Regional resilience, skill-relatedness and growth of plants[1]

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[1] Although the word *plant* might suggest an establishment in manufacturing industries, where on an industrial scale products are produced, in this research it refers to an individual establishment in any industry.

ABSTRACT

As the reaction of regions towards the economic crisis – regional resilience – deviates across the Netherlands. The question is whether this depends on its regional economic structure. As regional resilience is determined by the survival and growth of plants in a region, plant-level analysis is an interesting addition to existing resilience analysis. Focus in this thesis lies on cognitive relatedness between industries, as one of the agglomeration benefits of a regional economic structure.

The research question is "t*o what extent does regional relatedness influence the survival and growth potential of plants during and after economic shocks in the Netherlands?"* is answered by using state-of-the art indicators, distinguishing resilience subperiods, and uniquely analysing growth on the plant level. This thesis considers the regional economic structure ("agglomeration forces") as an explanatory variable for a plant's growth potential. By measuring relatedness, diversification and specialization, the impact on individual plants is analysed and their impact can be compared. Relatedness is measured both on a region specific (*cohesion*) and a region-industry specific (*closeness*) dimension. It is concluded that the region-industry specific dimension has higher explanatory value. The heterogeneity of agglomeration impact on employment growth between industries is unveiled, as the influence of the regional economic structure deviates when estimating its relation with plant growth for a selection of various industries. For knowledge-intensive sectors, like high-tech and creative industries, the number of related industries appears to have a positive impact, contrary to other industries. Overall, relatedness can positively influence employment growth of plants, however this is context (i.e. industry, phase of crisis) specific and not per se to a larger extent than other agglomeration forces like diversification or specialization.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

Regional economic structure is in its basics determined and facilitated by the plants and offices of various industries in the region. Having only a few industries implies a specialized region, whereas a various number of industries implies a diversified region. In academic literature, many researchers have analysed regional differences and discussed which structure presents the best environment for productivity or employment growth. A long time ago, Marshall (1920) already argued that productivity or employment growth is more likely to occur in specialized areas, where industries benefit from economies of scale or localization externalities (in the form of a skilled labour pool, shared suppliers, an/or knowledge spillovers). On the other hand, Jacobs (1969) suggested that diversified regions are more likely to experience growth because there is a higher chance of product renewal, crossovers and innovation. This has led to a heated discussion to clarify this contradictive image (Glaeser et al., 1992; Feldman and Audretsch, 1999; Beaudry and Schiffauerova, 2009; De Groot et al., 2016).

With related variety, Frenken, Van Oort and Verburg (2007) present an alternative, third concept to this discussion. Similar to Jacobs (1969), they argue that it is important to interact with other industries because this will increase learning opportunities and knowledge spillovers. However, this interaction is only favourable if the interaction occurs between cognitively related industries. One can learn from others if they do related, but not exactly the same things. The relatedness between industries does not imply that they are similar, however their core activities have similarities in technology used, customers served and business processes applied. This makes the interaction worthwhile for (radical) innovation and knowledge spillovers. Indicators of the degree of relatedness are the flows of labour recruits, as these flows are knowledge intensive by definition and are more likely to occur between related industries than between unrelated ones. The employees from related industries are expected to require similar skills and capabilities, which is a result of the similarities in core activities.

Diodato and Weterings (2015) link this concept with the ability of a region to recover after an economic shock in terms of employment, regional resilience. Laid-off labour recruits are expected to find a new job easier in a related environment, than an unrelated environment. This link between relatedness and the resilience towards economic shocks, is also analysed by Eriksson and Hane-Weijman (2017). They studied regional relatedness in Sweden and its association with regional resilience. They were interested in the question whether regions with a high degree of relatedness are more likely to be resilient in terms of employment towards economic shocks. They find a positive association between the concepts of relatedness and regional resilience. However, a question is whether relatedness will influence employment dynamics at plant level as well, and what types of plants in terms of sector and location may be more affected by shocks. Although plant level impacts are important to research because of addressing unobserved heterogeneity present at the regional level, and consequently inhibit policy relevance (should plants or regions be targeted by policies?), economic research on the plant-region interaction are sparse because of data availability.

Given the debate on specialization and diversification of regional economies, the research question of this thesis is: *To what extent does regional relatedness influence the growth potential of plants during and after economic shocks in the Netherlands?*

Five sub questions are proposed, to support the research question and identify the added value of the research. These steps are distributed among the qualitative literature review and the quantitative data description and analyses. Sub questions:

1. How to define the shock period? *(chapter 3)*
2. How to define relatedness, vis-à-vis other measures of specialization and diversification? *(chapter 4)*
3. To what extent does regional relatedness determine conditional plant growth, as hypothesized, more than specialization and/or diversification per se? *(chapter 5)*
4. What is the impact in the relatedness-growth analysis in terms of the relative and absolute starting position of regions in terms of industry-base? *(chapter 5)*

In *chapter 2*, the literature review will discuss the concepts relatedness, diversification and specialization, and the relation towards the growth potential of plants. At the end of this section, hypotheses are stated to support the sub questions as proposed above. Then, in *chapter 3*, the dataset and the data exploration are presented. In *chapter 4*, the methods and approach of analysis are discussed. By means of panel data analysis the quantitative analysis is executed, of which the results are discussed in c*hapter 5*. *Chapter 6* entails a discussion of the results, and in *chapter 7* the conclusion is presented.

2 LITERATURE REVIEW

In this chapter the relation between the concepts diversification, specialization, and related variety is discussed. This literature review gives a better intuition for the quantitative analysis in chapter 5 and supports answering the research question: *To what extent does regional relatedness influence the growth potential of plants during and after economic shocks in the Netherlands?* In chapter 2.1 the concepts of specialization, diversification, and related variety are discussed in relation to each other. Additionally, a discussion follows regarding these concepts in relation to regional growth. It is believed that human capital is an important driver of the interaction between industries. The more industries are cognitively related, the more this interaction will positively influence knowledge spillovers. Human capital is one of the most important assets of a plant or region, because workers' capabilities, skills and knowledge are expected to induce innovation and therefore productivity growth. In chapter 2.2, it is discussed how related variety (*relatedness*) can be measured and the importance of human capital in these measurements. Chapter 2.3 presents a summary and the proposed hypotheses.

2.1 SPECIALIZATION, DIVERSIFICATION, AND RELATED VARIETY

The economic competitiveness of a region is dependent on the activities supplied by its plants and workers. Literature suggests that plants and workers are the drivers of the local economy (Maskell and Malmberg, 1999; Boschma, 2004). This indicates that regional competitiveness is the direct result of the aggregated state of local plants. As regions consist of a various range of plants and industries, the industry-mix will reflect the regional structure. A higher variety of industries indicates diversification, whereas a smaller variety indicates specialization. These two concepts therefore entail an opposed definition of the structure in a region.

Marshall (1920) argues that a specialized structure can benefit a region by localization economies. More recent studies have contributed to this theory and are bundled together in MAR-externalities, named after its contributors (Marshall-Arrow-Romer). MAR-externalities grasp the benefits of a high degree of specialization, where plants belonging to the same industry are located in proximity or clusters (Glaeser, 1992). These benefits are presented in threefold, namely a specialized labour-pool, shared local suppliers, and knowledge spillovers. First, a specialized labour-pool offers plants workers with a certain set of skills and capabilities which is valuable for a specific industry. This presents plants in that industry with the advantage of a constant labour supply, where vacancies are expected to be filled efficiently with industry-specific skilled labour. This benefits workers as well, as they can find a suitable match for their skills relatively easy (Andini et al., 2013). Second, as plants in the same industry are expected to demand similar services, local suppliers can operate more efficiently. This results in lower costs in daily operations (e.g. transportation costs) and benefits the plants. Third, knowledge spillovers are expected to occur as a result of localization. The interaction between plants and workers in the same industry will induce information and idea sharing, which increases their problem-solving abilities. As the plants operate in similar processes, the innovations are expected to be merely incremental of nature. Specialization naturally benefits productivity, as a focus on the same technologies and industries induces these advantages of matching, sharing and learning.

A counterview is presented by Jacobs (1969), who argues that diversification rather than specialization will induce knowledge spillovers and innovation. The interaction of plants across industries encourages a more radical form of innovation because their processes are different and therefore they can learn from each other. By imitating industries and sharing knowledge, products and processes can be renewed by learning from and copying other industries. This leads to product innovations by the opening of new markets rather than process innovation, and hence also diversified regional employment growth rather than (or before) productivity growth (Frenken et al., 2007).

If one of the theories of either Marshall (1920) or Jacobs (1969) is correct, the other is implausible as the theories seem to exclude one another. This is reflected by Glaeser et al. (1992), who elaborate on both perspectives of innovation and regional productivity growth. MAR-externalities suggest that knowledge spillovers occur from the interaction *within* industries. Regional specialization therefore would be valuable for productivity growth, by incremental innovation and specialized skilled labour. On the other hand, Jacobs' theory suggests that the interaction *across* industries induces knowledge spillovers. Because these industries have different processes, and workers apply different skills, the learning opportunities are more favourable than inside a similar industry. Therefore, regional diversification would be valuable for productivity growth.

Beaudry and Schiffauerova (2009), Melo et al. (2009) and De Groot et al. (2016) present an overview of academic literature on specialization and diversification with divergent outcomes. Both concepts can empirically contribute to innovation, productivity and employment growth. De Groot et al. (2016) conclude that it is context-specific which agglomeration externality, either specialization or diversification, is more important. Many papers focus on a specific sector or region, and this explains the heterogeneity of the results. The same reasoning is followed by Melo et al. (2009), who emphasize that the relevance of the outcomes of an agglomeration externality research in a specific context, is not relevant in others. On the other hand, Beaudry and Schiffauerove (2009) discuss that measurement levels (aggregation) and other methodological issues may be the cause of these ambiguous results.

An alternative view on this discussion is presented by Frenken, Van Oort and Verburg (2007) introducing the concept of the *related variety*. They emphasize the importance of the interaction between plants across industries, which corresponds with Jacobs (1969). However, the interaction is most valuable when these industries are related to some extent in their core activities. The relatedness is important in the interaction because of a common understanding, or *language*, which facilitates information sharing. Similar to the before mentioned agglomeration externalities (specialization and diversification), it is expected that the interaction between plants will encourage knowledge spillovers and innovation by sharing skills (labour) and information. Nonetheless, the degree of relatedness determines the value of this interaction. Different from (specialization related) localization economies, the industries and their processes are not identical and therefore higher learning opportunities arise.

Moreover, a region with a high degree of relatedness is less dependent on a specific industry than specialized regions, as labour redundant in one industry can employ their skills in related industries that are still expanding. Criticism on specialization entails the dependence on one or a few industries, which increases the regional vulnerability to economic shocks (Diodato and Weterings, 2015). A classic example is the city of Detroit, where the specialized manufacturing city experienced difficulties to resist an economic shock as their core activities declined.

As argued by Van Oort et al. (2015), a larger variety of industries will encourage the exchange of different ideas and more radical innovation is expected. This applies to both diversification and related variety; however, an important difference exists. Diversification implies the interaction with all other industries, whereas related variety suggests a certain threshold of relatedness. Not all industries are productively related, and therefore the degree to which they do is introduced. Related variety therefore offers an additional component, as figure 1 displays. It is necessary to distinguish which industries are related, to understand which interactions will influence (radical) innovation, productivity and employment growth.

Figure 1 – Different types of agglomeration externalities

2.2 Measuring related variety

Various approaches have been applied to measure the concept of related variety in a quantifiable matter. Case studies have applied the concept by measuring product-, industry-, or skill-relatedness. Product- and industry-relatedness can also be labelled as technological relatedness because both focus on technological specifications of either products or processes. Depending on the aim of the study and the availability of data, academics have shown several methods to analyse relatedness. An important benefit of using the interaction between industries is the real exchange of knowledge, skills and capabilities, as they are expected to induce (radical) innovation. The skills and knowledge are embedded in the workers of an industry, and as an important resource they are called human capital.

Kline and Moretti (2014) argue that educated and experienced workers are expected to be more productive and are fostering knowledge transfer with the mobility of interactions. Their research shows that local productivity, perceived as the education and experience of workers, positively influences the growth of the local economy. Employment growth can arise because the industries are more likely to find a good match for their skilled labour. Moreover, Fagerberg, Knell and Srholec (2004) show that human capital is an explanatory factor for differences in growth of regions and countries. As our research tries to capture regional differences and the influence of these differences on individual plants, human capital as a driver of the local economy is an important factor to capture.

Human capital can be captured by both tangible and intangible characteristics of individual labour recruits. On the one hand, with tangible indicators such as educational accomplishments, diplomas or training certificates, and with intangible indicators such as skills and experience gained on the job on the other hand. The latter is rather difficult to measure, because these are not easily quantifiable on a large scale.

Neffke and Henning (2013) developed a method to capture the relatedness concept as introduced by Frenken et al. (2007) in a flow perspective, by measuring labour flows between industries, assuming that similar skills are used when workers switch jobs. The ease to which labour recruits can switch from one industry to another reflects the degree of cognitive relatedness between these industries. These flows of labour between industries can identify the relationship between industries, called *skill-relatedness*, that is not necessarily visible in other relatedness measurements like subcontracting, trade or investment relations. It is expected that industries with related core activities are more likely to recruit related skilled labour, than industries with unrelated core activities. By analysing labour flows between industries, it is expected that more flows arise between related industries than between unrelated industries.

Academics have analysed the flows of labour and refined the concept of skill-relatedness, applying it in several levels of measurements (e.g. industry, regional). On a regional level, Eriksson and Hane-Weijman (2018) applied skill-relatedness in a larger set of structural characteristics (i.e. diversification, specialization) to analyse the relationship with regional resilience to economic shocks. Their expectation was that the degree of relatedness would make a region resilient and more likely to respond to (recover from) economic shocks in terms of employment. Their relatedness definition is replicated from Neffke, Henning and Boschma, who introduced the term *cohesion* to capture the related variety concept as presented in Frenken (2007). They presume that regions with a relatively high degree of cohesion can transfer human capital more easily. During or after economic shocks, this would positively facilitate regional resilience as the flows of labour are exchanged between related plants – putting unemployed persons to work who have previously attained related skills in industries, and/or learning from each other in terms of innovation and crossovers (and hence stimulating subsequent employment growth). The labour recruits of declining industries are then transferred towards a (growing) related industry, whereas the effect of the economic shock would be less comprehensive. Or as Eriksson and Hane-Weijman (2017, p.90) describe this process:

"[...] a region with a combination of industries that are 'close' in terms of these human capital resources would be a region that is cognitively *cohesive* and that facilitates adaptability in times of crises."

Their results are ambiguous, as two types of crises are analysed, and their results show different patterns across the two shocks. However, they find that the structure of the region, which is determined by their industry set, is very important for the resilience towards economic shocks. Their correlation analysis shows that regional diversification and cohesion (their labelled relatedness indicator) are positively associated with resilience. This exploratory result shows a possible positive relationship between resilience and relatedness on the regional level.

Neffke, Henning and Boschma (2011) evaluate the survival rate of industries, instead of regional resilience, and the effect of relatedness during economic shocks. Their study of Swedish industries argues that industries which are technologically related with the region's industry-relatedness are more likely to survive throughout economic cycles and shocks. An even closer look is presented by Boschma, Cappelli, and Weterings (2017), where the flows of labour recruits between individual plants are analysed. They examine the flows of labour recruits between related, unrelated, and similar industries, and evaluate the survival rates of plants in different stages of the industry life-cycle. Their results show that it depends on the industry and stage in the life-cycle, which effect labour recruits have on the survival of plants. Although their research considers individual plants and their survival rates, the resilience towards economic shocks is not analysed in their study.

Clarification on resilience is given by Martin (2012), who argues that regional resilience towards economic shocks can appear in several ways. The vulnerability of a region towards economic shocks is defined as regional resistance. The resistance concept refers to the extent to which a region reacts to a shock, from the point just *before* the decline starts. Another important dimension is the reaction *after* the shock, and how well the region will recover. The two periods before and after the economic shock are of interest, as they are a direct consequence of the regional structure. The structure determines how vulnerable a region, and the plants in the region, are to the economic shock (before). Moreover, it also determines how well the entities are able to recover and are able to adapt towards (employment) growth (after). This is also argued by Diodato and Weterings (2005), who find that laid-off workers are expected to find a new job more easily in related environments, which would confirm the ability to adapt or recover after an economic shock in terms of employment.

Regional analysis as presented by Eriksson and Hane-Weijman (2017) describes the relation between regional structures and resilience. However, a gap in the literature is the question on how this influences individual plants in these regions. Is it important for a *plant's* employment growth to be situated in a region with a high degree of related plants or industries?

2.3 SUMMARY AND HYPOTHESES

In the foregoing paragraphs, the concepts of diversification, specialization, and related variety were discussed. On the one hand, localization economies (from specialization) can benefit plants and its region by a specialized labour-pool, local suppliers, and knowledge spillovers (Marshall, 1920). However, this makes a region more vulnerable for economic shocks by its dependence on a specific industry. Diversification is therefore used as an opposing hypothesis because it is expected to encourage interaction outside the industry and this positively influences innovation and renewal of products (Jacobs, 1969). Academic literature has provided proof for both situations. The concept of related variety (Frenken, Van Oort and Verburg, 2007) provides an alternative view on these ambiguous results. Interaction between industries is important for regional growth, however this is only the case when it occurs in related industries. Several relatedness measurements have been proposed in the literature (product, industry, skill), where one reflects human capital by analysing labour flows. Skill-relatedness reflects the extent to which labour recruits flow from one industry to another, and arguably these flows inhibit the strongest knowledge intensity compared to other flows (Neffke and Henning, 2013). Applied to regional resilience, Eriksson and Hane-Weijman (2017) clearly observed differences across regions in their reaction to economic shocks.

The research in this thesis will apply the methodology of Eriksson and Hane-Weijman (2017) in the Netherlands, introducing an additional level of analysis – that of plants. The literature has not analysed to what extent differences in regional relatedness impact individual plants' growth. A plant might benefit from a related environment, as knowledge sharing is expected to be more valuable between related industries. Therefore, knowledge spillovers are expected to occur between related industries which benefits the individual firm's employment growth in a related environment. This addition contributes to the academic literature as it analyses the influence of regional related variety on individual plants instead of merely the aggregate of regions or industries, and it has a clear societal relevance as plants and regional level economic resilience is at the heart of strategic decision making on both levels.

We analyse this through the framework of Eriksson and Hane-Weijman (2017), asking whether **resilience** is associated with the degree of related variety. By means of their measurements of *cohesion* per region, and their employment growth measurements, we hypothesize:

> *Hypothesis 1: The resilience of a region, in terms of employment, towards economic shocks is positively associated with a higher degree of regional skill-relatedness.*

An important added value of the research concerns the plant level performance that is measured. This research analyses the **growth potential** of a plant during or after economic shocks and the influence of regional skill-relatedness. The expectation is that plants located in a region with a high share of related industries (high industry-specific cohesion), will have a higher chance of positive growth compared to plants that are location in a region with a lower share of related industries. Because of the ease of sharing information and knowledge between related plants, it is expected to benefit the industries. Growth is expected to be positively influenced, because of this information sharing. However, a plant first needs to survive before it is able to growth, as a condition for growth. Therefore, we try to correct for this unconditional growth by adjusting the analyses, and hypothesize:

> *Hypothesis 2: The conditional growth potential of a plant, in terms of employment, during and after economic shocks is positively influenced by a high degree of regional related industries and employment.*

To address relative and absolute employment specializations of regions, we analyse the growth potential and survival of plants on two levels of relatedness: related industries and related employment. When executed on related industries, the share of employment of each industry is ignored. This implies that an industry with only one employee is treated the same as an industry with thousand employees. Therefore, also related employment is included in the analysis: large industries might induce overrepresentation. Clearly, these two concepts implicate two different levels of relatedness and therefore it is interesting to test their influence.

The impact of relatedness on growth, is compared with the impact of other regional economic structural characteristics as specified in the literature review: specialization and diversification. Theory highlights the supposedly (dis)advantages of these regional economic structures, and the question is whether relatedness presents a better economic environment for plant growth.

> *Hypothesis 3: Regional relatedness has a larger impact on the growth of plants compared to other agglomeration indicators, like specialization or diversification.*

Whether a plant will survive and then is able to grow, can be influenced as hypothesized above by the (changes in) regional economic structure. However, regions have a specific structure in nature, for instance more high-tech (Eindhoven; Zuidoost Noord-Brabant) or low-tech (Rotterdam, Groot-Rijnmond). These structural regional differences are determined by the industry-base and characterizes the starting position of a region. The change in regional relatedness can influence a plant's growth chances differently if the initial specialization and size of the regional economy variates. If the plant's industry is well embedded in the region, a plant is expected to benefit more from its related surroundings, than when the industry is not. With this hypothesis, a possible sorting effect is considered, in which industries are more likely to locate in certain regions (e.g. bioscience in Leiden, port related in Rotterdam).

Hypothesis 4: Regional relatedness has a larger impact on the growth of plants when these are regionally embedded in a relatively and absolutely larger industry base.

3 EMPLOYMENT DYNAMICS

In this chapter regional economic data is explored on several dimensions that are crucially important in the empirical analysis. Section 3.1 provides a description of the dataset and the observations. In section 3.2 an accurate delineation of periods of growth and decline in employment dynamics is presented. This will provide an answer to the first sub question how to determine a period of an economic shock. Section 3.3 consists of a decomposition of sector and region-specific employment dynamics to address the heterogeneity of employment growth (employment created by new plant formation, plant dissolution, and growth and decline of incumbent plants). The heterogeneity between regions is emphasized in section 3.4, where the regional resilience before and after the economic shock is analysed. These three sections will provide important insights for the analysis in chapter 5, to understand heterogeneity and its implications for the regional economic structure.

3.1 DATA

The dataset from the LISA register consists of individual plant's information on core activity, location and number of employees for each year from 1996 to 2016. A combination of these separate datasets is provided by the Netherlands Environmental Assessment Agency (PBL), which presents a set of 21,421,479 observations of 3,187,401 individual plants. This longitudinal dataset gives unique opportunities for panel data analysis on plants over a period of 20 years. The set is unbalanced as not every plant exists throughout the whole dataset, also many entered during this period.

Although the dataset consists of plant-level data from 1996 to 2016, not the whole set is available for this analysis. It must be noted that this longitudinal dataset is not yet used often in analyses by the PBL, as the administrators of the agency are still adjusting several errors that have arisen by merging the yearly dataset. Because of administrative changes between 1996 and 2003, the observations in this period are not trustworthy and kept out of the analysis. It is decided to analyse the period 2005 to 2015, because this period is clean of any changes that might influence the data and the outcomes. This reduces the set of observations to 14,504,926 of 2,455,758 individual plants.

3.2 EMPLOYMENT IN THE NETHERLANDS

In this section, it is described which period in 2005 to 2016 can be determined as the shock period. This information is required, as this thesis will look at the reaction towards the economic shock of the country, regions, and industries. First, total national employment is displayed in figure 2, with the absolute share of employment per NUTS2 region from 2005 to 2016. Zuid-Holland, Noord-Holland and Noord-Brabant represent the largest shares of the total employment in the Netherlands, whereas Flevoland, Zeeland and Drenthe represent the smallest shares. The overall positive change of total employment is only slightly visible in aggregate, yet the dynamics of growth and decline are hidden in the total regional employment. Underneath the surface of total employment figures, dynamics exist which will be unveiled further in this section.

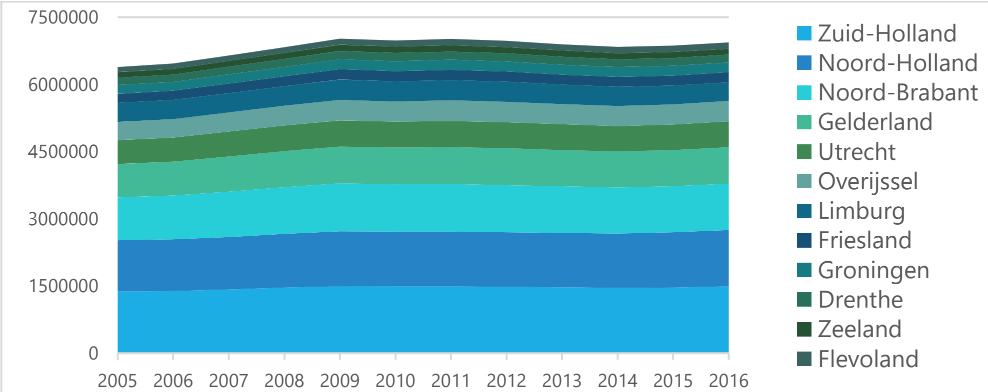

Figure 2 - Absolute number of employees in NUTS2 regions from 2005 to 2016

To begin with, the yearly net employment change per NUTS2 region are displayed in figure 3, from 2005-2006 to 2015-2016. A clear path of positive net growth is visible between 2005 and 2009, then the shock hits employment in 2009-2010. A small upward trend occurs in 2010-2011, except for Zuid-Holland, however a period of employment decline again appears (*double dip*) from 2011 to 2014. From 2014 onwards, a trend of positive net employment growth for the majority of NUTS2 regions.

The first subquestion is answered in this section: How to define the shock period? This is valuable information, as the explanatory model will consist of a resilience framework using the reaction towards economic shock. Also, in the regression analysis (chapter 5), this division will be used for subsamples. As presented in figure 3, the pre-crisis period occurs from 2005 to 2009, the crisis/shock period starts in 2009-2010 and lasts until 2013-2014, the recovering post-crisis period is determined from 2014 to 2016.

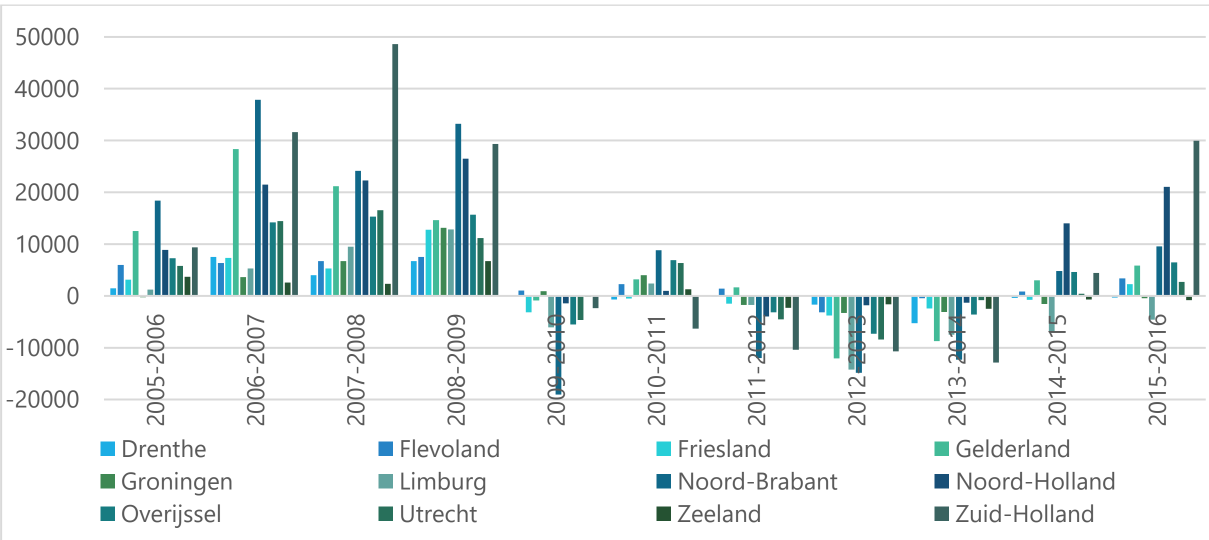

Figure 3 - Net regional employment change in NUTS2 regions from 2006 to 2016

The determination of the pre-crisis (I), crisis (II) and post-crisis (III) period is confirmed by figure 4, in which the relative employment growth of NUTS2 regions is displayed from 2005 to 2016. Employment growth is indexed in 2005 (100=2005). By looking at relative employment growth, instead of absolute employment growth in figure 3, the growth trends of regions can be compared as the employment growth is relative to the size of a region and therefore corrects for the differences of total employment per region. The trend in the country (dotted orange line), is followed by most regions: pre-crisis growth (2005-2009), crisis with double dip (2009-2014), and recovering post-crisis growth (2014-2016).

However, two outliers make the image somewhat skew, Flevoland on the top side and Limburg on the bottom side. Flevoland is a relatively new region, and therefore is still 'catching up' with the other regions. In the pre-crisis period (2005-2009), Flevoland's growth is much higher compared to the other regions. Limburg's employment growth is the only region under the level of 2005 in 2016 (<100) and does not experience growth in the recovery period. This suggests a structural declining trend of employment in the region.

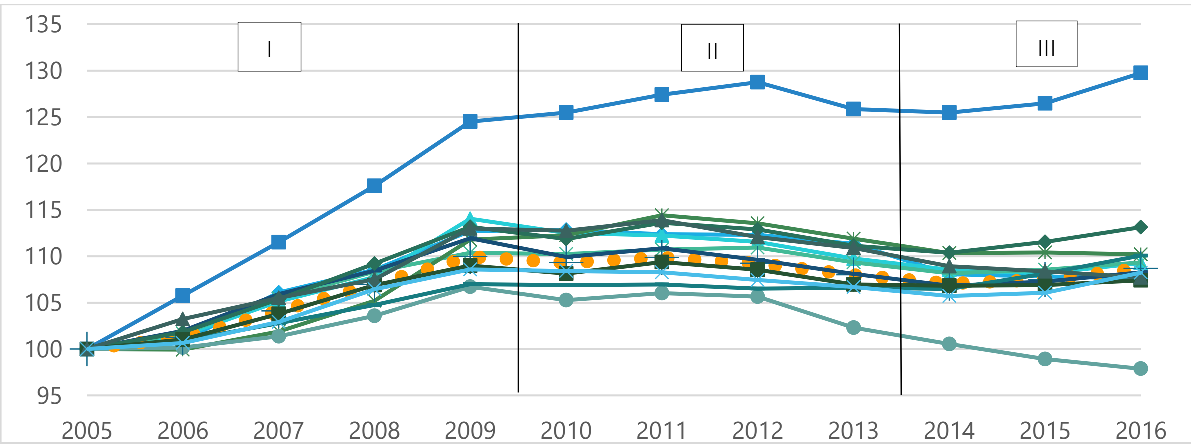

Figure 4 - Regional employment growth NUTS2 regions from 2005 to 2016 (indexed at 2005)

Regions clearly respond differently towards the economic shock; some are recovering well (e.g. Overijssel), whereas others are not (e.g. Limburg) in terms of employment, and we want to know why. Therefore, it is required to understand employment growth dynamics more in depth which will be discussed in the next section.

3.3 GROWTH DECOMPOSITION

The variation in the reaction of regional employment towards economic crises can be observed by a decomposition. Following Essletzbichler (2007) and Eriksson and Hane-Weijman (2017), employment growth figures are decomposed to examine the dynamics of growth across regions and industries. This will support the understanding of regional differences, and the difference between structural changes. Note that all non-basic, public service (e.g. education, arts, army) are excluded from this description as they are driven by public spending. Including these services would reveal a biased image of growing and declining entities during or after an economic shock, as employment is driven by the government and therefore expected to be more stable.

In table 1, the decomposition of employment is presented from 2005 to 2016. The percentages represent the average yearly employment change, as a share of total employment in 2005. The only exception is net employment change (Net 05-16), which is calculated by simply subtracting total employment in 2005 from total employment in 2016. This is an additional growth indicator, added by Eriksson and Hane-Weijman (2017) to the model of Essletzbichler (2007). This addition gives insight in the total employment growth from the first year of observation. Gross employment is a sum of total job creation (JC) and total job destruction (JD). Net employment is JD subtracted from JC. JC is calculated by the sum of the positive employment change of growing incumbents (INCGR from period *t* to *t+1*) and the employment change due to plant entry (ENTRY in period *t+1*). JD is calculated by the sum of the negative employment change of declining incumbent (INCDE from *t* to *t+1*) with declining employment due to plant exit in the year before (EXIT in *t*). Similar analyses are executed in the UK (Essletzbichler, 2007) and in Sweden (Eriksson and Hane-Weijman, 2017), therefore the results are compared with the foregoing analyses.

2005-2016	**N**	**Total EMP05**	**Net 05-16**	**Net AVRG**	**Gross**	**JC**	**JD**	**INC GR**	**INC DE**	**ENT RY**	**EXIT**
Netherlands		4458373	4.0	0.3	19.5	9.9	9.6	6.0	5.5	3.9	4.1
Expanding NUTS2	10	4055922	5.0	0.4	20.4	10.4	10.0	6.4	6.0	4.0	4.1
Declining NUTS2	2	402451	-6.0	-0.4	17.6	8.6	9.0	5.1	5.2	3.5	3.7
Expanding NUTS3	25	3324096	7.1	0.5	19.5	10.0	9.5	6.1	5.6	3.9	3.9
Declining NUTS3	15	1134277	-4.8	-0.5	18.1	8.8	9.3	5.2	5.2	3.6	4.0
Expanding industries	226	1898686	31.1	7.3	25.2	16.3	9.0	6.9	5.2	9.4	3.7
Declining industries	290	2559687	-16.0	-1.9	16.6	7.3	9.3	5.0	5.6	2.4	3.7
Expanding manufacturing	82	234160	23.2	4.9	18.3	11.6	6.7	6.8	4.5	4.8	2.2
Declining manufacturing	169	684064	-19.9	-2.1	14.9	6.4	8.5	4.7	5.6	1.7	2.9
Expanding services	41	654169	40.4	11.2	33.6	22.4	11.2	7.5	6.2	14.9	5.0
Declining services	20	319492	-22.1	-2.1	16.7	7.3	9.4	4.7	5.4	2.6	4.0
Net AVRG = JC – JD. Gross = JC + JD. JC = INCGR + ENTRY. JD = INCDE – EXIT. All growth specifiers are in period t+*1*, except for EXIT which is the lag (*t*) of exit.											

Table 1 - Employment change in the Netherlands from 2005 to 2016

In the country, see row 2, the average yearly net employment growth is 0.3%, which is just positive. However, as gross employment indicates, substantial labour flows have occurred. The job construction rate is explained more extensively by incumbent growth compared to plant entry, which is in line with Essletzbichler (2007) and Eriksson and Hane-Weijman (2017). On the other hand, incumbents decline explains a higher share of job destruction than plant exit. The latter differs from the research executed in Sweden and the United Kingdom. This analysis shows that both growing as declining incumbents are responsible for large shares of job creation and job destruction.

Row 3-6 display the decomposition of employment growth rates into regions: 12 NUTS2 regions, which are provinces with administrative status, and 40 NUTS3 regions, which are labour market regions without administrative status. By dividing them into expanding and declining entities, the nature of regions that experience either employment growth or decline can be examined. Most regions experience positive net employment growth (10 out of 12, and 25 out of 40), which indicates that the job creation rate (JC) is higher than the job destruction rate (JD). Similar for all regional entities, job creation is explained to a greater extent by growing incumbents than growth due to entries (INCGR > ENTR), and job destruction is explained to a greater extent by declining incumbents than by decline due to exits (INCDE > EXIT). Although expanding and declining regions are different in nature, the growth dynamics appear to be more or less similar, apart from average net growth.

On a lower level of measurement, industries are divided into expanding and declining industries (row 7 and 8). Different than for regions, a majority of the industries experiences negative net employment growth (290 out of 516). Notable are the much larger net and gross labour flows in expanding industries, compared to declining industries or expanding and declining regions. Another difference appears in the job creation, which is explained to a greater extent by growth due to entries instead of incumbents' growth (ENTRY > INCGR). This implies that in expanding industries, much more new entries occur than in other measured entities. Most probably, these industries are new, growing industries where many entrepreneurs entry the market.

A last distinction is made between manufacturing and service industries, see appendix for the industry division. These two large groups of industries are very different in nature, and this could explain the high differences between expanding and declining industries. As Frey and Osborne (2017) argue, employment in manufacturing can be more easily taken over by software because the core tasks are repetitive procedures. This implies that manufacturing industries are structurally declining, which would be visible in the decomposition.

In rows 9-12, a distinction is made between employment growth of manufacturing and service industries. A majority of the service industries are expanding, 41 out of 61, whereas only 82 out of 251 manufacturing industries are expanding. This confirms the research by Frey and Osborne (2017), that a high rate of mechanization occurs in manufacturing industries which implies a structural decline of employment (not necessarily productivity). However, still 82 manufacturing industries are expanding which indicates that not all manufacturing industries are structurally declining because of mechanization. These industries consist mainly of food related industries (sugar, condiments, fruit), plastics and transport (e.g. parts for motor vehicles) and are presumably population or consumer driven and therefore growing. More variation occurs in industries compared to regions, reflected by average net and gross employment flows. The largest gross labour flows occur in expanding services industries, compared to expanding manufacturing industries. This is dominantly caused by the large share of job creation, which is an almost equally proportioned consequence of incumbent growth and entering plants.

As argued by Essletzbichler (2007), a regional shift appears when net average growth of expanding regions is predominantly explained by job creation, and when for declining regions net average growth is predominantly explained by job destruction. An industry-shift would appear when net average growth of expanding industries is predominantly explained by job creation, and the net average growth for declining industries by job destruction. For expanding entities, the job creation is always larger than job destruction, and for declining entities the job destruction always larger than job creation. Otherwise, they would not be either expanding or declining entities. However, Essletzbichler (2007) aims for a more dominant explanation of job creation and destruction in expanding and declining entities respectively. Job creation and destruction rates are high for both expanding and declining entities, which confirms the conclusion of Essletzbichler (2007) and Eriksson and Hane-Weijman (2017). They do not find evidence for a predominant explanation of net growth, thus for a region or an industry shift.

The distinction between manufacturing and services industries brings an interesting dimension to the decomposition, as the outcomes are different. On the one hand manufacturing industries, in a structural declining trend, and the opposite seems to appear for services industries. What other industries are expanding or declining can be observed in table 2. The industries with the highest and lowest average net growth are displayed in the first and second column. This was calculated by measuring average net growth as a percentage of the employment in the foregoing year. In the third and fourth column, the ten industries with the highest and lowest absolute net growth are presented, by comparing employment in 2005 with 2016. It can be observed that among the largest growing industries, mobile and online services are dominantly represented (i.e. computer programming, mobile food services, software publishing). Among declining industries, manufacturing is dominantly represented. This was also observed in table 1, where manufacturing industries represent a large share of declining industries (163 out of 290). As mentioned before, this can be explained by the mechanization of these industries (Frey and Osborne, 2017). An interesting observation is that freight transport by road is declining, while freight air transport is growing. This suggests that a decline of freight transport by road is compensated by an expansion of freight air transport. Perhaps because of costs reductions in air transport, this change can be explained.

Ten industries with highest average net growth 2005-2016		**Ten industries with highest net growth 2005-2016**	
Code	**Industry**	**Code**	**Industry**
5121	Freight air transport	7022	Business and other management consultancy activities
990	Support activities for other mining and quarrying	4791	Retail sale via mail order houses or via Internet
6499	Other financial service activities, except insurance and pension funding n.e.c.	5610	Restaurants and mobile food service activities
610	Extraction of crude petroleum	6201	Computer programming activities
6130	Satellite telecommunications activities	6202	Computer consultancy activities
5829	Other software publishing	7112	Engineering activities and related technical consultancy
3520	Trade of electricity	9602	Hairdressing and other beauty treatment
5812	Publishing of directories and mailing lists	7490	Other professional, scientific and technical activities n.e.c.
9512	Repair of communication equipment	7410	Specialised design activities
5590	Other accommodation	5229	Other transportation support activities
Ten industries with lowest average net growth 2005-2016		**Ten industries with lowest net growth 2005-2016**	
Code	**Industry**	**Code**	**Industry**
7722	Renting of video tapes and disks	6419	Other monetary intermediation
2733	Manufacture of wiring devices	5310	Postal activities under universal service obligation
4763	Retail sale of music and video recordings in specialised stores	1812	Other printing
2640	Manufacture of consumer electronics	4941	Freight transport by road
4212	Construction of railways and underground railways	4120	Construction of residential and non-residential buildings
1439	Manufacture of other knitted and crocheted apparel	3299	Other manufacturing n.e.c.
2740	Manufacture of electric lighting equipment	6110	Wired telecommunications activities
1200	Manufacture of tobacco products	6512	Non-life insurance
3091	Manufacture of motorcycles	4651	Wholesale of computers, computer peripheral equipment and software
1310	Preparation and spinning of textile fibres	4511	Sale of cars and light motor vehicles

Table 2 - The ten industries with the highest and lowest employment growth rates in 2005-2016

As was seen in figure 3 and 4, employment growth responds to the shock by declining from 2010 on, and only a few recovery years are observed from 2014 on. As the pre-crisis, crisis and post-crisis years are very different in terms of employment growth, the dynamics might be as well. This can be explored by a decomposition for the three periods, see table 3.

The average net growth in the country is highest in the first period, which confirms the pre-crisis growth trend. It is negative in the second period, resembling the downward trend in the crisis years. In the last period, average net growth in zero. Although it is higher than the period before, recovery seems minimal since this figure is still not positive.

Period I – pre-crisis 2005-2009*	N	Total EMP05	Net 05-09	Net AVRG	Gross	JC	JD	INC GR	INC DE	ENT RY	EXIT
Netherlands		4458373	6.4	1.6	20.6	11.1	9.5	6.9	5.6	4.2	3.9
Expanding NUTS2	12	4458373	6.4	1.8	21.1	11.4	9.7	7.2	5.8	4.2	3.8
Expanding NUTS3	36	4300472	6.6	1.7	20.1	10.9	9.2	6.8	5.5	4.2	3.8
Declining NUTS3	4	157901	-0.7	-0.2	20.6	10.2	10.4	5.9	5.5	4.3	4.9
Expanding industries	286	3132738	12.6	7.6	24.1	15.8	8.2	8.0	5.2	7.8	3.1
Declining industries	226	1325635	-8.3	-2.7	17.1	7.2	9.9	5.0	5.8	2.2	4.1
Expanding manufacturing	103	459367	8.3	4.8	17.7	11.2	6.4	8.2	4.7	3.0	1.7
Declining manufacturing	146	458857	-12.7	-3.2	15.5	6.1	9.3	4.6	5.9	1.5	3.5
Expanding services	42	786659	19.2	9.4	26.4	17.9	8.5	9.5	5.1	8.4	3.4
Declining services	19	187002	-9.1	-3.0	19.1	8.1	11.0	4.5	5.3	3.6	5.7
Period II - crisis 2010-2013*	**N**	**Total EMP10**	**Net 10-13**	**Net AVRG**	**Gross**	**JC**	**JD**	**INC GR**	**INC DE**	**ENT RY**	**EXIT**
Netherlands		4666482	-2.0	-0.9	18.8	9.0	9.9	5.3	5.8	3.7	4.1
Declining NUTS2	12	4666482	-2.0	-0.9	19.3	9.2	10.1	5.5	6.1	3.7	4.1
Expanding NUTS3	9	1259852	1.3	0.1	18.2	9.1	9.0	5.2	5.2	3.9	3.9
Declining NUTS3	31	3406630	-3.3	-1.3	18.5	8.6	9.9	5.1	5.8	3.5	4.0
Expanding industries	212	1546371	9.1	9.1	26.9	18.0	8.9	6.4	5.3	11.6	3.6
Declining industries	304	3120111	-7.6	-3.2	17.1	7.0	10.1	4.6	6.1	2.4	4.1
Expanding manufacturing	101	287197	9.7	6.4	18.9	12.6	6.2	6.0	4.2	6.6	2.0
Declining manufacturing	151	586960	-9.0	-3.9	15.4	5.8	9.6	4.3	6.2	1.5	3.4
Expanding services	36	478417	10.3	18.7	46.6	32.6	14.0	6.8	8.1	25.8	5.9
Declining services	26	622669	-5.9	-2.6	17.4	7.4	10.0	4.7	6.0	2.6	4.0
Period III – post-crisis 2014-2016	**N**	**Total EMP14**	**Net 14-16**	**Net AVRG**	**Gross**	**JC**	**JD**	**INC GR**	**INC DE**	**ENT RY**	**EXIT**
Netherlands		4539315	2.2	0.0	18.4	9.2	9.2	5.4	5.0	3.8	4.2
Expanding NUTS2	8	3889716	2.7	0.0	19.4	9.7	9.7	5.8	5.4	3.9	4.2
Declining NUTS2	4	649599	-1.1	-1.2	17.4	8.1	9.3	5.0	5.1	3.1	4.1
Expanding NUTS3	31	3890612	2.8	-0.1	18.0	9.0	9.0	5.3	5.0	3.6	4.0
Declining NUTS3	9	648703	-1.4	-1.5	16.6	7.5	9.1	4.4	4.8	3.1	4.3
Expanding industries	307	2996977	6.0	3.7	18.5	11.1	7.4	5.9	4.1	5.2	3.3
Declining industries	208	1542338	-5.2	-2.8	15.7	6.4	9.2	4.4	5.4	2.0	3.8
Expanding manufacturing	145	470688	5.3	3.2	13.9	8.6	5.3	5.6	3.5	3.0	1.8
Declining manufacturing	106	366405	-6.9	-2.8	13.1	5.1	8.0	4.3	5.3	0.9	2.7
Expanding services	40	839552	7.5	8.4	27.5	18.0	9.5	7.1	4.4	10.9	5.2
Declining services	22	280420	-5.5	-2.7	16.6	6.9	9.6	4.0	5.7	2.9	4.0

*In period I, NUTS2 regions do not experience negative employment growth, and in period II no positive employment growth.

Table 3 - Employment change in the Netherlands in Period I, Period II and Period III

In the first period, none of the NUTS2 regions experience declining net employment growth, whereas in the second period none of the NUTS2 regions experience expanding net employment growth. This reflects the nature of the growth trend in figure 3 and 4, positive in period 1 and negative in period 2. On a lower regional level, NUTS3 regions, the majority follows this trend in period 1 (36 out of 40 expanding) and 2 (31 out of 40 declining). In the last period, a majority of regions is again expanding, namely 8 out of 12 NUTS2 regions and 31 out of 40 NUTS3 regions. The dynamics in all periods of NUTS2 and NUTS3 regions reflect similar trends as seen in table 1: job creation is explained to a greater extent by growing incumbents than by creation due to entries (INCGR > ENTR), and job destruction is explained to a greater extent by declining incumbents than by decline due to exits (INCDE > EXIT). This suggests that although the period is part of a positive or negative trend, the dynamics remain similar across periods.

Also, on the industry level, the majority of industries experiences positive net growth in the first and third period, and negative net growth in the second period. With the exception of the third period, for all expanding industries the growth due to entries explains a higher share of job creation than incumbents growth (ENTR > INCGR) as was also found in table 1. A consequence of the high number of entries, is the high net average growth for expanding industries, compared to other entities. For the declining industries, the dynamics are similar as found for industries (INGRC > ENTR and INCD > EXIT).

The division between manufacturing and services industries presents the following information about the differences of employment dynamics. A majority of the services industries experience positive employment growth, where the majority of manufacturing industries experiences negative employment growth, which is explained before by the mechanization in manufacturing industries (Frey and Osborne, 2017). This trend continuous in the second period, however in the third period a majority of manufacturing industries is expanding. For expanding service industries, the same composition of job creation is observed (ENTR > INCGR) in period I and II. In the third period, the job destruction of expanding services is explained to a greater extent by exits than by declining incumbents (EXIT > INCD). This indicates the dynamic and volatile character of service industries

Table 4-6 represent the three industries with the highest and the lowest growth, for Period I, II and III. The same trend as in table 2 is visible, where mobile services and Internet related services are among the highest growing industries. Business and other management consultancy activities experienced the highest net growth rate in all periods. On the other hand, the manufacturing industries suffer before, during and after the crisis, because of the structural declining trend and mechanization.

Three industries with highest average net growth 2005-2009		Three industries with highest net growth 2005-2009	
5121	Freight air transport	7022	Business and other management consultancy activities
0610	Extraction of crude petroleum	7112	Engineering activities and related technical consultancy
6130	Satellite telecommunications activities	6201	Computer programming activities
Three industries with lowest average net growth 2005-2009		**Three industries with lowest net growth 2005-2009**	
5829	Other software publishing	5310	Postal activities under universal service obligation
7735	Renting and leasing of air transport equipment	6110	Wired telecommunications activities
1431	Manufacture of knitted and crocheted hosiery	2611	Manufacture of electronic components

Table 4 - The three industries with the highest and lowest employment growth rates in Period I

Three industries with highest average net growth 2010-2013		Three industries with highest net growth 2010-2013	
0990	Support activities for other mining and quarrying	7022	Business and other management consultancy activities
6499	Other financial service activities, except insurance and pension funding n.e.c.	4791	Retail sale via mail order houses or via Internet
5829	Other software publishing	5610	Restaurants and mobile food service activities
Three industries with lowest average net growth 2010-2013		**Three industries with lowest net growth 2010-2013**	
3530	Steam and air conditioning supply	2431	Cold drawing of bars
2733	Manufacture of wiring devices	0892	Extraction of peat
2640	Manufacture of consumer electronics	3091	Manufacture of motorcycles

Table 5 - The three industries with the highest and lowest employment growth rates in Period II

Three industries with highest average net growth 2014-2016		Three industries with highest net growth 2014-2016	
3316	Repair and maintenance of aircraft and spacecraft	7022	Business and other management consultancy activities
6499	Other financial service activities, except insurance and pension funding n.e.c.	5610	Restaurants and mobile food service activities
9512	Repair of communication equipment	4791	Retail sale via mail order houses or via Internet
Three industries with lowest average net growth 2014-2016		**Three industries with lowest net growth 2014-2016**	
3299	Other manufacturing n.e.c.	6520	Reinsurance
6419	Other monetary intermediation	2849	Manufacture of other machine tools
5320	Other postal and courier activities	3520	Trade of electricity

Table 6 - The three industries with the highest and lowest employment growth rates in Period III

3.4 Resilience

Based on employment growth and decline for NUTS2 and NUTS3 regions, two regional indicators for economic (employment) and resilience towards the economic crisis are calculated. Both calculations are identical to those in Eriksson and Hane-Weijman (2017), which are based on Martin (2012). Resistance is calculated by comparing employment at the peak right before the crisis (index: 2009=100) with the lowest point of the crisis (2013), and therefore indicates how the economic shock affected the region's employment. Adaptability is calculated by the average net growth in the period after the lowest point of the crisis (2014-2016), as a percentage of the employment in the previous year. This indicates how well a region was able to respond to the economic shock in terms of employment. Figure 5 displays the resilience for NUTS2 regions, by the resistance and adaptability indicators, where the medians are indicated by the dotted lines.

As can be observed, none of the regions were able to obtain positive resistance figures and were able to completely endure the economic shock. However, several regions resisted the shock better than others. The regions that were less able to either 'resist' the shock, or 'adapt' after the shock, are situated in the bottom left corner (e.g. Limburg, Friesland). The opposite applies to the top right corner, where the highest net average growers and resistant regions are situated (e.g. Noord-Holland, Zuid-Holland, Flevoland: all part of the core region of the Netherlands). This suggests that economic density in general (like in the western core region of the Randstad) interacts with economic resilience.

The adaptability of the regions varies between a positive and negative 1.5 average net growth in 2014-2016, where only four regions endured negative growth after the crisis (Drenthe, Groningen, Zeeland, Limburg). These four regions are all located in the periphery of the country (where the provinces of Noord- and Zuid-Holland, Utrecht and Flevoland form the economic core region of the country).

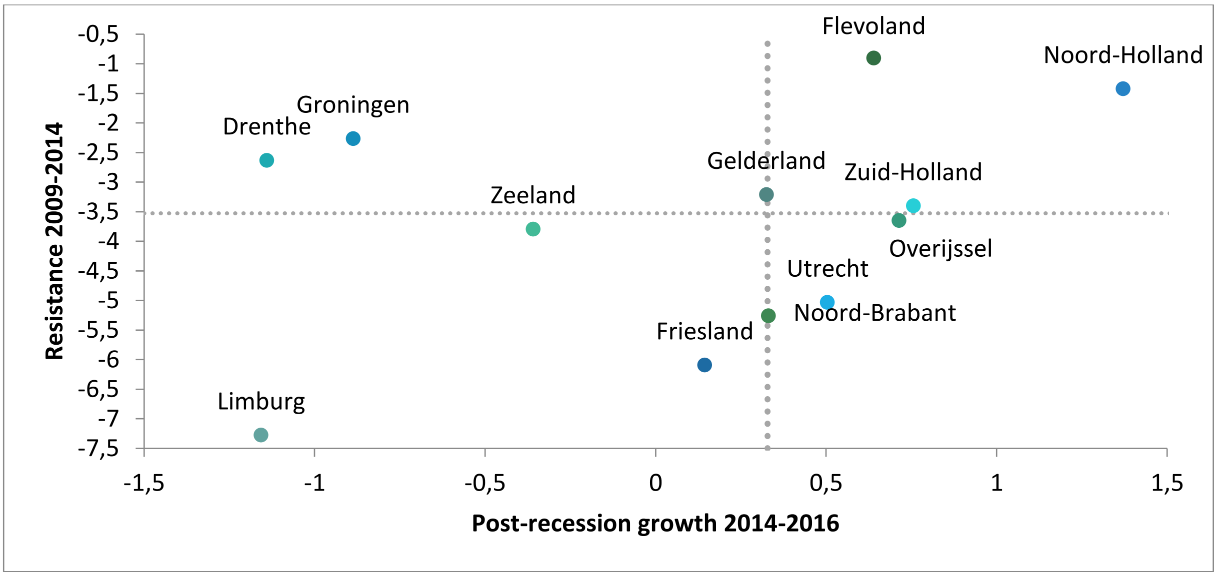

Figure 5 - Resistance and post-recession growth of NUTS2 regions

Figure 6 displays the same figure for NUTS3 regions, which gives a more detailed overview of the resilience of regions. NUTS3 regions that belong to the same NUTS2 can be very different, which skews the aggregated NUTS2 region figures. An example is NUTS2 region Noord-Holland, situated in the top right corner. Zaanstreek (bottom-left quadrant, a regional specialized in traditional food manufacturing) Groot-Amsterdam (top right corner, specialized in creative, financial and business services and distribution), Kop van Noord-Holland (top-left quadrant, mainly agricultural), and Agglomeratie Haarlem (bottom right corner, specialized in modern manufacturing and printing) belong to the same NUTS2 region of Noord-Holland.

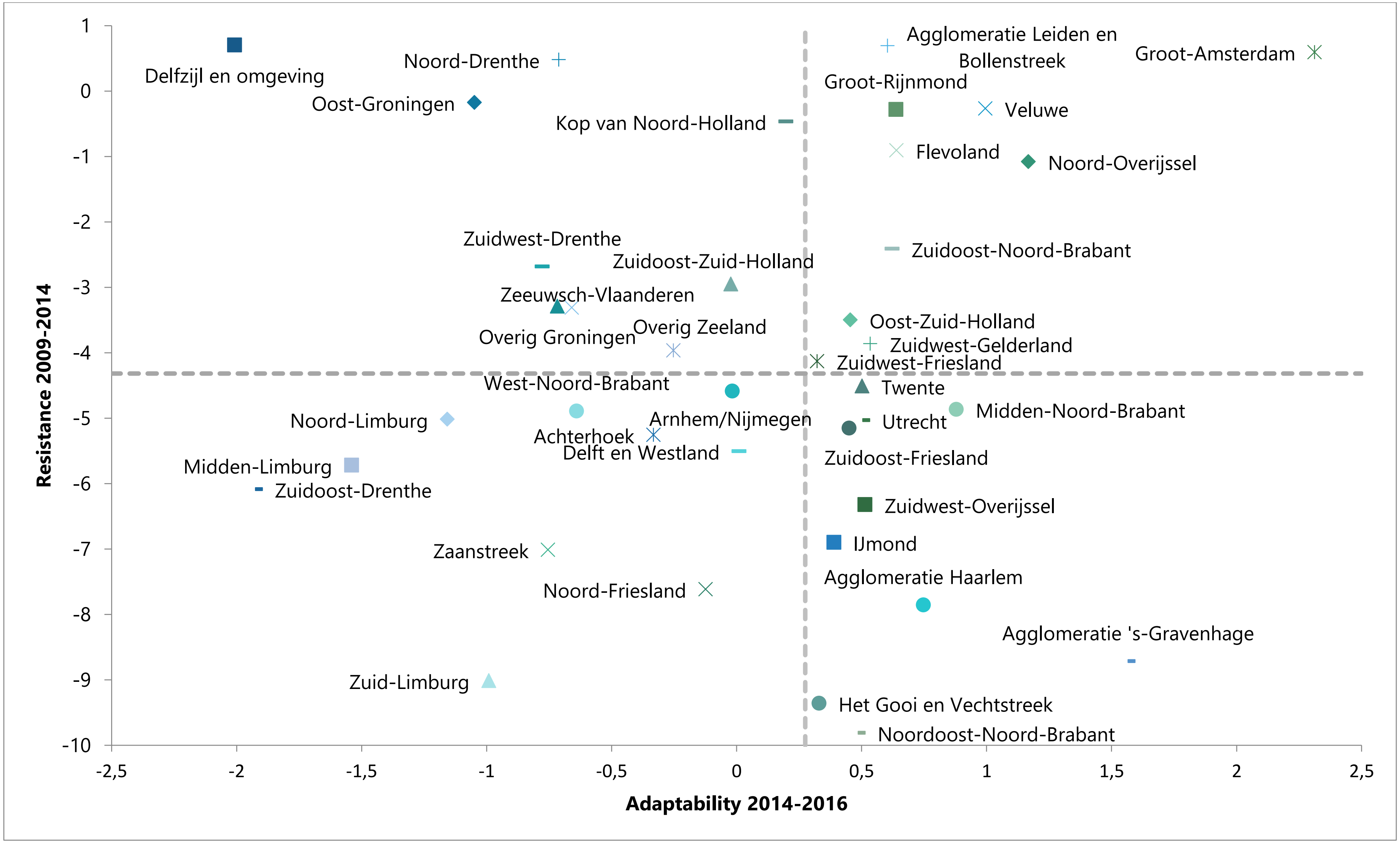

Figure 6 - Resistance and post-recession growth of NUTS3 regions

Resilient regions at the top-right quadrant, turn out to be the ones specialized in modern growth industries. Agglomeratie Leiden and the Veluwe inhibit large bioscience clusters in Leiden and Wageningen, Zuidoost Noord-Brabant inhibits a large high-tech cluster in Eindhoven, Rijnmond (Rotterdam) has large plants in port related distribution and petrochemical industries, Noord-Overijssel shows fast business services growth in Zwolle, while Amsterdam has its longer established services based growth industries. Flevoland is a peculiar growing region, that only came into existence in the 1970s and since has been growing from low base. Runner-up regions in the top of the bottom-right quadrant are fast growing regions of Utrecht (business services), Twente (high-tech systems and materials) and Midden-Brabant (modern manufacturing in Tilburg). This suggests that the initial relative and absolute specializations of regions matter to their resilience performance, and that these specializations are not random but are sorting in nature.

3.5 Conclusions

This section provided insights in the economic shock and the late effect of the shock on total employment. After a positive growth period, the highest point before the crisis was reached in 2009. Total employment started to decline from 2009 onwards, where the lowest point was reached in 2013. Therefore, the pre-crisis is determined from 2005 to 2009, the crisis from 2010 to 2013, and the post-crisis period from 2014-2016. This information is valuable in the final analysis in chapter 5, when the sample is divided in periods to determine the influence of the regional economic structure during and after an economic shock.

By decomposing total employment, other insights are presented on employment growth. It was observed that regions and sectors have responded differently towards the crisis, which is explained by the heterogeneity between these entities. As regions and sectors are different in nature, their starting point, their reaction on the economic shock varies as well. Regions variate in economic structure and their sectoral specialization (industry set). This insight is valuable for the empirical analysis in chapter 5, where these differences are addressed, and it is assessed how important these differences are for both plants and industries.

4 METHODOLOGY

In chapter 3, the employment dynamics exploration, the resilience of NUTS2 and NUTS3 regions is calculated and described. These insights are used to determine what kind of regions are more likely to be resilient (adapt and resist) to economic shocks. Three concepts that entail the regional structure are calculated to capture this relationship, namely diversification, specialization and relatedness. The second sub question is covered in this chapter: *How to define relatedness, vis-à-vis other measures of specialization and diversification?* Also, in the last section of this chapter the methods of analysis are discussed (growth analysis).

4.1 VARIABLES

In this section, the methods of measurements are discussed, starting with the variable of interest, relatedness. To capture the relatedness concept as well as possible, several dimensions are considered: threshold, level and dimension of measurement (industries and employment, region and region-industry specific). Then, the measurement of specialization and diversification is presented.

4.1.1 Relatedness, cohesion and closeness

In this section, the methods to measure the cognitive relatedness between industries are discussed. The calculations of relatedness are executed for several variables in different levels of measurements. First of all, it needs to be determined when industries are related. As discussed in chapter 2, this research focuses on the flows of labour and the corresponding measurements of skill-relatedness. We will adopt the measurements of Neffke, Otto and Weyh (2017) and Neffke (2017), who have calculated skill-relatedness based on German labour flows. The outcomes of Neffke, Otto and Weyh (2017) are merged with the dataset; labour flows are not analysed, and skill-relatedness is not calculated in this research. Choosing this skill-relatedness instead of Dutch measurements, reduces the chance of possible endogeneity, as both calculations as outcomes would otherwise be based on the same group of observations. To test for differences and sensitivity, the Dutch skill-relatedness will also be applied in the correlation calculations. A few alterations had to be made, as the Dutch industry codes not all correspond with the European NACE industry codes, see appendix.

The outcomes of skill-relatedness by Neffke, Otto and Weyh (2017) lie between -1 and 1. A matrix of relatedness is calculated of $I \times I$, where the diagonal outcomes are deleted as they represent the relatedness between identical industries and is equal to 1. The closer to 1, the more flows of labour have occurred between the industries and the higher degree of relatedness – the opposite accounts for -1.

The skill-relatedness calculations present the first level of analysis, based on national (German) labour flows. The outcomes are industry-specific: Industry i is similarly related with industry j throughout the country because labour flows are aggregated on the national level.

The other levels of measurement are replicated from Neffke, Henning and Boschma (2011). They calculate regional relatedness (*cohesion*) by counting the related industries in a region for each industry (*closeness*). Their approach is slightly different, as they focus on manufacturing industries and the *technical* similarities between industries based on an in- and output analysis. As this research focuses on skill-relatedness, rather than in- and outputs of industries, the approach is different. Skill-relatedness is preferred because of the availability of data, and the value of human capital for growth as discussed in chapter 2 and emphasized by Neffke and Henning (2013).

A drawback of the skill-relatedness approach is that it is relatively sensitive for the size of the industry. An industry with ten employees counts as heavily as an industry with 10,000 employees. To account for this mass effect, the relatedness variables are also measured based related *employment* instead of related *industries*. Counting related industries is the most common way of measuring relatedness, because a higher number related industries is expected to increase the chances of knowledge spillovers. However, small and large industries are treated equally which seems biased. Therefore, counting related employment instead of industries is expected to present a different view on relatedness. Though, a drawback of counting related employment instead of industries, is the overrepresentation of large industries in a region (e.g. Philips in Eindhoven). Both approaches of measuring relatedness, *industry* and *employment*, measure a different dimension of the relatedness concept. This research attempts to find possible implications of its differences.

The relatedness calculations by Neffke, Henning and Boschma (2011) consist of two components. In the first part, the number of related industries and jobs is counted for each industry in every regional portfolio (see equation 1.1). This measurement, *closeness*, is therefore region-industry specific. Which industries or jobs are *related*, depends on a specific minimum of relatedness (x). In Neffke, Henning and Boschma (2011) a 0.25 threshold is used, which indicates that the minimum degree of relatedness must be higher than 0.25. This approach will be applied, however to test for possible sensitivity and to compare the outcomes, also a threshold of 0.5 is chosen. This number is based on a working paper on skill-relatedness in the Netherlands by the PBL. A threshold of 0.25 presents a maximum number of 98 related industries, whereas the 0.5 threshold a number of 51. The higher the threshold, the stricter the definition of relatedness becomes and therefore, less industries and jobs will be related.

1.1 $closeness_{ir} = \sum_{j \in PF(r)} I(SR_{ij} > x)$

In the second part of the relatedness measurements of Neffke, Henning and Boschma (2011), a regional component is calculated (see equation 1.2). The sum of closeness of industries i to I in region r, is divided by the number of industries or total employment in the region. This variable, *cohesion*, is region-specific and therefore used to analyse the relation with regional resilience (see Eriksson and Hane-Weijman, 2017). A high degree of cohesion represents a relatively high amount of related industries or jobs. However, as it represents an aggregation of closeness, cohesion is not necessarily beneficial for plants in all industries. Consider industry i, j and k in region r. Industry j and k are related and because of this, a relatively high cohesion is measured. Industry j and k might benefit from the regional relatedness (knowledge spillovers, growth opportunities), however industry i does not as it are not related with the network.

1.2 $$cohesion = \frac{1}{N}\sum_{i \in PF(r)} closeness_{ir}$$

Closeness and cohesion therefore present different components of relatedness – see figure 7 and table 7 for an overview of the level of measurement. In figure 7, the steps of analyses are displayed. First, the skill-relatedness is determined (see Neffke, Otto and Weyh, 2017) based on country wide labour flows, which is unique for each industry ($I \times I$). Then, by counting related industries or employment in each region, the closeness is calculated for each industry ($I \times R$). Finally, a sum of closeness weighted by the number of industries or employment in a region is calculated, for each region (R).

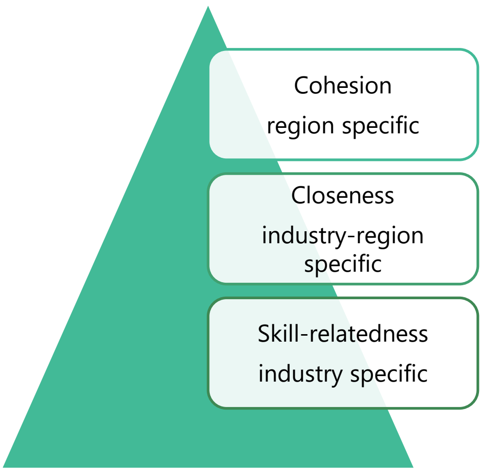

Figure 7 - Levels of measurement of relatedness

Variable	Measurement level
Cohesion (industries)	*Region specific*: Sum of related industries as a share of total industries in region r
Cohesion (employment)	*Region specific*: Sum of related employment as a share of total employment in region r
Closeness (industries)	*Region-industry specific*: Number of related industries for industry i in region r
Closeness (employment)	*Region-industry specific*: Number of related employment for industry i in region r

Table 7 - Overview of measurement level relatedness variables

4.1.2 Specialization and diversification

Apart from relatedness, two other regional economic structures are measured to understand the regional structure and the resilience of regions during and after economic shocks. Regional specialization is calculated by the Krugman Specialization Index (Krugman, 1991), as applied by Eriksson and Hane-Weijman (2017). Equation 1.3 displays specialization, where the share of employment of industry i in region r is divided by the nationwide employment of that industry, minus the employment of that region. Regional specialization represents the sum of specialization of each industry in the region, relative to its regional employment.

1.3 $$Krugman\ specialization = \sum_{i \in PF(r)} \frac{E_{ir}}{(E_i - E_{ir})}$$

For the measurements of diversification, Eriksson and Hane-Weijman (2017) consider the number of *unrelated plants*, the opposite of related plants. However, a diversified structure entails both related and unrelated plants, and a high chance of correlation with cohesion exists in their definition. Therefore, it is decided to consider other diversification indicators.

An alternative and much applied approach towards diversification is therefore used, the Herfindahl-Hirschman Index (HHI) as presented in equation 1.4. The HHI is commonly used and supported throughout academic literature. For each industry, the share of employment in region r for industry i is calculated (s), squared and divided by total regional employment. This index must be interpreted oppositely from its outcomes because it actually measures concentration (reciprocal interpretation). To avoid misinterpretations, the variable is transposed (1/HHI) before using in further analyses.

1.4 $$HHI = \sum_{i \in PF(r)} s_{ir}^2$$

Variable	**Measurement level**
Specialization	Region-industry specific
HHI	Region specific

4.2 Analyses

In this section, it is shortly described how the analyses of chapter 5 will be structured and why they are executed. In chapter 5, correlations are calculated, a regional analysis will be presented, and a statistical employment growth analysis is executed.

4.2.1 Correlations

A correlation analysis is executed to observe the initial association between regional resilience and the regional economic structures, being specialization, diversification, and employment-based and industry-based cohesion. As seen in section 3.4, the resilience differs among regions and it is interesting to test whether the correlation shows a certain pattern between these regional economic structures and resilience. By calculating the correlation coefficients for both industry- and employment-based cohesion, differences among these relatedness variables are also analysed.

4.2.2 Regional evaluation

In the regional evaluation, the variation in the regional structures are made visible in a spatial analysis. By mapping the calculations of specialization, diversification and coherence, it is possible to observe any spatial pattern. The same is done for the resilience indicators, resistance and adaptability, to analyse patterns that seem spatially relevant.

4.2.3 Regression analyses

The dataset consists of data on plants from 2005 to 2016, which is a panel structure in the analysis. By means of this structure, the impact of time-varying variables can be observed, and it controls for fixed plant and/or locational aspect, which would not be possible in a cross-section where only one year per observation is available. Moreover, by including fixed effects we are able to control for plant-specific characteristics. The panel data is unbalanced, not all plants are observed in each year because for some the year of establishment is after 2005 or the year of exit lies in this period. This suggests that not all plants have similar opportunities to survive or to grow, and this attrition will have to be corrected for in the analyses. It is discussed below how adjustments are made to the growth assessment.

The growth analysis consists of a fixed effect panel regression. The fixed effects in the regression correct for the non-time varying plant-specific characteristics, as the dataset does not consist of many plant-specific variables. As discussed in chapter 3, the dataset only contains plant-specific data on core activity, location, and number of employees. In this model, available independent region- and region-industry specific variables are regressed on the dynamics in the number of employees of a plant. By a panel regression, the influence of the changes in the independent variables on changes in the dependent variable can be analysed.

As hypothesized, for a plant to grow, it needs to survive (conditional growth). This suggests that growth is conditional, as the survival of plants must be assured for it to be able to grow. A possible selection bias might be present in the growth model above, as growth is estimated for all plants and does not take survival into account. To correct for the selection bias, often a two-stage Heckman model is estimated (see Audretsch and Dose, 2007; Raspe and Van Oort, 2008). However, this model cannot be applied in a panel data structure, instead averages of growth are calculated to create a cross-section analysis. As mentioned before, a panel data is valuable as the influence of time-varying variables can be assessed and the analysis is controlled for plant-specific characteristics. Therefore, it is decided to not use the Heckman model and approach the conditional growth differently.

In the first stage of a Heckman model, the chance of survival is estimated. In the second stage, the growth assessment, only the estimated proportion of survivors is considered. It is attempted to approach this model, however merely in an exploratory nature. A binary variable of exit is added to the model, and its interaction with the variable of interest (relatedness). The binary exit variable is 1 when the plant exits in $t + 1$, and 0 otherwise. In this approach, the condition of survival is added to the model with the aim of correcting for a selection bias. Also, by including an interaction effect with our variable of interest, relatedness as measured by *coherence* and *closeness*, with the exit dummy, the possible relation between the survival of plants and the relatedness can be assessed.

Additionally, to test for the heterogeneity among industries, the analyses are also executed for several samples in the dataset. A division of industries is applied based on several sources, see appendix for the corresponding NACE codes and adjustments. In this way, we can observe possible biased outcomes due to industry specific characteristics. Characteristics of a specific group of industries can influence the coefficients when all industries are included in the analyses, as the effect can differentiate across industries. By estimating the same analysis for several subsamples, the differences can be observed.

5 RESULTS

This chapter will present the results of the various analyses. In section 5.1, the correlation coefficients between our variables of interest and the other regional structures is presented. Thereby, the association between resilience (i.e. resistance and adaptability) and relatedness is analysed. In section 5.2, by means of several maps and tables, the regional differences are observed. Then in section 5.3, the outcomes of the regression analyses are displayed. This chapter provides the empirical background for the discussion in chapter 6.

5.1 CORRELATIONS

The relation between the regional structural characteristics with resistance and adaptability can first be explored by pairwise correlation coefficients, as displayed in table 8 and table 9 with a minimum skill-relatedness of 0.25 and 0.5 respectively. The coefficients are calculated for both skill-relatedness thresholds to analyse the differences and possible consequences for the survival and growth analysis.

SR25	**Resistance**	**Adaptability**	**Cohesion (in)**	**Cohesion (em)**	**Specialization**	**Diversification**
Resistance	1	0.3698*	0.1331*	-0.0058*	-0.0537*	0.1824*
Adaptability	0.3698*	1	0.2501*	0.3333*	0.3301*	0.0056*
Cohesion (in)	0.1331*	0.2501*	1	0.8734*	-0.0635*	0.5873*
Cohesion (em)	-0.0058*	0.3333*	0.8734*	1	0.0204*	0.5157*
Specialization	-0.0537*	0.3301*	-0.0635*	0.0204*	1	-0.2429*
Diversification	0.1824*	0.0056*	0.5873*	0.5157*	-0.2429*	1
* Significant at a 0.01 confidence level.						

Table 8 - Correlation coefficients at a minimum skill-relatedness of 0.25 (German population)

Resilience was operationalized by measuring resistance *towards* the economic shock over the period 2009-2013, and adaptability *after* the shock over the period 2013-2016. Resistance and adaptability are positively associated (0.37), which indicates that both indicators for resilience can occur simultaneously in regions. This partially complies with Eriksson and Hane-Weijman (2017), as their results are positive but ambiguous throughout two different economic shocks. As this research only captures one shock, this comparison is only partially possible.

Both relatedness coefficients are positively associated with adaptability (0.25 and 0.33), and industry-based cohesion is positively associated with resistance (0.13). On the other hand, employment-based cohesion is negatively associated with resistance (-0.01), although it is a weak association. This indicates that industry cohesive regions are expected to show more resistance towards an economic shock, than less cohesive regions. On the other hand, cohesive regions are expected to adapt more easily after an economic shock, than less cohesive regions. However, the association between cohesion and resistance is quite weak, whereas the association with adaptability is much stronger.

Diversification is positively associated with resistance (0.18) and weakly with adaptability (0.01). As cohesion was positively correlated with adaptability, this indicates the difference between diversification and related variety. In regions with a relatively high cohesion, workers are able to change their job more easily than in unrelated diversified regions because their skills and capabilities are valued similarly.

Specialization is negatively associated with resistance (-0.05), which corresponds with the results of Eriksson and Hane-Weijman (2007) and confirms the theory that specialized regions are more vulnerable to shocks. On the other hand, a positive association between specialization and adaptability is found (0.33) which indicates that specialized regions are more likely to adapt more easily, compared to less specialized regions. The correlation coefficient with employment-based cohesion is slightly positive (0.02), which implies only a weak association with specialization. This relation was expected weak, or even negative, because specialization represents a concentration of one industry, and cohesion represents a mix of industries.

Specialization is weakly negatively correlated with industry-based cohesion (-0.06) and negatively with diversification (-0.24), whereas diversification and cohesion are positively correlated (0.59 and 0.52). The positive correlation with cohesion and diversification seems logical, as there is a higher chance of a higher degree of cohesion as the number of different industries increases. Therefore, there is a higher chance of a high rate of related jobs or industries in diversified regions. Even though specialized regions are more likely to adapt after an economic shock compared to diversified regions, and cohesion is positively associated with diversification, regions with a high rate of cohesion in employment are even more likely to adapt after an economic crisis.

Comparing table 8 and table 9, the differences between the skill-relatedness thresholds can be observed. Mainly, the size of the correlation coefficients between the minimum of 0.25 and 0.5 varies, however the direction of the associations is equal for all associations.

SR50	**Resistance**	**Adaptability**	**Cohesion (in)**	**Cohesion (em)**	**Specialization**	**Diversification**
Resistance	1	0.3698*	0.1331*	-0.0058*	-0.0537*	0.1824*
Adaptability	0.3698*	1	0.2501*	0.3333*	0.3301*	0.0056*
Cohesion (in)	0.1331*	0.2501*	1	0.8734*	-0.0635*	0.5873*
Cohesion (em)	-0.0058*	0.3333*	0.8734*	1	0.0204*	0.5157*
Specialization	-0.0537*	0.3301*	-0.0635*	0.0204*	1	-0.2429*
Diversification	0.1824*	0.0056*	0.5873*	0.5157*	-0.2429*	1
* Significant at a 0.01 confidence level.						

Table 9 - Correlation coefficients at a minimum skill-relatedness of 0.5 (German population)

In table 10, correlation coefficients are displayed with a skill-relatedness threshold of 0.5, similar to table 9. However, the outcomes of relatedness between industries is now based on a Dutch population instead of a German population. The focus lies on the cohesion indicators, where differences are observed between the Dutch and German skill-relatedness measurements. The employment-based cohesion switches sign in the association with resistance and adaptability, and also with specialization. This indicates that the decision does influence the degree of regional cohesion, merely based on employment. From the Dutch measurements, it seems as if employment-based cohesion is positively associated with resistance (0.06), and negatively with adaptability (-0.04). However, both associations are rather weak. German measurements assume the opposite, whereas the association with adaptability is much stronger (0.40). This shows that, based on Dutch labour flows, the outcomes of relatedness are very different. This is explained by the difference between the Dutch market and the German market, and which types of industries are more dominant (Netherlands: food and chemical industry, Germany: steal and car industry).

SR50	Resistance	Adaptability	Cohesion (in)	Cohesion (em)	Specialization	Diversification
Resistance	1	0.3683*	0.1512*	0.0550*	-0.0552*	0.1844*
Adaptability	0.3683*	1	0.2968*	-0.0390*	0.3296*	-0.0004
Cohesion (in)	0.1512*	0.2968*	1	0.7370*	0.0026*	0.5664*
Cohesion (em)	0.0550*	-0.0390*	0.7370*	1	-0.1953*	0.8144*
Specialization	-0.0552*	0.3296*	0.0026*	-0.1953*	1	-0.2442*
Diversification	0.1844*	-0.0004	0.5664*	0.8144*	-0.2442*	1
* Significant at a 0.01 confidence level.						

Table 10 - Correlation coefficients at a minimum skill-relatedness of 0.5 (Dutch population)

In table 11, all regional relatedness correlation coefficients are displayed for resistance and adaptability. These coefficients are of particular interest, as the association of relatedness and resilience can support our research question and test the first hypothesis. The German skill-relatedness measurements present a positive association of a majority of the relatedness coefficients with resistance and adaptability, with the exception of the employment-based cohesion and resistance. For resistance, this seems ambiguous as the industry-based cohesion is negative and the employment-based cohesion is positive. This emphasizes the difference in the implications of the different methods of measurement. For the resistance of a region, related industries are perhaps more important than the related employees. The number of related industries indicates the possible partners for interaction and knowledge spillovers, whereas the number of jobs could belong to merely one industry. The association between relatedness and adaptability is positive. This implies that regions with many related industries or employment are expected to adapt more easily after an economic shock.

For the Dutch skill-relatedness, the association of employment-based cohesion is opposite from industry-based cohesion. This indicates the possible consequences of choosing measurements stemming from outside the dataset, in Germany instead of the Netherlands. Industries are differently related in the Netherlands than in Germany, which explains the differences of the associations with resistance and adaptability. It is decided to use the Germans skill-relatedness measurements by Neffke (2017) for further analysis, as this still corrects for possible endogeneity issues.

		Resistance	Adaptability
German SR – 0.25	**Cohesion (industries)**	0.1331*	0.2501*
	Cohesion (employment)	-0.0058*	0.3333*
German SR – 0.50	**Cohesion (industries)**	0.1213*	0.2972*
	Cohesion (employment)	-0.0682*	0.3986*
Dutch SR – 0.50	**Cohesion (industries)**	0.1512*	0.2968*
	Cohesion (employment)	0.0550*	-0.0390*

Table 11 - Correlation coefficients of relatedness and resilience

5.2 Regional evaluation

In table 12, the ten highest and lowest scoring regions are presented for all measured structural characteristics. The regions with the highest degree of cohesion appear also among the highest scoring regions for diversification (e.g. Zuidoost Noord-Brabant, Groot-Rijnmond). Reversed this relationship is also visible, where regions with a low degree of diversification appear among the lowest scoring cohesive regions (e.g. Delfzijl, IJmond). The positive association between specialization and cohesion is also visible among regions (e.g. Utrecht, Groot-Amsterdam).

The most resilient regions, or the regions with a high resistance and adaptability, are Groot-Amsterdam, Veluwe, Groot-Rijnmond, and Agglomeratie Leiden en Bollenstreek. Groot-Rijnmond appears among the highest scoring regions for both cohesion variables, which also accounts for Veluwe and Groot-Amsterdam. Groot-Rijnmond appears also among the highest scoring regions for specialization and diversification, whereas Groot-Amsterdam only appears among the highest scoring regions for specialization. This indicates that for a region to be diversified, or have a high degree of cohesion, it can also be relatively specialized. However, this is not a condition for a high degree of resilience, as Groot-Amsterdam is not among the highest scoring regions for diversification.

	Resistance	Adaptability	Cohesion (ind)	Cohesion (emp)	Specialization	Diversification
Highest scores	Alkmaar en omgeving	Groot-Amsterdam	Utrecht	Utrecht	Agglomeratie 's-Gravenhage	West-Noord-Brabant
	Delfzijl en omgeving	Agglomeratie 's-Gravenhage	Arnhem/Nijmegen	Agglomeratie 's-Gravenhage	Groot-Amsterdam	Midden-Noord-Brabant
	Agglomeratie Leiden en Bollenstreek	Noord-Overijssel	Veluwe	Zuidoost-Noord-Brabant	IJmond	Zuidoost-Noord-Brabant
	Groot-Amsterdam	Veluwe	Zuidoost-Noord-Brabant	Noordoost-Noord-Brabant	Het Gooi en Vechtstreek	Noordoost-Noord-Brabant
	Noord-Drenthe	Midden-Noord-Brabant	Groot-Rijnmond	Veluwe	Noord-Limburg	Groot-Rijnmond
	Oost-Groningen	Agglomeratie Haarlem	Groot-Amsterdam	Groot-Rijnmond	Groot-Rijnmond	Zuidoost-Zuid-Holland
	Veluwe	Flevoland	West-Noord-Brabant	Oost-Zuid-Holland	Utrecht	Oost-Zuid-Holland
	Groot-Rijnmond	Groot-Rijnmond	Noordoost-Noord-Brabant	Achterhoek	Zuidoost-Noord-Brabant	Twente
	Kop van Noord-Holland	Zuidoost-Noord-Brabant	Zuid-Limburg	Zuidwest-Gelderland	Midden-Noord-Brabant	Zaanstreek
	Flevoland	Agglomeratie Leiden en Bollenstreek	Midden-Noord-Brabant	Groot-Amsterdam	Zuid-Limburg	Achterhoek
	Resistance	**Adaptability**	**Cohesion (ind)**	**Cohesion (emp)**	**Specialization**	**Diversification**
Lowest scores	Noordoost-Noord-Brabant	Delfzijl en omgeving	Delfzijl en omgeving	Delfzijl en omgeving	Oost-Groningen	IJmond
	Het Gooi en Vechtstreek	Zuidoost-Drenthe	Zuidwest-Friesland	Zuidwest-Overijssel	Zuidwest-Drenthe	Agglomeratie 's-Gravenhage
	Zuid-Limburg	Midden-Limburg	Zeeuwsch-Vlaanderen	Zuidwest-Drenthe	Alkmaar en omgeving	Delfzijl en omgeving
	Agglomeratie 's-Gravenhage	Noord-Limburg	Zuidwest-Overijssel	Zuidwest-Friesland	Noord-Drenthe	Oost-Groningen
	Agglomeratie Haarlem	Oost-Groningen	Agglomeratie Haarlem	Oost-Groningen	Zuidwest-Overijssel	Zeeuwsch-Vlaanderen
	Noord-Friesland	Zuid-Limburg	IJmond	Zeeuwsch-Vlaanderen	Agglomeratie Haarlem	Overig Groningen
	Zaanstreek	Zuidwest-Drenthe	Noord-Drenthe	Zuidoost-Friesland	Zuidwest-Friesland	Agglomeratie Leiden en Bollenstreek
	IJmond	Zaanstreek	Zuidwest-Drenthe	Noord-Drenthe	Zuidwest-Gelderland	Kop van Noord-Holland
	Zuidwest-Overijssel	Overig Groningen	Alkmaar en omgeving	Zuidoost-Drenthe	Zaanstreek	Delft en Westland
	Zuidoost-Drenthe	Noord-Drenthe	Zuidoost-Friesland	Zaanstreek	Noord-Friesland	Noord-Drenthe

Table 12 - Ten highest and lowest scoring NUTS3 regions, averaged over the period 2005-2016

The regional economic structures across NUTS3 regions are presented in figures 8.1-8.6. Figure 8.1 and 8.2 display the cohesion in NUTS3 regions, based on employment and industries respectively. Some overlap between these figures can be observed, as the correlation coefficient indicated (0.82). Differences are noticeable in a few parts of the country (e.g. Limburg, Noord-Holland). In both figures, the most coherent regions are situated in the South which partially complies with the higher degree of diversification that was found in the same regions (see figure 8.3). That diversification and cohesion are positively associated, is confirmed by the figures.

Figure 8.3 displays the degree of diversification across NUTS3 regions. The concentration of diversification (HHI) in the south of the country (Noord-brabant) can arguably be explained by fact that many manufacturing industries are situated in that area. These industries have a relatively high number of related industries (whereas the maximum number of related industries in manfuacturing industries is 51 and for services 36). However, the actual average number of related industries is higher for services (see table 13). This is possible because services often share other input-output linkages to manufacturing and services as well, like subcontracting in business services, that may reinforce relatedness and cohesion. Nonetheless, there are more manufacturing industries – more industry codes for manufacturing industries – which increases the chance of being related to one another.

	All industries	Manufacturing	Services
Observations	569	240	62
Mean	13.37	12.73	14.29
Standard deviation	8.17	9.02	7.12
Minimum	1	1	1
Maximum	51	51	36

Table 13 - Average maximum number of related industries

The diversification measurements are calculated based on 4-digit industry codes and compared with the figures for 2-digit industry codes. Because of the statistically insignificant outcomes using 2-digit codes in further analyses, it is chosen to carry out the analyses using 4-digit industry code.

Figure 8.4 represent the specialization indicator (weighted average on number of jobs). Although specialization seems evenly distributed across the country in 8.4 with the Krugman index calculations, the least specialized regions are situated in the rural areas (e.g. Friesland, Zeeland) whereas the more specialized areas are the urbanized areas (i.e. Utrecht, Zuid-Holland).

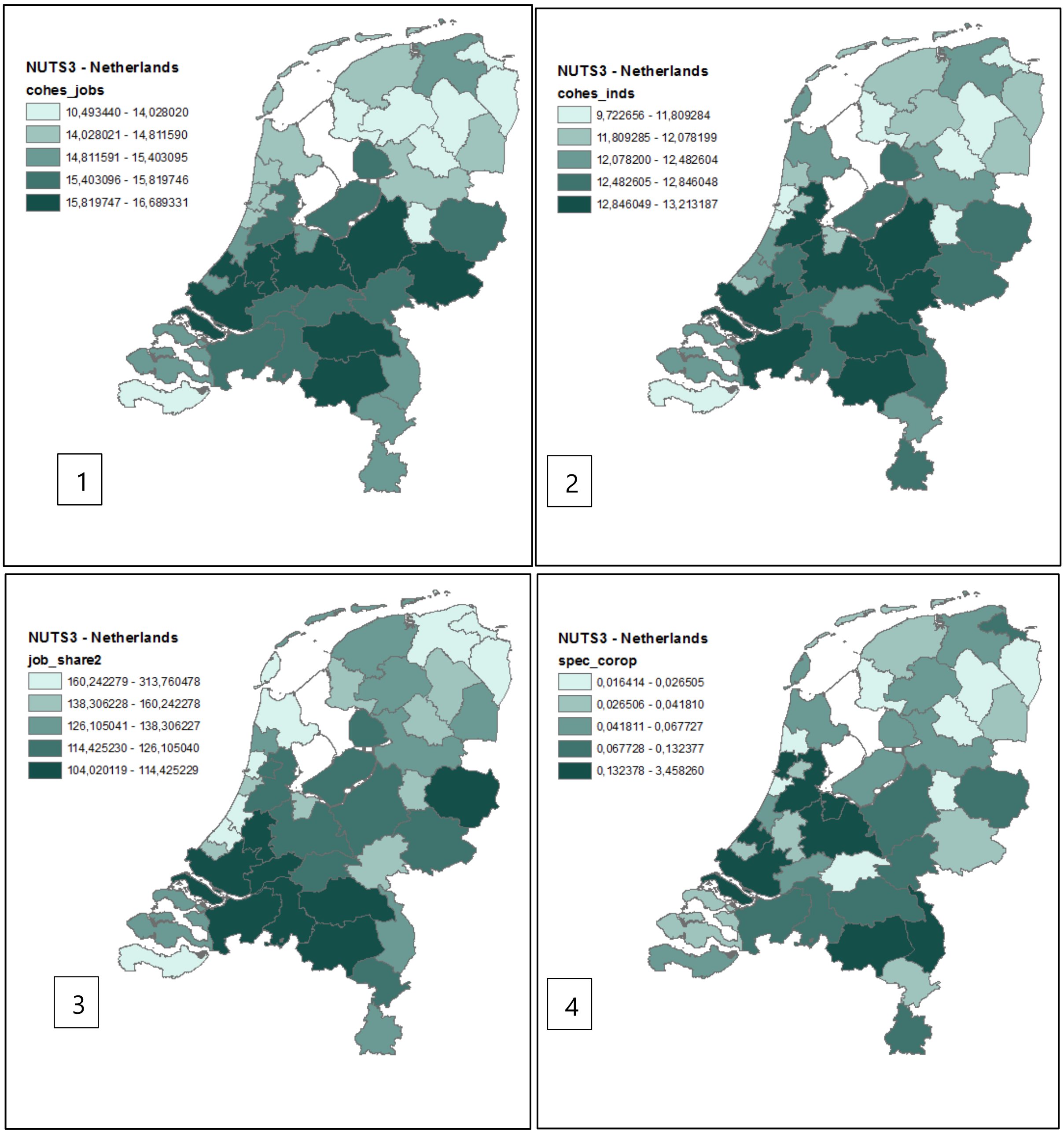

Figure 8 – Regional economic structure of NUTS3 regions
(1) cohesion (employment), (2) cohesion (industries), (3) diversification, (4) specialization

Figure 9 displays the resistance and adaptability of the NUTS3 region. Resistance is more geographically evenly distributed across the Netherlands, which implies there is not a clear pattern geographically. Adaptability appears more concentrated. The regions that were least able to adapt are the peripheral provinces (Zeeland, Groningen, Limburg), whereas the opposite accounts for more urbanized provinces (Zuid-Holland, Noord-Brabant, Noord-Holland).

In the larger urban agglomerations in the Western part of the country, as well as in the recently fast growing and specifically specialized regions of Eindhoven and Tilburg (high-tech systems and materials, 5th and 6th cities in size of the country), Zwolle (cleantech and business services) and Veluwe (biosciences), resistance to and adaptation after the crisis go hand in hand.

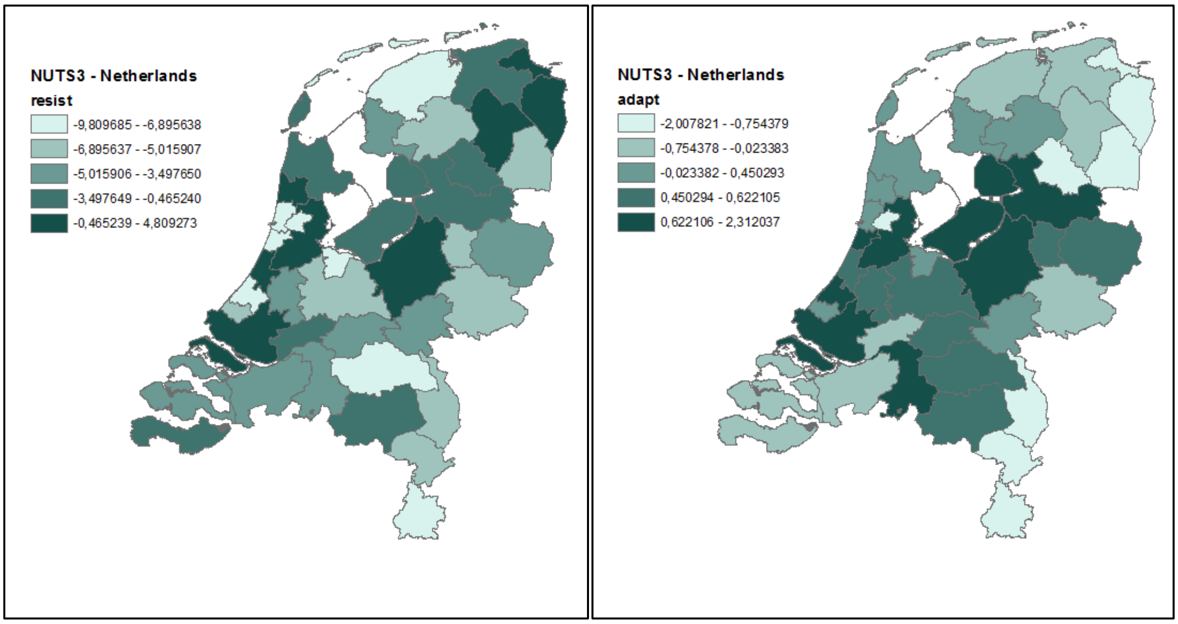

Figure 9 – Resilience of NUTS3 regions. (l) resistance and (r) adaptability

5.3 GROWTH ANALYSIS

In this section, the estimations of the growth model are presented. Table 14 displays the estimation for all industries, table 15 for a division between manufacturing and service industries, and table 16 and 17 for a division between high-tech, low-tech and creative industries. All regression analyses are estimated with fixed effect and panel structure, which will correct for variables that stay constant over time. No problems occurred after testing for the variance inflation factor or multicollinearity.

Table 14 displays the results for all industries, where model 1-4 present the growth analysis and model 5-8 the adjusted growth analysis. In the adjusted growth analysis the same model is estimated. However, with an additional correction for conditional growth – taking care of plants to first survive, before growth can be analysed. The binary exit variable indicates whether the plant exits the year after. The interaction effect between our variable of interest (cohesion or closeness) and the exit variable, indicates what impact relatedness might have in relation with the survival of firms. A significant interaction effect indicates that when a plant exits in the year after, their growth potential is influenced by the region or region-industry specific relatedness to a more or lesser extent than for non-exiting plants, depending on the sign of the interaction coefficient.

All relatedness coefficients (cohesion and closeness) are negative, which implies a negative impact of relatedness on the growth potential of plants. A possible explanation is that a large share of industrial industries is structurally declining (i.e. manufacturing). Because there are many industry codes belonging to manufacturing (table 13), their structural declining trend might make the coefficients more negative. Both specialization and diversification variables have a positive coefficient and are therefore showing opposite correlations compared to the relatedness coefficients. Region specific relatedness (cohesion) is more negative than region-industry specific relatedness (closeness). On the other hand, the effect of related employment on the growth potential of plants is less small than related industries. This implies significant differences between the approaches and levels of measurement, however the sign remains negative. The difference is also visible in the interaction variables, where the coefficient is negative for employment-based *cohesion* and positive for employment-based *closeness*. The interactions for industry-based cohesion or closeness are insignificant, which implies the difference of the measurement level on either industries or employment.

The exit dummy has a positive effect in the first two models, whereas a negative effect is observed in the last two models. The only difference between these models is the measurement level of the relatedness variable. Therefore, this is expected to be the cause of the difference. As discussed earlier, and will be more explicitly discussed in chapter 6, the implications of the employment-based relatedness and industry-based relatedness are different. This is visible in the growth analysis as well. Industry based relatedness is purely the diversity of the economic structure, whereas the employment-based relatedness captures the concept with an effect of mass (e.g. many employees in one specific related industry).

As described, there may be considerable heterogeneity because of the variation in industries, and therefore coefficients can be aggregated and not accurately reflecting relations for (sub)sectors. The impact of the regional economic structure on the growth potential of plants may be more important for some industries than others, which could explain the aggregate effects found. Therefore, the models are estimated for a division of industries (see appendix for the industry division).

	All industries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)
cohesion industries (log)	-0.199***				-0.195***			
	(0.0101)				(0.0101)			
cohesion employment (log)		-0.0107				-0.00374		
		(0.00677)				(0.00677)		
closeness industries (log)			-0.00509***				-0.00487***	
			(0.00103)				(0.00103)	
closeness employment (log)				-0.00247***				-0.00251***
				(0.000585)				(0.000585)
Krugman specialization (log)	0.0306***	0.0289***	0.0288***	0.0296***	0.0306***	0.0288***	0.0289***	0.0296***
	(0.000421)	(0.000418)	(0.000411)	(0.000455)	(0.000421)	(0.000418)	(0.000411)	(0.000455)
HHI (log)	0.0252***	0.0143***	0.0136***	0.0140***	0.0242***	0.0125***	0.0129***	0.0137***
	(0.00292)	(0.00294)	(0.00286)	(0.00286)	(0.00292)	(0.00294)	(0.00286)	(0.00286)
exits					0.0120	0.0557**	-0.0243***	-0.0487***
					(0.0282)	(0.0223)	(0.00238)	(0.00362)
exit*cohesion (industries)					-0.0155			
					(0.0111)			
exit*cohesion (employment)						-0.0302***		
						(0.00810)		
exit*closeness (industries)							-0.00112	
							(0.000865)	
exit*closeness (employment)								0.00235***
								(0.000394)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moved dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.549***	1.016***	0.993***	1.010***	1.532***	0.987***	0.987***	1.007***
	(0.0406)	(0.0361)	(0.0286)	(0.0293)	(0.0406)	(0.0361)	(0.0286)	(0.0293)
Observations	10,117,323	10,117,323	10,117,116	10,117,108	10,117,323	10,117,323	10,117,116	10,117,108
R-squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Number of num_id	1,729,078	1,729,078	1,729,055	1,729,055	1,729,078	1,729,078	1,729,055	1,729,055

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 14 – Growth analysis for all industries (2005-2016)

Table 15 displays the results of the estimations for a division of industries between service and manufacturing industries. For service industries, all the relatedness variables, except employment-based cohesion, negatively influences the growth potential of a plant. For manufacturing industries, industry-based cohesion is negative as with services, however the other coefficients are insignificant. This can be explained by the heterogeneity between manufacturing industries, high-tech versus low-tech for instance.

Specialization is more important than relatedness for both services and manufacturing industries, as the coefficients are larger. The exception is employment based cohesion for services industries, where the share of related employment explains growth to a larger extent than specialization. For manufacturing plants this also accounts for diversification. However, for services industries diversification is insignificant. This implies that a diversified region is more important for the growth of manufacturing plants than for services plants.

The interaction variable is positive and significant in three models estimated for service industries, whereas for manufacturing industries one is significant and negative. This indicates that for service industries, the related environment is more important for exiting plants than for manufacturing exiting plants.

Altogether, large differences occur between manufacturing and services industries which provides proof of the large degree of heterogeneity in employment growth across industries. Therefore, another division of industries will zoom in on three specific manufacturing industries: high-tech, low-tech and creative. It is expected that high-tech and creative industries can be characterized by their knowledge intensive activities and therefore are more influenced by knowledge spillovers. On the other hand, low-tech industries are chosen for comparison as a counterpart of high-tech and creative industries. By specifying these groups of industries, it is expected to capture the heterogeneity between industries and the influence of the economic structure.

The independent variables are only regressed on the region-industry specific variant of relatedness (closeness). The region-specific variable (cohesion) is excluded, as its level is less specific and therefore less meaningful in plant-level analysis. See table 16 for the outcomes.

	Services				Manufacture			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
VARIABLES	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)
cohesion industries (log)	-0.131***				-0.228***			
	(0.0187)				(0.0456)			
cohesion employment (log)		0.0500***				-0.0143		
		(0.0122)				(0.0316)		
closeness industries (log)			-0.00517**				0.00373	
			(0.00222)				(0.00399)	
closeness employment (log)				-0.00533***				0.000549
				(0.00104)				(0.00230)
Krugman specialization (log)	0.0161***	0.0137***	0.0146***	0.0171***	0.0531***	0.0527***	0.0527***	0.0526***
	(0.000703)	(0.000688)	(0.000663)	(0.000844)	(0.00124)	(0.00124)	(0.00124)	(0.00125)
HHI (log)	0.00583	-0.00761	-0.00175	-0.000339	0.0597***	0.0461***	0.0451***	0.0450***
	(0.00507)	(0.00511)	(0.00495)	(0.00495)	(0.0141)	(0.0142)	(0.0138)	(0.0139)
exits	-0.114**	-0.0931**	-0.0200***	-0.0384***	0.0885	0.173	-0.0707***	-0.0376**
	(0.0515)	(0.0415)	(0.00708)	(0.00656)	(0.136)	(0.106)	(0.0106)	(0.0185)
exit*cohesion (industries)	0.0362*				-0.0578			
	(0.0203)				(0.0537)			
exit*cohesion (employment)		0.0256*				-0.0844**		
		(0.0151)				(0.0386)		
exit*closeness (industries)			-0.000882				0.00461	
			(0.00248)				(0.00380)	
exit*closeness (employment)				0.00169**				-0.00248
				(0.000689)				(0.00220)
Constant	0.865***	0.325***	0.508***	0.556***	2.443***	1.841***	1.793***	1.791***
	(0.0593)	(0.0474)	(0.0265)	(0.0283)	(0.237)	(0.223)	(0.199)	(0.200)
Observations	2,479,366	2,479,366	2,479,366	2,479,366	544,164	544,164	543,965	543,960
R-squared	0.002	0.002	0.002	0.002	0.008	0.008	0.008	0.008
Number of num_id	470,753	470,753	470,753	470,753	83,280	83,280	83,256	83,256

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15 - Growth analysis for services and manufacturing industries (2005-2016)

	HIGHTECH		LOWTECH		CREATIVE	
	(17)	(18)	(19)	(20)	(21)	(22)
VARIABLES	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)
closeness industries	0.00992**		-0.00708		0.0106***	
(log)	(0.00455)		(0.00644)		(0.00300)	
closeness employment		-0.000294		-0.00897***		-0.0140***
(log)		(0.00195)		(0.00341)		(0.00134)
Krugman specialization	0.0286***	0.0289***	0.0570***	0.0580***	0.0162***	0.0241***
(log)	(0.00127)	(0.00139)	(0.00216)	(0.00219)	(0.000802)	(0.00108)
HHI (log)	0.0335***	0.0348***	-0.00926	-0.00572	-0.0157**	-0.0116*
	(0.0106)	(0.0106)	(0.0200)	(0.0201)	(0.00648)	(0.00649)
exits	-0.0682***	-0.0399***	-0.0378**	-0.0753***	0.00601	0.0213***
	(0.0179)	(0.0139)	(0.0169)	(0.0259)	(0.00542)	(0.00800)
exit*closeness	0.0118*		-0.00502		-0.00577***	
(industries)	(0.00617)		(0.00615)		(0.00193)	
exit*closeness		0.000640		0.00287		-0.00341***
(employment)		(0.00155)		(0.00307)		(0.000871)
Constant	0.892***	0.932***	1.216***	1.293***	0.212***	0.414***
	(0.0643)	(0.0662)	(0.119)	(0.123)	(0.0343)	(0.0370)
Observations	671,080	671,080	240,000	240,000	927,600	927,600
R-squared	0.003	0.003	0.011	0.011	0.006	0.006
Number of num_id	119,847	119,847	38,590	38,590	179,415	179,415

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 – Growth analysis for high-tech, low-tech and creative industries (2005-2016)

Clear differences appear among the industries, whereas the employment growth of plants in high-tech and creative industries are positively influenced by the number of related industries (*closeness industries*). This impact is insignificant for plants in low-tech industries. The employment-based closeness coefficient is negative for all industries, except for high-tech industries which coefficient is insignificant.

The coefficient of specialization is again larger than that of relatedness, which implies a larger positive influence on the growth potential of plants. Specialization seems most important for low-tech industries, followed by high-tech and creative industries. The impact of diversification, on the other hand, appears with larger deviations across industries. Diversification appears positive for high-tech industries, negative for creative industries, and insignificant for low-tech industries.

The exit dummy is significantly negative for high-tech and low-tech industries, whereas for creative industries it is either insignificant or significantly positive. A negative coefficient of exit indicates that when a plant exits the following year, it has a negative influence on the employment growth potential of firms. The interaction effect also variates in its sign and significance across industries. The interaction effect is negative and significant for creative industries, insignificant for low-tech industries, and either positive and significant or insignificant for high-tech industries.

In table 17, the estimations are presented for the high-tech, low-tech and creative industry division for two periods as determined in chapter 3. The division in time periods is executed to analyse the impact on employment growth in times of crisis and in the recovery period. In this way, the resilience hypothesis can be tested. Period II presents the crisis period from 2010 to 2013, and Period III the recovery period from 2014 to 2016. Only the relatedness variables are displayed with the exit dummy and interaction effect, for a clearer overview of coefficients.

PERIOD II – 2010-2013	**HIGHTECH**		**LOWTECH**		**CREATIVE**	
	(23)	(24)	(25)	(26)	(27)	(28)
VARIABLES	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)
closeness industries	-0.00884		-0.00466		0.0108*	
(log)	(0.00835)		(0.0109)		(0.00576)	
closeness employment		-0.0136***		-0.00296		-0.0103***
(log)		(0.00369)		(0.00616)		(0.00256)
exits	-0.0419*	-0.0294*	-0.0392*	-0.0791**	0.00791	0.00771
	(0.0235)	(0.0177)	(0.0236)	(0.0354)	(0.00697)	(0.0103)
exit*closeness	0.00724		0.000581		-0.00484*	
(industries)	(0.00808)		(0.00857)		(0.00250)	
exit*closeness		0.000956		0.00496		-0.00142
(employment)		(0.00197)		(0.00420)		(0.00113)
Observations	254,755	254,755	87,648	87,648	357,932	357,932
R-squared	0.001	0.001	0.008	0.008	0.004	0.004
Number of num_id	82,132	82,132	26,924	26,924	120,707	120,707
PERIOD III – 2014-2016	**HIGHTECH**		**LOWTECH**		**CREATIVE**	
	(29)	(30)	(31)	(32)	(33)	(34)
VARIABLES	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)	jobs (log)
closeness industries	-0.00587		-0.0111		-0.00621*	
(log)	(0.00662)		(0.0106)		(0.00338)	
closeness employment		-0.00229		-0.0119**		-0.00332*
(log)		(0.00338)		(0.00545)		(0.00186)
exits	-0.00162	-0.0165	0.00632	0.0336	-0.00537	-0.0177
	(0.0375)	(0.0285)	(0.0370)	(0.0569)	(0.00911)	(0.0135)
exit*closeness	-0.00346		-0.00914		0.000981	
(industries)	(0.0128)		(0.0135)		(0.00331)	
exit*closeness		0.000532		-0.00618		0.00163
(employment)		(0.00314)		(0.00674)		(0.00145)
Observations	204,792	204,792	66,621	66,621	331,367	331,367
R-squared	0.002	0.002	0.002	0.002	0.000	0.000
Number of num_id	81,159	81,159	25,929	25,929	133,720	133,720

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 - Growth analysis for high-tech, low-tech and creative industries (2010-2013 and 2014-2016)

With the exception of the number of related industries (closeness industries) for creative industries in the crisis period 2010-2013, relatedness either negatively or insignificantly influences the growth potential of firms. The positive coefficient of relatedness for creative industries implies that in a period of crisis, the number of related industries positively influences the resistance in terms of employment towards the shock. However, as all other relatedness variables are negative or insignificant, this cannot be generalized.

The coefficients are quite different in the two time periods, also compared to the whole period (table 16). Period I resembles the pre-crisis period, Period II resembles the crisis, and period III resembles the recovery period. The largest growth employment growth figures appear in the first period, which explains the differences between table 16 and table 17. Where in table 16, the coefficient of industry-based closeness for high-tech industries was positive, in table 17 they are both insignificant. Only the impact on creative industries remains, compared to the crisis and recovery period.

6 SYNTHESIS

In this chapter, the most important insights are discussed from the analyses in chapter 5. The key findings are presented in section 6.1, a discussion on the results follows in section 6.2, and limitations applicable for the research are discussed in section 6.3.

6.1 KEY FINDINGS

The most insightful results follow from the adjusted growth model, in which the analyses are executed for a division of industries (high-tech, low-tech and creative) to correct for the heterogeneity between industries. A diverse impact is found in models 17 to 22 of cohesion and closeness, as indicators of relatedness, on the employment growth of plants across industries. For plants in high-tech and creative industries, a positive impact is found of the number of related industries on the employment growth of plants, whereas for plants in low-tech industries this is insignificant. A negative impact is found of the number of related jobs for plants in low-tech and creative industries, whereas for high-tech industries the impact is insignificant. This implies that for creative and high-tech plants, the related environment is more valuable in terms of related industries compared to related jobs.

The results show a high degree of heterogeneity between industries. For knowledge intensive industries (i.e. service, creative and high-tech), relatedness has a more significant and positive impact on the growth potential of plants, compared to other industries (i.e. manufacturing, low-tech). This implies that for the knowledge intensive industries, it seems more important to be located in a related environment (near related industries). These industries are expected to absorb knowledge spillovers more easily, and therefore they are also more likely to benefit from a related environment.

However, it must be noted that in almost all models, either specialization or diversification has a larger or more significant impact on the growth potential of firms. The only exception was found when the analyses are performed for two separate periods, as distinguished in chapter 3. During a period of crisis, plants in the creative industries are more likely to experience a positive employment growth when they are surrounded by related industries.

6.2 DISCUSSION

An important level of analysis in this research is the focus on the impact of relatedness on the plant-level. In this way, it can be analysed whether plants from *which industries* will have a higher growth potential in *which regional economic structure*. For instance, a plant from a creative industry will have more growth *opportunities* in an industry-related economic environment. On the other hand, a plant from a low-tech industry will have more growth opportunities in a diversified economic environment.

This is a valuable insight for policy makers, as analyses on their regional economic structure can present growing opportunities for plants in specific industries.

The differences between relatedness measurements on employment and on industries, implies that both approaches measure a different concept in essence. The chance of overrepresentation of an industry because of one large company (Philips in Eindhoven) are higher using employment measurements. However, industry measurements might also induce misrepresentation of an industry as every industry is weighted equally independent on its size. Both measure the relatedness concept differently, and it depends on the context (e.g. data, industry, region) whether one is more suitable for analysis than the other. Industry based relatedness measures purely the diversity of the economic structure, whereas the employment-based relatedness is influenced by the effect of large plants.

It was decided to only execute the analysis with a division of industries and periods for the region-industry specific variable of relatedness (*closeness*), because this coefficient is measured in more detail than the region-specific variable (*cohesion*). Consider a plant located in a region in which a high degree of cohesion is measured. However, the plant is not part of the related network in the region because its core activities are not related to those of other plants who create this regional cohesion. Therefore, the plant will not benefit from the potential benefits of the related regional economic structure. The region-industry specific closeness is therefore a more suitable predictor of the impact of a related economic environment.

As was concluded by several comparable studies on the economic regional structures (Beaudry and Schiffauerova (2009), Melo et al. (2009) and De Groot et al. (2016), who focus on the differences between diversification and specialization, it is very context specific which structure is beneficial for regional productivity or employment growth. This is shown by this research as well, where one industry benefits from a related environment and the other does not. Proof of the heterogeneity between industries is also presented by differences in the impact of specialization and diversification across industries. A specialized economic environment seems more important for plants who are active in low-tech industries, followed by plants in high-tech, and creative industries. Low-tech industries might benefit more from the localization economies, as described by Marshall (1920), because they benefit more from process innovations as are assumed in localization economies. A diversified economic environment on the other hand seems particularly important for plants in high-tech industries, whereas for the other industries it has a negative impact on the growth of plants.

However, this must be carefully argued as the specialization variable is measured region-industry specific, whereas diversification is region specific and relatedness is both region-industry specific (closeness) and region specific (cohesion). The specialization coefficients indicate that when a plant operates in an industry that is relatively specialized in a region in relation to the total national employment of the industry, this will benefit the plant's growth opportunities. This definition of specialization therefore implies a specialization of an industry in a region, rather than a specialized region.

6.3 LIMITATIONS

Data limitations do influence the outcomes of the research in twofold. First, a limitation of the plant-level analysis is the availability of data. This research data availability of plant information was limited to the number of employees, location and their core activity. A more detailed dataset on plants, would provide a better understanding on plant growth. Second, the administrative division, NUTS3 level, as a regional indicator presents limitations. When the economic structure could be attained in continuous space, the research would be more specifically for one plant than it is now. A plant could be at the border of one NUTS3 region, and also obtain benefits from the region across that border.

This research considered several indicators for relatedness, diversification and specialization. Even though many academics have attempted to find the most suitable measurements, there still remains a discussion on the robustness of the indicators. Therefore, it must be noted that the results are highly dependent on the variables chosen, which is a limitation of this research and other studies as well.

6.4 FUTURE RESEARCH

Suggestions for further research follow from these limitations. First, it is valuable to execute a similar research in continuous space, counting the industries not in the administrative division of a NUTS3 region, but instead cross those borders to establish a precise regional definition which then is plant specific. Second, more plant level data is better to obtain specific results on plant survival and growth. This is partially captured by the fixed effects, however still some changes inside a plant are not considered in this research. For instance, the reason for the exit of a plant can either be positive (e.g. merger) or negative (e.g. bankruptcy), however in this research both are treated as the exit (non-survival) of a plant. This information would be valuable to distinguish between these types of exit.

7 CONCLUSION

The research question that was proposed in chapter 1 is supported by a number of hypotheses that will first be answered. The first hypothesis stated:

> *Hypothesis 1: The resilience of a region, in terms of employment, towards economic shocks is positively associated with a higher degree of regional skill-relatedness.*

As was presented in chapter 3, the correlation calculations show that skill-relatedness is positively associated with the ability of a region to resist and adapt after an economic shock in terms of employment, with the exception of one relatedness variable (employment-based cohesion). Therefore, this hypothesis is only partially accepted. It depends on the level of measurement of relatedness, and therefore the nature of the relatedness - related *jobs* or related *industries*. As was discussed in chapter 6, both concept measure relatedness differently and chances of misrepresentation are present because of outliers in the number of jobs per plant. It depends highly on the context of the research (e.g. data, industry, region) which approach is more suitable.

> *Hypothesis 2: The conditional growth potential of a plant, in terms of employment, during and after economic shocks is positively influenced by a high degree of regional related industries and employment.*

The second hypothesis on the conditional growth potential of a plant can partially be accepted. For specific samples in the dataset, based on a division of industries, the degree of relatedness has a positive impact on the growth potential of plants. However, as this is industry specific and only applicable for a small sample, this result cannot be generalized.

> *Hypothesis 3: Regional relatedness has a larger impact on the survival and growth of plants compared to other agglomeration indicators, like specialization or diversification.*

The hypothesis above cannot be accepted, as the majority of analyses shows that relatedness did not influence the employment growth of plants with a larger impact than specialization and diversification did. In several models, relatedness had a negative impact whereas specialization and diversification suggested a positive impact on the growth of plants. Results show that only for plants in the creative industries, the number of related industries does impact the growth of plants in a period of crisis to a larger extent than the other regional economic structures do.

> *Hypothesis 4: Regional relatedness has a larger impact on the survival and growth of plants when these are regionally embedded in a relatively and absolutely larger industry base.*

The last hypothesis was tested by means of testing for industries in separate samples of analysis. By analysing the impact of relatedness with a division of industries, this hypothesis can partially be accepted. It highly depends on the specific industry, which regional economic structure is most beneficial for a plant's survival or growth potential. Thereby, it also matters which measurement is applied for relatedness – either industries or employment. The number of relatedness industries appear to positively impact the growth potential of plants in high-tech and creative industries. However, this impact was not observed in low-tech industries.

The above hypotheses support answering the following research question:

> *To what extent does regional relatedness influence the survival and growth potential of plants during and after economic shocks in the Netherlands?*

Skill-relatedness as a regional economic structure does only influence the growth potential of plants in a specific context, for certain knowledge-intensive industries. The division of industries in this research presents that, for plants in high-tech and creative industries a positive impact on the growth potential of plants is found of the number of related industries. However, this impact is not larger than the positive effect of diversification or specialization in a majority of analysis. Thereby, when looking at specific periods, only plants in creative industries are positively influenced by the number of related industries during a period of economic shock. Because the results are context specific, it confirms the expectation of the heterogeneity of employment growth between industries. Large differences occur between industries who are different in nature, where knowledge intensive industries benefit different from its direct environment than other industries.

The contribution of this research is a confirmation of the heterogeneity of growth between industries, and thereby the differences in value of the regional economic structure. As beforehand stated, the influence of a related structure on plant-level growth was not researched before. This is a valuable addition to academic literature. Although its limitations (i.e. use of administrative region division, data availability), the research gives insight in the impact of relatedness on the individual plant.

APPENDIX – INDUSTRY CODES ALTERATIONS

The NACE codes and the industry codes (SBI) in the Netherlands are not completely similar. Some codes are combined, separated, or non-existent in the Dutch industry division. Therefore, adjustments are made in the skill-relatedness dataset which are presented in table 18 below. The SBI codes in the second column are replaced by the NACE codes in the first column.

NACE	SBI – Netherlands
3320	3322, 3324, 3329
8690	8691, 8692
9312	9314, 9315

Table 18 - Translation Dutch SBI and NACE codes

For the exploration of employment dynamics in chapter 3, the plants with NACE codes of the second row in table 19 are excluded. The first two-digit industry codes, 00 and 01, represent agricultural sectors which go hand in hand with several administrative problems (registration of plants) and are therefore excluded. The other industries that are excluded represent public financed industries (e.g. education, arts). The fifth row represents NACE codes that are excluded from the regression analyses because of the biased effect they might have (e.g. employment agencies, head offices).

NACE codes dropped for growth decomposition
00, 01, 84-88, 90, 91, 93, 94, 98, 99
NACE codes dropped for skill-relatedness
00, 01, 7810, 7820, 97, 98

Table 19 - Industry codes excluded from dataset

APPENDIX – DIVISION OF INDUSTRIES

Two divisions of industries are presented in the tables below. Two divisions are applied, whereas the first (manufacturing, services) is applied in chapter 3 to observe the heterogeneity between industries. The manufacturing industries are merely a copy of the division of Eurostat (2018a), whereas the service industries are an adjusted version of their definition. It is decided to leave out consumer-driven activities (tourism, retail, real estate). The second division is added in chapter 5, as an extra level of measurement in the regressions analyses. The division of high-tech, low-tech and creative industries is based on

Division for growth decomposition (chapter 3)	
Manufacturing (Eurostat, 2018a)	05-39
Service (Eurostat, 2018a)	58-66, 69-74
Division for regression analysis (chapter 5)	
High-technology (CBS, 2017)	2211, 2229, 24, 2520-2562, 2573, 2591, 2593, 2594, 2599, 26, 27, 28, 2910, 2920, 2931-2932, 3020-3099, 3250, 3311-3314, 3316-3317, 3319, 3320-3329, 6201, 7112, 7120, 7219
Low-technology (Eurostat, 2018b)	10-18 (excl. 18.2), 31-32 (excl. 32.5)
Creative (CBS, 2017)	58, 59, 7021, 7111, 7311, 7410, 7420, 9001-9003, 9101-9103

Table 20 - Division of industries

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