithms such as the ‘Hot Spot Analysis (Getis-Ord Gi*)’ that uses both data points as coordinates as well as polygons as input of which the latter would correspond to the 371 LADs (Esri, N.D.). This step is not carried out as the spatial analyses would become too encompassing.

Referring to clustering and proximity of knowledge and industries, the LAD-level’s HHIs resemble economic activity in local labour markets of which the industry shares under consideration now represent these underlying elements. It can be argued that the index in this line of thought is too simplistic and overlooks important idiosyncrasies within and across the regions. Case-studies would in this regard be interesting. In the following chapter, several LADs are picked out and are related to real-life examples too make interpretation more meaningful. Nevertheless, the HHI is used relatively often and also recently in the literature – moreover in the particular context of the current research project (see Kitsos, 2020).

According to Brezina et al. (2016, p. 53), “[the] HHI can result in two extreme values, a maximum value of one (in the case where a market supply is represented by a single operating entity) or a minimal value 1/n (in the case where all entities have equal market share)”.

In the particular context of this thesis, the use of the HHI is slightly different compared to the usage in the source paper; the index is tweaked according to the research question. Specifically, instead of using market shares, the shares of 4-digit industries with regard to the broader 2-digit industries are calculated by dividing each smaller industry’s employment figure by the summation of the three larger industries (64, 65, 66) for each LAD before squaring them. Obtained is then an HHI for every LAD which has a minimum of 0 and a maximum of 1.0. The equation of the HHI that will be used in this paper is given in specification (8) below and is adapted from Brezina et al. (2016, p. 53):

$$HHI = \sum_{i=1}^{n} (s_{ir})^{2} \tag{8}$$

The *r* representing regions is added by the author as the employment shares of industries *i* are calculated per LAD. The equation can be rewritten as follows:

$$HHI = \sum_{i=1}^{n} \left(\frac{E_{ir}}{E_r}\right)^{2} \tag{9}$$

E_{ir} is employment in sector *i* in region *r* and can take values related to sectors *i* = 1, 2, …, *n*. E_r stands for employment in region *r*, and as stated above this employment is embodied by the broad industrial group K (Finance and insurance). Importantly, in order to be able to test robustness across models, a sub-section of sector C (SIC 26, 27 and 28 out of manufacturing) is used to calculate both the HHIs and Entropy indices. This sector is classified by the author as high-tech manufacturing and consists of 41 4-digit industries (see Appendix VI for the full list). The decision to only include these three 2-digit industries was made because including all manufacturing sectors results in a very large number that would moreover be less comparable to sector K in this regard. Furthermore, high-tech industries likely share more characteristics with sector Finance and Insurance. Regarding knowledge spillovers, industrial sectors benefit more from these similarly as sector K (Frenken et al., 2007, p. 691).

In terms of interpretation, an HHI-value of less than 0.15 means an industry is *unconcentrated* in space, a value between 0.15 and 0.25 points at *moderate concentration*, and values of 0.25 and above mean industries are *highly concentrated* in space (Brezina et al., 2016, p. 53)[16]. For convenience and

[16] These classifications are according to Brezina et al. (2016, p. 53) adopted from the European Commission.

interpretative purposes, as industry *relatedness* is (also) the main variable of concern and both indices have different ranges, the HHI as an explanatory variable will be converted into a dummy variable with value '0' as unconcentrated (and moderately concentrated), and '1' for all values above 0.25 that are thus highly concentrated. 'Moderately concentrated' is not provided with a third category as most LADs are have relatively higher indices. A sensitivity check was included in the regression model and yielded non-significant results.

4.5 Relatedness within concentration: combining the indices

Levarlet et al. (2018) have examined 'the impact of the UK's withdrawal from the EU on regions and cities in EU27' in an economic report and also made use of the HHI. Their assumptions in employing the HHI include the same as adopted by Kitsos (2020), but they add to the rationale that a *complex* and *developed* economic structure[17] – which may be exemplified by the indices to an extent as explained in the sections above – in that perspective strengthens regions' ability to deal with shocks. In other words, the use of the HHI can be extended so that it arguably better captures the complexity and development of regional economic structures. This in particular can be achieved by adding the element of industry relatedness, or, related variety. The latter has been extensively discussed in the theoretical chapter above, and following Kitsos' (2020) suggested avenue for further research and also Frenken et al.'s (2007) deliberations, it can be argued that the growing interest in increasing economic complexity – for instance by smart specialization policy endeavors – and relating this to resilience is a pertinent way of analyzing the UK's recovery and growth after economic crises and being a precedent for future events.

Importantly, it is also argued and concluded in the report by Levarlet (2018) that the diverse economic structure relates to trade. This can be linked to the discussed phenomena of lock-in as well, because industries (or clusters) are on a spectrum of openness with regard to other industries either within their vicinity or not. It also matters in what stage an industry or cluster finds itself in, thereby briefly referring to cluster and/or industry lifecycles. As will be discussed in section 5.6 in more detail, there is a certain trade-off between relatedness and concentration in regard to being beneficial or not for regional resilience. Trade in itself will not be covered in this thesis however, yet is of course a significant part of economic structures and their behavior in space and therefore serves as an element of illustration in how agglomerations of different natures operate.

In addition, what Black and Henderson (1999, p. 327) are saying is that "individual industry mobility seems to be constrained by interindustry linkages". Their observation is that industry mobility is not limited by size of a particular agglomeration, yet Faggian et al. (2018) are saying that medium-sized cities (50,000-100,000 inhabitants) are most *resilient* in the Italian context but also beyond because of their assumed 'responsiveness' and ability to adapt faster to economic change. Because population density accrues more to agglomeration economies however, the latter is included. Further, in order to control for population size yet in a more detailed way, the above-mentioned age groups are included as well in all models. It has also been tested that these age groups have more statistical explaining power than solely using population size. This breakdown including population density thus contributes conceptually more to the notion of economic complexity.

How all this relates to using both indices in the current thesis is the possibility to combine outcomes in the models. Basically, industry concentration which is captured by the HHI can be linked to the degree of relatedness which the *within* entropy index captures by interacting the explanatory variables. This results in a measure of 'relatedness within concentration' as a more basic alternative to

[17] It is apparently assumed by these authors that a 'complex' and 'developed' economic structure is exemplified by a 'diverse' economic structure. However, it can also be argued that specialization within certain sectoral domains leads to economic complexity. The latter then can of course be complemented with external and/or technologically more distant yet *related* sources of knowledge to prevent negative lock-in (Bathelt et al., 2004).

using patent data for instance (see Boschma et al., 2015 who measure relatedness this way). The reader may have noticed that both indices are 'fed' with the same data in order to make interpretation meaningful.

The explanatory variable of an industrial concentration measure (see section 4.4.1) multiplied by the within-entropy index results in a two-by-two matrix that is shown below in figure 6. The matrix gives insight into economic complexity and allows for extending the analysis of resilience as has been carried out by Kitsos (2020) and also Faggian et al. (2018).

Regarding regional resilience of the LADs, this matrix is used to interpret findings and place them on a spectrum of less to more resilience regions. Generally speaking, it is assumed – also based on the theoretical framework – that higher relatedness means higher economic complexity and thus is more beneficial in regard to resilience. However, now we are speaking of resilience as enduring an *impact*. In the current thesis, recovery or *growth* is analyzed, which suggests that specialization (proxied by concentration) is more important. Moreover, the cluster and/or industry lifecycle – which however is empirically *not* covered in this thesis – comes in again where the top left quadrant is prevalent in early phases, and the bottom-right may be linked to more mature stages of economic development. These ideas will be tested on real-life data that are presented in the following section.

Low relatedness; Low concentration	Low relatedness; High concentration
High relatedness; Low concentration	High relatedness; High concentration

Figure 6: Economic complexity matrix (Source: own elaboration – see acknowledgements)

As already has been argued on above, the addition of the picked control variables adds to this notion of economic complexity. As the (spatial) distribution of all variables included suggest, (complex) knowledge is not evenly distributed across space as for instance Balland and Rigby (2016) have demonstrated empirically, again using patent data. Their focus however is specifically on *knowledge* complexity, and this thesis lays its focal point more toward industrial structures and related factors. What can be taken over from the latter authors however is the observation that economic complexity or complexity of knowledge contributes to economic development and growth, also embodied by industrial relatedness. The spatial and socio-economic unevenness as depicted in the following sections can furthermore be extrapolated from the idea that 'absorptive capacity' of economic agents and entities (see theoretical framework) constrains or enhances economic development in an evolutionary manner. Hidalgo (2015) in his book 'Why Information Grows' deepens these ideas which may be conceptually and empirically linked to the above-mentioned claim by Black & Henderson (1999, p. 327) that "individual industry mobility seems to be constrained by interindustry linkages" amongst others. The latter is of course reserved for future research endeavors and is not covered in this thesis as such analyses go far beyond the limits of this project.

The following chapter lays out the gathered results and attempts to interpret them effectively demonstrating the relevance of theory and methods as elaborated on above. There is an order following summary statistics, a correlation matrix, regression results – including robustness checks –

and finally the spatial patterns as depicted in the maps featuring in Appendices VII and VIII. Both the conceptual framework (figure 5) and the economic complexity matrix (figure 6) are used as guidelines for linking results and marking their significance.

5. Results

In this section the results of the regressions as outlined in the previous chapter will be elaborated on in order to shed light on the regional differences in resilience. Furthermore, the two indices – Entropy and Herfindahl-Hirschmann – that are input for the regression analysis will be depicted in maps to show regional variation and potential patterns as these two variables are the most important referring to the research questions and chapter 4.

5.1 Summary statistics dependent and explanatory variables

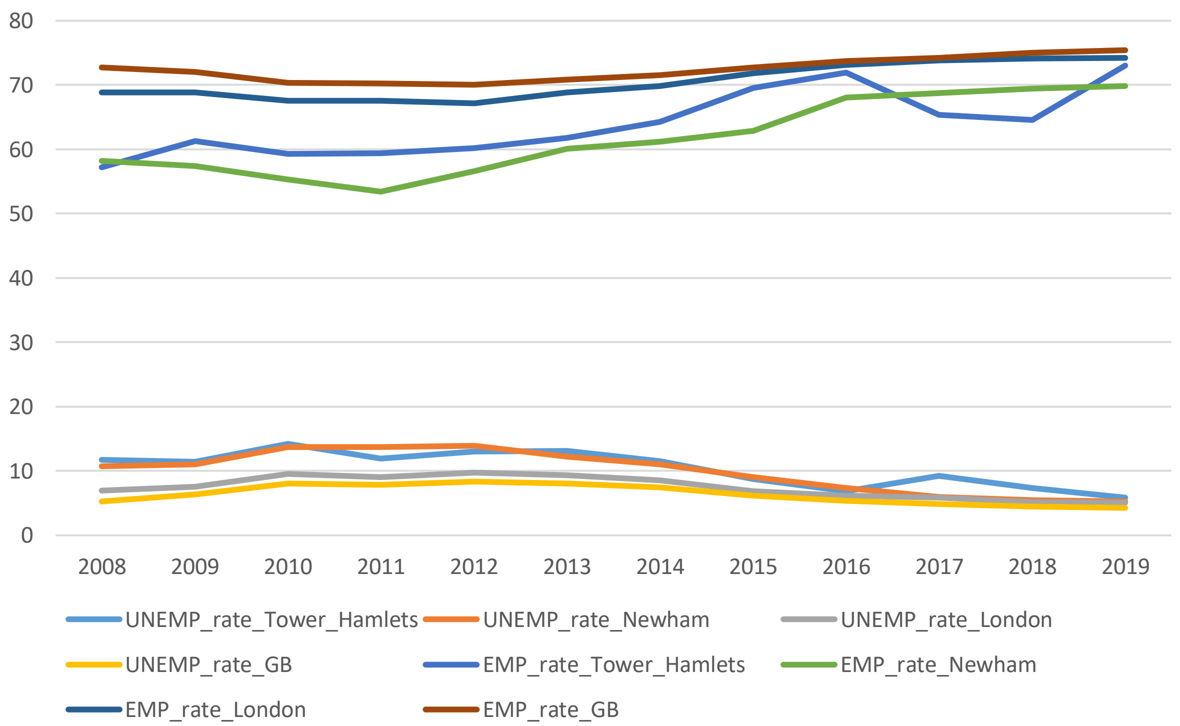
Below in table 4 some descriptive statistics of the dependent variables which are elaborated on in section 4.2.1 are shown. As noted in that section, there are some missing values from the total of 371 observations – the most regarding unemployment figures which are model-based and *not* missing at random (more on this above).

Table 4: Descriptive Statistics dependent variables

Variable	Obs	Mean	Std. Dev.	Min	Max
EMP-recovery	369	4.571	2.522	-3.800	12.186
UNEMP-recovery	364	2.615	1.106	.081	6.814

With regard to the first dependent variable, it can be seen that there is much variability in its values; Appendix VII shows two maps of the dependent variables by Local Authority District. What can be seen very clearly is that there is some overlap regarding the LADs in the two maps: for example Scotland which performs quite weak in terms of resilience, and London which scores rather high in resilience. However, there is much contrast as well. In the map representing EMP-recovery there are more high values of resilience, and, as table 4 above shows, there is more variability. Further, most LADs that score very high on the latter variable do not reach similar heights when it comes to UNEMP-recovery.

Figure 7: (un)employment rates London boroughs Newham and Tower Hamlets 2008-2019 (Source: ONS, 2022)



There are three exceptions to this observation however (Newham, Tower Hamlets and Kingston upon Hull), of which the first two LADs are situated in Inner London that will be elaborated on some more. *Tower Hamlets* – which also features in later sections of the results regarding relatedness and concentration – is the financial headquarters in London with *Newham* geographically adjacent to it. These two LADs are amongst the most resilient regions in the entire analysis.

Figure 7 above shows that these two LADs – and in particular Tower Hamlets (see years 2017-2018) – had relatively high unemployment rates during most of the period compared to London's average and even more so compared to Great Britain's average, yet recovered remarkably. These observations align with the outcomes of the dependent variable at the unemployment side: 5.77 for Tower Hamlets and 6.81 (highest) for Newham. Looking at the precise construct of this variable (section 4.2.1, table 3), this tells that the average of the three minimum unemployment rates of a LAD for 2015-2019 during recovery has been low and/or initial unemployment during the crisis years (2008-2014) has been higher. Referring to figure 7, it can be stated that – considering the fact and common knowledge of London's above national average unemployment rate – the two boroughs' had relatively very high unemployment rates initially which tightened after the crisis, yet Tower Hamlets saw a 'surge' in employment growth after a huge dip, both between 2016 and 2019. The other dependent variable (EMP-recovery), to continue this line of thought, actually moderately and significantly at the 0.01-level positively correlates (0.360***) with variable 'UNEMP-recovery' (see table 6 in section 5.2). Further, by regressing the two variables on each other by means of a *simple regression* technique, a highly significant (p>0.000) positive coefficient of 0.83 (rounded) is found. This basically means that if the 'independent variable' related to unemployment recovery increases with 1 unit, dependent variable 'EMP-recovery' increases on average with 0.83 units, yet with an R^2 of 0.13 there remains much variation in this dependent variable unexplained.

Table 5: Descriptive Statistics independent variables (Various sources)

Variable	Obs	Mean	Std. Dev.	Min	Max
EMP rate 2014	369	72.916	5.462	59.200	86.400
UNEMP rate 2014	369	6.590	2.318	2.500	13.600
HHI K 2019	370	.307	.124	.125	.888
concentration 2019	371	.615	.487	0	1
Within entropy 2019	370	.909	.480	0	3.686
within share 2019	370	52.330	13.655	0	84.591
Across Entropy 2019	370	.742	.163	.218	1.096
across share 2019	370	47.670	13.655	15.409	100
DEGREE percentage 2019	370	31.159	11.025	7.200	68.400
noDEGREE percentage 2019	363	7.426	3.398	1.900	21.500
Qualification percentage 2019	370	39.406	11.037	15	100
Job training 2019	366	10809.840	8945.054	1200	70400
percent selfemp 2019	369	11.031	3.691	3.700	25
avFirmBirthrate 15 19*	371	.727	3.376	.248	65.302
avgFirmDeathrate 15 19*	371	.608	2.968	.221	57.480
Density 2019*	371	1605.922	2509.664	9	16427
Age 16 24 2019	371	18512.992	16936.189	174	169819
Age 25 49 2019	371	57177.914	44053.435	667	390383
Age 50 64 2019	371	33584.005	20452.745	485	173425
South East (SE)	371	.181	.385	0	1
South West (SW)	371	.081	.273	0	1
EAST	371	.121	.327	0	1
LONDON	371	.065	.246	0	1
North East (NE)	371	.032	.177	0	1
North West (NW)	371	.113	.317	0	1
SCOTLAND	371	.086	.281	0	1

*Variables with a * are actually logarithms in the analyses yet shown here differently for illustrative purposes; 'Density 2019' is population density

This, together with the two maps in Appendix VII and by looking at figure 7 above, raises questions that will be attempted to address in the following sections. Table 5 shows descriptive statistics of the explanatory variables used in both the employment- and unemployment-related models. The reasons for including these variables have been elaborated on in the methodology section.

Some interesting points to mention here are with respect to the variables 'HHI K 2019' up to 'across share 2019'. On average, there are more LADs that are industrially concentrated (1) than not (0) with a mean of 0.615. The average HHI is 0.307 which is above the 0.25-threshold of high concentration. Regarding the *within entropy* index, the mean of the index in itself does not say that much, yet by comparing the *share* (0.523) to the share of the *across entropy* index (0.477), it can be seen that on average industrial variety is more 'related' than 'unrelated' regarding sector K (finance and insurance). This resonates with the (author's) assumption that this sector – along with the subsection of sector C – is in essence more 'related' (and concentrated) and is accompanied more by knowledge spillovers (see Frenken et al., 2007). These variables, along with the other explanatory variables, are tested and modeled in differing specifications – including interaction terms – in the following sections.

5.2 Correlations 'key variables'

Correlations between variables as shown in table 6 below – next to underlying theoretical assumptions and empirical outcomes of others – form the basis of investigating relationships amongst others by means of performing regression analyses. As briefly noted in the previous section, both the sign and size of the Pearson correlation coefficient say something about the relationship between the variables under consideration[18].

The relationship between the two dependent variables has been discussed above, yet this particular relationship – while interesting – is not the main interest of investigation in this thesis. The variables that are 'added' in a sense to the initial UK resilience analyses performed by Kitsos (2018; 2020) are the outcomes of the entropy indices, and, in particular, their relationship with industry concentration in Local Authorities. Striking is the rather strong and negative relationship between 'Within_entropy_2019' and 'HHI_K_2019' (-0.478***). This indicates that about half of the variation in the latter variable is explained by the former, and that when 'within entropy' goes up, 'HHI_K' goes down. In other words, higher degrees of industry relatedness are accompanied by lower degrees of concentration – also interpreted as specialization (in sector K). This is what Essletzbichler (2015, p. 752) indirectly claims by stating that "… technological relatedness is positively related to metropolitan industry portfolio membership (and industry entry and negatively related to industry exit)" (brackets added). Portfolio membership is regarded by the latter as related to a process of industries/firms diversifying into *related* or 'proximate'[19] industries, and are also characterized by spin-off mechanisms that were elaborated on in the theoretical framework referring to Klepper (2007). More light will be shed on these observations in the following subsections and in particular section 5.6 that deepens the understanding between these two variables (related variety and industry concentration).

Appendix VIII tellingly shows the contrasting pattern between them for Great Britain, and also in case of London, where LAD Tower Hamlets – next to but contrasting the other Inner London boroughs – 'flips' color as in this particular borough there is higher concentration of industries and lower relatedness. To be more precise, total diversification in Tower Hamlets as measured by the 'Total

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[18] Explanatory variable 'concentration_2019' was left out of the correlation matrix featuring Pearson's correlation coefficient because the variable is categorical which violates the assumption of the coefficient. HHI_K_2019 does the job in a similar way as it represents the index' raw outcomes (between 0 and 1).

[19] Proximity, as has been touched upon in chapter 3, knows at least five dimensions according to Boschma (2005): cognitive, social, organizational, institutional and geographical, of which geographical proximity is not always implied. Yet, the first and fifth dimensions are most relevant is this thesis referring to relatedness and concentration.

Entropy index' is lower, yet the *share* of related variety compared to unrelated variety is still rather high with 0.59 to 0.41 respectively. In other words, this London-borough is rather specialized/concentrated *and* characterized by high industrial relatedness. The relationship between related variety, or, the calculated index outcomes, and the *share* of related variety is depicted in figure 8 below. It basically shows that the correlation coefficient shown in table 6 makes sense, however the relationship is not linear. As mentioned earlier, both variables are used yet they conceptually each tell a slightly different story.

The other boroughs in Inner London show higher values of 'within entropy' which indicates higher total variety, and the shares of related variety are similar to Tower Hamlets as seen in Appendix VIII. Table 7 below in section 5.3 gives more insight in these phenomena (not only in London) and in particular with regard to resilience – represented by *employment recovery* after the 2008 financial crisis.

On top of this, it is interesting to see that population density ('lnDensity_2019') shows significant correlations with all other variables included in the table except with industry relatedness ('Within_entropy_2019'). Regarding the dependent variables, 'Dependent_var_EMP' is enhanced in terms of resilience with a rather weak yet highly significant coefficient (0.152***), but on average an increasing population density seems to have a rather strong and positive effect on resilience with regard to 'Dependent_var_UNEMP' which makes sense. In Kitsos (2020, p. 199) it can be seen that in all four specifications of his model representing 'employment impact', larger population density is accompanied by a larger crisis impact, i.e. the positive and highly significant coefficients on average increase his dependent variable by approximately 0.3 to 0.36 units (with similar ranges compared to the dependent variables in this thesis). Regarding the models in the current study, population density does not appear to be significant. The reasons for this are explored further in the following sections, as are the effects of the other covariates that were not mentioned in this section.

Figure 8: Relationship between related variety and its share

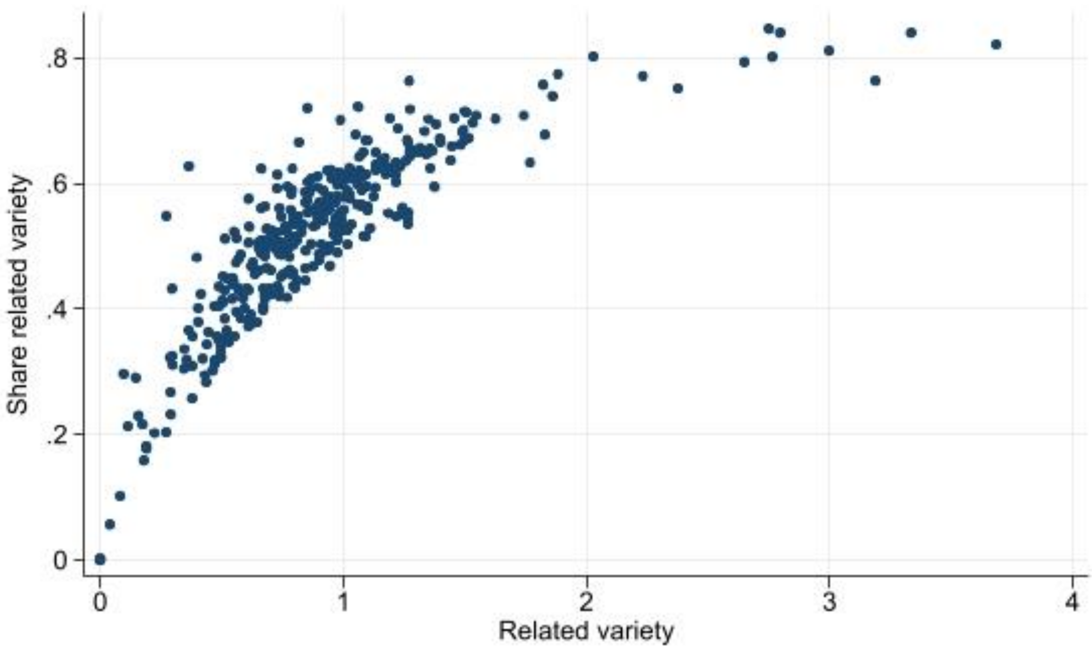


Table 6: Pair-wise correlations 'key variables' (Various sources)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Dependent_var_EMP	1.0000														
(2) Dependent_var_UNEMP	**0.360*** **	1.0000													
	(0.000)														
(3) HHI_K_2019	0.0130	**0.112** **	1.0000												
	(0.799)	(0.032)													
(4) Within_entropy_2019	0.0630	**-0.180*** **	**-0.478*** **	1.0000											
	(0.229)	(0.001)	(0.000)												
(5) within_share_2019	0.0700	**-0.106** **	**-0.391*** **	**0.819*** **	1.0000										
	(0.181)	(0.044)	(0.000)	(0.000)											
(6) Across_Entropy_2019	-0.0780	-0.0400	**-0.493*** **	-0.0500	-0.391***	1.0000									
	(0.137)	(0.451)	(0.000)	(0.333)	(0.000)										
(7) across_share_2019	-0.0700	**0.106** **	**0.391*** **	**-0.819*** **	-1.000***	**0.391*** **	1.0000								
	(0.181)	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)									
(8) Degree_percentage_2019	0.0760	-0.264***	-0.294***	0.279***	0.249***	0.113**	-0.249***	1.0000							
	(0.144)	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.000)								
(9) Job_training_2019	0.090*	0.298***	**-0.166*** **	-0.0010	-0.0040	**0.207*** **	0.0040	0.221***	1.0000						
	(0.086)	(0.000)	(0.001)	(0.978)	(0.936)	(0.000)	(0.936)	(0.000)							
(10) percent_selfemp_2019	0.0390	-0.354***	-0.125**	0.247***	0.236***	-0.0480	-0.236***	0.347***	-0.134**	1.0000					
	(0.454)	(0.000)	(0.016)	(0.000)	(0.000)	(0.355)	(0.000)	(0.000)	(0.010)						
(11) avFirmBirthrate_15_19	0.0100	-0.0370	-0.0820	0.0650	0.0440	0.0690	-0.0440	0.190***	0.142***	0.204***	1.0000				
	(0.850)	(0.485)	(0.116)	(0.211)	(0.401)	(0.184)	(0.401)	(0.000)	(0.006)	(0.000)					
(12) lnDensity_2019	0.152***	0.501***	-0.233***	0.0830	0.136***	0.127**	-0.136***	0.283***	0.357***	-0.181***	0.096*	1.0000			
	(0.003)	(0.000)	(0.000)	(0.112)	(0.009)	(0.014)	(0.009)	(0.000)	(0.000)	(0.000)	(0.064)				
(13) Age_16_24_2019	0.0370	0.412***	-0.102*	-0.0360	-0.0330	0.191***	0.0330	0.165***	0.854***	-0.175***	-0.0400	0.428***	1.0000		
	(0.483)	(0.000)	(0.050)	(0.488)	(0.528)	(0.000)	(0.528)	(0.001)	(0.000)	(0.001)	(0.438)	(0.000)			
(14) Age_25_49_2019	0.0670	0.431***	-0.130**	0.0020	0.0300	0.152***	-0.0300	0.242***	0.861***	-0.124**	-0.0400	0.501***	0.934***	1.0000	
	(0.200)	(0.000)	(0.012)	(0.973)	(0.570)	(0.003)	(0.570)	(0.000)	(0.000)	(0.017)	(0.446)	(0.000)	(0.000)		
(15) Age_50_64_2019	-0.0440	0.312***	-0.0800	-0.0210	0.0090	0.130**	-0.0090	0.0670	0.836***	-0.113**	-0.0750	0.266***	0.855***	0.903***	1.0000
	(0.400)	(0.000)	(0.122)	(0.684)	(0.865)	(0.012)	(0.865)	(0.198)	(0.000)	(0.029)	(0.152)	(0.000)	(0.000)	(0.000)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.3 Model validation

Before diving into the regression table results, several diagnostic steps that have been carried out in order to make sure the analysis yields valid results are provided in this brief section. Firstly, as the main method employed is Ordinary Least Squares regression, there are six important assumptions that have to be met that will be worked through here by mentioning the particular test results. The first assumption – that the error term has a conditional mean of zero – should not be tested directly because this is ingrained in the OLS-method itself and is always the case and if not, the deviance will be 'absorbed' by the model's constant (Mehmetoglu & Jakobsen, 2017).

The second assumption – that of homoscedasticity and meaning that the error term has constant variance – is met most of the times except for models (3) and (4) in table 7 resulting from some age groups that however have been decided on to keep them as they are for reasons of interpretability and because they cause no problems in the other models. All models in table 8 suffer heteroscedasticity as well resulting from the dependent variable. This dependent variable was *log-transformed* which however did not change the statistically significant results of the 'Breusch-Pagan hettest'. Moreover, the employment-related dependent variable could not be log-transformed anyhow because it contains negative values should both variables be transformed. Also standardizing the variables did not work. Thus, in order to correct for the issue of heteroscedasticity, robust standard errors have been employed that make the results trustworthy.

The assumption of uncorrelated errors can be tested in STATA with the 'Durbin-Watson' test that is however used for nested data. Yet, even for simple cross-sectional data, in software package ArcGIS pro 2.4 there can be tested for spatial autocorrelation using the 'Global Moran's I' test. For Employment-recovery there was no spatial autocorrelation found. For the other side of the analysis – related to unemployment recovery – there was found spatial autocorrelation using Moran's I, yet for the sake of maintaining the research project manageable, no Geographically Weighted Regression that corrects for this has been carried out. STATA furthermore has a 'Shapiro-Wilk W normality test' to check for normally distributed errors which are in regard to UNEMP-recovery thus potentially problematic. However, by plotting the error terms along a Gauss curve, it can be seen that the sample is rather 'normal' and because of its large size (approximately 370 cases) also is rather unproblematic. Performing an 'sktest' that searches for skewness and kurtosis values significantly different from the 'normal' situation, it can be seen that skewness is near insignificant with a p-value of 0.047 and a value of 0.26 that is close to 0.00. Kurtosis – which says something about the 'heaviness' of the tails in the distribution – is 4.49 with a p-value of 0.0002, and differs somewhat from the desired Kurtosis value of 3.00. There are thus relatively heavy tails, yet there are no relevant outliers or 'influential observations' considering Cook's distance. Taking the above together, there is no direct reason to worry about these deviations.

Further, performing 'Linktests', it has been concluded that there are no specification problems as the p-values are rather large and don't exceed the threshold. Of course there may be (multiple) extra explanatory variables that have explaining power regarding the models – especially regarding Employment-recovery which has the lowest R-squared of around 0.20. This discussion will be held more in detail in section 5.3.

With regard to multicollinearity, it can be said that this has been largely eliminated from the models. However, as also Kitsos (2020) reported, the age groups carry some collinearity with 'Variance Inflation Factors' (VIF) of around 13.00. As these variables are important for the models and can be conceptually justified, next to model specifications where two out of three have been left out to show (the lack of) overall impact, there are some models that include age groups 25-49 and 50-64 together which demonstrates mutual (high) significance with contrasting signs.

To conclude, there are no functional form issues (linearity between explanatory and dependent variables) in the models or they had been eliminated by log-transformations.

5.3 Ordinary Least Squares Regression results: 'EMPrecovery'

Table 7 below shows the relationships between dependent and explanatory variables in more detail and in differing specifications controlling for certain (hypothesized) effects. It can be seen that the R^2 ranges from about 0.19 to 0.23 which according to Mehmetoglu and Jakobsen (2017, p.60) is in social disciplines (near) satisfactorily. Higher values may be obtained when more industries and their accompanying 'key covariates' similar to sector K were included (this might however introduce multicollinearity problems). Of course there will also be other variables with potentially higher explanatory power that are not included. Some of these include industry shares of (high-tech) manufacturing and construction, yet these interfere with the main variables of interest – concentration and related variety – and are therefore left out. High-tech will be subject of analysis in itself in section 5.5 where it is included as a 'robustness check' of the main models.

In section 5.4 the regression results of the unemployment side are shown and it immediately stands out that the R^2 is much, much larger – i.e. around 0.80. The latter is discussed in more detail in both the methods section and in section 5.4 itself. What can be said in general is that employment figures are more difficult to (statistically) explain than unemployment rates.

Looking at table 7, it draws attention that the coefficient of the first explanatory variable, 'EMP_rate_2014', is highly significant with $p < 0.01$ and the sign is negative. The 'starting point' – as Kitsos (2020) calls it – is seemingly of great importance. The coefficient tells that a 1-unit increase in the employment rate of 2014 (i.e. 1 percentage point) on average decreases the value of the dependent variable with 0.12 units, approximately and across specifications. Interpretation is important here, as this observation tells that employment *recovery* has been lower due to an initially higher employment rate. However, it could of course be the case that a certain LAD had a higher employment rate initially (in 2014) *because* it was more resilient during the crisis. On the other hand, as the ability to recover from the 2008 financial crisis is of importance in this thesis, the variable is still relevant by empirically marking the point of departure. This also means that LADs with very low 2014 employment rates might have 'bounced back' remarkably, or not, and they may or may not have greater abilities to adapt to economic change/shocks. This will be discussed and put into further perspective below and has been touched upon in section 5.1 above.

The main variables of interest which had to be calculated are 'concentration_2019' and 'Within_entropy_2019'. As stated, the former is a dummy created out of the *Herfindahl-Hirschmann Index*' outcomes, and the latter has also been transformed into 'within_share_2019' which is the share of related variety out of total variety (compared to unrelated variety). This HHI had been calculated for a different time period and different industry shares compared to Kitsos (2018; 2020), yet the Entropy Index – especially the *within* part of it representing related variety – broadens the analysis by adding another dimension that has according to the latter as stated above not been examined extensively in the current literature with regard to resilience. Looking at the results in table 7, the concentration variable is significant in all model specifications, yet only at the 0.1-level. In the specifications where the variable representing related variety ('Within_entropy_2019') is included, the latter is significant as well, yet only in model (5) at the 0.05-level. This seemingly destines from including firm death rates (instead of birth rates), and the particular choice of age groups. Controlling for the latter seems to have some influence on the main variables, which as has been discussed above accrues to population structures related to particular urban dynamics.

In models (2) and (6), when 'within_share_2019' is interacted with the concentration variable, the interaction term is significant at the 0.1-level. Interpreting this terms' coefficient gives that a unit increase in 'within_share_2019', so a 1 percentage point increase in the share of related variety (as opposed to the share of unrelated variety) on average in the LADs and for industry group K the effect of concentration on 'EMP-recovery' is -0.0004 rounded. This negative effect means that resilience seen from the employment side is decreased by this amount of units which is very marginal. This effect can also be seen in figure 9 below which is discussed in more detail in section 5.6. The effect of non- to weakly concentrated LADs can be characterized as quite a striking contrast.

Concentration is likely positive in sign because in times of economic recovery economic this phenomenon which could also be interpreted as specialization is expected to foster (employment) growth. In particular, Romer (1987) stresses that specialization has since a very long period (logically) been associated with growth due to increasing returns. He adds to this in the latter article that the existence and/or emergence of knowledge spillovers contribute to these increasing returns in the shape of externalities that as has been discussed in section 3.1.5 have been assumed to benefit from industry concentration, or, more specific, from *proximity* in differing industrial configurations.

This growth then is accompanied by several other factors; i.e. variables related to (regional) 'learning processes' which have been described in the theoretical framework (see especially sections 3.1.1 and 3.2.1). It is this learning process that to an extent can be captured by the variable representing related variety because when inter-industry, and probably also intra-industry linkages are established, this is accompanied by knowledge spillovers brought about by employees that generally are higher educated in the case of sector K (and high-tech manufacturing which will be dealt with in section 5.5). Considering table 7, both related variety ('Within_entropy_2019') and its share have positive coefficients with respect to employment recovery, with the second variable individually also found to be positively statistically significant with a small effect (0.04) yet resulting from percentual change. Importantly contributing to the regional learning processes as well and in conjunction with the main variables of interest (see correlation coefficients in table 6) seems to be on-the-job training. It is unrelated variety and industry concentration that are respectively positively and negatively correlated to on-the-job training. The latter's characteristic of more *tacit* knowledge (Boschma et al., 2002) and its transfer within and across the company on the one hand brings about risks of unwanted knowledge spillovers, and on the other hand positively contributes to resilience regarding both dependent variables. Following Nelson and Pack (1999), the adoption of advanced and/or superior technologies and in evolutionary-economic terms *routines*, leads to (rapid) economic development as experienced by several Asian countries in the 20th century. The negative relationship of industry concentration with 'job_training_2019' in particular may be because these knowledge spillovers are not effectively kept within the firm or concentration. This idea is then 'confirmed' by the positive correlation coefficient with unrelated variety representing more economic diversity in the LADs. Another assumption is that – again following evolutionary thinking (Boschma et al., 2002; Boschma & Martin, 2010) – the most successful firms and their routines survive in processes of competition and creative destruction and disseminate their superior knowledge and technologies across the (un)related economic landscape, however rather unpredictably. Job-training in itself has a positive coefficient of 0.0001** at the 0.05 significance level regarding EMP-recovery.

Continuing with learning-related variables in table 7, having a degree does not have a statistically significant effect on resilience, yet *not* having a degree does. The latter has a negative effect on employment recovery across all model specifications and is moderately significant at the 0.1 and 0.05-level. Having NVQ4+ (National Vocational Qualifications) qualifications which is at the highest possible level also does not improve employment recovery. The reason why having high degrees or qualifications does not (positively) contribute to resilience in the manner defined might be because these people might on average tend to not lose their jobs so quickly during crises. The opposite, people with no degree at all are the ones that generally are more at risk regarding the labour market (Boeri & van Ours, 2013).

Extending this line of thought, there are several age groups that are of interest when thinking of resilience of the LADs. All three of the groups, 16-24, 25-49 and 50-64 years are statistically significant with the first and last as negative covariates (with a very small coefficient yet 50-64 with the greatest) and the middle group as positive – with only 50-64 years at the 0.01-level in *every* model. Interestingly, the latter group turns slightly less negative when on-the-job training is included, and the middle group turns more positive. This again indicates that on-the-job training plays a relatively important role with regard to resilience and thus following the definition used in this thesis, growth.

Those early working age shares of the population may be regarded in rather blunt terms as 'most productive', or, perhaps better phrased, they are the people that have generally (just) left education and are in their early to mid-careers that moreover can be expected to be rather mobile in the labour market – especially in the industries under consideration. Regarding the oldest group included, Boeri and Van Ours (2013) state that employees approaching retirement age are generally less mobile and/or productive. This seems – looking at the greatest and most significant coefficient of the three groups – important in sector K where networking, sharing information and cooperation, which are to an extent captured by (un)related variety as a variable in association with the other controls like the mentioned on-the-job training, are important factors contributing to resilience.

Population density however, as briefly touched upon in section 5.2 where it has been shown to be very often statistically significant in correlations, does not seem to show significance in the models below. This may seem as a surprise as in the research of Kitsos (2020) population density is highly significant across model specifications. However, when in the current thesis the age groups and also the regional dummies are omitted, population density turns significant. In the latter's research, this variable has a detrimental effect on employment *impact* of the 2008 Great Recession. In this thesis the variable – while *not* significant – has also a negative effect on employment recovery after the recession when the latter two age groups are included, and otherwise positive. However, when found significant at the 0.1-level with the mentioned omissions, population density has a *positive* effect on resilience, i.e. recovery. This makes sense as more population-dense areas are usually accompanied by more urbanization economies and inter-industry economic linkages that might spur growth and/or absorption of the unemployed (see chapter 3 and referring again to Essletzbichler (2015) who relates *urban* portfolio membership positively to industry entry), and are also likely to house more young people.

Regarding these latter observations, average firm birth- and death rates in the period 2015-2019 are both found to be statistically significant with respect to employment recovery, with very strong and larger (negative) significant coefficients for the latter. This might be because the afore-mentioned yet conceptually rather broad phenomenon of 'creative destruction' in regional economies is important and also depends on other factors that are important in times of growth. Differently put, forces of creative destruction may be prevalent in times of growth when more new firms emerge and simultaneously struggle for shares of the market (Boschma & Martin, 2010). On the other hand, it can also be argued that in times of economic decline firms struggle to survive which may affect these forces differently, but this lies not within the scope of the current thesis. However, this and also creative destruction in times of growth again likely depends on the industry type as well. In this line of thought, resilience, or, employment recovery, is not statistically significantly impacted by unrelated variety when looking at table 7. The latter author who again said that "… technological relatedness is positively related to metropolitan industry portfolio membership (and industry entry and negatively related to industry exit)" (p. 752, brackets added), might thus be correct in the sense that *related* variety spurs growth[20], yet, adding to this, *unrelated* variety does not per se. Looking at the (insignificant!) coefficients in table 7, the relationship is negative which is also confirmed by Frenken et al. (2007, p. 692). Importantly, the latter's coefficients of unrelated and related variety tested on employment growth are respectively statistically insignificant *and* significant at the 0.01-level and share the same

[20] Amongst others because there might be an employment-enhancing effect that operates by means of more *related* industries where employees are more easily matched and picked up by the labour market due to tighter interpersonal and professional networks, referring to the relevant dimensions of proximity (Theoretical framework).

signs. Frenken et al. study The Netherlands in the period 1996-2002 and for 'industrial sectors' and 'knowledge-intensive service sectors' which are according to them accompanied by strong existence of knowledge spillovers (which has also been mentioned above by the author regarding such sectors).

It is further important to note that industry shares of construction and manufacturing (high-tech) are in general beneficial regarding employment in table 7, yet these have been *excluded* from the models as they statistically interfere with the main variables of interest (i.e. concentration and relatedness). The mentioned economic benefits also count for recovery of 1979-1983 and 1990-1993 recessions of which the latter is measured up to 2008 by Martin (2012, p. 25). Manufacturing in general performs rather weakly, yet the impact of high-tech as defined earlier by the author seems to make sense as this sector is in general characterized by high productivity and contributions to growth (referring again to Nelson and Pack, 1999). The industry share of financial services (and insurance activities) is not significant which aligns with Kitsos (2020, p. 199) in his specification for employment impact in the UK. It can be argued that this makes sense because this particular sector, or services in general, do not contribute to economic growth and productivity as much as the other sectors. From a perspective nested in a different economic context, Rodrik (2016) claims that *industrialization* in (former) third-world or developing countries lead to convergence towards Western countries. Examples he names are amongst others Japan, South Korea and also Taiwan that as mentioned above benefitted greatly from productive assimilation of superior production techniques and the learning processes embodying these (Nelson & Pack, 1999).

Further, the share of self-employment has no significant effect on employment recovery across specifications in table 7. It might be the case that this variable is too broad to capture any meaningful effects. Section 2.3 above states that self-employment is about 16% and also includes non-paid work, e.g. at home.

To wrap up this section, the regional differentiations that are captured by the seven dummies (also interpreted as regional 'fixed effects') show that (as expected) London has a relatively strong effect on employment recovery which can be interpreted as being a rather *resilient* region in the UK. Looking at the calculated dependent variable(s) of (un)employment recovery, five London boroughs are present in the top-10 most resilient LADs. More details on their accounts of industry concentration and relatedness are presented in section 5.6 and have been discussed with respect to the maps in Appendix VIII. Scotland on the other hand has a very strong negative effect on employment recovery, and the region appears in the bottom-10 least resilient regions regarding the calculated dependent variable(s). One of the reasons may be that Scotland has been largely manufacturing-based which is as discussed a far less resilient sector. Further, considering the maps in Appendix VIII, it can be seen that the region is more 'industrially concentrated' and less 'economically related' in sector K (more on this below). Region North East also shows a strong negative effect on resilience in several specifications, and this region has according to Martin (2012, pp. 24-25) only very weakly experienced 'structural re-orientation' compared to South East which says something about adaptability. Concluding, Martin (2016, p. 568) shows that the above findings on resilience of London, Scotland and North East align with his outcomes of recoverability regarding these UK (NUTS-1) regions in the 2010-2014 recovery-period after 2008-2010.

Table 7: Ordinary Least Squares (OLS) regression of 'EMPrecovery'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMP_rate_2014	-0.1213***	-0.1217***	-0.1560***	-0.1561***	-0.1175***	-0.1180***	-0.1522***	-0.1525***
	(0.0320)	(0.0320)	(0.0327)	(0.0357)	(0.0320)	(0.0320)	(0.0327)	(0.0327)
concentration_2019=1	1.2373*	2.7160*	1.2505*	2.3861*	1.2494*	2.7474*	1.2511*	2.4223*
	(0.6522)	(1.4444)	(0.6610)	(1.3177)	(0.6488)	(1.4393)	(0.6577)	(1.4571)
Within_entropy_2019	0.8594*		0.7986*		0.8748**		0.8170*	
	(0.4387)		(0.4441)		(0.4367)		(0.4421)	
concentration_2019=1 x Within_entropy_2019	-0.9175		-0.8990		-0.9368		-0.9146	
	(0.5804)		(0.5881)		(0.5778)		(0.5855)	
within_share_2019		0.0441*		0.0330		0.0448*		0.0344
		(0.0245)		(0.0230)		(0.0244)		(0.0246)
concentration_2019=1 x within_share_2019		-0.0428*		-0.0373		-0.0434*		-0.0381
		(0.0246)		(0.0229)		(0.0246)		(0.0249)
Across_Entropy_2019	-0.8475	-0.3569	-0.5634	-0.3702	-0.9410	-0.4409	-0.6675	-0.4450
	(0.8246)	(0.9951)	(0.8392)	(1.0855)	(0.8237)	(0.9939)	(0.8380)	(1.0100)
DEGREE_percentage_2019	-0.0041	-0.0051	0.0117	0.0121				
	(0.0178)	(0.0180)	(0.0180)	(0.0188)				
noDEGREE_percentage_2019	-0.0980*	-0.1008*	-0.1032**	-0.1055**	-0.1030**	-0.1059**	-0.1083**	-0.1108**
	(0.0517)	(0.0517)	(0.0517)	(0.0507)	(0.0522)	(0.0522)	(0.0523)	(0.0524)
Qualification_percentage_2019					-0.0004	-0.0014	0.0141	0.0143
					(0.0189)	(0.0191)	(0.0191)	(0.0193)
Job_training_2019	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0304	0.0300	0.0053	0.0055	0.0374	0.0368	0.0146	0.0147
	(0.0435)	(0.0435)	(0.0436)	(0.0454)	(0.0433)	(0.0433)	(0.0435)	(0.0435)
lnFirmBirthrate_15_19	-1.1175**	-1.1598**	-0.9701*	-1.0026**				
	(0.5081)	(0.5078)	(0.5011)	(0.4755)				
lnFirmDeathrate_15_19					-1.5166***	-1.5530***	-1.3820**	-1.4073**
					(0.5624)	(0.5627)	(0.5575)	(0.5583)
lnDensity_2019	-0.0429	-0.0462	0.0773	0.0774	-0.0518	-0.0565	0.0804	0.0792
	(0.1413)	(0.1415)	(0.1368)	(0.1441)	(0.1395)	(0.1398)	(0.1338)	(0.1341)
Age_16_24_2019			-0.0000**	-0.0000***			-0.0000**	-0.0000**
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000	0.0000*			0.0000*	0.0000*		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0001***	-0.0001***			-0.0001***	-0.0001***		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.2340	-0.2310	-0.2268	-0.2168	-0.2108	-0.2085	-0.2048	-0.1960
	(0.4060)	(0.4059)	(0.4099)	(0.4331)	(0.4051)	(0.4050)	(0.4091)	(0.4095)
SW	-0.1642	-0.1293	-0.2379	-0.1849	-0.1479	-0.1095	-0.2394	-0.1845
	(0.5289)	(0.5282)	(0.5340)	(0.4411)	(0.5255)	(0.5246)	(0.5300)	(0.5296)
EAST	0.0662	0.0593	0.1686	0.1578	0.1095	0.1014	0.2163	0.2043
	(0.4397)	(0.4401)	(0.4461)	(0.4457)	(0.4394)	(0.4398)	(0.4459)	(0.4467)
LONDON	1.6314**	1.6088**	1.7802**	1.7739**	1.6737**	1.6481**	1.8612**	1.8511**
	(0.7292)	(0.7303)	(0.7258)	(0.7137)	(0.7280)	(0.7291)	(0.7215)	(0.7231)
NE	-0.9359	-0.8834	-1.4575**	-1.4478***	-0.9370	-0.8813	-1.4651**	-1.4495**
	(0.7382)	(0.7409)	(0.7352)	(0.4533)	(0.7347)	(0.7372)	(0.7315)	(0.7332)
NW	-0.1146	-0.1035	-0.3146	-0.3021	-0.0389	-0.0261	-0.2470	-0.2334
	(0.4454)	(0.4456)	(0.4484)	(0.4769)	(0.4453)	(0.4455)	(0.4478)	(0.4484)
SCOTLAND	-1.8009***	-1.7655***	-1.8111***	-1.8275***	-1.8016***	-1.7545***	-1.9161***	-1.9258***
	(0.5348)	(0.5429)	(0.5364)	(0.5678)	(0.5776)	(0.5876)	(0.5809)	(0.5908)
Intercept	13.5982***	11.7528***	14.6763***	13.5361***	12.7173***	10.8664***	13.6465***	12.4538***
	(3.1198)	(3.4874)	(3.1695)	(3.6633)	(3.1679)	(3.5245)	(3.2180)	(3.5731)
R-squared	.2197666	.2185857	.1962977	.1937099	.2254635	.2241914	.2019163	.1992345
N	361	361	361	361	361	361	361	361

*** p <0.01", "** p <0.05", "*p <0.1
SE = South East", "SW = South West", "NE = North East", "NW = North West
Models 3 and 4 have robust standard errors due to heteroscedasticity issues with age groups

5.4 Ordinary Least Squares Regression results: 'UNEMPrecovery'

When the other side of the resilience regression – unemployment recovery – is taken under consideration, there are several differences but also commonalities in the results. Firstly, when examining the main variables of interest in the top of table 8, it can be seen that there are many yet somewhat less in amount significant coefficients. However, now unrelated variety represented by 'Across_Entropy_2019' also turns significant as opposed to the regressions in table 7 – this will be discussed below in further detail.

As in 'EMPrecovery', there is a starting point yet this time the *unemployment* rate in 2014 which is again highly significant and also explains quite a large share of the variation in the dependent variable (approximately 16%). Basically, when the unemployment rate increases with 1 percentage point, unemployment recovery increases with approximately 0.40 units. This means, as elaborated on from the opposite direction in the former section, that recoverability was effectively higher when the initial rate is higher, which makes sense. To stick with the narrative of section 5.3, it can be said that regions with initially low unemployment rates (that may have less experienced less recovery) were actually more resilient during the crisis period. Yet, as will be discussed in section 5.6, (relatively) high unemployment rates do not always mean less resilience in the LADs under consideration.

Further, high levels of concentration (value = 1) and HHI have a positive effect on resilience as well, which could be due to the fact that clustering of economic activity fosters job-finding processes in those areas. Firm birth but more so firm death rates show negative effects yet both far less pronounced compared to EMP-recovery in table 7. The coefficients of concentration are similarly far less strong. The less pronounced effects of both of these variables compared to the situation related to EMP-recovery could lie in the idea that unemployment rates are more difficult to counter or 'turn around' – i.e. they seem more rigid than employment rates. This makes sense as lifting people out of unemployment is generally a difficult task with differences in segments of the population (Boeri & Van Ours, 2013), also thinking of hidden unemployment as discussed in section 2.3. Looking at the range of the dependent variable in table 4 above, it can also be seen that the values related to UNEMP-recovery are less dispersed (0.081 – 6.814) compared to EMP-recovery (-3.800 – 12.186). So, the ranges are 6.733 and 15,986 respectively, which likely has some influence as well.

The interaction term 'concentration_2019=1 x Within_entropy_2019' is still (negatively) affecting *un*employment recovery yet also to a lesser extent. As stated before, this means that a unit increase in 'Within_entropy_2019' on average in the LADs and for industry group K the effect of concentration on 'UNEMP-recovery' is now -0.26** rounded. While concentration is statistically significant by itself, related variety is not.

The share of related variety itself and interacted with industry concentration is not significant in this table. The effect of concentration is however as stated less strong than in table 7 above, and now unrelated variety embodied by 'Across_Entropy_2019' is quite steadily statistically significant regarding unemployment recovery with a negative sign. This effectively means that more economic diversity or more spread-out sectoral employment in the LADs negatively impacts unemployment recovery. In Kitsos (2020) who studies the *impact* of the 2008 Great Recession on these LADs, the effect of (unrelated) economic variety is not significant yet is assumed to be positive in the sense that it acts as a 'shock-absorbing' portfolio. Bishop (2019) assumes the same and finds supportive evidence. Regarding growth after the financial crisis in the UK and in the same line of thought, Bishop (2019, p. 496) argues that "unrelated knowledge diversity is of particular importance in stimulating new entrepreneurial opportunities and structural change" and that "in the aftermath of a crisis, the birth rate of new firms will recover more rapidly in regions with a strong and diverse knowledge stock". Just as Boschma (2015), he stresses the importance of regional adaptation (and adaptability) in this regard. Bishop also claims that 'knowledge intensive services' are particularly supported by this (unrelated) economic diversity in times of recovery. The deviation of Bishop's results from the current thesis could lie within the fact that interregional knowledge flows could not be captured which the latter states yet what he actually managed to do with advanced spatial econometric methods. Boschma on the other hand remains quite indecisive whether unrelated and/or related variety is more beneficial for post-crisis growth. This particular distinction and combination of economic structures is dealt with in more detail in section 5.6 below.

Following Bishop's (2019) argument on the importance of a 'strong and diverse knowledge stock' for growth and recovery after crises, and by looking at the results in table 8, some question marks can be placed by the stressed importance of unrelated economic variety. As we have seen, industrial branching thrives by strong knowledge links and by *related* economic activity which is new but close to the current knowledge base (Boschma et al., 2015; Essletzbichler, 2015). Balland et al. (2015b), loosely paraphrased, stress the importance of avoiding negative technological lock-in with regard to being more resilient as an American city. Taken the current results, assumed absence or a shortage of strong and 'cohesive' learning processes in combination with less efficient job-finding processes regarding unrelated variety in UK regions might explain the negative relationship on employment recovery.

Regarding the workforce's education- and training levels, it can be seen that there are no significant coefficients whatsoever. It has to be clarified however that below qualifications of NVQ4-level or below-degree education levels are not included in these models which might have actual effects, yet, as stated above, because of the nature of the sector(s) under consideration and to limit the scope of the analysis in general these were left out. The absence of any effects by the variables that were included could point at – again – recovery to an extent 'omitting' highly educated people that on average did not as often lose their jobs. As stated in section 5.3, labour market analysts like Boeri and Van Ours (2013) claim that workers at the lower ends of the labour market more often risk losing their jobs – likely even more during economic crises – as is also portrayed by the OECD (2020c) who mention the difficult position of middle-skill workers that in turn relate to certain sectors (e.g. manufacturing). This is to an extent also reflected in the Country Profile (chapter 2) referring to declining middle-skill employment shares. Why having no degree at all is not statistically significant (yet all coefficients are negative), is not clear to the author. No significant coefficient for on-the-job training could mean that this type of training is less effective in lifting people out of unemployment which makes sense as they are unemployed, and, on the other hand, employees receiving such training seemingly do not enhance job-matching processes as much to reduce unemployment levels but may rather stimulate other business processes for the better. In particular, on-the-job training – as the notion itself suggests – mainly benefits the position and/or department to which it accrues. It is therefore not the intention of the employer to train workers so that they can switch to another company (Boeri & Van Ours, 2013); even more so as particular knowledge is not allowed to be shared once the worker leaves its current employer. This is characterized by so-called 'non-compete covenants' (Carey, 2001) that however are of course not watertight – also referring again to knowledge spillovers as discussed in section 3.1.3.

Self-employment is like in table 7 not statistically significant when estimating unemployment recovery, probably for the same reasons as explained in section 5.3, as is (again) population density. Age groups share the same sign regarding table 7, and only the second two groups (25-49 and 50-64) are statistically significant yet now at the 0.05-level instead of the 0.01-level. As in the analysis of employment recovery, these variables are quite important (in statistical terms) and impact many other variables due to their correlations that can be seen in table 6 above. Controlling for them in both tables furthermore interferes with the regional dummy variables. Because including all three age categories leads to very large variance inflation factors (VIFs) or simply multicollinearity, there are only sets of two included and alternated with including single age group 16-24 years which however by itself does not show any statistically significant effect on the dependent variables as opposed to the coefficients in table 7. No significant (negative) effect similar to table 7 because of inclusion of young adults in the models might lie in the idea that young people may be lifted out of unemployment more easily after an economic crisis. This however can be questioned as youth unemployment (in the UK) during/after crises is in general a big issue (Gregg, 2017). In fact, "in many countries of the world, youth unemployment is much higher than adult unemployment" (Choudhry, 2012, p. 77), which according to the former seems to be the case for the UK as well – also looking at the coefficients in table 7. It can further be the case that young adults are simply not registered as unemployed when they are in education.

Looking at the regional dummy variables, it can be seen that interestingly South East in all specifications shows a negative effect on resilience at the 0.1 and 0.05 significance levels. Appendix VII (second map) shows indeed that there are many LADs in the lowest category of the calculated dependent variable UNEMP-recovery. ONS (2019) shows that in 2019 the unemployment rate of South East actually was relatively not very high with 3.3%, yet the dependent variable says something about the recoverability of the LADs which then can be aggregated into these larger NUTS-1 regions. The average unemployment rate for South East from 2008-2014 was 5.35% which is relatively low and thus shows rather low recoverability.

North East and Scotland on the other hand have rather strong and negative statistically significant effects on unemployment recovery: approximately -0.90*** and -0.42*** in the first model and rather consistently across models. In the case of Scotland, the public sector is relatively important and prominent which may have mitigated mass job losses during the crisis and/or may have supported recovery; hence the (much) smaller coefficient compared to table 7. Kitsos (2020) interestingly finds no statistically significant results (in mitigating crisis impact) from including the industry shares of this sector in his models. It could also be a reason for employment recovery that Scotland is – according to Appendix VIII map 1 that shows that relatively high HHI values in the region – rather specialized/concentrated. Because, as can be seen in table 8 and which has been discussed above as well, high levels of industry concentration are beneficial for unemployment recovery, yet regarding table 7 less than employment recovery. Region North East shows a similar spatial pattern, and its regression coefficients are about twice as high compared to Scotland. More on these relationships in the following section.

In sum, regarding (un)employment recovery, industry concentration – may also be interpreted as specialization – *and* related variety are affecting the dependent variables positively, and unrelated variety does so negatively (albeit not statistically significant in table 7). This raises questions of whether this is also the case in other industries. Tables 10 and 11 that are shown in Appendix IX can be characterized as depicting a robustness check that demonstrates an analysis of a self-compiled high-tech share of manufacturing (sectors 26, 27 and 28) which has been defined in the methods section above. The following section sheds light on the differences and similarities between these two sectors.

Table 8: Ordinary Least Squares (OLS) regression of 'UNEMPrecovery'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UNEMP_rate_2014	0.3928***	0.3948***	0.4136***	0.4148***	0.3950***	0.3911***	0.4125***	0.4096***
	(0.0315)	(0.0316)	(0.0319)	(0.0319)	(0.0319)	(0.0318)	(0.0323)	(0.0242)
concentration_2019=1	0.3233***	0.4340	0.3264***	0.3993		0.4182		0.3197**
	(0.1207)	(0.2775)	(0.1199)	(0.2812)		(0.2779)		(0.1453)
Within_entropy_2019	0.1153		0.1089					0.1055
	(0.0748)		(0.0740)					(0.0972)
concentration_2019=1 x Within_entropy_2019	-0.2609**		-0.2526**					-0.2488*
	(0.1021)		(0.1042)					(0.1290)
within_share_2019		0.0031		0.0018		0.0028		
		(0.0047)		(0.0048)		(0.0047)		
concentration_2019=1 x within_share_2019		-0.0067		-0.0061		-0.0065		
		(0.0048)		(0.0049)		(0.0048)		
Across_Entropy_2019	-0.2926*	-0.3333	-0.2653	-0.3434*	-0.3146*	-0.3539*	-0.1279	-0.2773
	(0.1725)	(0.2041)	(0.1716)	(0.2059)	(0.1658)	(0.2040)	(0.1827)	(0.1865)
HHI_K_2019							0.4948*	
							(0.2577)	
DEGREE_percentage_2019	-0.0054	-0.0050	-0.0022	-0.0017				
	(0.0041)	(0.0042)	(0.0039)	(0.0040)				
noDEGREE_percentage_2019	-0.0007	-0.0004	-0.0006	-0.0001	-0.0017	0.0003	0.0011	0.0005
	(0.0126)	(0.0126)	(0.0126)	(0.0126)	(0.0127)	(0.0127)	(0.0128)	(0.0122)
Qualification_percentage_2019					-0.0025	-0.0026	0.0007	-0.0002
					(0.0043)	(0.0043)	(0.0042)	(0.0043)
Job_training_2019	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0036	0.0031	0.0016	0.0014	0.0008	0.0032	0.0008	0.0021
	(0.0088)	(0.0088)	(0.0090)	(0.0090)	(0.0086)	(0.0087)	(0.0087)	(0.0096)
lnFirmBirthrate_15_19	-0.1579	-0.1623*	-0.0879	-0.0932				
	(0.0976)	(0.0975)	(0.0964)	(0.0964)				
lnFirmDeathrate_15_19					-0.3044***	-0.2853**	-0.2155**	-0.2070*
					(0.1107)	(0.1104)	(0.1082)	(0.1245)
lnDensity_2019	0.0163	0.0163	0.0381	0.0380	0.0039	0.0154	0.0357	0.0410
	(0.0413)	(0.0416)	(0.0405)	(0.0407)	(0.0404)	(0.0409)	(0.0387)	(0.0332)
Age_16_24_2019			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000**	0.0000**			0.0000**	0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0000**	-0.0000**			-0.0000**	-0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.1410*	-0.1448*	-0.1520*	-0.1541*	-0.1718**	-0.1416*	-0.1669**	-0.1497*
	(0.0847)	(0.0846)	(0.0845)	(0.0842)	(0.0840)	(0.0851)	(0.0843)	(0.0901)
SW	-0.0232	-0.0065	-0.0330	-0.0143	-0.0275	-0.0094	-0.0290	-0.0407
	(0.1089)	(0.1101)	(0.1086)	(0.1095)	(0.1081)	(0.1099)	(0.1061)	(0.1215)
EAST	0.0276	0.0265	0.0448	0.0425	0.0181	0.0402	0.0435	0.0588
	(0.0840)	(0.0846)	(0.0858)	(0.0862)	(0.0827)	(0.0860)	(0.0853)	(0.0998)
LONDON	-0.1298	-0.1295	-0.0428	-0.0453	-0.1131	-0.1182	-0.0092	-0.0237
	(0.2032)	(0.2048)	(0.2197)	(0.2211)	(0.2044)	(0.2077)	(0.2226)	(0.1613)
NE	-0.9015***	-0.8980***	-1.0152***	-1.0137***	-0.8739***	-0.9027***	-1.0091***	-1.0203***
	(0.1988)	(0.2010)	(0.1938)	(0.1944)	(0.1945)	(0.1969)	(0.1910)	(0.1645)
NW	-0.0666	-0.0629	-0.0957	-0.0909	-0.0631	-0.0496	-0.0793	-0.0862
	(0.1080)	(0.1080)	(0.1075)	(0.1079)	(0.1064)	(0.1074)	(0.1065)	(0.0980)
SCOTLAND	-0.4161***	-0.4261***	-0.3965***	-0.4135***	-0.4392***	-0.4268***	-0.4418***	-0.4135***
	(0.1272)	(0.1309)	(0.1254)	(0.1289)	(0.1394)	(0.1446)	(0.1372)	(0.1292)
Intercept	0.1042	0.0650	-0.2605	-0.2043	0.1947	-0.0693	-0.5245	-0.4321
	(0.3244)	(0.4557)	(0.2934)	(0.4424)	(0.3129)	(0.4689)	(0.3273)	(0.3809)
R-squared	.8000885	.7989875	.7946627	.7938668	.7979459	.8002008	.7942441	.795781
N	356	356	356	356	356	356	356	356

*** p <0.01", "** p <0.05", "*p <0.1

SE = South East", "SW = South West", "NE = North East", "NW = North West

All models have robust standard errors due to heteroscedasticity issues with the dependent variable

5.5 Robustness check high-tech sector

When comparing tables 7 and 8 with 10 and 11 with the same dependent variables yet with the main variables of interest calculated for different industries (2-digit industries 26, 27 and 28), high concentration in the year 2019 has a similar yet higher effect on the dependent variable EMP-recovery in the uneven model specifications – compared to table 7 – where the variable representing related variety is included. This indicates that industry concentration is more important or more beneficial with regard to (employment) growth in this share of the manufacturing sector. In the even model specifications however, the benefit of industry concentration is much lower compared to table 7 and the coefficients are not statistically significant. A follow-up conclusion may be that besides concentration, related variety is even so important as the interaction term of these two variables *is* significant as opposed to table 7 where only the *share* of related variety interacted with concentration is significant.

Comparing variables representing education levels, there is a similar pattern visible with only the coefficients related to the shares of the working-age population having no degree at all being slightly smaller in size. The somewhat less negative effect on employment recovery might be because of shares in this manufacturing industry that require no degree compared to sector K in which this instead might be of more importance. Having a National Vocational Qualification (at the highest level) or having a degree however does not show any effect on the dependent variable. On-the-job training instead *does* at the 0.05 significance level and consistently. It is not hard to image why the latter is important in high-tech manufacturing industries; high levels of skill, cooperation and effectively making use of codified but also *tacit* knowledge are regarded important elements in these types of sectors – also regarding entrepreneurship (Amoroso et al., 2018). This then in turn can also be related to the main variables of interest, i.e. concentration and related variety.

Firm birth- and death rates on the other hand have stronger effects on the dependent variable and have the same sign. This indicates that for the high-tech sector creative destruction and/or competition among firms is more intense compared to sector Finance and Insurance. This intuitively makes sense when for instance considering involved patent requirements and sophisticated technical know-how that are to be protected and developed during emergence of such businesses. However, according to Boldrine and Levine (2013), it is a 'competitive environment' which is more crucial with regard to innovation (and growth) than the mere patent itself. This competitive environment can be linked to the discussed learning processes that regions, firms and agents undergo and which attributes to differing extents areas characterized by industrial concentration – i.e. clusters (Porter, 2000) – that in turn are characterized to differing extents by industry relatedness as follows from the analyses and maps in Appendix VIII.

Coefficients of the age groups are – at the 4 decimal level and in sign – the same. However, the second age group (25-49) is not statistically significant which raises some questions. It may be the case that these industries benefit more from built-up experience and less from rather labour-mobile employees in younger ages. Amoroso et al. (2018, p. 55) claim that regarding the high-tech sector "in South/East European countries, the importance of internal know-how is positively associated with age and education, but negatively associated with experience". Age thus plays an important role in such business mechanics what also Boeri and Van Ours (2013) stress regarding the labour market in general. Why experience (in South/East European countries) is negatively related to business founding in this sector broadly speaking does not count for North/West countries according to the former. Arguments can be made going both directions however: experience provides the worker/entrepreneur with more knowledge to draw from in founding a new firm for instance, but less experience could be related to individuals that are younger and more eager to take 'risks'.

Looking at the regional dummy variables, London shows similar patterns compared to table 7 which might be related amongst others to high-tech clusters in that area which likely contribute to employment recovery and growth. Region North East shows a similar (negative) pattern compared to table 7 as well, which may be related to industry concentration and levels of related variety (see next section). Concluding, Scotland has a relatively very large negative effect on employment recovery, considerably higher than with respect to sector Finance and Insurance. An explanation for this may be that, as mentioned above, Scotland is more manufacturing-based in its economic structure. Workers in these industries can be more difficult to match to new jobs, amongst others because of their very specific skills and (tacit) know-how acquired in their jobs. This compared to workers in (financial) services that more often rely on formal education, e.g. a degree, which in general is more widely applicable when laid off (Boeri & Van Ours, 2013).

Regarding tables 8 and 11, the unemployment side of resilience, it stands out that the core variables – concentration and (un)related variety – are almost always non-significant, with two exceptions of concentration in models (3) and (8) yet only at the 0.1-level. Besides firm birth rates that are more (often) statistically significant, there are not many differences between the coefficients and also the R-squared values are rather similar. Again, the stronger effects of firm birth/death rates point at more impact of creative destruction in these industries.

5.6 The 'relatedness-concentration' interaction term in more detail

Trying to answer the posed question by Boschma (2015) of whether related or unrelated variety (and in which composition) is more beneficial for regional recovery/growth after economic downturn, the mentioned interaction term is elaborated on in some detail here. As described in section 4.3.3, statistically interacting variables (industrial) concentration with (un)related variety brings about a new perspective that provides insight into the possible benefits and disadvantages concentration ignites along with a measure of industrial relatedness. Figure 9 below which plots this interaction term shows that up to a share of related variety of approximately 0.65 (whilst controlling for the variables depicted in table 7 model 2), a LAD with high concentration (concentration = 1) is more beneficial to employment recovery. Above that share, no to moderate concentration (HHI of 0.0-0.15 and 0.15-0.25 respectively) is more beneficial, and is increasing rather rapidly compared to the curve representing high concentration. It has to be noted here that the blue curve is accompanied by larger confidence intervals and thus has less statistical power in predicting the actual values. However, the interaction term is significant in model specification 2 in table 7, and interpreting the figure is still meaningful.

In other words, a sectoral distribution of 65% related variety and 35% unrelated variety while controlling for the relevant variables marks an intersection where either no/low concentration or high concentration of economic activities related to industry group K per LAD gets decisive for different reasons that will be discussed below. The figure implies that after a share of 65% related variety, unconcentrated or less specialized LADs are in theory best able to recover from financial downturn in terms of employment. Relating this to the literature, the mentioned concept of (negative) technological and/or regional lock-in may hamper growth and recovery after economic shocks which is particularly relevant in the context of (old) industrial areas or clusters (Hassink, 2010). Crespo et al. (2014) in the light of resilience argue that ex-ante analyses in such areas intended to identify any 'missing links' with (external) parties would be most desirable. Referring again to the learning processes discussed above extensively, Boschma and Iammarino (2009, p. 289) stress that

> "… related extraregional knowledge [is] sparking intersectoral learning across regions. When the cognitive proximity between the extraregional knowledge and the knowledge base of a region is neither too small nor too large, real learning opportunities are present, and the external knowledge contributes to growth in regional employment".

Also referring to figure 9, large shares of industry relatedness combined with high industry concentration or specialization may result in lock-in. Differently put, the regions may become too inward-looking and get stuck with old or obsolete *routines* which then gets in the way of innovation and renewing their economic structures and related institutions. A telling example of how to do this actually the 'right way' however in a different national yet European context is the Dutch City of Eindhoven. The old industrial area, where multinational Philips was catalytic and gave birth to many firms and also was closely related to the technical university, was able to reinvent itself and grow out of decline (Fernandez-Maldonado & Romein, 2010). This process was well-designed and can be characterized by a so-called Triple-Helix governance model. As there is no space here to zoom in on governance modes, the only observation that will be shared here is that intelligent and synergetic cooperation between firms, government and academia – of which the latter but also the first element will be likely to facilitate external linkages through networking cross-border and so on – referring here to 'local buzz' but importantly also to 'global pipelines' (Bathelt et al., 2004). Fernandez-Maldonado and Romein (2010) also stress the importance of urban and regional learning processes where knowledge creation and assimilation is crucial. This is so to say ingrained in rather holistic, 'place-based' development (Pike et al., 2016) if you will. Interesting in this regard is also the institutional climate in the UK and the particular regions that perform either very well or the opposite. Nevertheless, success-stories are there to learn from, and with recent developments of *smart specialization* in Europe aimed at stimulating economic complexity and resilience in a context-sensitive manner (McCann & Ortega-Argilés, 2015), there are interesting new perspectives to explore in industrial and regional economic development.

Having said this, it has to be mentioned as well that specialization and concentration of economic activity is likely more beneficial in times of growth (as said above). In these initial phases where industry entry is high and strong ties between firms and actors – referring to related variety – have not yet been established which however may be different regarding spin-offs from parent firms in clusters (see Klepper, 2007), and thus induce a concentration premium which is however limited along the lines of regional economic development. This paragraph can be linked to the notion of cluster lifecycles, yet in order to maintain focus on the research questions no detailed accounts of this will be given.

To give a more complete picture regarding resilience, the unemployment side will be briefly discussed as well. Because the variable that represents the share of related variety is statistically non-significant in all specifications in table 8, the main variables of interest have been turned around. This means that regarding dependent variable UNEMP-recovery, across-share (the share of unrelated variety) has been interacted with industry concentration which gives the appropriate coefficients. Figure 10 shows this interaction term, and in essence the figure is the mirror of figure 9, with however different values for the dependent variable on the Y-axis. The intersection point is the same (0.35 unrelated variety and 0.65 related variety), and, now following the share of unrelated variety from 0.0 to 1.0, high levels of concentration are beneficial (or necessary) when the share of unrelated variety is high. This could mean that a certain region that is characterized by a more diverse and 'loosely coupled' sectoral or economic structure basically requires the activities to be spatially concentrated in order to foster employment growth. This aligns with the ideas of Castaldi et al. (2015) who state that related variety, as mentioned often now, contributes to innovation and growth, but *unrelated* variety also ignites more radical innovation by cross-sectoral collaborations and/or knowledge flows. Industry concentration here comes in as such cooperation thrives better in tighter geographical proximity (Boschma, 2005), e.g. clustering of economic activity. The above-mentioned research by Bishop (2019) that also captures cross-regional knowledge flows in which unrelated variety is found to be statistically significant for economic growth might be explained (partly) by Castaldi's arguments.

Concluding, relating the above discussions to the maps in Appendix VIII, there are several interesting observations to mention. Firstly, industry K is characterized by a large amount of highly concentrated LADs in Great Britain which, as has been mentioned in section 5.2, are largely contrasting the spatial pattern pertaining to related variety (resembling the -0.48*** correlation coefficient between the two) with Inner London as the most pronounced example. Linking these findings to resilience outcomes depicted in Appendix VII and by looking at the data, it can be seen that (Inner) London, which also has a large positive effect considering the regression tables above, is highly resilient in mostly the *employment* side of the recovery aspect. Actually, there are five London boroughs in the top-10 most resilient LADs, and three of these also feature in the top-10 most resilient LADs of the unemployment side of the analysis. These, and more, London boroughs are characterized by high levels of related variety (with Tower Hamlets having however lower *total* variety), and lower levels of concentration and/or specialization – except thus for Tower Hamlets which is the financial headquarters. The latter, thinking of the discussions about age groups, has an exceptionally large share of people between 30 and 34 years (see ONS, N.D.). This fact contributes to the beneficial effects of this age group (25-49) on resilience which had quite some statistical power looking at R-squared values in table 7 amongst others. Further, in general it can be stated that regions/LADs that fit into the quadrant of 'high relatedness; low concentration' and sometimes 'high relatedness; high concentration' (see figure 6) perform best in times of recovery and growth. The 'premium' of relatedness – yet up to a point where negative lock-in starts to kick in – aligns with most of the literature that has been explored in this and the previous sections. Unrelated variety has been found non-significant in EMP-recovery and negatively significant in UNEMP-recovery. This contrasts the recent work of Bishop (2019) which focuses on Great Britain as well yet with an emphasis on *entrepreneurship* in knowledge-intensive services. He concludes that the size of the 'knowledge stock' in a particular region or in regions is of great importance with regard to firm births. What can be added to this is the notion of knowledge complexity as elaborated on in chapter 3, and also firms' absorptive capacity to appropriate such knowledge (learning processes). The interaction variable depicted below with the relevant controls added to the models in the author's viewpoint to a considerable extent capture this complexity and evidence is found that the latter contributes to growth and recovery. A critical note here would be that the indices used in the current thesis are too limited in empirical mechanics, i.e. they do not effectively capture the degree of knowledge complexity (and relatedness) as would be desired for. However, comparing the results to work of others in the field, a serious attempt to contribute to the literature on resilience has been made. More concluding remarks are reserved for the next chapter.

The aim of this section (and chapter 5) is to link theory with real data concerning resilience and the contributing factors. Furthermore, several discussions in the field of economic geography have been touched upon. What follows in chapter 6 are concluding remarks, concise answers to the research questions and suggestions for further research. Before concluding, there is included a small section that shows the top- and bottom 10 most/least resilient regions in Great Britain following the calculations of the dependent variables as discussed above.

Figure 9: Interaction term share of related variety and industrial concentration EMP

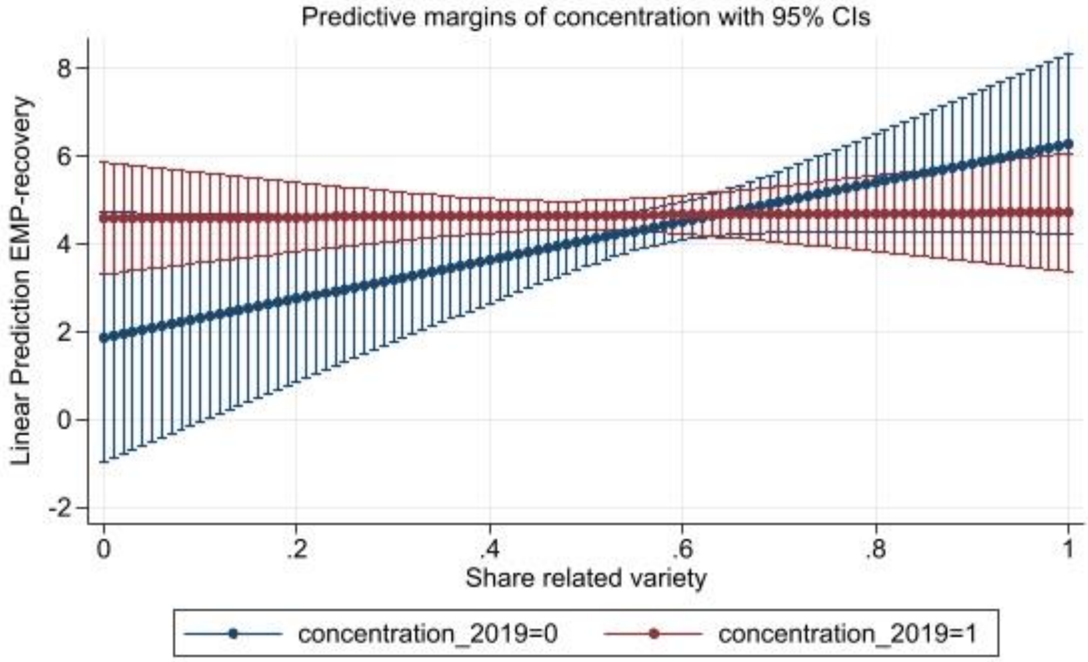
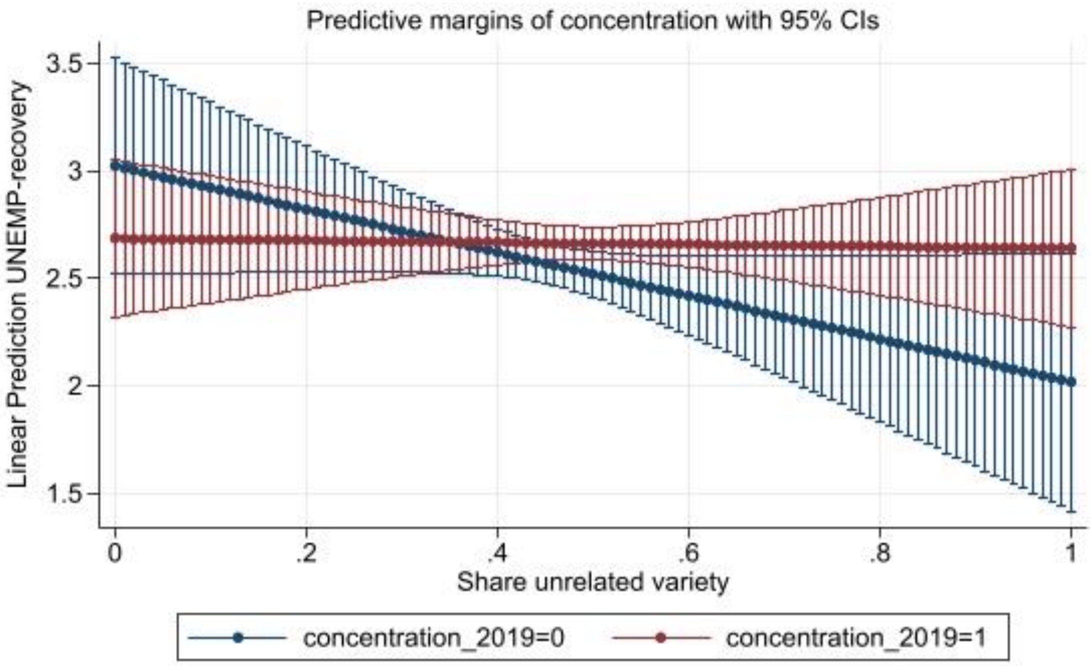


Figure 10: Interaction term share of unrelated variety and industrial concentration UNEMP



5.7 The top- and bottom 10 most/least resilient regions

This rather brief section gives a summary view of 20 LADs that are in the bottom and top 10 ends of (un)employment-related resilience. Table 9 below gives some insight into the spatial patterns and representation of regions (e.g. London and Scotland) that are either performing rather strong and/or weakly in terms of resilience. As discussed above, London performs exceptionally well and is represented heavily – 50% of the LADs in the top 10 – and three times correspondingly in the unemployment side of resilience. Tower Hamlets is (two times) in the top 10 as well.

At the other side of the coin, Scotland is heavily listed in the bottom 10 group – especially in regard to unemployment recovery. From the regression tables both regions seem to align with the results, yet Scotland has lower coefficients in unemployment recovery compared to employment recovery. This may also lie within the range of the dependent variables as discussed earlier.

Interestingly, Liverpool and Manchester – the old industrial (textiles) core of England – are in the top 10 most resilient LADs from the unemployment side. An explanation could be that unions are still strong in these areas that mitigate job loss and the like. Further, there are local/regional economic development initiatives that strive to foster an attractive business climate and so on (Liverpool City Council, 2019). Revitalization of such former industrial cores may be effective. Next to that, the region experienced an economic shift toward more service-oriented activities – also regarding sector K (Christie, 2013). Looking at the maps in Appendix VIII, these two LADs fit into the larger region's overall profile of industry concentration and related variety, yet may they might be changing in their underlying socio-economic structures towards better economic performance. As Faggian et al. (2018, pp. 396-397) state: "two different communities, with the same exact index score, might have very different underlying values for the different components, concealing potentially important heterogeneity". This counts for a differently constructed regional resilience indicator in Italy, yet the bottom line and core arguments still hold.

Concluding, employment- and unemployment-related recovery show similarities across table 9, even in such a small sample. Relating these observations to the main variables of interest, it can be argued that the regression tables make sense generally speaking. It would be interesting to conduct more in-depth case-studies on one or more of the LADs below to find out what really makes their economic structures promising – in particular from an evolutionary perspective that allows for context-sensitive analysis identifying past and potential growth paths for instance. More recommendations for further research will be given in the following chapter.

Table 9: top- and bottom 10 most/least resilient Local Authority Districts in Great Britain

#	LAD	D_EMP	LAD2	D_UNEMP
1	Dartford [SE]	12,19	**Newham [L]**	**6,81**
2	**Newham [L]**	**11,84**	Blaenau Gwent [W]	6,81
3	Southwark [L]	11,26	Kingston upon Hull City of [Y&H]	6,55
4	**Tower Hamlets [L]**	**10,97**	Knowsley [NW]	5,93
5	**Waltham Forest [L]**	10,84	Leicester [Emid]	5,92
6	Lewisham [L]	10,78	**Tower Hamlets [L]**	**5,77**
7	North Warwickshire [WMid]	10,32	Liverpool [NW]	5,58
8	Tamworth [WMid]	10,06	Manchester [NW]	5,21
9	Castle Point [EA]	9,83	**Waltham Forest [L]**	5,20
10	Mansfield [Emid]	9,65	Middlesbrough [NE]	5,11

#	LAD	D_EMP	LAD2	D_UNEMP
1	**Moray [S]**	**-3,80**	**Aberdeen City [S]**	**0,08**
2	**Brentwood [EA]**	**-2,20**	Aberdeenshire [S]	0,31
3	Uttlesford [EA]	-1,62	**Moray [S]**	**0,59**
4	West Lancashire [NW]	-1,35	Richmond upon Thames [L]	0,69
5	Sevenoaks [SE]	-0,93	Shetland Islands [S]	0,75
6	Dundee City [S]	-0,91	Melton [Emid]	0,93
7	Mid Suffolk [EA]	-0,73	St Albans [EA]	0,96
8	**Aberdeen City [S]**	**-0,43**	**Brentwood [EA]**	**0,97**
9	Bromsgrove [Wmid]	-0,32	Mole Valley [SE]	0,99
10	Guildford [SE]	-0,27	Orkney Islands [S]	1,03

Notes: SE = South East, L = London, Wmid = West Midlands, EA = East, Emid = East Midlands, W = Wales, Y&H = Yorkshire and the Humber, NW = North West, NE = North East, S = Scotland, SE = South East

6. Conclusion

This master's thesis has attempted to shed light on Britain's recovery from the 2008 Great Recession from an evolutionary economic-geographical perspective by posing the following research question: *What is the influence of (un)related variety and industrial concentration on resilience of Great Britain's regions after the 2008-2014 Great Recession?* The main empirical strategy consisted of a regression analysis that incorporates two calculated indices: the Herfindahl-Hirschmann Index and an entropy index of diversification of which the former captures industry concentration per Local Authority District and the latter is used to measure (un)related variety. Resilience as stated has been measured by exploiting and adapting the construction of a particular dependent variable employed by Kitsos (2020). The Y-values represent employment-related and unemployment-related recovery *after* the crisis period of 2008-2014 – Kitsos studied the periods pre-crisis (2004-2007) and crisis (2008-2014). Furthermore, spatial analyses making use of GIS have been carried out leading to several interesting regional patterns supporting and/or questioning assumptions. In particular, as can be seen in the appendices (VII and VIII) and what has been discussed above, the dependent variables as well as the outcomes of the two indices have been mapped for Great Britain on the Local Authority District scale-level. These results support interpretation and put into perspective regional differentiations – also referring to existing literature produced by prominent scholars in the field of economic geography and in particular regional resilience.

Martin (2012; 2016), who laid an important foundation regarding studying regional resilience for the UK in regard to the Great Recession, found that (financial) services as an economic sector has proven rather *resilient* during and after economic crises between 1979 and 2008 with clear regional differentiations. In his 2012-study he found that employment growth in the 1993-2008 recovery period was much greater in South East compared to North East. The latter region regarding the Great Recession in the current thesis as shown in chapter 5 has a rather strong negative effect on employment growth, but South East has no significant effect. More recently, in Martin's 2016-study, regional recovery from the Great Recession (2010-2014 in his models) aligns rather well with results in this thesis. London is the most pronounced 'winner'; North East and Scotland are on the lower end of recovery. Noteworthy here is the fact that Martin shows impact *and* recovery yet on a quite aggregated geographical scale-level; namely portraying the 12 NUTS-1 regions that have (partly) been added to the models in this thesis as regional dummies or regional fixed effects. Kitsos (2018; 2020) on the other hand takes on a much more fine-grained level of data aggregation for the UK, yet only considers *impact* of the Great Recession. He introduces more structural economic characteristics in order to assess regional capabilities to cope with the effects of this economic shock. Faggian et al. (2018) follow Martin in methodology measuring resilience, yet – in the Italian national context – use more disaggregated spatial units which both the latter and also Kitsos argue for is necessary to more meaningfully assess regional resilience by covering local labour markets. Faggian et al. make use of explanatory variables related to urbanization economies and vocations which turn out to have an effect on resilience (including recovery), yet Boschma (2015) asks for 'an evolutionary perspective on regional resilience' in order to capture growth paths regions may take on. The current thesis can be seen as an attempt to initiate such an approach borrowing from the above-mentioned studies in both theory and empirics. Interesting results have been found that shed light on the influence of industry relatedness and concentration on recovery/growth and also combining them statistically; a novel approach that to the author's knowledge has not been studied in this particular set-up so far.

In answering the research question, it became clear that main variables of interest – industry concentration and (the share of) (un)related variety and their interaction terms – are, also controlling for a set of covariates, considerably important in explaining regional resilience. This adds another dimension to the work of Kitsos (2018; 2020) which in adapted form lays at the foundation of the regression analyses in this thesis. He studied, as stated above, the Financial Crisis in Great Britain as well from the perspective of regional economic structures, yet did not include the element of industry relatedness (but points at its relevance in future research endeavors). As elaborated on in chapter 4, several control variables have been added to or omitted from Kitsos' original set of covariates such as the self-employment rate that however has not been found statistically significant, likely because of the broad nature of the measure. Industry shares have been left out of the analyses because these interfered with the main variables of interest. Nevertheless, the industry shares of construction and high-tech manufacturing actually were positively statistically significant, but have been excluded in order to capture the effects of interest while acknowledging the significant contributions of these industries to employment rates. What comes out of the robustness checks is that industry concentration has a rather strong and positive effect on resilience (employment recovery) in high-tech, which may be one of the reasons that its industry share interferes with this variable because this effect may be already 'absorbed' by the industry share. This is an interesting avenue for further research which could focus on this and/or or other share(s) of the manufacturing sector but of course also other sectors adding to the literature which is still in its infancy. Martin (2012) found that construction is a relatively resilient sector in the UK, yet the manufacturing sector measured in its entirety is not.

Returning to sector Finance and Insurance, the variables representing related variety and industry concentration are strongly and negatively correlated (-0.48***) which can also be seen in the maps under Appendix VIII. In terms of resilience, it seems that regions which are most 'related' and less concentrated in industries (Finance and Insurance and similarly in High-Tech manufacturing) outperform their neighbors. When the LADs are aggregated into larger NUTS-1 regions like London, South-East, Scotland and Wales, there are statistically significant results as well. As expected, London has the largest positive effect on the dependent variables playing the role of the UK's financial center. The region is relatively unconcentrated (except LAD Tower Hamlets which is the financial headquarters within London) and high in related variety; a combination that as mentioned above works out well however with of course the recognition that other factors play an important role as well. Out of these factors with R-squared values of approximately 0.22 and 0.80 for EMP-recovery and UNEMP-recovery respectively, the (un)employment starting point at the end of the crisis marks an important effect, as do particular elements of human capital. In particular, on-the-job training that is also linked to the notion of related variety, plays an important role in defining resilience. Reasons have been laid out in the results section referring to regional *learning processes* in evolutionary terms sorting out 'winners' and 'losers'. These learning processes have been extensively discussed in the theoretical framework as well with examples of (South-)East Asian countries like Japan and South Korea that have demonstrated exceptional economic performance in catching-up the West (see Nelson & Pack, 1999).

Firm birth- and death rates representing to an extent the process of *creative destruction* are statistically significant and important variables as well. They both negatively impact the dependent variables with a much larger effect on EMP-recovery however. This points at side-effects of economic growth when many firms are in competition and each strive for portions of market share. Referring again to Essletzbichler (2015, p. 752): "… technological relatedness is positively related to metropolitan industry portfolio membership and industry entry and negatively related to industry exit". This marks the indication that regional branching into new and/or related – to existing knowledge bases as elaborated on in chapter 3 – economic activities spurs economic growth which is in accordance with the results in the current thesis. The addition is that of industry concentration, and, in particular, its connection with related variety. The former alone spurs employment growth according to the models, yet when interacting this variable with the *share* of related variety shows that there is a certain tipping point of where too much relatedness in highly concentrated LADs slowly becomes less beneficial to the dependent variable representing resilience. This tipping points lies around 65% related variety and 35% unrelated variety. This in turn indicates that after the intersection depicted in figure 7 above, a more diverse economic structure becomes more supportive toward employment recovery (while controlling for the other explanatory variables).

The latter observations are what Boschma (2015) broadly asks for with regard to research into post-crisis economic contexts, or, in particular, recovery in economic terms. The latter, as also Faggian et al. (2018) mention, argues that long-term growth paths after crises are still largely unexplored from an evolutionary perspective.

Kitsos (2020) stresses the importance of *relatedness* in future research endeavors with regard to regional resilience next to the effects of variety-specialization he studied. He however did not find any significant effects from variety and specialization on resilience, and this might be because his calculations of the variables were broad in the sense that he calculated them for all sectors and/or because the effects may be more prevalent in times of growth/recovery.

The current study paves the way for further inquiry that focuses on industrial relatedness with respect to resilience, for instance in other (national) contexts and/or in other time periods. An obvious addition to this thesis would be an analysis over time, i.e. exploiting longitudinal regression analyses. In fact, most of the data are already stored and prepared from the period 2008-2019 by the author and may be provided on request. The pre-crisis period may be taken under consideration as well in order to measure possible effects of regions 'bouncing back' or 'bouncing forward'. Data-availability will be an important factor when studying such effects. For instance, Nordic countries but also The Netherlands have rather rich data that can be drawn from. Generalization is an important aspect as well to take into account, but more studies in different countries would enrich the current body of knowledge on regional resilience.

Further, the role(s) of innovation are interesting to explore further. For instance, Pierre-Alexandre Balland, Ron Boschma and co-workers at Utrecht University who are particularly interested in evolutionary thinking study the effects of innovation in regard to resilience based on patent data. The latter shed light on such ideas from a different (empirical) standpoint which tracks inventors/knowledge workers' innovative behavior in time and space. Bathelt et al. (2017) are elaborate on this topic in their handbook on 'innovation and knowledge creation'. Furthermore, as Bishop (2019) demonstrated with advanced econometric methods, interregional and/or cross-border knowledge flows can be captured nowadays which allows for much more integrated and dynamic research approaches that capture 'missing links' in conventional approaches as used in this thesis.

Furthermore, regional abilities to recovery from economic shocks could be interpreted as an economic 'readiness' for future crises as mentioned briefly in chapter 1. This relates in a sense more to enduring impact, yet from an evolutionary perspective a focus on long-term growth paths implies that regions are to differing extents capable of diversifying and/or specializing into new sectors and economic activities. This means that for instance Brexit urges regions to develop in different directions with a certain degree of uncertainty (and opportunity?), yet regions that show promising structural economic characteristics as discussed above will likely be more ready to shake off negative effects.

Concluding, in terms of policy suggestions that however stand-alone do not take part in this thesis, Smart Specialization Strategies (S3) could be adopted and adapted. McCann (2015) in this regard links evolutionary economic concepts like industry relatedness to ideas of resilience and growth. However, S3 implicitly suggests government investments and initiatives which is a good first step. On the other hand, as elaborated on above regarding the Dutch city-region of Eindhoven, government is not the only party involved and certainly not the only party that has all the relevant knowledge in setting up such strategies. Therefore, the only attempt in policy advice that will be given here is that industrial development spurring growth should really be *smart* and be characterized as a learning process. Experiences of other firms and places can be exemplary, however, the unique national and regional contexts that characterize Great Britain, the UK and its Local Authority Districts and beyond should of course be appreciated in any type of cooperative endeavors.

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Appendix I: Continuation 'Country Profile' regarding future prospects and Brexit

2.4 Trade deals and future prospects

Bilateral trade deals will most likely become the UK's essential building block along which future economic development will be aligned. It is logical to focus on notions of competitiveness, and Minford and Meenagh (2020) argue that the UK has a large economic emphasis on financial services. The latter are in his line of reasoning moreover less dependent on trade relations with the EU27 (what can also be seen in section 2.1), which in turn advocates in a sense for more independence in itself. One might argue that this particular perspective is somewhat reductive, yet it draws attention that most Western (European) media report negative aspects and predominantly pessimistic foresights with regard to trade and economic development. This can be expected when considering that the EU loses a political and economic heavyweight with comparative advantages such as its financial services that are connected outwards into the rest of the world (including Europe).

The Department for International Trade (GOV.UK, 2021) reports current trade agreements that are either ratified (as of January 1, 2021), 'not fully in effect' or 'still in discussion'. What can be seen on their website is that most deals have been ratified, of which Japan and Switzerland and to a lesser extent South-Korea and Singapore are some of the economically larger countries on the list, and also Iceland, Norway, Israel and Turkey constitute trading partners with considerable amounts of exchange. Regarding the details and differences with the pre-Brexit situation it is interesting to highlight several bilateral trade deals – non-exhaustive – with both proximate and distant countries that constitute a large amount of trade, as they will have the most economic impact and also give a picture of what the UK exchanges in terms of goods and services.

To start with the geographically most proximate (non-EU) countries, Norway and Iceland, it is mentioned in the official agreement in the first article (Crown, 2020a) that:

> "The objective of this Agreement is to ensure continuity of the preferential trade in goods, to the extent possible, between the United Kingdom and Iceland, and between the United Kingdom and Norway, respectively, as provided for by the Trade-Related Agreements between the European Union and one or both of Iceland and Norway" (p. 3).

It is also noteworthy that under article 12 ('Continuation of Time Periods') it is stated that "if a period in the Trade-Related Agreements between the European Union and one or both of Iceland and Norway has ended, any resulting rights and obligations shall continue to be applied between the Parties". This implies that these countries remain intertwined with the EU27, which might also impact the relationship between these countries and the UK. Moreover, with regard to services, the Department for International Trade (GOV.UK, 2021) states that 'interdependencies with EU laws and systems' restrict trade and the UK finds itself in a position of being less able to intervene in this respect. Nevertheless, this applies to Norway and Iceland that are EFTA states and are part of the EEA (as described in section 1.1).

With regard to Switzerland which is an EFTA state but has *not* joined the EEA, in the trade agreement (Crown, 2019) the following objective is formulated:

> "The overriding objective of this Agreement is to preserve the existing trading relationship between the Parties under the Switzerland-EU Trade Agreements and to provide a platform for further trade liberalisation and development of the trade relations between them" (p. 5).

It is interesting to consider the position of Switzerland with regard to the EU, as the country is land-locked and the surrounding EU-countries constitute its largest trading partner, yet conversely the EU is also dependent on Switzerland's commercial services and export of distinct chemical, medical and other highly specialized industrial and consumer goods. Different compared to the UK is that Switzerland has complied with free movement of people across borders – it is part of *Schengen* – and has comprehensive bilateral agreements including contributions to the EU for "economic and social cohesion" (European Commission, 2021). To an extent similar to the UK are the distinct financial activities which are rooted in history and geography. Overall, next to having their own national currencies, these countries thrive as independent European nations with however close affiliations with the EU.

The last case of bilateral trading partners that is considered in this section is Japan. This country is both geographically and culturally very distant, yet there are also comparisons to be made with regard to its geographical position regarding continental East Asia compared to continental Europe for the UK. In particular, while acknowledging the distinct regional idiosyncrasies in Asia and Europe, Japan's geographical position regarding the ASEAN-countries and more proximately the technologically advanced country South-Korea and economic hotspots like Hongkong but also China itself which are among Japan's major trading partners, next to the US (Britannica, 2021), it can be stated that there are considerable economic and geopolitical interests similar to the situation at home. Further, both countries are island-states and have a hegemonic and imperial history and are also part of the G7. The UK is in fact the world's fifth largest economy (Whyman & Petrescu, 2020, p. 122). Japan's population however is with approximately 125.65 million in 2020 bigger than that of the UK which has about 67.89 million inhabitants in 2020 (Statistics Bureau of Japan, 2021; United Nations, 2019). GDP per capita in 'purchasing power parity' (PPP) in Japan is 43,710.26 international dollars in 2019 and total GDP in 2019 was $5,515.82 billion, compared to the above mentioned $3,246.54 billion GDP and $48,603.04 GDP per capita for the UK in 2019 (International Monetary Fund, 2021). These figures are shown to draw a sketch of these two countries and briefly compare them as Japan is a developed, advanced and prosperous Asian country with similarities that are interesting to briefly investigate. It is an example that a single country can 'survive' and thrive, which may be exemplary for the UK as we look at the status quo and future prospects.

What makes bilateral trade agreements such as with the country just discussed promising is the fact that they can be tailored to the national economies (GOV.UK, 2020), which contrasts the more encompassing deals of the EU27 (Whyman & Petrescu, 2020). This means that domestic interests are better safeguarded and there is more flexibility as there are no 27 countries that have to sign them. It is further interesting to note that the deal with Japan has according to GOV.UK "big benefits for digital and data, financial services, food and drink, and creative industries" (para. 5). More formally, the trade deal is accompanied by the following statement: "The objectives of this Agreement are to liberalise and facilitate trade and investment, as well as to promote a closer economic relationship between the Parties" (Crown, 2020b, p. 10). Investment will be paid closer attention to in the following section.

2.5 EU-UK-Japanese relations and FDI

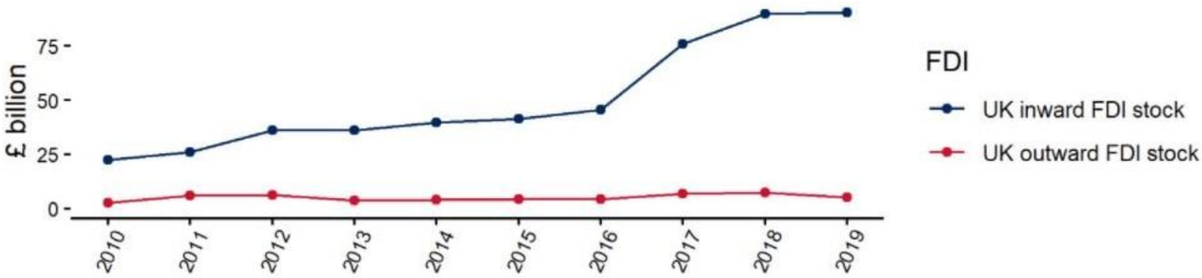
Digging a little bit deeper into the particular economic relationship of the UK with Japan, it is interesting to make a comparison with the trade deal the EU has with Japan. In other words, what benefits does the bilateral trade agreement between the UK and Japan bring forth which could not have been exploited when the former would have remained an EU-member?[21]

[21] What is important to note here is that the post-Brexit situation as said brings to bear a manifold of new opportunities and challenges that are however in all likeliness *not* symmetric in the sense that withdrawal from the EU does not bring into motion contra-mechanisms in similar pace and quantities with respect to the ones before and during accession to the EU (Whyman & Petrescu, 2020). This does not mean that analysis is not possible. It is a more fundamental question which will be expanded on in the paragraphs below.

As said, the new post-Brexit situation provides the UK with an opportunity of nationally tailored interests to be safeguarded. The trade deal “goes beyond existing EU deals” (GOV.UK, 2020, para. 5), which is particularly important with respect to (financial) services. Essentially, it is remarked that frameworks to well facilitate trade in services across the EU are still rather underdeveloped (Whyman & Petrescu, 2020). This implies that EU trade with Japan in the realm of services may be less efficient. This is pressing as UK export has a considerable share in services (see section 2.1) which also counts for trade with Japan (Department for International Trade, 2020).

The latter state that “the EU-Japan Agreement baseline for financial services has been transitioned”, regarding “additional legal certainty and recourse to UK financial services suppliers operating in or trying to access the Japanese market”. This also works the other way around. Moreover, ‘regulatory cooperation’ between the governmental and financial bodies involved is better elaborated on in their framework (p. 24). Further, it is important to note that investment of Japan in the UK in 2019 has been substantial with £90.5bn, and vice versa with £5.2bn (£7.4bn in 2018) (Department for International Trade, 2021, p. 10). Actually, in can be seen in figure 11 below that after a steady and relatively modest increase in inward investment originating from Japan, from 2016 onwards there has been a striking boost in FDI which *might* be related to Brexit. However, considering FDI of Japan with regard to the EU27 (excluding the UK), it can be seen that there is a steep increase from 2018 to 2019 as well (€176.5 to €217.0bn which is about £151 to £186bn), yet in the period 2016-2017 these amounts are respectively €181.3 to €177.4bn (European Commission, 2021) which is actually a relatively small decline – even more so when comparing this to the trend in figure 11.

Figure 11: “Stock of foreign direct investment between the UK and Japan” (Source: Department for International Trade, 2021, p. 10)



Source: ONS, 2019 FDI main release. Data is on a directional basis, data supression can cause breaks in the trends.

Moreover, the £90.5bn of FDI into the UK in 2019 is almost 50 per cent of the FDI into the EU27. Comparing these figures, it is an interesting question why investment has risen by such amounts and in this time-frame. This discussion will not be held here, but it leads to thought-provoking arguments and questions about economic development in both the EU and the UK and how third countries respond to these. At least, the economic relations between Japan and the UK are an extraordinary case with regard to investment that can serve as input material for further analysis.

Regarding the EU-Japan Agreement in general compared to the new UK-Japan deal (Department for International Trade, 2020, p. 26) there is much continuity, yet ‘investment protection’ is what has not been given shape and thus provides the UK with an opportunity here (Morita-Jaeger, 2020). Below, in table 14, an overview is given of several services companies in the UK that are part of the ‘Top 30’ Japanese employers in 2019-2020. The companies increased their number of employees significantly – mostly by means of acquisitions – and, importantly, investments are often strongly tied to the UK domestic market which makes them “Brexit proof”. Simultaneously, financial services companies like

MS&AD that were (still) more affected by EU regulations have taken measures like securing linked activities on the European mainland anticipating Brexit (Rudlin Consulting, 2018).

Table 14: 2019-2020 Japanese service companies' employment changes in the UK (Source: adapted from Rudlin Consulting Ltd., 2018)

Rank 2019-20	**Rank 2018-9**	**Company/Group**	**UK employees 2018-9**	**UK employees 2019-20***	**Change**
12	13	SoftBank	2,838	3,219	13.4%
18	25	MS&AD**	1,711	1,932	12.9%
24	26	Outsourcing	1,688	1,854	9.8%

* "greater part of year occurs in 2019, eg Apr 2019 to Mar 2020 or Jan to Dec 2019";
** "employee figure is an estimate" (Rudlin Consulting Ltd., 2018).

In relative terms, most of the larger contributors to increasing employment from Japanese companies in this top 30 are in the service sector. There are however also companies (significantly) reducing their number of employees, such as Nissan, Fujitsu and Honda that are in the top 5 and which are predominantly manufacturing enterprises.

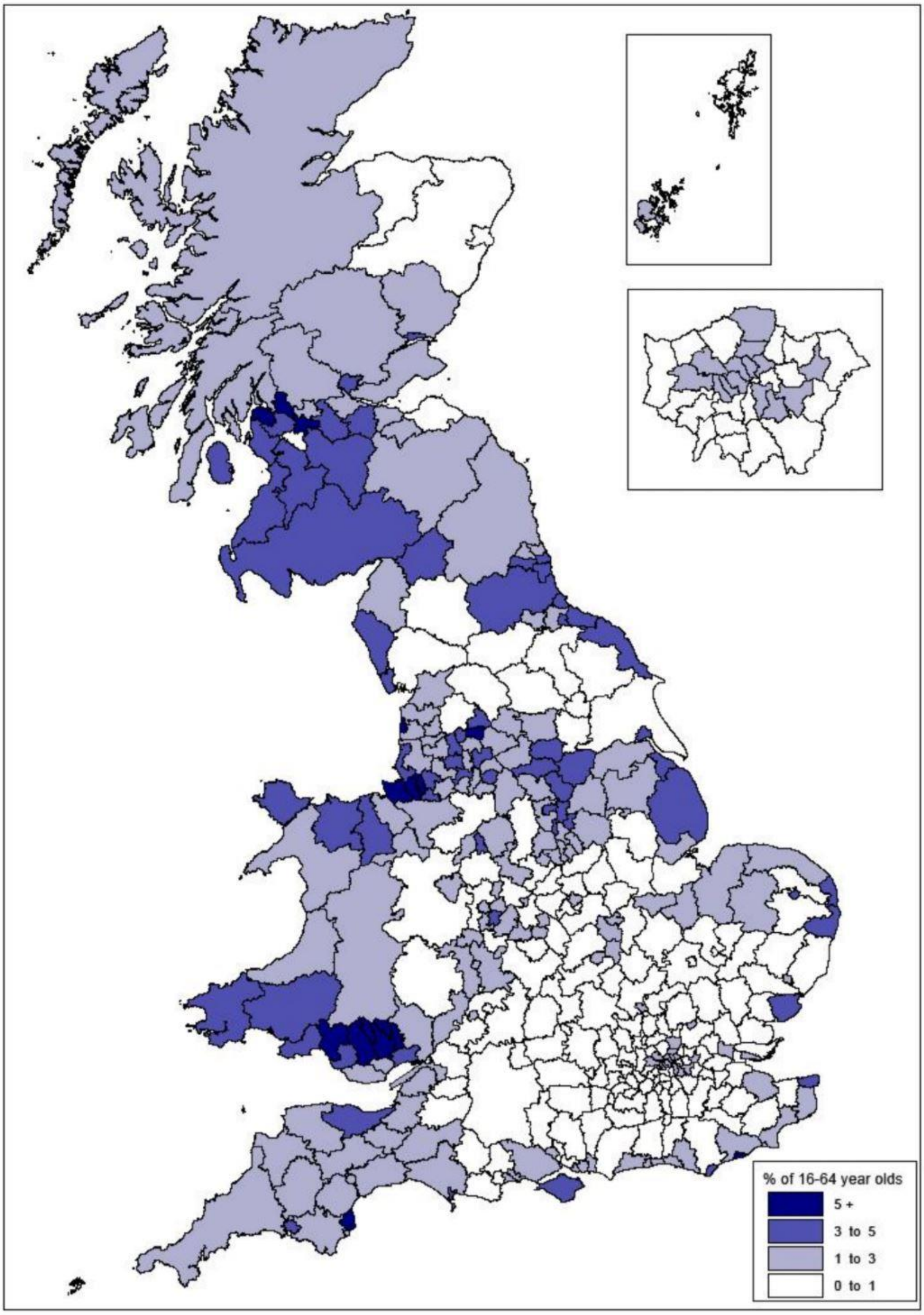
With regard to the position of the UK and EU-trade, the so-called *gravity model* has gotten much attention in economic debates as opposed to classical models (Minford & Meenagh, 2020; see also Whyman & Petrescu, 2020). The former state that advocates for the gravity model claim trade can be interpreted as "a function of distance and size", and regarding distance-related friction costs such as transport costs are expected to affect demand. This trade model more aligns with the EU rationale for trade across its (internal) borders, and contrasts with the 'classical model' that stems from early economists like Ricardo (1817) that rests on international competition and the role of supply (Minford & Meenagh, 2020, pp. 27-29).

Relating this to the discussions in sections 2.1 and 2.2, it can be argued that the UK will be focusing even more on (inter)national competition based on comparative advantages. For instance, the highly (financial) service-based and knowledge-intensive nature of its economy which is also reflected in its trade deals are arguably decisive in future economic trajectories that may deviate from the former EU-oriented ones. In particular, Whyman & Petrescu (2020) argue that the UK has been economically more distant from the EU before and even during EU membership, and has more trading antennas into the Commonwealth nations and the US amongst others. Moreover, it can be questioned whether the UK has benefitted from EU membership in its most basic sense – namely in terms of money and economic growth. This is contested by the latter authors who scrutinize a large deal of economic studies claiming almost solely negative impact resulting from Brexit based on 'questionable assumptions' that have seemingly been mindlessly adopted by media and policymakers.

Exemplary and influential counterarguments in scientific debates regarding Brexit, like presented by Thissen et al. (2020) who study the economic geography of Brexit and the UK in particular, include interregional trade relationships with the EU. These also depend on geographical distances with regard to economic interdependencies and inherent sensitivity of regions towards unfolding probable scenarios resulting from the possible Brexit deals these authors mention. In essence, they argue that "adverse international competitive vulnerabilities of UK regions are much larger than those of the rest of the EU due to the dependency of the UK on the EU via global value chains" (p. 1). As described above, these arguments can be explained by a certain perspective that considers the EU as a most proximate political and economic partner that purportedly determines much of the UK's future economic development. Also important with respect to the economic functioning of the EU are enduring and growth-impairing bureaucracy, all kinds of protection and government interference regarding market forces as compared to the US which experienced much higher growth figures. This amongst others leads to higher overall production costs in the different European countries and thus has an impact on competitiveness (de Pater et al., 2004). These arguments can be interpreted as important contextual economic mechanisms characterizing the EU from which the UK retracts.

Valuable from the analysis by Thissen et al. are the sensitivity assessments regarding the different British (and EU27) regions because they reveal the (historically developed) economic viability of these regions when exposed to post-EU trading scenarios. However, scholars specialized in Brexit in particular like the in this section oft-mentioned authors Whyman & Petrescu (2020) stress the very importance of the economic *assumptions* made by many academics that study (possible) consequences of Brexit for the UK. Relating this to the different and arguably more 'distant' economic position of the UK with regard to the EU27 – Anglo-Saxon and more proximate to the US – the promising bilateral trade deals like with Japan open up new possibilities. Moreover, it has been stressed in footnote 20 above that exiting the EU does not set in motion symmetric contra economic developments compared to the country joining the EU which may or may not have fostered economic growth and development. This also affects value-chain interdependencies that Thissen et al. mention in their research. What all authors in this paragraph share in their views however, is the observation that different types of Brexit deals do not significantly change the UK's and/or its internal region's sensitivity with regards to opening up to trade by leaving the EU. It is an interesting question therefore how the UK and thus its internal regions can foster and stimulate future growth as Brexit is now a fact.

Appendix II: United Kingdom hidden unemployment by district in 2016



Source: “Sheffield Hallam estimates based on ONS and DWP data” (Beatty et al., 2017, p. 11)

Appendix III: Harmonization Local Authority Districts 2015-2019

<u>Firm birth rate 2015-2018 dataset *merge* in STATA:</u>
Bournemouth, Christchurch and Poole > three former seperate LADs with the same name
North Lanarkshire > copy pasted
Glasgow City > copy pasted
Dorset > five former separate LADs: East Dorset, North Dorset, Purbeck, West Dorset, Weymouth and Portland
East Suffolk > Suffolk Coastal, Waveney
West Suffolk > Forest Heath, St Edmundsbury
Somerset West and Taunton > Taunton Deane, West Somerset

Appendix IV: Explanatory variables main regression analyses

EMP_rate_2014	Employment rate 2014
UNEMP_rate_2014	Unemployment rate 2014
concentration_2019=1	Industry concentration *high* (Herfindahl-Hirschmann Index)
Within_entropy_2019	Related variety ('Within' Entropy Index of diversification)
concentration_2019=1 x Within_entropy_2019	'Relatedness within concentration' interaction term
within_share_2019	Share of related variety to unrelated variety
concentration_2019=1 x within_share_2019	'Share relatedness within concentration' interaction term
Across_Entropy_2019	Unrelated variety ('Across' Entropy Index of diversification)
DEGREE_percentage_2019	Education level (having a degree)
noDEGREE_percentage_2019	Having no degree/qualification
Qualification_percentage_2019	Education level (having a NVQ4+ qualification)
Job_training_2019	On-the-job training
percent_selfemp_2019	Self-employment rate
lnFirmBirthrate_15_19	Firm birth rates (average 2015-2019)
lnFirmDeathrate_15_19	Firm death rates (average 2015-2019)
lnDensity_2019	Population density (log)
Age_16_24_2019	Age groups (16-24, 25-49, 50-64)
Age_25_49_2019	
Age_50_64_2019	
SE, SW, EAST, LONDON, NE, NW, SCOTLAND	Regional dummies (London, South East, South West, East, North East, North West, Scotland) a.k.a. regional fixed effects

Appendix V: Industrial categories pertaining to group K (Finance and Insurance)

2-digit level:

1. 64 : Financial service activities, except insurance and pension funding
2. 65 : Insurance, reinsurance and pension funding, except compulsory social security
3. 66 : Activities auxiliary to financial services and insurance activities

4-digit level:

1. 6411 : Central banking
2. 6419 : Other monetary intermediation
3. 6420 : Activities of holding companies
4. 6430 : Trusts, funds and similar financial entities
5. 6491 : Financial leasing
6. 6492 : Other credit granting
7. 6499 : Other financial service activities, except insurance and pension funding
8. 6511 : Life insurance
9. 6512 : Non-life insurance
10. 6520 : Reinsurance
11. 6530 : Pension funding
12. 6611 : Administration of financial markets
13. 6612 : Security and commodity contracts brokerage
14. 6619 : Other activities auxiliary to financial services, except insurance and pension funding
15. 6621 : Risk and damage evaluation
16. 6622 : Activities of insurance agents and brokers
17. 6629 : Other activities auxiliary to insurance and pension funding
18. 6630 : Fund management activities

Source: Office for National Statistics (2021e)

Appendix VI: Industrial categories pertaining to a selection of group C (Manufacturing)

2-digit level:

1. 26 : Manufacture of computer, electronic and optical products
2. 27 : Manufacture of electrical equipment
3. 28 : Manufacture of machinery and equipment n.e.c.

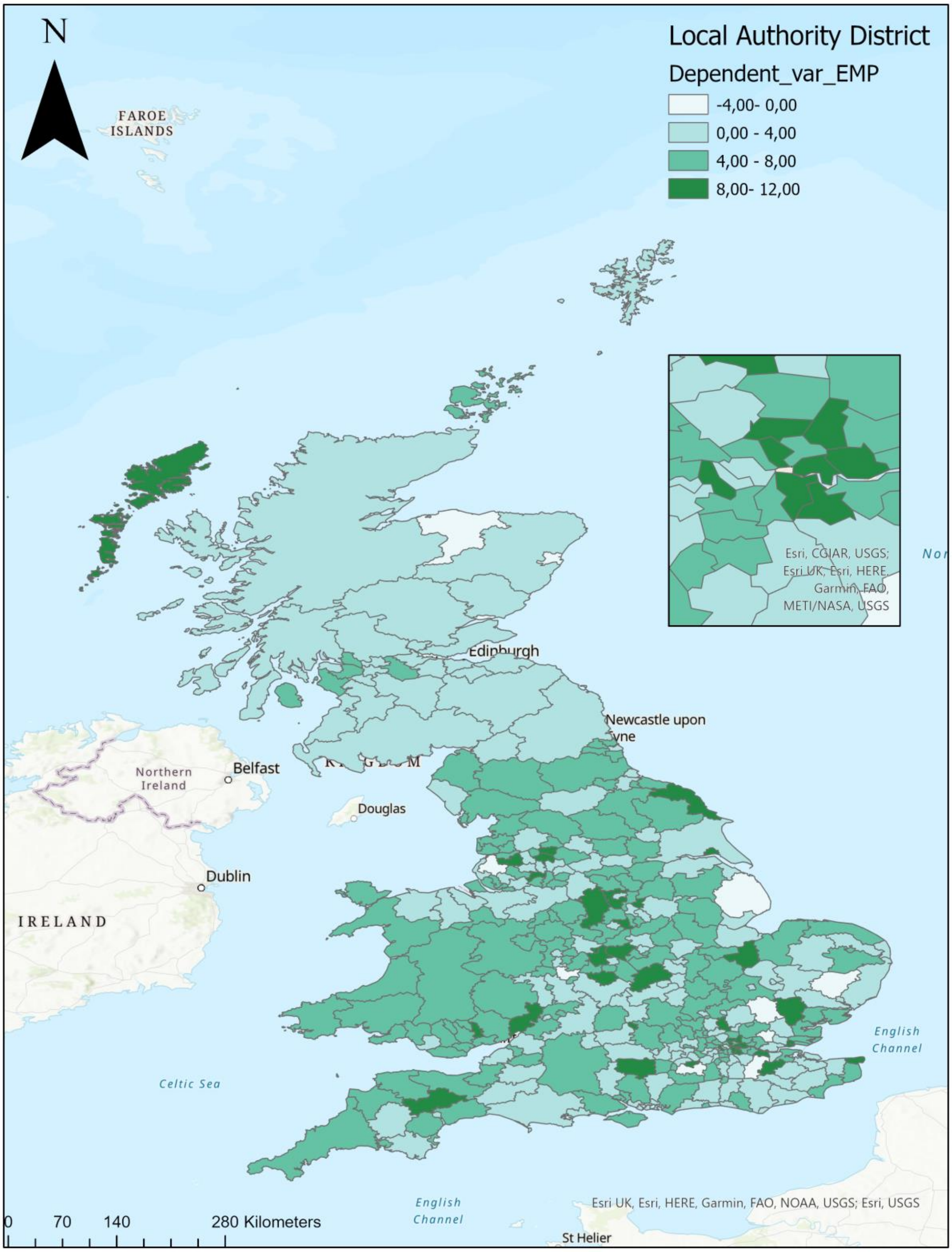
4-digit level:

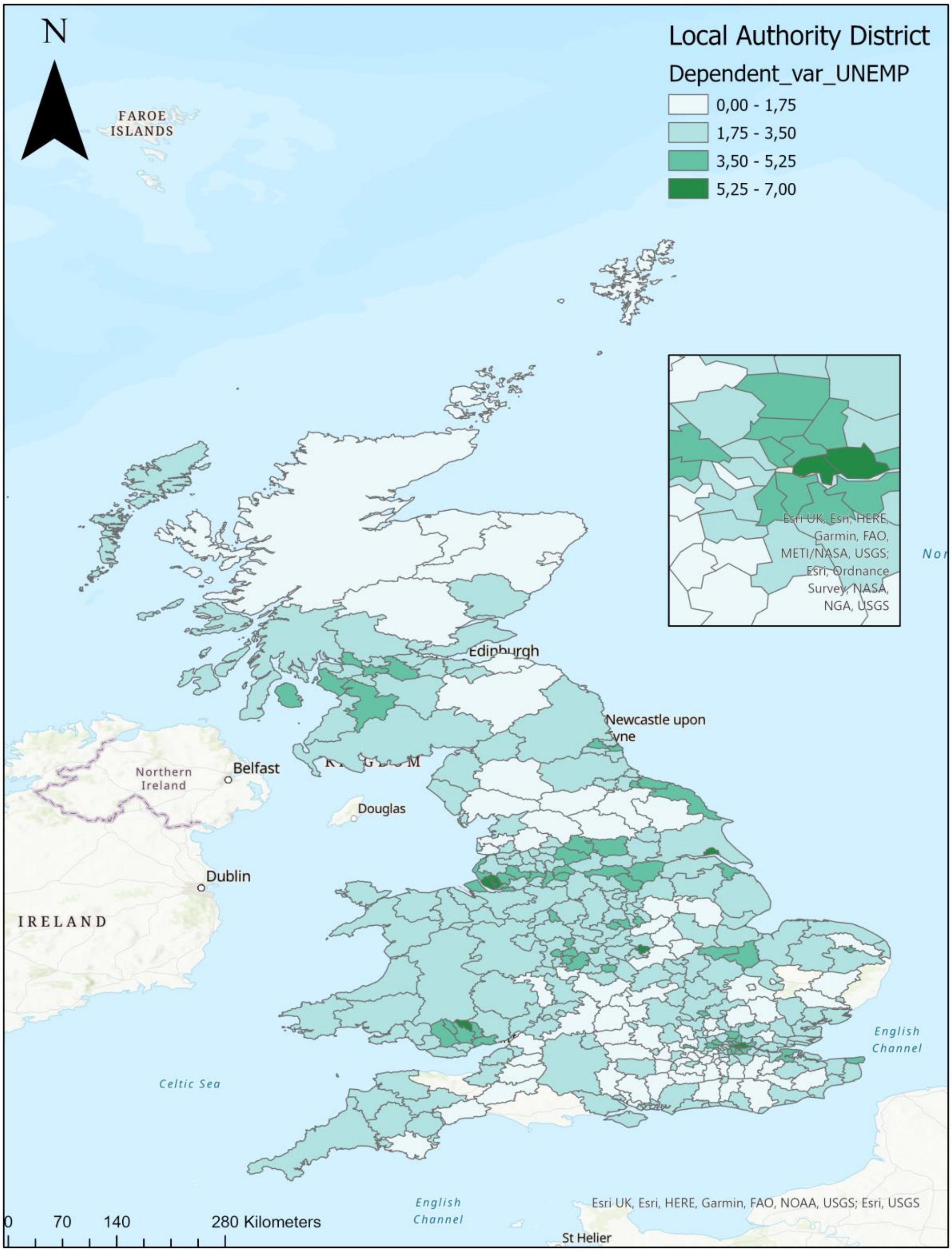
4. 2611 : Manufacture of electronic components
5. 2612 : Manufacture of loaded electronic boards
6. 2620 : Manufacture of computers and peripheral equipment
7. 2630 : Manufacture of communication equipment
8. 2640 : Manufacture of consumer electronics
9. 2630 : Manufacture of communication equipment
10. 2651 : Manufacture of instruments and appliances for measuring, testing and navigation
11. 2652 : Manufacture of watches and clocks
12. 2660 : Manufacture of irradiation, electromedical and electrotherapeutic equipment
13. 2670 : Manufacture of optical instruments and photographic equipment
14. 2680 : Manufacture of magnetic and optical media
15. 2711 : Manufacture of electric motors, generators and transformers
16. 2712 : Manufacture of electricity distribution and control apparatus
17. 2720 : Manufacture of batteries and accumulators
18. 2731 : Manufacture of fibre optic cables
19. 2732 : Manufacture of other electronic and electric wires and cables
20. 2733 : Manufacture of wiring devices
21. 2740 : Manufacture of electric lighting equipment
22. 2751 : Manufacture of electric domestic appliances
23. 2752 : Manufacture of non-electric domestic appliances
24. 2790 : Manufacture of other electrical equipment
25. 2811 : Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
26. 2812 : Manufacture of fluid power equipment
27. 2813 : Manufacture of other pumps and compressors
28. 2814 : Manufacture of other taps and valves
29. 2815 : Manufacture of bearings, gears, gearing and driving elements
30. 2821 : Manufacture of ovens, furnaces and furnace burners
31. 2822 : Manufacture of lifting and handling equipment
32. 2823 : Manufacture of office machinery and equipment (except computers and peripheral equipment)
33. 2824 : Manufacture of power-driven hand tools
34. 2825 : Manufacture of non-domestic cooling and ventilation equipment
35. 2829 : Manufacture of other general-purpose machinery n.e.c.
36. 2830 : Manufacture of agricultural and forestry machinery
37. 2841 : Manufacture of metal forming machinery
38. 2849 : Manufacture of other machine tools
39. 2891 : Manufacture of machinery for metallurgy
40. 2892 : Manufacture of machinery for mining, quarrying and construction

41. 2893 : Manufacture of machinery for food, beverage and tobacco processing
42. 2894 : Manufacture of machinery for textile, apparel and leather production
43. 2895 : Manufacture of machinery for paper and paperboard production
44. 2896 : Manufacture of plastics and rubber machinery
45. 2899 : Manufacture of other special-purpose machinery n.e.c.

Source: Office for National Statistics (2021e)

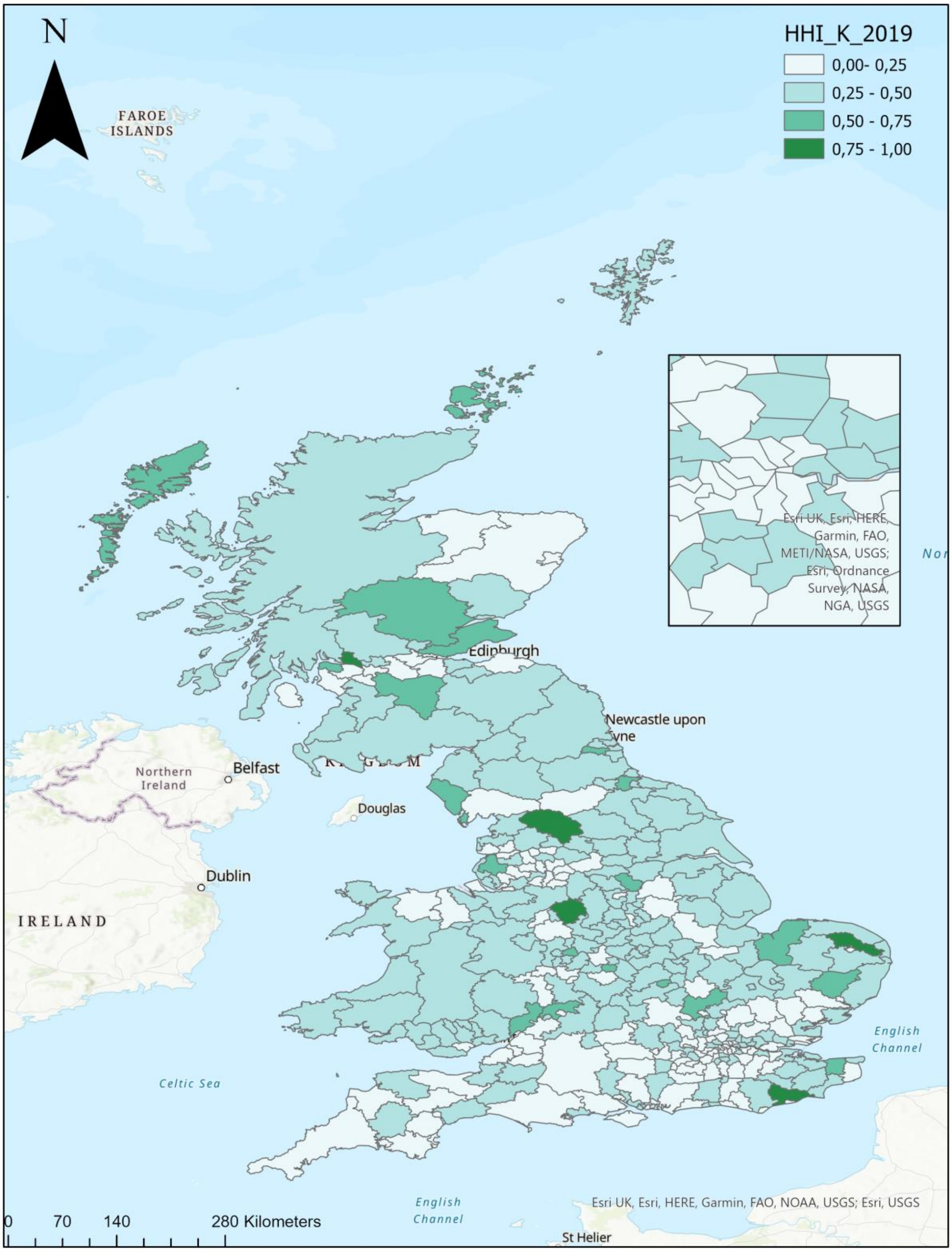
Appendix VII: geographical representation of the dependent variables

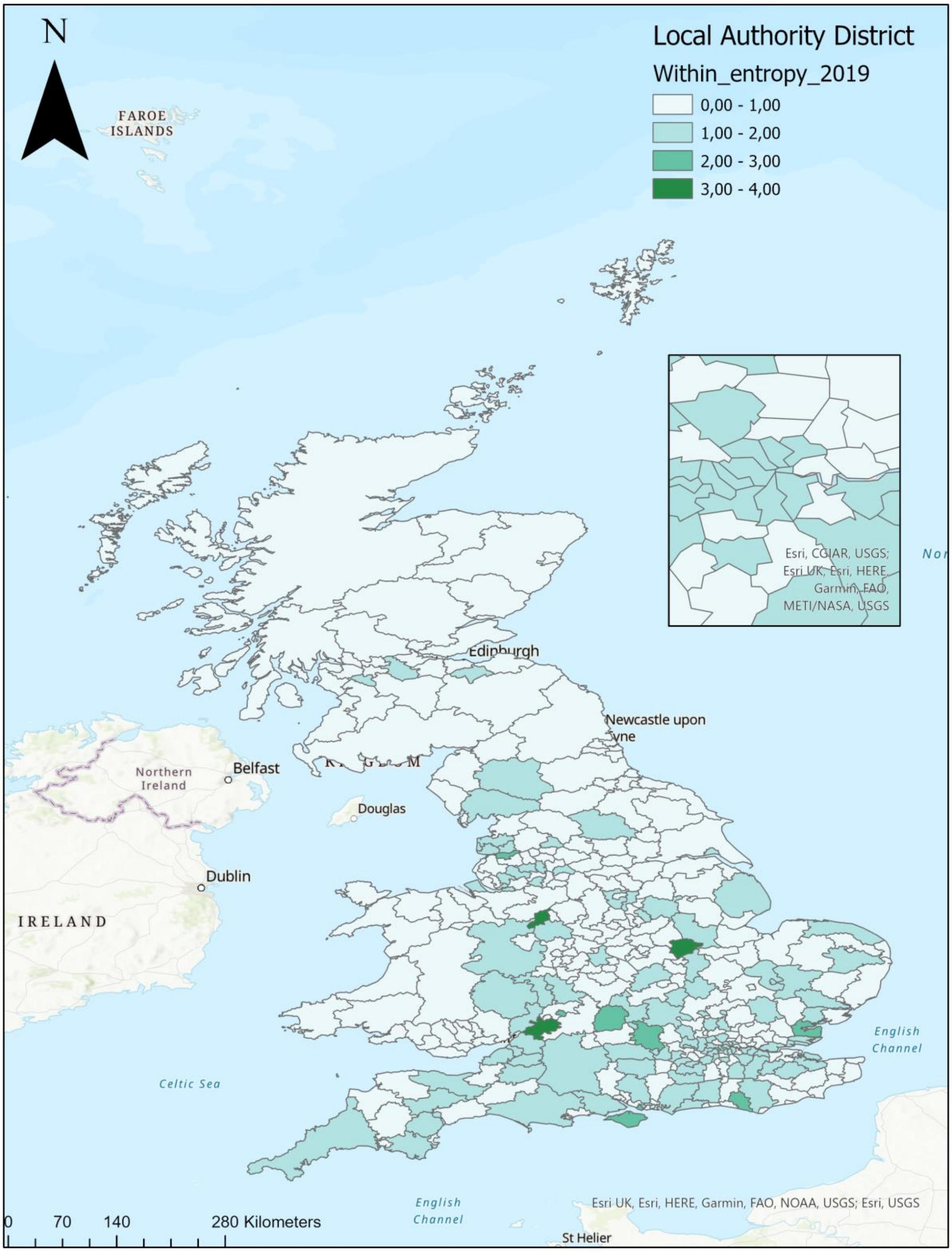


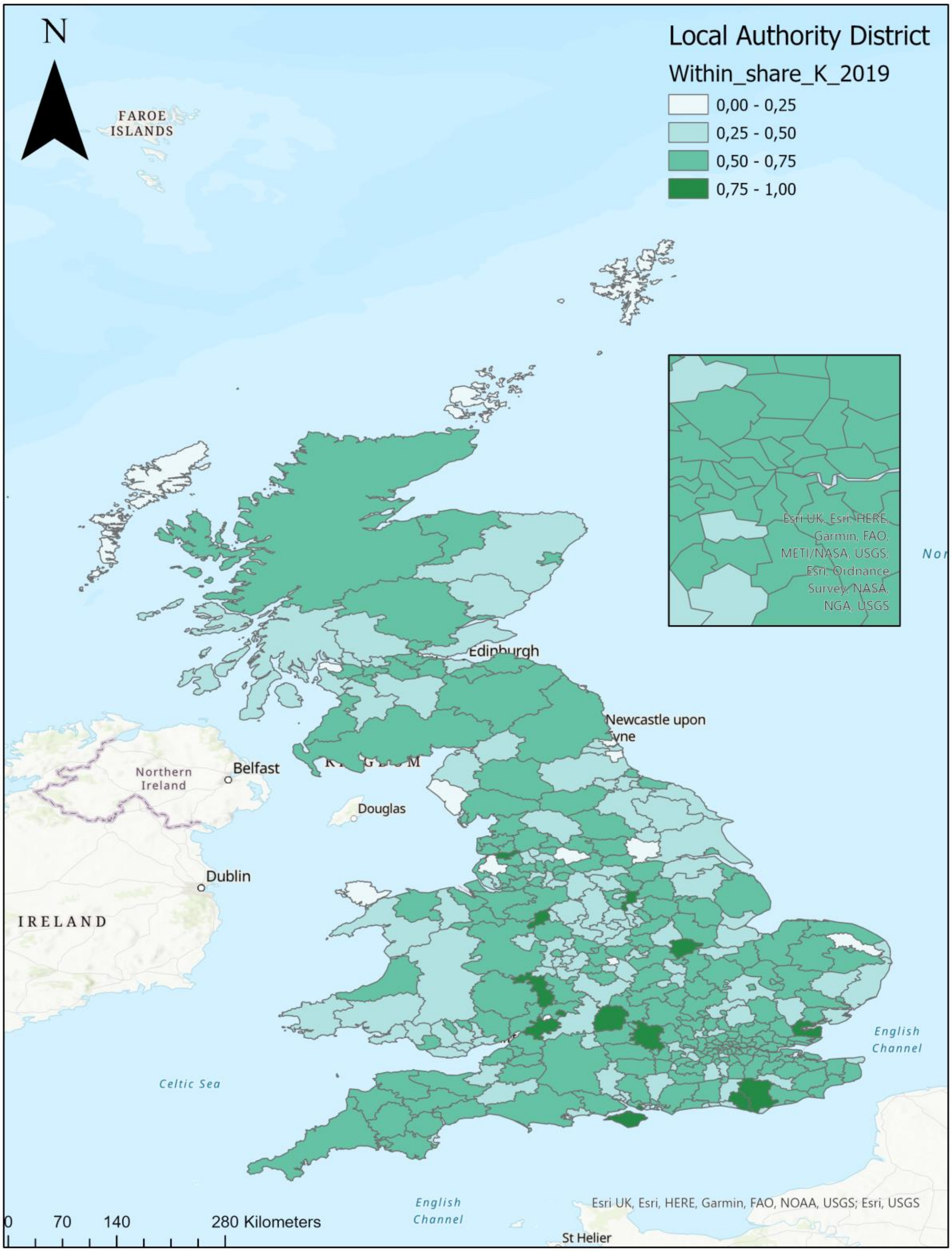


N
Local Authority District
Dependent_var_UNEMP
0,00 - 1,75
1,75 - 3,50
3,50 - 5,25
5,25 - 7,00
FAROE ISLANDS
Edinburgh
Newcastle upon Tyne
Northern Ireland
Belfast
Douglas
Dublin
IRELAND
Celtic Sea
English Channel
St Helier
0 70 140 280 Kilometers
Esri UK, Esri, HERE, Garmin, FAO, NOAA, USGS; Esri, USGS
Esri UK, Esri, HERE, Garmin, FAO, METI/NASA, USGS; Esri, Ordnance Survey, NASA, NGA, USGS

Appendix VIII: geographical representation of outcomes Herfindahl-Hirschmann Index and 'Within Entropy Index' / 'Within Entropy share'




N
Local Authority District
Within_entropy_2019
0,00 - 1,00
1,00 - 2,00
2,00 - 3,00
3,00 - 4,00
FAROE ISLANDS
Esri, CGIAR, USGS; Esri UK, Esri, HERE, Garmin, FAO, METI/NASA, USGS
Edinburgh
Newcastle upon Tyne
Northern Ireland
Belfast
Douglas
Dublin
IRELAND
English Channel
Celtic Sea
English Channel
Esri UK, Esri, HERE, Garmin, FAO, NOAA, USGS; Esri, USGS
0 70 140 280 Kilometers
St Helier


N
Local Authority District
Within_share_K_2019
0,00 - 0,25
0,25 - 0,50
0,50 - 0,75
0,75 - 1,00
FAROE ISLANDS
Edinburgh
Newcastle upon Tyne
Northern Ireland
Belfast
Douglas
Dublin
IRELAND
Celtic Sea
English Channel
English Channel
St Helier
Esri UK, Esri, HERE, Garmin, FAO, METI/NASA, USGS; Esri, Ordnance Survey, NASA, NGA, USGS
Esri UK, Esri, HERE, Garmin, FAO, NOAA, USGS; Esri, USGS
0 70 140 280 Kilometers

Appendix IX: OLS-tables (UN)EMPrecovery for sector high-tech manufacturing and (UN)EMPrecovery with unrelated variety

Table 10: Ordinary Least Squares (OLS) regression of 'EMPrecovery' for industry High-Tech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMP_rate_2014	-0.1202***	-0.1239***	-0.1489***	-0.1560***	-0.1173***	-0.1213***	-0.1461***	-0.1534***
	(0.0321)	(0.0322)	(0.0327)	(0.0366)	(0.0321)	(0.0323)	(0.0328)	(0.0330)
concentration_2019_C=1	1.4901**	1.3643	1.5268**	1.1394	1.4999**	1.3211	1.5305**	1.1085
	(0.7352)	(1.1975)	(0.7395)	(1.1869)	(0.7321)	(1.1935)	(0.7366)	(1.2034)
Within_entropy_Cselect	0.6550		0.4431		0.6645		0.4633	
	(0.4526)		(0.4495)		(0.4495)		(0.4470)	
concentration_2019_C=1 x Within_entropy_Cselect	-1.0025*		-1.0226*		-1.0109*		-1.0326*	
	(0.5447)		(0.5488)		(0.5423)		(0.5464)	
within_entropy_Cselect_share		2.2643		1.0462		2.1626		1.0271
		(1.7468)		(1.4720)		(1.7310)		(1.7107)
concentration_2019_C=1 x within_entropy_Cselect_share		-1.8642		-1.4658		-1.7914		-1.4297
		(1.9718)		(1.9542)		(1.9639)		(1.9816)
Across_entropy_Cselect	0.2302	0.5898	0.0099	0.0569	0.2530	0.5958	0.0348	0.0848
	(0.5820)	(0.6644)	(0.5830)	(0.6475)	(0.5804)	(0.6610)	(0.5816)	(0.6488)
DEGREE_percentage_2019	0.0039	0.0012	0.0187	0.0178				
	(0.0177)	(0.0178)	(0.0177)	(0.0185)				
noDEGREE_percentage_2019	-0.0848	-0.0918*	-0.0776	-0.0851*	-0.0910*	-0.0969*	-0.0838	-0.0902*
	(0.0522)	(0.0522)	(0.0520)	(0.0512)	(0.0528)	(0.0528)	(0.0527)	(0.0527)
Qualification_percentage_2019					0.0061	0.0040	0.0200	0.0196
					(0.0188)	(0.0189)	(0.0188)	(0.0189)
Job_training_2019	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0351	0.0427	0.0062	0.0087	0.0437	0.0496	0.0171	0.0186
	(0.0445)	(0.0449)	(0.0438)	(0.0455)	(0.0443)	(0.0447)	(0.0437)	(0.0440)
lnFirmBirthrate_15_19	-1.3027**	-1.2847**	-1.1227**	-1.0758**				
	(0.5155)	(0.5139)	(0.5032)	(0.4822)				
lnFirmDeathrate_15_19					-1.6540***	-1.6140***	-1.4957***	-1.4419**
					(0.5696)	(0.5669)	(0.5595)	(0.5577)
lnDensity_2019	0.0120	-0.0087	0.1092	0.1015	0.0000	-0.0221	0.1093	0.1009
	(0.1430)	(0.1429)	(0.1377)	(0.1494)	(0.1412)	(0.1413)	(0.1346)	(0.1349)
Age_16_24_2019			-0.0000**	-0.0000***			-0.0000**	-0.0000***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000	0.0000			0.0000	0.0000		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0001***	-0.0001***			-0.0001***	-0.0001***		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.3159	-0.2806	-0.2925	-0.2450	-0.2953	-0.2617	-0.2723	-0.2263
	(0.4107)	(0.4110)	(0.4122)	(0.4332)	(0.4097)	(0.4102)	(0.4113)	(0.4126)
SW	-0.0066	0.0241	-0.0687	-0.0550	0.0247	0.0539	-0.0548	-0.0438
	(0.5262)	(0.5289)	(0.5277)	(0.4609)	(0.5228)	(0.5259)	(0.5237)	(0.5277)
EAST	0.0557	0.0434	0.1316	0.1427	0.1003	0.0881	0.1825	0.1939
	(0.4320)	(0.4339)	(0.4351)	(0.4374)	(0.4325)	(0.4347)	(0.4358)	(0.4387)
LONDON	1.7300**	1.8102**	1.6554**	1.7613**	1.7782**	1.8469**	1.7450**	1.8423**
	(0.7265)	(0.7249)	(0.7225)	(0.6820)	(0.7251)	(0.7238)	(0.7181)	(0.7187)
NE	-0.9827	-0.8620	-1.4904**	-1.4068***	-0.9607	-0.8460	-1.4763**	-1.3967*
	(0.7364)	(0.7345)	(0.7226)	(0.4568)	(0.7330)	(0.7315)	(0.7190)	(0.7213)
NW	-0.1964	-0.0166	-0.4264	-0.2746	-0.1084	0.0657	-0.3451	-0.1966
	(0.4550)	(0.4522)	(0.4512)	(0.4749)	(0.4553)	(0.4529)	(0.4510)	(0.4502)
SCOTLAND	-2.2426***	-2.0538***	-2.4359***	-2.2531***	-2.2616***	-2.0649***	-2.5559***	-2.3784***
	(0.5659)	(0.5659)	(0.5606)	(0.5775)	(0.6083)	(0.6083)	(0.6015)	(0.6045)
Intercept	11.9632***	11.6682***	13.3770***	13.9480***	11.0786***	10.9305***	12.3234***	12.9466***
	(3.2313)	(3.4288)	(3.2651)	(3.4161)	(3.2882)	(3.4653)	(3.3216)	(3.4850)
R-squared	.2237007	.2197654	.2113325	.2036041	.2286072	.2242117	.2160338	.208213
N	359	359	359	359	359	359	359	359

*** p <0.01", "** p <0.05", "*p <0.1
SE = South East", "SW = South West", "NE = North East", "NW = North West

Table 11: Ordinary Least Squares (OLS) regression of 'UNEMPrecovery' for industry High-Tech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UNEMP_rate_2014	0.3940***	0.3944***	0.4132***	0.4148***	0.3943***	0.3908***	0.4152***	0.4088***
	(0.0315)	(0.0316)	(0.0315)	(0.0317)	(0.0321)	(0.0318)	(0.0321)	(0.0319)
concentration_2019_C=1	0.2707	0.2271	0.2972*	0.1835		0.2187		0.3070*
	(0.1654)	(0.2472)	(0.1674)	(0.2421)		(0.2479)		(0.1682)
Within_entropy_Cselect	0.1549		0.1203					0.1303
	(0.1026)		(0.0958)					(0.0959)
concentration_2019_C=1 x Within_entropy_Cselect	-0.1386		-0.1550					-0.1636
	(0.1234)		(0.1236)					(0.1239)
within_entropy_Cselect_share		0.4217		0.1862		0.4020		
		(0.3430)		(0.3133)		(0.3454)		
concentration_2019_C=1 x within_entropy_Cselect_share		-0.2167		-0.1329		-0.2033		
		(0.4082)		(0.3991)		(0.4088)		
Across_entropy_Cselect	0.0720	0.1663	0.0372	0.0768	0.0978	0.1655	0.0101	0.0402
	(0.1181)	(0.1368)	(0.1183)	(0.1297)	(0.1189)	(0.1351)	(0.1363)	(0.1177)
HHI_C_select_2019							-0.1813	
							(0.2309)	
DEGREE_percentage_2019	-0.0049	-0.0052	-0.0015	-0.0016				
	(0.0041)	(0.0041)	(0.0040)	(0.0040)				
noDEGREE_percentage_2019	-0.0010	-0.0011	0.0013	0.0010	-0.0007	-0.0005	-0.0001	0.0021
	(0.0127)	(0.0127)	(0.0127)	(0.0128)	(0.0129)	(0.0128)	(0.0130)	(0.0128)
Qualification_percentage_2019					-0.0030	-0.0031	0.0000	0.0002
					(0.0043)	(0.0043)	(0.0043)	(0.0043)
Job_training_2019	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0053	0.0056	0.0018	0.0016	0.0012	0.0057	0.0003	0.0027
	(0.0089)	(0.0091)	(0.0089)	(0.0092)	(0.0086)	(0.0090)	(0.0088)	(0.0089)
lnFirmBirthrate_15_19	-0.2134**	-0.2041**	-0.1339	-0.1199				
	(0.0992)	(0.0979)	(0.0987)	(0.0984)				
lnFirmDeathrate_15_19					-0.3132***	-0.3176***	-0.2448**	-0.2481**
					(0.1105)	(0.1100)	(0.1087)	(0.1104)
lnDensity_2019	0.0215	0.0180	0.0437	0.0407	0.0062	0.0162	0.0317	0.0465
	(0.0422)	(0.0420)	(0.0416)	(0.0414)	(0.0406)	(0.0411)	(0.0393)	(0.0401)
Age_16_24_2019			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000**	0.0000**			0.0000**	0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0000**	-0.0000**			-0.0000**	-0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.1692*	-0.1675*	-0.1778**	-0.1738**	-0.1860**	-0.1647*	-0.1961**	-0.1760**
	(0.0868)	(0.0872)	(0.0865)	(0.0870)	(0.0856)	(0.0875)	(0.0844)	(0.0865)
SW	0.0100	0.0102	-0.0009	-0.0037	-0.0284	0.0083	-0.0408	-0.0068
	(0.1160)	(0.1161)	(0.1132)	(0.1126)	(0.1101)	(0.1159)	(0.1086)	(0.1126)
EAST	0.0350	0.0319	0.0496	0.0506	0.0388	0.0458	0.0504	0.0633
	(0.0805)	(0.0803)	(0.0822)	(0.0821)	(0.0809)	(0.0817)	(0.0830)	(0.0837)
LONDON	-0.0650	-0.0677	-0.0092	-0.0064	-0.0730	-0.0572	0.0163	0.0120
	(0.1969)	(0.2004)	(0.2134)	(0.2178)	(0.2066)	(0.2041)	(0.2254)	(0.2181)
NE	-0.8460***	-0.8406***	-0.9738***	-0.9692***	-0.8499***	-0.8419***	-0.9685***	-0.9737***
	(0.1974)	(0.1972)	(0.1940)	(0.1953)	(0.1962)	(0.1937)	(0.1923)	(0.1913)
NW	-0.0503	-0.0297	-0.0934	-0.0727	-0.0565	-0.0150	-0.0908	-0.0816
	(0.1120)	(0.1108)	(0.1105)	(0.1094)	(0.1058)	(0.1107)	(0.1056)	(0.1096)
SCOTLAND	-0.4043***	-0.3907***	-0.4230***	-0.4064***	-0.4437***	-0.3832**	-0.4438***	-0.4357***
	(0.1409)	(0.1414)	(0.1358)	(0.1369)	(0.1451)	(0.1537)	(0.1490)	(0.1487)
Intercept	-0.3270	-0.4258	-0.6096*	-0.5746	-0.1219	-0.5637	-0.3891	-0.8040**
	(0.3462)	(0.4086)	(0.3250)	(0.3938)	(0.3089)	(0.4228)	(0.2948)	(0.3429)
R-squared	.7978347	.7972798	.792754	.7918309	.7964268	.7985041	.7916785	.7941301
N	354	354	354	354	354	354	354	354

*** p <0.01", "** p <0.05", "*p <0.1
SE = South East", "SW = South West", "NE = North East", "NW = North West
All models have robust standard errors due to heteroscedasticity issues with the dependent variable

Table 12: Ordinary Least Squares (OLS) regression of 'EMPrecovery' with unrelated variety

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMP_rate_2014	-0.1229***	-0.1230***	-0.1576***	-0.1592***	-0.1194***	-0.1194***	-0.1541***	-0.1556***
	(0.0321)	(0.0320)	(0.0328)	(0.0326)	(0.0321)	(0.0320)	(0.0328)	(0.0327)
concentration_2019=1	-0.2369	-1.5154	0.3396	-1.0574	-0.2405	-1.5778	0.3395	-1.1454
	(1.3584)	(1.1907)	(1.3745)	(1.2079)	(1.3546)	(1.1854)	(1.3709)	(1.2027)
Within_entropy_2019	0.3570	0.0744	0.3077	0.3339	0.3625	0.0503	0.3179	0.2971
	(0.3048)	(0.5043)	(0.3079)	(0.5112)	(0.3035)	(0.5030)	(0.3067)	(0.5100)
Across_Entropy_2019	-1.3139		-0.5281		-1.4088		-0.6250	
	(1.4702)		(1.4894)		(1.4647)		(1.4837)	
concentration_2019=1 x Across_Entropy_2019	0.7373		0.0280		0.7341		0.0097	
	(1.7187)		(1.7366)		(1.7143)		(1.7322)	
across_share_2019		-0.0448		-0.0233		-0.0474		-0.0270
		(0.0302)		(0.0305)		(0.0300)		(0.0303)
concentration_2019=1 x across_share_2019		0.0430*		0.0330		0.0444*		0.0349
		(0.0258)		(0.0262)		(0.0257)		(0.0260)
Degree_percentage_2019	-0.0023	-0.0057	0.0139	0.0117				
	(0.0179)	(0.0179)	(0.0180)	(0.0180)				
noDegree_percentage_2019	-0.0989*	-0.0994*	-0.1042**	-0.1005*	-0.1038**	-0.1050**	-0.1091**	-0.1068**
	(0.0518)	(0.0520)	(0.0519)	(0.0522)	(0.0524)	(0.0525)	(0.0525)	(0.0527)
Qualification_percentage_2019					0.0014	-0.0025	0.0164	0.0130
					(0.0190)	(0.0190)	(0.0192)	(0.0191)
Job_training_2019	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0257	0.0293	0.0003	0.0039	0.0326	0.0362	0.0096	0.0132
	(0.0436)	(0.0435)	(0.0437)	(0.0436)	(0.0434)	(0.0433)	(0.0435)	(0.0435)
lnFirmBirthrate_15_19	-1.1637**	-1.1578**	-1.0227**	-0.9918**				
	(0.5089)	(0.5087)	(0.5018)	(0.5014)				
lnFirmDeathrate_15_19					-1.5494***	-1.5416***	-1.4237**	-1.3806**
					(0.5641)	(0.5644)	(0.5591)	(0.5591)
lnDensity_2019	-0.0519	-0.0500	0.0697	0.0722	-0.0622	-0.0614	0.0710	0.0735
	(0.1418)	(0.1411)	(0.1372)	(0.1367)	(0.1400)	(0.1394)	(0.1342)	(0.1337)
Age_16_24_2019			-0.0000**	-0.0000**			-0.0000**	-0.0000**
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000	0.0000*			0.0000*	0.0000*		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0001***	-0.0001***			-0.0001***	-0.0001***		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.2756	-0.2335	-0.2780	-0.2247	-0.2545	-0.2100	-0.2582	-0.2023
	(0.4070)	(0.4062)	(0.4109)	(0.4103)	(0.4061)	(0.4054)	(0.4101)	(0.4095)
SW	-0.0805	-0.1320	-0.1609	-0.1878	-0.0590	-0.1122	-0.1567	-0.1880
	(0.5287)	(0.5283)	(0.5337)	(0.5336)	(0.5251)	(0.5247)	(0.5294)	(0.5295)
EAST	0.0266	0.0878	0.1231	0.2139	0.0679	0.1307	0.1691	0.2583
	(0.4405)	(0.4390)	(0.4470)	(0.4453)	(0.4402)	(0.4389)	(0.4468)	(0.4453)
LONDON	1.6724**	1.6529**	1.8226**	1.8320**	1.7096**	1.6970**	1.8954***	1.9143***
	(0.7313)	(0.7275)	(0.7278)	(0.7228)	(0.7304)	(0.7266)	(0.7237)	(0.7190)
NE	-0.8267	-0.8468	-1.3674*	-1.3918*	-0.8231	-0.8374	-1.3704*	-1.3883*
	(0.7399)	(0.7358)	(0.7361)	(0.7325)	(0.7364)	(0.7320)	(0.7323)	(0.7286)
NW	-0.0782	-0.0893	-0.2802	-0.2805	-0.0006	-0.0103	-0.2100	-0.2120
	(0.4464)	(0.4444)	(0.4493)	(0.4478)	(0.4463)	(0.4444)	(0.4488)	(0.4473)
SCOTLAND	-1.7943***	-1.7364***	-1.8247***	-1.7995***	-1.8036***	-1.7074***	-1.9435***	-1.8778***
	(0.5383)	(0.5370)	(0.5400)	(0.5388)	(0.5821)	(0.5785)	(0.5853)	(0.5819)
Intercept	14.7249***	15.9654***	15.3752***	16.0130***	13.8806***	15.2438***	14.3642***	15.2104***
	(3.2619)	(3.4297)	(3.3121)	(3.4774)	(3.3109)	(3.4578)	(3.3608)	(3.5060)
R-squared	.2144571	.21834	.1907905	.1944007	.2198964	.2237652	.1962059	.1995751
N	361	361	361	361	361	361	361	361

*** p <0.01", "** p <0.05", "*p <0.1

SE = South East", "SW = South West", "NE = North East", "NW = North West

Table 13: Ordinary Least Squares (OLS) regression of 'UNEMPrecovery' with unrelated variety

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UNEMP_rate_2014	0.3959***	0.3957***	0.4165***	0.4171***	0.3950***	0.3924***	0.4125***	0.4128***
	(0.0321)	(0.0318)	(0.0323)	(0.0321)	(0.0319)	(0.0320)	(0.0323)	(0.0243)
concentration_2019=1	0.1481	-0.3366	0.2421	-0.2655		-0.3347		0.2491
	(0.2675)	(0.2216)	(0.2769)	(0.2299)		(0.2226)		(0.3047)
Within_entropy_2019	-0.0263	-0.0837	-0.0278	-0.0438		-0.0868		-0.0291
	(0.0557)	(0.0895)	(0.0556)	(0.0897)		(0.0888)		(0.0677)
Across_Entropy_2019	-0.1979		-0.0946		-0.3146*		-0.1279	-0.1002
	(0.2572)		(0.2666)		(0.1658)		(0.1827)	(0.3308)
concentration_2019=1 x Across_Entropy_2019	-0.1081		-0.2159					-0.2289
	(0.3346)		(0.3460)					(0.3862)
across_share_2019		-0.0100*		-0.0072		-0.0101*		
		(0.0055)		(0.0057)		(0.0055)		
concentration_2019=1 x across_share_2019		0.0096**		0.0082*		0.0095**		
		(0.0047)		(0.0048)		(0.0047)		
HHI_K_2019							0.4948*	
							(0.2577)	
DEGREE_percentage_2019	-0.0046	-0.0056	-0.0014	-0.0021				
	(0.0042)	(0.0041)	(0.0040)	(0.0040)				
noDEGREE_percentage_2019	-0.0013	-0.0011	-0.0011	-0.0004	-0.0017	-0.0006	0.0011	0.0001
	(0.0127)	(0.0127)	(0.0126)	(0.0127)	(0.0127)	(0.0128)	(0.0128)	(0.0122)
Qualification_percentage_2019					-0.0025	-0.0034	0.0007	0.0007
					(0.0043)	(0.0043)	(0.0042)	(0.0044)
Job_training_2019	0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
percent_selfemp_2019	0.0022	0.0032	0.0002	0.0012	0.0008	0.0032	0.0008	0.0007
	(0.0089)	(0.0088)	(0.0090)	(0.0090)	(0.0086)	(0.0087)	(0.0087)	(0.0096)
lnFirmBirthrate_15_19	-0.1706*	-0.1709*	-0.1025	-0.0987				
	(0.0965)	(0.0991)	(0.0959)	(0.0974)				
lnFirmDeathrate_15_19					-0.3044***	-0.2881**	-0.2155**	-0.2182*
					(0.1107)	(0.1114)	(0.1082)	(0.1250)
lnDensity_2019	0.0131	0.0120	0.0346	0.0340	0.0039	0.0103	0.0357	0.0370
	(0.0416)	(0.0417)	(0.0409)	(0.0410)	(0.0404)	(0.0410)	(0.0387)	(0.0333)
Age_16_24_2019			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Age_25_49_2019	0.0000**	0.0000**			0.0000**	0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
Age_50_64_2019	-0.0000**	-0.0000**			-0.0000**	-0.0000**		
	(0.0000)	(0.0000)			(0.0000)	(0.0000)		
SE	-0.1573*	-0.1422*	-0.1692**	-0.1526*	-0.1718**	-0.1387	-0.1669**	-0.1675*
	(0.0853)	(0.0843)	(0.0850)	(0.0839)	(0.0840)	(0.0849)	(0.0843)	(0.0905)
SW	0.0001	-0.0052	-0.0107	-0.0127	-0.0275	-0.0072	-0.0290	-0.0177
	(0.1108)	(0.1121)	(0.1099)	(0.1112)	(0.1081)	(0.1120)	(0.1061)	(0.1214)
EAST	0.0139	0.0403	0.0302	0.0617	0.0181	0.0541	0.0435	0.0440
	(0.0824)	(0.0837)	(0.0839)	(0.0852)	(0.0827)	(0.0850)	(0.0853)	(0.1002)
LONDON	-0.1158	-0.1089	-0.0322	-0.0181	-0.1131	-0.0969	-0.0092	-0.0162
	(0.2021)	(0.2058)	(0.2180)	(0.2224)	(0.2044)	(0.2087)	(0.2226)	(0.1621)
NE	-0.8825***	-0.8724***	-0.9976***	-0.9898***	-0.8739***	-0.8753***	-1.0091***	-1.0026***
	(0.1990)	(0.2022)	(0.1944)	(0.1956)	(0.1945)	(0.1982)	(0.1910)	(0.1651)
NW	-0.0563	-0.0519	-0.0853	-0.0791	-0.0631	-0.0379	-0.0793	-0.0752
	(0.1081)	(0.1077)	(0.1079)	(0.1076)	(0.1064)	(0.1071)	(0.1065)	(0.0983)
SCOTLAND	-0.4236***	-0.4004***	-0.4076***	-0.3878***	-0.4392***	-0.3924***	-0.4418***	-0.4309***
	(0.1299)	(0.1298)	(0.1280)	(0.1275)	(0.1394)	(0.1427)	(0.1372)	(0.1304)
Intercept	0.1918	0.5484	-0.2373	0.0118	0.1947	0.4035	-0.5245	-0.4253
	(0.3705)	(0.4415)	(0.3539)	(0.4186)	(0.3129)	(0.4629)	(0.3273)	(0.4413)
R-squared	.797655	.7979863	.7925265	.7925391	.7979459	.7990598	.7942441	.7937346
N	356	356	356	356	356	356	356	356

*** p <0.01", "** p <0.05", "*p <0.1

SE = South East", "SW = South West", "NE = North East", "NW = North West

All models have robust standard errors due to heteroscedasticity issues with the dependent variable