THE ROLE OF RELATEDNESS AND ENTREPRENEURSHIP IN REGIONAL ECONOMIC DEVELOPMENT

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THE ROLE OF RELATEDNESS AND ENTREPRENEURSHIP IN REGIONAL ECONOMIC DEVELOPMENT

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Voor mijn ouders

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Jeroen Content

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Chapter 1

Introduction

Globalisation has increasingly exposed regions within countries across Europe to international competitive pressure. As a result, the current policy climate in the European Union is characterised by a strong emphasis on the implementation of policies designed to promote economic restructuring, entrepreneurial activity, and innovation among its member states. With its Smart Specialisation Strategy, the European Commission endorses place-based policy making, by supporting regions to identify and develop their own competitive advantages, in order to create new jobs and to stimulate economic development. Within this context, we examine the role of relatedness and entrepreneurship in the economic development of regions across Europe.

The central finding of this research indicates that policies to promote regional entrepreneurship or research and development (R&D) that do not consider regional contexts are less likely to foster innovation, job creation, and economic prosperity. This corroborates the place-based approach underlying the EU's Smart Specialisation Strategy. However, we also find that relatedness affects many aspects of economic development. This suggests that the effectiveness of regional policymaking can be improved by recognising and incorporating the important role of relatedness in policies that promote regional entrepreneurship and innovation to develop competitive advantages, foster job creation, and secure economic prosperity across Europe.

1.1 Theoretical background

Starting with the writings of Adam Smith (1776), we came to understand that nations grow wealthy through refinements in the division of labour; enabling growing levels of specialisation, greater efficiency, and eventually leading to prosperity. The disaggregation of complex tasks into simpler and more specialised ones enables individuals and firms to become more skilled or to automate them, increasing the efficiency by which they are carried out. Although Smith's proposition has resonated particularly well, the principle of efficiency through specialisation may not matter that much for long-term economic development. Instead, as Jane Jacobs (1969) has argued, the key for long-term economic development is that refinements in the division of labour increase the scope for new innovations. In her view, new tasks branch-out of or are combined with existing tasks, when "new work [is] added to old work" (1969, p. 52). With a greater division of labour, greater opportunities for recombination emerge, sometimes adding new activities (new goods and services) to the existing division of labour.

Similar to Jacobs' principle of recombination, Joseph Schumpeter described new combinations of existing ideas as "Neue Kombinationen" (1934). He regarded the courage of entrepreneurial human actions as the key driver behind innovations, which in turn are driven by the opportunity to transform inventions (or new combinations) into profitable businesses. In his words, entrepreneurship is:

> ". . . simply the doing of new things or the doing of things that are already being done in a new way." (1942, p. 151)

According to this point of view, economic development is driven by the introduction of novelty (stemming from inventors that combine knowledge into new ideas), with which entrepreneurs create new value through refinements of or alterations in the division of labour.

1.1.1 Knowledge, economic development, and agglomeration

Especially since the understanding of knowledge as endogenous driver of technological change in economic growth theory (Lucas, 1988; Romer, 1986), have scholars demonstrated their interest in studying processes through which knowledge is created, combined, and utilised as a factor of economic production. Globalisation alongside with technological progress have ensured both the extensive development and diffusion of new knowledge and technologies as well as a historical reallocation of economic activity

in the world economy. This implicates nations, but certainly regions too, as is also postulated by the political traction that region-specific policy such as the Smart Specialisation Strategy of the European Commission has gained. For regions, these developments can serve equally as an opportunity and a necessity, to timely restructure their economy in order to maintain or develop new competitive advantages, that will ensure long-term economic prosperity.

Central in the question of how economies maintain or develop new competitive advantages is a process of 'creative destruction', identified by Schumpeter as the:

> " . . . process of industrial mutation . . . that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." (1942, p. 83)

According to this view, new ideas and discoveries can initiate this process. However, the appropriation of new ideas, through the recombination with existing knowledge into new and more productive activities, is eventually what drives structural transformations. It is entrepreneurs that are expected to introduce such new activities, activities that render established and less productive activities irrelevant and obsolete. Economic development in this view is best understood as a perpetual process of creation, destruction, and restructuring, while the competitive advantages of an economy, in turn, are built upon those activities that are the most productive and prevail for longer periods of time.

Knowledge spillovers play an important role in the creation of new competitive advantages. Despite the openness of economies, the non-rival nature of knowledge, and the rapid technological advancements in particularly information, communication, and transportation technologies, geographical proximity to the places of knowledge still explains the intensity of such spillovers by significant extent (Bottazzi & Peri, 2003). As a consequence, innovative activities concentrate geographically, more so than what would be proportional to other economic activities (Audretsch & Feldman, 1996; Feldman & Florida, 1994; Simmie, 2003). Locating close to one another benefits firms and individuals not only in terms of cost-efficiencies, but it also creates opportunities for mutual learning. Such learning opportunities, or knowledge spillovers, can originate from different sources and operate through different channels, depending on specific local conditions.

One channel through which geographic proximity may benefit firms is co-location with other firms operating in the same industrial sector, as this allows for labour market pooling, the use of common suppliers, and intra-sectoral knowledge spillovers (Henderson,

2003). Such 'localisation externalities' materialise into increased aggregate productivity when local economic activity concentrates within a common industry, inducing the exchange of knowledge and ideas. Another channel through which geographic proximity may benefit firms is through locating in an agglomeration that contains a diversified variety of economic activity, as such an environment promotes inter-sectoral knowledge spillovers. This channel is often referred to as 'Jacobs externalities' and predicts that a diversified agglomeration of knowledge is what is crucial for creating opportunities for recombining ideas.

These opposing theories on the sources of agglomeration externalities originate from different views on innovation. Regarding localisation externalities, Alfred Marshall was one of the first to write elaborately about this phenomenon, famously arguing that:

> "When an industry has thus chosen a location for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighborhood to one another." (1920, p. 255)

Besides the possibilities for labour market pooling and the common use of infrastructure and suppliers, Marshall is referring to processes where people can learn more when they are in close proximity to other people doing the same thing. The later writings of Kenneth Arrow (1962a) can be regarded as an early operationalisation of this idea. He explained that investments and production activities of firms, through learning-by-doing, can generate new knowledge, in turn benefiting aggregate productivity. Extending on this, Paul Romer (1986) argued that knowledge as capital input exhibits increasing returns to scale, i.e. the marginal product to learn new opportunities from knowledge does not diminish but rather increases with the stock of knowledge.

In the theories of Marshall, Arrow, and Romer (MAR), innovation is essentially understood as an incremental process, in which new innovations build upon previous knowledge and ideas. In contrast, Jane Jacobs views innovation as a recombinant process, which she illustrates as:

> " . . . the greater the sheer numbers and varieties of divisions of labor already achieved in an economy, the greater the economy's inherent capacity for adding still more kinds of goods and services. Also the possibilities increase for combining the existing divisions of labor in new ways." (1969, p. 59)

In other words, innovation in this view is best understood as a process where the production of something new necessarily builds on a pre-existing variety or division of knowledge, but recombined in a novel way. The greater the sheer number of varieties of knowledge, the more opportunities there are for recombination.

While agglomeration externalities theoretically seem well described[1], this is not translated as such into empirical evidence. Glaeser, Kallal, Scheinkman and Shleifer (1992) represents one of the first efforts to empirically identify or estimate local knowledge spillovers stemming from different types of agglomeration externalities. Their findings show that in the US, industries grow slower in cities where they are more overrepresented, whereas they grow faster when the rest of the city is less specialised. The authors take these findings as supporting the view of Jacobs: That diversity promotes growth through inter-industry spillovers, while they do not support the view of MAR that specialisation promotes growth through intra-industry spillovers.

Following the seminal contribution of Glaeser et al. (1992), the literature has witnessed a large number of studies investigating these economies of agglomeration. The resulting body of evidence is rather mixed and remains inconclusive as to what type of agglomeration externalities is more prevalent.

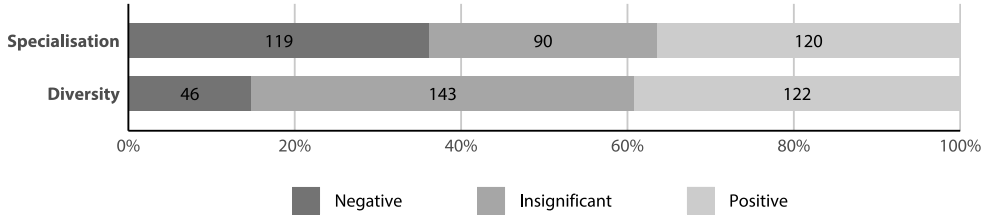


Figure 1.1: *Findings of studies investigating agglomeration externalities. Source: de Groot et al. (2016)*

This is illustrated in figure 1.1, which shows that although a large share of studies finds evidence confirming Jacobs externalities, a substantial share of studies finds no evidence that diversity affects regional development or even reports evidence of negative effects.

[1]Besides localisation and Jacobs externalities, a third type of agglomeration externality can be distinguished, known as 'urbanisation externalities'. This type of externality is concerned with the size of local markets. Urbanisation externalities, mainly arise from the increased demand in large local markets in cities. This effect can be negative as well, as large agglomerations often have to manage or suffer from congestion.

As for regional specialisation, the evidence is even more ambiguous with roughly similar shares of studies finding positive, negative, or insignificant effects. These results suggest that the contexts of agglomeration economies may affect their impacts (Beaudry & Schiffauerova, 2009; de Groot et al., 2016).

The heterogeneity of these findings can be explained by measurement and methodological differences as well as differences in the levels of geographical and industrial agglomeration (Beaudry & Schiffauerova, 2009; de Groot et al., 2016). At low (broad) levels of industrial disaggregation, specialisation is found to have a positive effect somewhat more often than diversity, at medium levels the probability seems comparable, and at high (detailed) levels of industrial disaggregation, diversity is more often found to have a positive effect. An explanation for these different findings may be that, as low and medium levels of industrial disaggregation still contain a wide variety of economic activities, effects from specialisation could partly be driven by Jacobs externalities. Besides differences in industrial disaggregation, differences in the geographical unit of aggregation also seem to contribute to the inconsistency of these findings. Furthermore, some evidence seems to indicate that in knowledge-intensive industries diversity has a stronger positive effect than specialisation, while industries that are less knowledge-intensive benefit more from specialisation (Marrocu, Paci & Usai, 2013). Another issue regards the maturity of the industry. Diversity is favoured in early stages of the industry life cycle, while as the industry becomes more mature, specialisation becomes more important. Related to that is the idea of 'Nursery Cities', advanced by Duranton and Puga (2001), who argue that diversified cities foster innovation and development of new activities, but once such activities mature, reallocate to specialised places to benefit from cost-efficiencies. Another factor that explains some variation in these results, is the indicator that is used to measure growth. Employment growth is found to benefit more from diversity than from specialisation, in terms of productivity growth, specialisation is more commonly found to have a positive impact.

1.1.2 Related and unrelated variety of economic activity

Considering the heterogenous nature of the evidence and the many studies yielding insignificant results, could indicate that the theoretical notions of specialisation and diversity are too simplistic to capture the varied effects of a region's industrial composition on its further economic development. Some have argued that, for knowledge spillovers to be effective, geographical proximity is not the only prerequisite and that other factors such as cognitive proximity are important as well (Nooteboom, 2000). When knowledge or capabilities are cognitively similar but not the same, economic agents are able to com-

municate and understand each other, while still some room is left for mutual learning, increasing the likelihood for knowledge spillovers (Breschi, Lissoni & Malerba, 2003). The cognitive distance should thus be neither too large, making it very difficult to effectuate spillovers, or too small, leaving little potential to learn. In addition, other forms of proximity may be relevant to spillovers as well, including organisational, social, and institutional proximity (Boschma, 2005).

Contributing to the debate whether MAR or Jacobs externalities are more important for regional economic development, Frenken, Van Oort and Verburg (2007) introduced the concept of related variety. Although they agreed with Jacobs and Schumpeter that in essence innovation is a recombinant process, they further specified the notion of recombination by arguing that some pieces of knowledge are easier to recombine than others. The authors emphasised that inter-industry spillovers occur mainly between sectors that draw on similar knowledge. Knowledge originating from one sector is most relevant to, and can most effectively be absorbed by, another sector that is related in the sense that firms in these sectors draw on similar technologies, knowledge, and/or capabilities. Hence, variety of economic activity is especially supportive for innovation and ultimately regional development when it is 'related'.

Studying regions in the Netherlands, Frenken et al. (2007) present evidence in support of their hypothesis that related variety increases the rate of employment growth, as increased recombination of knowledge is expected to lead to new products and services, viz. new employment. They also find support of their hypothesis that unrelated variety decreases the rate of unemployment growth, as the presence of unrelated sectors would act as a portfolio against sector-specific shocks. Successive studies that attempt to replicate these findings for regions in other countries, as reviewed by Content and Frenken (2016), generally find support for the hypothesis that related variety acts as a driver for regional employment growth[2], especially concerning knowledge-intensive activities. Regarding the effects of unrelated variety on unemployment growth, the evidence is less clear. Moreover, some authors have argued that, granted that the opportunities for recombination from unrelated varieties occur less frequently, if successful, they are more likely to produce radical innovations (Castaldi, Frenken & Los, 2015).

Although the evidence is suggestive of the workings of recombinant mechanisms that exploit related variety among a region's activities into new business opportunities, the

[2] Frenken et al. (2007) also hypothesised that localisation externalities, as measured by specialisation using the LOS-index (2000), would positively impact upon regional productivity growth. Studies reviewed in Content and Frenken (2016) report mixed findings of the effects of both specialisation and related variety on productivity growth.

question through which channels this materialises into economic growth remains unanswered in these studies. Factors such as patent applications, social networks, labour mobility, and entrepreneurship may all facilitate or transmit knowledge spillovers, preceding the actual introduction of new products or services. Measuring knowledge creation and innovation more directly, as is commonly done using patent applications or scientific publications, can help us understand how knowledge spillovers stemming from related varieties eventually lead to growth.[3]

Entrepreneurship may well be another channel through which (un)related variety of economic activity leads to growth. As illustrated by the Knowledge Spillover Theory of Entrepreneurship, entrepreneurship can serve as a channel through which knowledge spillovers are exploited (Acs, Audretsch & Lehmann, 2013; Audretsch, 1995). Extending this theory to the notion of knowledge spillovers stemming from related variety, the familiarity of individuals with a particular knowledge domain makes them more likely to identify and pursuit opportunities for recombining their knowledge with other related knowledge domains (Shane, 2000), sometimes by starting a business.[4] Depending on local conditions, new firm formation is then expected to promote regional employment growth (Acs & Armington, 2004; Audretsch & Fritsch, 2002; Stuetzer et al., 2018; Van Stel & Suddle, 2008). Similarly, related variety may affect the entrepreneurial behaviour of individuals within organisations as well, when they recognise business opportunities by relating their knowledge with other related knowledge domains, which they exploit within the boundaries of their organisations.

1.1.3 Industrial diversification and the product space

Consonant with related variety is the notion of the product space.[5] It was introduced by Hidalgo, Klinger, Barabási and Hausmann (2007) to show that economies develop over time by diversifying their export portfolio into new products that are technologically related to existing products. More specifically, they showed that products which are closely related or proximate to the products that are currently exported have an increased probability of entering the country's export basket in the future. The degree of

[3] Indeed, some have analysed the effects of related and unrelated variety on patents (Castaldi et al., 2015; Tavassoli & Carbonara, 2014).

[4] Studies that have looked at this have mostly examined associations between the variety in the stock of knowledge with rates of new firm formation, rather than variety in economic activity. In most cases, these studies report positive findings (Bishop, 2012; Colombelli, 2016; Guo, He & Li, 2016; Tavassoli & Jienwatcharamongkhol, 2016).

[5] An important difference between the concepts of related variety and product space is that the former is used to explain aggregate regional or national growth patterns, while the latter is used to explain diversification into specific new products or industries at the regional or national level.

relatedness, or 'proximity', between a pair of products is inferred from the frequency by which countries are contemporaneously exporting the pair of products[6]. It is assumed here that with rising proximity or relatedness between pairs of products, the extent to which they draw on similar knowledge and capabilities rises as well. A country that has obtained the knowledge and capabilities necessary to export a particular good, has a higher probability of diversifying into products that are related or proximate to it. As such, industrial diversification of economies can be understood as a branching process[7], in which new economic activities branch-out of or are combined with established activities (Boschma & Frenken, 2011; Frenken & Boschma, 2007). A growing number of empirical studies presents evidence showing that, as is similar for countries, regions have a higher probability of diversifying into industries that are related to pre-existing activities, relative to industries that are unrelated (Boschma, 2017; Content & Frenken, 2016).

However, exceptions to this general pattern of path-dependent development have been identified as well (Coniglio, Lagravinese, Vurchio & Armenise, 2018), showing that economies sometimes diversify into random or unrelated activities (Henning, Stam & Wenting, 2013). This raises the questions of whether certain economies might be better equipped to diversify into unrelated activities, and what underlying factors might determine this. These questions are relevant for at least two reasons. First, the development of regional economies needs to be analysed within the context of growing levels of global competition and integration, increasingly exposing regions to advancements in technology, the entry of emerging economies on the world market, and shifts in global demand. Such events potentially render irrelevant certain capabilities or knowledge that existing competitive advantages rely upon, resulting in a loss of economic activity, viz. unemployment growth. Second, solely relying on related diversification as a means of economic development may in the long-term create adverse technological lock-ins, as diversification is more efficiently realised in related industries (Saviotti & Frenken, 2008), at some point a region may find its diversification possibilities limited. Moreover, due to the consolidation of local learning, search routines, and utilisation of resources, over time a region may find it increasingly difficult to break-out of such technological lock-ins and path-dependent processes of development (Ahuja & Katila, 2004; Maskell & Malmberg, 2007; Neffke, Henning & Boschma, 2011).

[6] Instead of using the export value of products, this approach has been replicated by other scholars using location quotients of regional industries as unit of observation, capturing industry proximity.

[7] Industrial diversification through branching can occur either when a new sector branches out of an established sector or when a new sector branches out through recombinating of capabilities from different sectors.

In this respect, the concept of unrelated diversification also relates to the literature on the (regional) resilience of economies. Although resilience is often treated as the ability of an economy to resist or recover from shocks (Sensier, Bristow & Healy, 2016; Webber et al., 2017), some authors have argued that resilience should not be seen as a stable end point, but rather as a means to install a cycle of continues structural renewal (Boschma, 2015; Simmie & Martin, 2010). According to the product space literature, structural renewal in this context is expected from diversification into distant or unrelated products. For policymaking, this is a substantially more demanding task to accomplish, highlighted by Hidalgo and colleagues as:

> ". . . the incentives to promote structural transformation in the presence of proximate opportunities are quite different from those required when a country hits a dead end. It is quite difficult for production to shift to products far away in the space, and therefore policies to promote large jumps are more challenging. Yet it is precisely these long jumps that generate subsequent structural transformation, convergence, and growth." (2007, p. 487)

Still, the question remains whether some economies may be better equipped to achieve structural change through unrelated diversification. For unrelated diversification, economic activities need to be developed that require different knowledge and capabilities than those used by existing activities. Some scholars have examined the conditions that facilitate economies to acquire such knowledge and capabilities, although more evidence is needed to sufficiently understand how and which conditions enable or constrain patterns of diversification. Nonetheless, the growing set of studies that have investigated this question show that factors such as innovative capacity, the presence of liberal-market institutions and bridging social capital, high-income levels, extra-regional linkages, and (non-local) entrepreneurs are identified as enabling economies to diversify into new and less related activities (Boschma & Capone, 2015; Cortinovis, Xiao, Boschma & Van Oort, 2017; Neffke, Hartog, Boschma & Henning, 2018; Petralia, Balland & Morrison, 2017; Xiao, Boschma & Andersson, 2018; Zhu, He & Zhou, 2017).

1.2 Contribution and research questions

The main objective of this dissertation is to examine the roles of industry relatedness and entrepreneurship in processes of regional economic development. Specifically, in light of globalisation and constantly changing global competition, the relevance of these

objectives is constituted by the need of regional economies to develop new or maintain and strengthen existing competitive advantages, in order to ensure long-term economic prosperity.

In this research, we combine insights from the field of evolutionary economic geography with the literatures on entrepreneurship and regional economic development. Recent empirical findings in the field of evolutionary economic geography suggest that opportunities and constraints of regions to develop new activities are best understood in the context of their industrial legacy, as processes of industrial diversification are expected to extend upon already existing knowledge and capabilities embedded in firms and individuals. As such, industrial diversification can be seen as a path-dependent process, restricting processes of structural transformation of economies. Although some conditions have been identified that enable economies to acquire new unrelated knowledge and capabilities, the literature is still far from being able to formulate a clear perspective on this.

Moreover, related variety through increased knowledge spillovers stimulates regional growth. However, through which channels this materialised exactly has remained implicit. Entrepreneurship may be an important mechanism for change, by introducing new and more productive activities that make redundant established and less productive activities. The scope to which entrepreneurship in this context can become productive, in turn, depends on local conditions embedded in entrepreneurial ecosystems. The empirical evidence on this, however, is scarce.

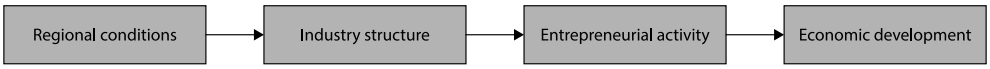


Figure 1.2: *Conceptual framework*

Figure 1.2 illustrates the core of the conceptual framework of this dissertation. First, we are interested in the regional conditions that enable economies to acquire new (and possibly unrelated) knowledge and capabilities, which impacts the industry structure due to the entry of new activities. The industry structure, specifically related and unrelated variety, in turn determines the potential for knowledge spillovers affecting the rate and type of entrepreneurship in a region. Finally, the question holds how entrepreneurial activ-

ity leads to regional growth. The remainder of this section will discuss more elaborately each of the three steps in our conceptual model guiding the dissertation.

1.2.1 Related variety, the product space, and economic development

Before making the three steps in our conceptual model, a systematic literature review on relatedness and regional development would benefit us with a clear overview on the topic. The related variety hypothesis, which holds that Jacobs' externalities are positively related to employment growth (as increased recombination of knowledge is expected to lead to new products and services, and ultimately to new employment), has motivated a large number of empirical studies linking related variety in the sectoral composition of an economy to national and regional development as indicated by employment, income, or productivity. Alongside this, the product space concept has motivated a large number of empirical studies to concentrate on the effect of relatedness density on regional diversification, measured as the entry probability of products or industries. Hitherto, an overview of these studies is lacking. Accordingly, the first aim of this dissertation is to provide a systematic review of these empirical studies as carried out in **chapter 2**.

1.2.2 Regional diversification

There have been quite some studies looking into the question of how a region's industry structure changes over time. A persistent finding of studies investigating the process of industrial diversification based on the concept of the product space seems to be that pre-existing activities constrain regional development to a highly path-dependent process (Boschma, 2017; Content & Frenken, 2016). Yet, there are examples of regions that diversify into unrelated products. Changing global competition and advances in technology jointly cause uncertainty about the sustainability of competitive advantages, as underlying capabilities and knowledge might become obsolete. In this context, the ability to diversify into unrelated products, or activities more generally, may well be key to regional development in addition to the more salient process of related diversification. It is therefore important to understand how regional economies can acquire new and unrelated capabilities and knowledge, giving rise to the question whether certain conditions enable economies to do so, i.e. how can economies escape the forces of path-dependence?

One condition that potentially facilitates the acquisition of new and unrelated knowledge and capabilities are extra-regional linkages that provide inflows of external knowledge (Asheim & Isaksen, 2002; Binz, Truffer & Coenen, 2016). Such inflows can change

the interpretation and perceived potentialities of local knowledge (Bathelt, Malmberg & Maskell, 2004), possibly leading to new and original recombinations of local and non-local knowledge. We propose that a second condition that potentially facilitates the acquisition of new and unrelated knowledge and capabilities, takes shape in networks within the region that connect both related and unrelated firms, but also universities, research institutes, and governments. Such networks may trigger knowledge spillovers between (un)related activities, increasing the probability for new and original recombination of ideas and knowledge. In **chapter 3**, we examine whether the presence of Knowledge-Intensive Business Services (KIBS), the participation in Global-Value-Chains (GVCs), and investment in Research & Development (R&D) might provide regions with either or both of these conditions.

First, as KIBS supply intermediate services to a variety of firms in many different – and unrelated – industries, they may act as a bridging platform between these firms and facilitate knowledge spillovers (Czarnitzki & Spielkamp, 2003). Second, the involvement in GVCs may enhance a region's ability to provide products to a variety of different sectors. Once a region becomes specialised in a particular task performed within a GVC, it can potentially supply many different value chains (Gereffi, Humphrey, Kaplinsky & Sturgeon, 2001; Humphrey & Schmitz, 2002b), increasing the potential for unrelated knowledge to spill over. Third, as regional firms and research institutes engaged in R&D frequently enter in collaborative relationships with research institutes or firms in other regions and countries, the capacity of an economy to attract, absorb, and transform external knowledge into innovations is likely to be related to the level of regional R&D (Cohen & Levinthal, 1990). Knowledge spillovers stemming from globally connected firms may eventually benefit local firms as well. Drawing on these findings and theoretical considerations, we formulate the following research question:

> *Research question 1: Can – and to what extent do – bridging and/or external linkages support the entry of new and unrelated activities?*

The aim of this analysis is to investigate whether the presence of networks and linkages within and outside regions, as provided by KIBS, GVCs, R&D increases the ability of a region to both develop new industrial specialisations and whether it makes the regions less reliant on related knowledge and capabilities to do so.

1.2.3 Related variety and entrepreneurship

Next, we are interested in how a region's industry structure affects entrepreneurship. While studies that associate related variety with regional development are suggestive of processes that inter-industry spillovers among related varieties lead to new business opportunities, the question remains through which mechanisms such opportunities are recognised and exploited? How do knowledge spillovers stemming from related varieties materialise into growth and what role might institutions play in this respect? Some authors have explored these questions, for instance by looking at the effects of related and unrelated variety on patent applications (Castaldi et al., 2015; Tavassoli & Carbonara, 2014).

Research that associates related variety with rates of entrepreneurship is sparse. Studies that do examine this link tend to report positive findings (Bishop, 2012; Colombelli, 2016; Fritsch & Kublina, 2017; Guo et al., 2016; Tavassoli & Jienwatcharamongkhol, 2016). These studies, however, use new firm formation as their proxy for entrepreneurship. We argue that in the context of knowledge spillovers and the recognition of opportunities this measure is limited, as entrepreneurship does not start with the creation of a new firm. Rather, it is the discovery of opportunities that is key, which (often much later) results in the creation of new firms (Shane, 2000). Therefore, indicators of entrepreneurship should not only focus on the level of new firm creation, but also be able to distinguish between firms that are created to exploit new opportunities and firms that are created for other reasons. In our study presented in **chapter 4**, we distinguish between such different types of entrepreneurship that result in new firm formation. Moreover, previous studies do not take into consideration that the effects of (un)related variety on economic development and the prevalence of different types of entrepreneurial activity, may differ significantly across institutional contexts. Taking this into account, we formulate the following research question:

> *Research question 2: To what extent and how are different types of entrepreneurship affected by related and unrelated variety?*

The aim of this analysis is to investigate whether knowledge spillovers stemming from related variety have an effect on both the level as well as the composition of different types of entrepreneurship, and whether this effect is constant across institutional context.

1.2.4 Entrepreneurship and economic growth

Entrepreneurship is an important mechanism for change, by introducing new and more productive activities that make redundant established and less productive activities. Yet, despite the agreement among economist that aggregate growth is not a function of capital and labour alone, the role of entrepreneurship has long been neglected in their research. Starting from the late 1980s this changed, with entrepreneurship increasingly being studied as a cause of economic growth (Wennekers & Thurik, 1999). By now, the theoretical channels through which entrepreneurship may stimulate economic development are well described and can be divided into three important streams of literature: innovation creation (Metcalfe, 2004; Rosenberg, 1992; Schumpeter, 1934), innovation diffusion (Kirzner, 1997; Shane & Venkataraman, 2000), and competition (Aghion, Blundell, Griffith, Howitt & Prantl, 2009; Fritsch & Changoluisa, 2017). The innovation creation view stresses the role of the entrepreneur as driver of structural change, whereas in the innovation diffusion view the entrepreneur observes opportunities for profit maximisation in market inefficiencies. The neoclassical view is primarily concerned with the competition effect of entrepreneurs.

In empirical research, entrepreneurship as a cause of economic development is investigated using different levels of spatial aggregation, different proxies for entrepreneurship as well as different outcome variables. Indeed, a growing recognition of the role of entrepreneurship as important driver of economic growth and development has emerged in the empirical literature (Bjørnskov & Foss, 2016; Block, Fisch & Van Praag, 2017; Van Praag & Versloot, 2007). This literature, nonetheless, is characterised by several limitations and shortcomings, the most important of which will be elaborated upon here. First of all, there is the measurement problem of entrepreneurship. Not only is there a lack of internationally comparable information, commonly used proxies usually do not capture the composition of entrepreneurship in terms of the relative prevalence of different types of entrepreneurs. Moreover, the contribution of entrepreneurship to growth is dependent on the type of entrepreneurship as well. The primary difference between entrepreneurs relates to the underlying motivations to become an entrepreneur. For instance, distinguishing between opportunity-driven and necessity-driven entrepreneurs has proven to be relevant, as the former type is over-represented in developed and underrepresented in less-developed regions, while for the latter type it is the other way around (Wennekers, Van Stel, Thurik & Reynolds, 2005). Moreover, from a policy perspective this distinction is also relevant, as opportunity-driven entrepreneurs have a higher probability of entry and also tend to setup more profitable firms than necessity-driven entrepreneurs (Block & Wagner, 2010; Vivarelli, 2004).

Second, as economic growth is expected to foster entrepreneurship as well, the possibility of reverse causality makes it hard to robustly identify the effect of entrepreneurship on growth. Third, findings from most of the studies are limited as they do not recognise that the relationship between entrepreneurship and economic performance is embedded in regional conditions (e.g. institutions, industry structure, or local demand), as well as differences across time, i.e. the time it takes for entrepreneurship to become productive following the start of a firm.

Acknowledging these concerns, the entrepreneurial ecosystems approach builds on the notion that for entrepreneurship to contribute to growth "a set of interdependent actors and factors [need to be] coordinated in such a way that they enable productive entrepreneurship" (Stam, 2015, p. 1765). Entrepreneurship in such an ecosystem is both a result and a mediator of the relationship between institutions (interdependent actors) and aggregate economic outcomes. The extent to which entrepreneurs can become productive, i.e. the type of entrepreneurship that is expected to contribute to growth (Baumol, 1990), is dependent on the quality and interdependence of the various ecosystem elements, their interactions, as well as aggregate economic outcomes. Among policy makers and publicly minded entrepreneurs, the importance of entrepreneurial ecosystems is increasingly recognised (Feld, 2012; Isenberg, 2010). However, until recently, the approach remained undertheorized (Stam, 2015; Stam & Spigel, 2017), suffers from measurement problems (Stam, 2018), and empirical evidence on the effects of these ecosystems is lacking (Bruns, Bosma, Sanders & Schramm, 2017). In addition, the literature on entrepreneurial ecosystems largely overlooks the industry structure as a factor of influence. However, relatedness in the industrial structure of a region affects the potential for knowledge spillovers significantly, which likely has an offset in the form of entrepreneurial action of individuals. Accordingly, in **chapter 5**, we address the following research question:

> *Research question 3: To what extent and how do entrepreneurial ecosystems condition the relationship between entrepreneurship and regional economic growth?*

The aim of this analysis is to investigate whether and how entrepreneurial ecosystems influence the relationship between entrepreneurship and regional economic growth.

1.3 Overview of this dissertation

As a summary, figure 1.3 presents a visualisation containing the main factors and their relationships under investigating in this dissertation. The numbers refer to the chapter where the relationship in question is addressed. The links indicated by *2* refer to the literature review in the second chapter, where we review the studies both on how relatedness affect regional diversification measured by the entry of new industries or products (*2a*) and on the relationship of related variety with economic growth (*2b*). Link *2a* captures the effect of relatedness among present economic activities on the entry of new specialisations, thus changing the industry structure of a region. Link *2b* captures the effect of relatedness among varieties economic activities, which is expected to impact employment growth.

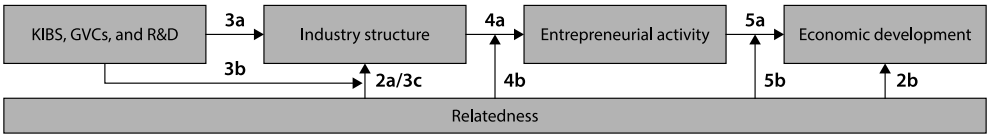


Figure 1.3: *Visualisation of the relationships under investigation*

Links *3* indicate the direct impact of relatedness (3c) and of KIBS, GVC, and R&D (*3a*) on changes in a region's industry structure, while link *3b* represents the moderating effect of KIBS, GVC, and R&D on the relationship between relatedness and changes in a region's industry structure. Links *4* refer to the effects of the industry structure (*4a*) on the prevalence of entrepreneurial activity, specifically measured as the related and unrelated variety of a region's industry structure, as indicated by link *4b*. Finally, links *5* consider the effect of entrepreneurial activity on economic development (*5a*), and how relatedness (*5b*) might affect this relationship.

1.3.1 Analyses

In **chapter 2** we provide a systematic review of the related variety literature, analysing how related variety affects regional and national economic development, as well as the branching literature, which analyses how relatedness density affects the probability that a region/nation becomes specialised in a specific new industry or product. We limit our

review to papers that have been either published or accepted for publication in scientific journals.

In **chapter 3** we investigate whether the presence of KIBS, the participation in GVCs, and investment in R&D increase the ability of a region to develop new industrial specialisations and whether they make regions less reliant on related knowledge and capabilities to do so. For this analysis we rely on data from Bureau van Dijk covering 554 industries at the 4-digit level, measured annually from 2008 until 2014, for 269 NUTS-2 regions, spread over 28 EU countries. We estimate a linear probability model, with a binary variable capturing industry entry in 2014 as the dependent variable, and KIBS, GVC, and R&D as well as their interaction with relatedness density as main explanatory variables.

In **chapter 4** we investigate whether knowledge spillovers stemming from related variety have an effect on both the level as well as the composition of different types of entrepreneurship and whether this effect is constant across institutional contexts. For this analysis we combine data from the Global Entrepreneurship Monitor (GEM), Bureau van Dijk, and Eurostat. The data cover 184 regions measured at the NUTS-2 level and 20 regions measured at the NUTS-1 level, for the years 2007 until 2014. We estimate a cross-sectional regression model with opportunity-driven and necessity-driven entrepreneurship as the dependent variables and related and unrelated variety as main explanatory variables. By distinguishing between different 'Varieties of Capitalism' (Hall & Soskice, 2001), we control for and estimate differences in the prevalence rates of entrepreneurship across institutional contexts.

In **chapter 5** we investigate whether and how entrepreneurial ecosystems affect the relationship between entrepreneurship and regional economic growth. For this analysis we use the same dataset as chapter 4. We start by estimating a cross-sectional and a multilevel neo-classical growth model to establish the association of entrepreneurship with growth uniformly across all regions in the sample. To further examine whether this relationship might be differentiated across regions in the sample, we then estimate a latent class model that captures whether and to what extent this is the case. As an exploratory analysis, we then compare the latent groups of regions on a number of regional conditions closely related to the entrepreneurial ecosystem elements.

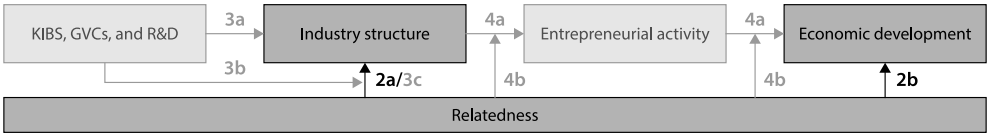
Finally, in **chapter 6** we conclude this dissertation by summarising the main findings of chapters 2-5, highlighting the implications for policymaking, discussing the limitations of this research, and indicating some directions for a future research agenda.

	Type of the analysis	Level of aggregation	Link in fig. 1.3
1	Introduction		
2	Systematic literature review of studies associating (un)related variety with economic development.	Country & region	2
3	Linear probability model, in which the direct and interaction effect of relatedness density with KIBS, GVC, and R&D on the entry probability of a new industry is analysed. *Dependent variable: Entry probability* *Explanatory variables: Density, KIBS, GVC, and R&D* *Research question: Can – and to what extent do – bridging and/or external linkages support the entry of new and unrelated activities?*	4-digit industries within NUTS-2 regions	3
4	Cross-sectional regression analysis, in which the effect of related variety on entrepreneurship is investigated. *Dependent variable: Entrepreneurship* *Explanatory variables: Related and unrelated variety* *Research question: To what extent and how are different types of entrepreneurship affected by related and unrelated variety?*	NUTS-1/2 regions	4
5	Multilevel regression and latent class analyses are estimated to reveal different clusters and corresponding associations of entrepreneurship with regional growth. *Dependent variable: GDP p/c growth* *Explanatory variables: Entrepreneurship, related variety, and unrelated variety* *Research question: To what extent and how do entrepreneurial ecosystems condition the relationship between entrepreneurship and regional economic growth?*	NUTS-1/2 regions	5
6	Conclusion		

Table 1.1: *Types of analyses used in each chapter and their relation to figure 1.3*

Chapter 2

Related variety and industrial branching: A literature review[1]



2.1 Introduction

In recent research in economic geography, an empirical body of literature has emerged on the role of related variety in regional development. The concept of related variety was put forward by Frenken et al. (2007) as to further specify the common hypothesis that regions may benefit from producing a variety of products and services, as more variety implies more potential for inter-industry knowledge spillovers. Frenken et al. (2007) emphasised that: "one expects knowledge spillovers within the region to occur primarily

[1]This chapter is based on Content en Frenken (2016), Related variety and economic development: A literature review, European Planning Studies.

among related sectors, and only to a limited extent among unrelated sectors" (p. 688). That is, they hypothesised that inter-industry spillovers occur mainly between sectors that draw on similar knowledge: knowledge originating from one sector is most relevant to, and can most effectively be absorbed by, another sector that is related in the sense that firms draw on similar knowledge (about technology, markets, etc.).

The concept of related variety was introduced in an attempt to resolve an earlier empirical question put forward by Glaeser et al. (1992) whether regions benefit most from being specialised or being diversified. This "controversy" is commonly referred to as "MAR versus Jacobs", referring to the theories of Marshall, Arrow, and Romer suggesting spillovers to take place primarily within a single industry versus the theory of Jacobs (1969, p. 59) who argued that "the greater the sheer numbers and varieties of divisions of labour already achieved in an economy, the greater the economy's inherent capacity for adding still more kinds of goods and services". The theories of MAR view innovation mainly as incremental where firms learn from knowledge and innovation from same-industry firms (otherwise known as 'localisation economies'), while Jacobs views innovation essentially as a recombinant process that necessarily builds on a pre-existing variety of knowledge and artefacts that are being combined in new ways leading to new products and services, viz. new employment.

As reviewed by de Groot et al. (2016), the many empirical studies on MAR versus Jacobs, which followed on the seminal study by Glaeser et al. (1992), have provided very mixed results (Figure 2.1).[2] There are almost as many studies that find evidence for the MAR hypothesis, as there are studies that disprove it. And, while a large share of studies finds evidence confirming Jacobs externalities, still a substantial share of studies finds no effect of variety on regional growth, or even opposite effects. It also seems evident from the many studies yielding insignificant results, that the theoretical notions of specialisation and variety seem too simplistic to capture the varied effects of an economy's composition on its further development.

Frenken et al. (2007) agreed with Jacobs that innovation is essentially a recombinant process (what Schumpeter famously called "Neue Kombinationen"), but qualified the notion of recombination arguing that some pieces of knowledge and artefacts are much easier to recombine than other pieces of knowledge and artefacts. Hence, variety is especially supportive for innovation and regional development when variety is related, be it in a technological sense or in a market sense. The reasoning here is similar to that of diver-

[2] Note that most studies also take into account a competition variable, following Porter's (1990) work on the advantages of competition (in clusters).

sified firms, where it has been argued that firms undergoing related diversification outperform firms undergoing unrelated diversification, because only the former profit from economies of scope.[3]

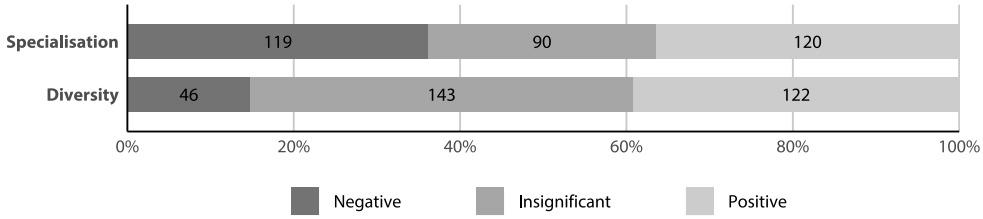


Figure 2.1: *Overview of outcomes of empirical studies on the effect of MAR (specialisation) vs. Jacobs (diversity) externalities on regional growth. Note that competition is often taken as a third explanatory variable. Taken from: de Groot et al. (2016).*

Frenken et al. (2007) specifically hypothesised that related variety would spur employment growth, as new combinations lead to new products or services and, hereby, to new jobs. Localisation economies stemming from the spatial concentration of firms in the exact same industry, instead, would enhance process innovation as specialised knowledge is used to optimise production processes in existing value chains. Such innovations spur labour productivity, and do not necessarily lead to more jobs. The related variety thesis is thus consistent with product life-cycle theory, which poses that young industries with high rates of product innovation create jobs in diverse urban areas, while mature industries with high rates of process innovation spur productivity in specialised peripheral areas (Capasso, Cefis & Frenken, 2016; Duranton & Puga, 2001).

The concept of related variety is also consonant with the concept of product space introduced by Hidalgo et al. (2007). They argued that countries develop by diversifying their export portfolio over time. They showed that countries typically do so by 'branching-out', that is, by entering export products that are closely related to the products they already export. The reasoning underlying this phenomenon holds that once a country has developed the capabilities to specialise in exporting particular products, it can easily diversify in related products that require very similar capabilities to produce them. By calculating, for each possible new product, the 'proximity' of related products already present

[3] Analogously, some authors prefer to speak of geographies of scope (Florida, Mellander & Stolarick, 2012) instead of related variety.

in a country's export portfolio, the authors could show that the higher the average proximity of related products vis-à-vis a new potential product (which they called 'density'), the higher the chance that a country will diversify into this new product. This idea is in line with related variety, because the more products a country already exports related to a product that it does not yet export, the more likely it will start exporting that product in the future. The difference between the related variety and the product space concepts is that the former is used to explain aggregate regional or national growth, while the latter is used to explain diversification events into specific new products or industries at the regional or national level.

The related variety and product space hypotheses have motivated a large number of empirical studies on the effect of related variety in the sectoral composition on national and regional economic development as indicated by employment, income, or productivity, or on the effects of proximity on diversification measured as a country's or region's entry into a new industry. We provide a systematic review of empirical studies at the regional and national level in the next section. That means that we focus on the related variety literature following Frenken et al. (2007) analysing how related variety affects regional/national growth as well as the branching literature following Hidalgo et al. (2007) analysing how related variety vis-à-vis a specific industry affects the probability that a region/nation becomes specialised in that specific industry[4]. We limit our review to papers that have been either published or accepted for publication in scientific journals[5]. Hence, we omit current working papers on the topic.

2.2 Related-variety studies

Below, we review 16 studies we found that analysed the effect of related variety on employment growth, or another economic performance indicator, at either national or regional levels. We summarise the set-up and results of each study in table 2.1.

[4] Given the macro-scope of the review with a focus on regional and national growth, we do not go into micro-level studies investigating the effect of regional related variety on firm performance. This is, to a large extent, already covered by a recent review by Frenken, Cefis and Stam (2015) on industrial dynamics in clusters. From this review, it became apparent that firms profit most if co-located with firms in other, but related, industries rather than being co-located with firms operating in the same industry. In the latter environments, the benefits from learning from firms in the same industry may well be offset by increased competition as well as knowledge spillovers to direct competitors, especially for the more advanced firms.

[5] We selected papers to review by searching for papers that i. cited Frenken et al. (2007) in case of the related variety studies, or ii. Hidalgo et al. (2007) in case of the branching studies, or iii. contained the keyword 'related variety', or iv. Contained the keywords 'revealed comparative advantage' and 'proximity'.

The first study to associate variety with regional economic growth is Frenken et al. (2007), who looked at employment growth in a study on 40 Dutch regions. They argued that on the one hand related variety is expected to increase employment growth and on the other hand unrelated variety is expected to decrease unemployment growth. Unrelated variety in this respect can be described as a measure of risk-spreading that cushions the effects of external demand shocks in a certain sector. This is explained by the fact that a higher degree of unrelated variety in a region will cause that region overall to be affected just moderately in the case of a sector specific shock in demand. Whereas the specialisation in one or few sectors will result in the opposite scenario, as the region is exposed to the probability of a severe slowdown. Empirically, using the Standard Industrial Classification scheme, Frenken et al. (2007) measured related variety as the average entropy across employment in five-digit industries within each two-digit class, while unrelated variety is the entropy in employment across 2-digit classes. They showed that related variety, as hypothesised, enhances employment growth. Their results also confirm the portfolio effect, as they found that unrelated variety is negatively related to unemployment growth.

Using OECD export data on the national level, Saviotti and Frenken (2008) later found related export variety to stimulate GDP growth per capita and labour productivity, while unrelated export variety only promotes growth with a considerable time lag. They explain this finding by the type of innovation that benefits from variety. Related variety means that knowledge is easily recombined in new products causing direct growth effects. Unrelated variety is harder to recombine, but if successful, can lead to complete new industries sustaining long-term growth. This study, however, did not include control variables and calls for more refined follow-up studies.

Boschma and Iammarino (2009) used regional trade data of Italy to study the effects of variety in regional exports and found that variety per se was not found to explain regional growth. However, related export variety was found to have a positive and significant association with regional growth and employment, in contrast to unrelated export variety. The authors also looked at the similarity between the importing and exporting sectors and found some evidence that it will support regional employment. This finding, however, is not robust in the sense that this effect was not found for regional growth in labour productivity or value added growth.

Other studies looked at the effect of related variety on growth indicators other than employment growth. Boschma, Minondo and Navarro (2012) showed that Spanish regions with higher levels of related variety are likely to have higher levels of value-added

growth. They did so using two additional measures of related variety in order to overcome some limitation of the entropy measure that is based on the standard industrial classification (SIC), which defines relatedness 'ex ante'. One of the alternative 'ex post' methods they employ is based on Porter's (2003) study on clusters where relatedness is measured on the basis of the spatial correlation of employment between sectors. The other measure is based on the proximity index of Hidalgo et al. (2007), based on the co-occurrence of products in production portfolios. Boschma et al. (2012) found that related variety is positively related with regional growth using any of the three measures, and that the effect is stronger for the cluster (Porter) and proximity (Hidalgo) indicators relative to the entropy (Frenken) measure.

Falcıoğlu (2011) looked at productivity growth in Turkish regions, and found that related variety, rather than variety as a whole, of regional economic activity positively impacts a region's productivity. The author defined productivity in two ways, as output divided by labour and value added dived by labour. Instead of looking at the industrial structure, Quatraro (2010) also analysed regional productivity growth, and specifically how knowledge affects regional growth in Italy. The results suggest that, not only the regional knowledge stock affects regional productivity growth rates but also the composition and the variety of the knowledge stock matter. Related knowledge variety seems to positively affect regional productivity, while unrelated knowledge variety was found to be insignificant.

Author(s)	Unit	Coverage	Period	Data source	Main iV(s)	Digits	dV(s)	RV	UV
Frenken, Van Oort and Verburg (2007)	NUTS3	Netherlands	1996-2002	CBS	Related variety Unrelated variety	RV = 5 in each 2 UV = 2	Employment growth Productivity growth Unemployment growth	+ - o	o o -
Saviotti and Frenken (2008)	National	OECD	1964-2003	OECD trade data	Unrelated export variety Semi related export variety Related export variety	UV = 1 SV = 2 in each 1 RV = 3 in each 2	GDP per cap Labour productivity	+ +	- -
Boschma and Iammarino (2009)	NUTS3	Italy	1995-2003	ISTAT	Export variety Related export variety Unrelated export variety Import variety Related trade variety	Variety = 3 RV = 3 in each 2 UV = 1	Employment growth Value-added growth Labour-productivity growth	M + M	o + o
Bishop and Gripaios (2010)	Sub-national	Great Britain	1995-2002	NOMIS	Related variety Unrelated variety	RV = 4 in each 2 UV= 2	Employment growth at 2-digit industry-level	M	M
Quatraro (2010)	NUTS2	Italy	1981-2002	ISTAT & EPO	Total variety Unrelated variety Related variety	RV = 3 in each 1 UV = 1 TV = 3	Productivity growth	M	o
Bosma, Stam and Schutjens (2011)	NUTS3	Netherlands	1990-2002	CBS & Chambers of Commerce	Related variety	RV = 5 in each 2	Productivity growth	M	
Falcıoğlu (2011)	NUTS2	Turkey	1980-2000	Turkish statistical institute	Related variety Variety	RV = 3 in each 2 Variety = 3	Productivity growth	+	

(This table continues on the next page)

Author(s)	Unit	Coverage	Period	Data source	Main iV(s)	Digits	dV(s)	RV	UV
Boschma, Minondo and Navarro (2012)	NUTS3	Spain	1995-2007	INE, Ivie, and Agencia Tributaria	Related variety Unrelated variety Porter relatedness measure Hidalgo relatedness measure	RV = 6 in each 2 UV = 1	Value-added growth	+	o
Hartog, Boschma and Sotarauta (2012)	NUTS4	Finland	1993-2006	Statistics Finland	Related variety RV-HiTech RV-LowTech Unrelated variety	Variety = 5 RV = 5 in each 2 UV = 2	Employment growth	M	o
Mameli, Iammarino and Boschma (2012)	ISTAT	Italy	1991-2001	ISTAT	Variety Related variety Unrelated variety	Variety = 3 RV = 3 in each 2 UV = 1	Employment growth	+	+
Cortinovis and Van Oort (2015)	NUTS2		2004-2012	ORBIS, Bureau van dijk	Unrelated variety Related variety Specialisation Technological regime	RV = 4 in each 2 UV = 1	Employment growth Productivity growth Unemployment growth	M M M	o M M
F. Van Oort, de Geus and Dogaru (2015)	NUTS2	Europe	2000-2010	Amadeus	Related variety Unrelated variety	RV = 4 in each 1 UV = 2	Employment growth Productivity growth Unemployment growth	+ o o	M o o
Caragliu, de Dominicis and de Groot (2016)	NUTS2	Europe	1990-2007	Cambridge Econometrics	Related variety Unrelated variety	RV = 2 in each 1 UV = 1	Employment growth at industry-level	o	+

Table 2.1: *Overview of the related-variety studies. iV stands for independent variable; dV stands for dependent variable. The columns RV and UV show the significance of related and unrelated variety on the dependent variables shown in the column dV(s). + and – indicate significant positive or negative effects, respectively, whereas o and M indicate no significant and mixed results, respectively.*

Yet other studies analysed whether the effect of related variety differs across industries. Bosma et al. (2011) distinguished between total factor productivity growth in manufacturing and in services for 40 Dutch regions. They found that related variety had a positive effect on productivity growth in manufacturing, but a slightly negative effect on productivity growth in services. Mameli et al. (2012) examined the relationship between related variety and regional employment growth in local labour systems of Italy. Without making further distinctions both related and unrelated variety in general have a positive effect on regional employment growth. Distinguishing between manufacturing and services, related variety positively affected regional employment in services, while unrelated variety positively affects regional employment growth in manufacturing. Hartog et al. (2012) investigated the impact of related variety in Finland, they did not found evidence that related variety in itself influences employment growth. Rather when decomposed into a low/medium-tech sectors and high tech sectors, related variety between high-tech sectors seems to positively impact regional employment growth. The distinction between sectors here is based on the R&D intensity and the share of tertiary educated persons employed.

Bishop and Gripaios (2010) looked at the effect of related variety on regional employment growth per industry in Great Britain. They argue that distinguishing between the manufacturing and services industry might be an oversimplification as these sectors themselves are also heterogeneous and therefore the mechanisms and extent to which spillovers occur differ between sectors. Motivated by this argument the authors make use of a disaggregated approach, and look at employment growth in each 2-digit sector as dependent variables. Their assumed heterogeneity between sectors is reflected in the results, as related variety has a significant positive impact on employment growth only in 3 out of the 23 sectors (telecom, computing and other business activities), and – surprisingly – unrelated variety has a significant positive impact in 8 out of the 23 sectors.

More recently, Cortinovis and Van Oort (2015) conducted their research using a pan-European dataset. Following the original set-up of the study by Frenken et al. (2007), they hypothesise that related variety is positively related to employment growth due to knowledge spillovers across sectors, unrelated variety is negatively related to unemployment growth due to portfolio effects associated with a diversified economy and as a result dampens the effects of sector-specific shocks. Specialisation is positively related to productivity due to cost-reduction and efficiency gains achieved through localisation externalities. They fail to find evidence supporting these hypotheses. However, when introducing technological regimes, they found related variety to positively affect employ-

ment growth and productivity in regions characterised by high technology. F. Van Oort et al. (2015) also looked at the pan-European level and made a distinction between smaller and larger regions' urban size in order to account for differences in agglomerative forces. They found that related variety has a positive effect on employment growth, which seems to be stronger for small and medium urban regions compared to large urban regions. No significant effect was found for unrelated variety. In a most recent pan-European study on employment growth at the sectoral level, Caragliu et al. (2016) did not find evidence for the hypothesis that related variety enhanced employment growth. Instead, they found a positive and significant effect of unrelated variety on employment growth. This study is rich in that it looks at 259 NUTS2 regions in the EU and for an extensive period (1990-2007). However, given data limitations, the authors defined unrelated variety as the entropy at the one-digit industry level and related variety as the weighted sum of the entropy at the two-digit level, within each one-digit class. Hence, their results are not fully comparable with studies looking at a more fine-grained industrial level in line with Frenken et al. (2007). Furthermore, their dependent variable was employment growth within a single sector, as only Bishop and Gripaios (2010) did before, rather than overall employment growth in a region as most studies did before.

2.3 Branching studies

The concept of related variety as introduced by Frenken et al. (2007) associated related variety in a regional economy with total employment growth of that regional economy. A complementary perspective is to analyse whether related variety vis-à-vis a specific industry enhances the growth of that particular industry, because that industry benefits from spillovers from related industries. This research design was first introduced by Hidalgo et al. (2007) and later followed by a number of studies both at national and regional levels. We summarise the set-up and results of each study in table 2.2.

Hidalgo et al. (2007) introduced the concept of product space, where each product has a certain proximity to each other product, indicting its relatedness. They measure relatedness of products using a proximity indicator based on how often two products co-occur in countries' export portfolios. The idea here holds that if many countries have a comparative advantage both in product A and in product B, apparently A and B are somehow related, sometimes referred to as "revealed relatedness" (Neffke & Henning, 2008). Hidalgo et al. (2007) argue that if a country has a comparative advantage in producing a certain

product, chances are high it will also obtain a comparative advantage[6] in products that are related to it in terms of, for instance what kind of skills, institutions, infrastructure, physical factors, or technology is needed. Their study shows that countries indeed generally become specialised in new products which are related to products it already is producing.[7] They also show that some countries are located in the centre of this product space exporting products that are related to many other products, while other countries are located more to the periphery with fewer connections to related products. Being located more to the periphery thus means having to "travel" a larger distance to the centre, which in turn might help explain that poorer countries are struggling to develop competitive products and therefore might fail to converge as they are located more to periphery of the product space with less connections to related products.[8]

Neffke et al. (2011) ask the same question as the original study by Hidalgo et al. (2007), but at the regional level. Indeed, as for countries, regions are most likely to branch-out into industries that are technologically related to the pre-existing industries in the region. Using data on products being co-produced at the same plants, they were able to measure in detail the relatedness structure between products based on co-occurrences. They then show for 70 Swedish regions during the period 1969-2002 that industries that were technologically related to pre-existing industries in a region had a higher probability to enter the region, as compared to unrelated industries. Furthermore, they show that unrelated industries had a higher probability to exit the region.

[6] A country has a comparative advantage in a product, if the product's share in a country export portfolio exceeds the product's share in total trade worldwide.

[7] A more extensive study was reported in the working paper Hausmann and Klinger (2007).

[8] Hidalgo and Hausmann (2009) later developed a method that captures an economy's complexity and show that higher levels of complexity of an economy are associated with higher levels of income. Their method is based on two dimensions, the first is the ubiquity of the products exported (by how many countries is a product exported?) and the second is the diversification of an economy (how many products does a country export?). They show there is a negative relationship between these two dimensions, i.e. diversified countries tend to export less ubiquitous products. For further refinements, see Tacchella, Cristelli, Caldarelli, Gabrielli and Pietronero (2012) and Cristelli, Tacchella and Pietronero (2015).

Author(s)	Unit	Coverage	Period	Data source	Digits	Main iv(s)	dv(s)
Hidalgo, Klinger, Barabási and Hausmann (2007)	National	132 countries	1990-1995	World Trade Flows	SITC-4	Density	Entry
Neffke, Henning and Boschma (2011)	A-region	Sweden	1969-2002	Statistics Sweden	SNI69-6	Closeness	Membership Entry Exit
Boschma, Minondo and Navarro (2013)	NUTS3	Spain	1988-2008	NBER World Trade & Agencia Tributaria	SITC-4	Density at country level Density at province level	Entry
Bahar, Hausmann and Hidalgo (2014)	National	123 countries	1962-2008	World Trade Flows & UN COMTRADE & WDI & UNCTAD	SITC-4	Density RCA neighbor	Entry
Boschma and Capone (2015) Boschma & Capone (2015)	National	23 countries	1970-2010	NBER UN & BACI	4-digits	Density Institution indicator	Entry
Essletzbichler (2015)	Metropolitan areas	US	1975-1997	Bureau of Economic Analysis	SIC-4	Closeness	Membership Entry Exit
Boschma and Capone (2016)	National	EU27 ENP16	1995-2000	BACI	4-digits	Density Import density	Entry
Boschma, Martín and Minondo (2016)	State	US	2000-2012	US Census Bureau Comtrade	HS-4	Density RCA neighbour	RCA Growth

Table 2.2: *Overview of branching studies. iV stands for independent variable; dV stands for dependent variable. All studies showed a significant effect of density or closeness on the probability of entry into a new product or industry, or a rise of the RCA.*

Similarly, Boschma et al. (2013) analysed the emergence of new industries in 50 Spanish regions in the period 1988–2008. A novel element in this study is the inclusion of a measure indicating how related a local industry is vis-à-vis the national production profile. In line with Neffke et al. (2011), this study also provides evidence that regions tend to diversify into new industries that use similar capabilities as existing industries in these regions. They show that proximity to the regional industrial structure plays a much larger role in the emergence of new industries in regions than does proximity to the national industrial structure. This finding suggests that capabilities at the regional level enable the development of new industries. This result was further confirmed by a more recent study of Essletzbichler (2015) on 360 U.S. metropolitan areas.

Another question holds whether certain countries or regions are better capable of diversifying into unrelated industries compared to other countries or regions. Boschma and Capone (2015) took up this question at the national level, and hypothesised that certain types of institutions enable unrelated diversification more than other types of institutions. In particular, following the distinction made by Hall and Soskice (2001), they found that liberal-market institutions (e.g., United States) are more flexible than coordinated-market institutions (e.g., Germany) in reallocating labour and capital from one sector to another unrelated sector. This can be explained by the actors in coordinated-market economies being primarily oriented towards collaboration and stability. Hence, they will tend to diversify into related industries as to maximally leverage existing knowledge, institutional arrangements and collaborative relationships. In liberal-market economies, this is less so, as both firms, suppliers, employees, and other stakeholders are relatively more self-interested and driven by opportunities rather than on preserving existing arrangements and relationships per se.

A final topic that has been addressed building on the original study by Hidalgo et al. (2007) is the question of spatial spillovers. If a region or country lacks a certain local capability rendering it difficult to diversify into related products, it may still be able to do so if it can leverage the spatial proximity to such capabilities through spillovers. Bahar et al. (2014) address this question and show that a country is more likely to start exporting a product when a neighbouring country is already exporting the product. In addition, they find that having a neighbouring country with a strong comparative advantage in a certain product, has positive predictive power on future growth in the country's own comparative advantage of that same product. Their results furthermore indicated that, regardless of size, income level, cultural and institutional dimensions, and factor endow-

ments, the variety of products exported by countries is remarkably similar to their neighbours.

Boschma, Eriksson and Lindgren (2014) extended this line of research by analysing the effect of neighbouring regions and the probability a region develops a new industry for US states. They show that a region has a higher probability to develop a certain industry if the neighbouring region is specialised in it. This might be explained by knowledge spillovers that are more easily absorbed at small distances, that is, the strong distance-decay effect of knowledge spillovers over spatial distance. In addition they find that neighbouring states show a high similarity in the variety of exported products, suggesting a convergence process. A more recent study by Boschma and Capone (2016) looked more specifically at import profiles at the country level. Here, they found that a country tends to enter into a new product not only when its own product portfolio is close to this new product ('density') but also when its import portfolio is close to this new product ('import density').

2.4 Future research

The review of related variety research made clear that – although the evidence base is still rather small with 21 studies – most studies find support for the initial hypothesis by Frenken et al. (2007) that related variety supports some form of regional growth. Those who looked at inter-industry differences found that the effects of related variety on growth may be specific to certain industries only, especially manufacturing and knowledge-intensive ones (Bishop & Gripaios, 2010; Bosma et al., 2011; Cortinovis & Van Oort, 2015; Hartog et al., 2012). Concerning the studies looking how countries or regions develop new industries following Hidalgo et al. (2007), it was also found that if a region or country already hosts industries that are related to a specific industry, it is much more likely to become specialised in that industry.

A number of follow-up research questions come to mind that can be taken up in future research to be analysed:

1. Though evidence is generally in support of the related variety thesis, the possibility of publication bias is not inconceivable given a more general tendency to under-report negative results, especially in the emerging stage of a new topic area. Future research would benefit from more standardised research designs as well as more comprehensive reporting of possible model specifications. In particular, various dependent variables indicating economic development are being used includ-

ing employment growth, productivity growth and GDP growth, and sometimes measured in different ways. Future research could follow the original related variety theory arguing that related variety spurs product innovation and, hereby, employment growth. Hence, ideally, any empirical analysis includes an analysis of the effect of related variety on employment growth, possibly next to other dependent variables. Regarding the measurement of related variety with entropy measures or density as the average proximity of products to a new product, authors do use standardised measures. However, the empirical data on which the measures are applied can be different, for example, different digit levels or a different population of products. Again, in so far as possible, standardisation is needed.

2. Findings that suggest that related-variety effects on growth are confined to certain sectors (Bishop & Gripaios, 2010; Cortinovis & Van Oort, 2015; Hartog et al., 2012; Mameli et al., 2012) deserve further theoretical and empirical elaboration. A common thread among these studies point to the role of knowledge intensity. Indeed, one theoretical line of argument may build on the idea that more knowledge spills over across related industries, when these industries are knowledge-intensive in the first place.

3. Methodologically, the key question at present holds: what is the best method and data source to capture related variety? Frenken et al. (2007) relied entirely on the pre-given hierarchical classification as provided by the Standard Industrial Classification scheme. This has the advantage of being amenable to entropy decomposition into related and unrelated variety, yet has the disadvantage that relatedness is defined ex ante from a hierarchical classification scheme that was never intended to capture technological relatedness viz. spillovers. Hidalgo et al. (2007) derive relatedness from the co-occurrences of products in countries' portfolios. This method derives relatedness ex post from data rather than ex ante from a classification scheme, yet only measures relatedness indirectly and remains agnostic about the exact source of relatedness causing industries to co-locate in countries. As an alternative to Frenken et al. and Hidalgo et al., the work by Neffke and Henning (2013) seems promising. They measure relatedness by the number of people changing jobs between two industries, thus capturing directly 'skill-relatedness'. Alternatively you could explore, at least for the industries that patent large parts of their knowledge base, the relatedness of patents by looking at patent classes, citations, and inventor mobility. The best results are probably obtained by a smart triangulation of these approaches.

4. Theoretically, there are many reasons to expect that regions or countries generate product innovation from related variety (Frenken et al., 2007) and diversify into related industries (Hidalgo et al., 2007). However, this leaves unexplained why, and under what conditions, regions/countries with unrelated variety can also yield product innovation (especially radical ones), and also leaves unexplained why some regions/countries manage to diversify into unrelated industries. To break with path-dependence and create new growth paths through true new recombinations, regions will have to rely more on knowledge and resources residing in other regions. Hence, (policies attracting) multinationals, immigrant entrepreneurs and mobile scientists may well underlie new path creation. Some evidence on this thesis is already available but more research would be needed to come to a more comprehensive understanding (Binz, Truffer & Coenen, 2014; Neffke et al., 2018).

5. Another question concerns the geographical sources of spillovers through related variety. Rather than solely looking at a region's internal structure, the relatedness vis-à-vis other regions with which a regions intensively interacts, may also matter. That is, most studies did not pay attention to knowledge spillovers originating from extra-regional activity. These type of spillovers can occur in numerous ways, for instance the trading of goods and services, foreign direct investment, and global value chains are relations that may cause otherwise tacit knowledge to spillover between regions. The extent to which a region can benefit from foreign knowledge inflows trough these types of relationships depends also on the region's own knowledge and know how, i.e. its absorptive capacity. In addition to that, the inflow of knowledge needs to exhibit complementarities to the existing knowledge. It should be related, however not similar. More research along these lines would highlight the role of trade and global value chains in particular, in generating spillovers between related industries.

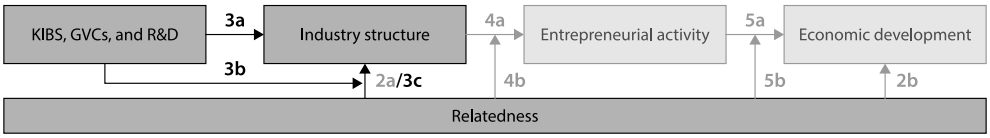
6. A natural extension of the current research – both theoretically and empirically – is to look at relatedness in other dimensions than those related to technological knowledge. For example, Tanner (2014) developed a market relatedness indicator and has showed how this indicator predicts quite well regions' technological development in fuel cell technology. A similar argument can be made regarding institutional relatedness. Regions are more likely to diversify into industries that are institutionally related to the industries already present, not only as actors can build on existing institutional arrangements and practices, but also as actors are likely to face less resistance moving into institutionally relate industries than into institutionally unrelated industries.

7. Since most studies focus on the effect of related variety on either employment growth or the emergence of a new export specialisation as dependent variable, the mechanism how related variety leads to growth and export specialisations remains rather implicit. What can be done in future studies is to analyse directly the impact of related variety on entrepreneurship, knowledge, and innovation, which in turn are expected to lead to employment and exports. Quite some studies already analysed the effects of related and unrelated variety on patents as dependent variable (Castaldi et al., 2015; Kogler, Rigby & Tucker, 2013; Rigby, 2015; Tanner, 2016; Tavassoli & Carbonara, 2014), but fewer of such studies exist looking at scientific publications (Boschma, Heimeriks & Balland, 2014; Heimeriks & Balland, 2016) or new firm formation (Colombelli, 2016; Colombelli & Quatraro, 2013; Guo et al., 2016) as dependent variables.

8. Finally, related-variety studies hitherto focuses on how related variety affects economic development, while research on the geography of knowledge recombination processes at the micro-level remains rather unconnected to the related-variety literature. A challenge for future research will be to combine the macro-level work reviewed here with the emerging micro-level work on related variety, both theoretical (Davids & Frenken, 2015; Strambach & Klement, 2012), and empirical (Aarstad, Kvitastein & Jakobsen, 2016; Antonietti & Cainelli, 2011), as to come to a better multi-scalar understanding how regional conditions and constraints as well as various forms of proximity affect recombination processes of knowledge among related and unrelated domains.

Chapter 3

Regional diversification and industry relatedness: On the importance of KIBS, GVCs & R&D



3.1 Introduction

In the long run, prosperity of economies is dependent on the adoption and development of new activities and associated jobs offered by more efficient firms that push out established firms and industries. This continuous process, described by Schumpeter (1942) as creative destruction, has inspired many economists and geographers until today to study the mechanisms supporting it. Since the seminal article by Hidalgo et al. (2007), we

have witnessed a renewed interest of studies looking at the emergence of new regional specialisations. A persistent finding of this group of studies is that the process of industrial diversification in countries and regions is dependent on pre-existing activities in related industries (Boschma, 2017; Content & Frenken, 2016). As such, new industrial specialisations emerge as a branching process, in which new economic activities branch-out of established activities (Boschma & Frenken, 2011; Frenken & Boschma, 2007). Underlying this notion of industrial branching, is the assumption that once an economy has developed the capabilities or acquired the knowledge to specialise in a particular industry, it becomes easier to diversify into industries related to it as these would require similar capabilities and knowledge. From an evolutionary perspective, we can then understand economic development as a path-dependent process in which the presence or lack of related industries preconditions an economies' future diversification patterns (Isaksen, 2015; Martin & Sunley, 2006).

In light of for instance, advancements of technology or changes in global demand, certain capabilities or knowledge might become obsolete or irrelevant. It is therefore of great interest to understand how regional economies can structurally renew their industrial landscapes and diversify into unrelated activities, as related diversification is unable to guarantee economies sustainable growth and prosperity. This gives rise to the question of whether certain conditions determine an economy's capability to diversify unrelated with respect to their current industrial profile, i.e. how might economies escape the forces of path-dependence? Foregoing studies have shown that innovative capacity, liberal-market institutions, bridging social capital, high-income levels, extra-regional linkages, and entrepreneurs seem to be factors that enable regions to break with path-dependence and diversify into novel territory (Boschma & Capone, 2015; Cortinovis et al., 2017; Neffke et al., 2018; Petralia et al., 2017; Xiao et al., 2018). However, more knowledge is still needed to sufficiently understand the conditions underlying unrelated diversification.

In this study, we propose that the presence of Knowledge-Intensive Business Services (KIBS), the participation in Global-Value-Chains (GVC), and investment in Research & Development (R&D) might provide regions the capabilities to diversify into less (more) related (unrelated) directions by giving it access to extra-regional knowledge linkages (Trippl, Grillitsch & Isaksen, 2017). As KIBS supply intermediate services to a variety of firms in many different – and unrelated – industry contexts, KIBS can sometimes act as a bridging platform between these firms and facilitate knowledge spillovers (Czarnitzki & Spielkamp, 2003). Presence of KIBS might therefore not only foster a region's ability

to develop industrial specialisations in general, but might render the demand for having related specialisations less important. Second, as regions increasingly focus on specific tasks involved in GVCs rather than on specific products (Baldwin, 2016; Baldwin & Robert-Nicoud, 2014), the involvement in GVCs may enhance a region's ability to provide products to a variety of different sectors. Once a region becomes specialised in a particular task performed within a GVC, it can potentially supply different value chains as well (Gereffi et al., 2001; Humphrey & Schmitz, 2002a), increasing the potential for unrelated knowledge spillovers. Third, the ability of regions to develop economically is related to the level of investment in R&D, which is mediated by the ability to develop and exploit innovations to increase or sustain competitive industries. As firms and research institutes doing R&D frequently enter in collaborative relationship with distant research institutes or firms, the absorptive capacity of an economy, in this case referring to the capacity to attract, absorb, and transform external knowledge into development, is related to the investment in R&D as well (Cortinovis & van Oort, 2018). The knowledge spillovers stemming from global connected firms will benefit local firms as well.

This paper furthers our knowledge in determining additional factors that enable regions to develop new industrial specialisations and contributes to our understanding of how regional economies can develop new growth paths and thereby increase their long-term resilience and secure sustainable growth. We construct a new dataset including EU regions for the post-crisis period 2008-2014 that combines detailed information of regional sectoral employment at the 4-digit level with information on regional levels of KIBS, GVCs, and R&D. With this dataset we can establish in what industries region are specialised during this period for each year. By looking at the timing of co-occurrences of industry specialisations we can measure inter-industry relatedness in terms of the probability of regions to be specialised in a particular set of industries at the same time. We then estimate both the direct effect and relatedness-moderating effect of KIBS, GVCs, and R&D on a region's ability to specialise in new industries. Results suggest that under some conditions KIBS, GVCs, and R&D support the emergence of new specialisations as well as moderate the effects of industry relatedness. The latter result suggests that regions hosting many KIBS, GVCs, and R&D indeed allows for diversification into more unrelated directions relative to regions with few KIBS, GVCs, and R&D.

Furthermore, we find that splitting our sample into four broad industry groups (industry and manufacturing, distribution, business services, and personal services) conditions our general findings. We notice that effect of KIBS is strongest in the industry group, as it directly impacts the probability of regions developing a new specialisation and negatively

moderates the effect of relatedness. GVCs only substitute the relatedness effect for the industry groups distribution, business services, whereas for R&D we find a similar pattern as we find for KIBS. Moreover, once the sample is split up into groups of regions with either, low, medium, or high levels of industry density, the effects seem to be conditional on the level of industry density as well.

In the remainder of this paper we will review the literature relevant for this study in section 2, present the data and methodology used in section 3, and discuss the results from this in section 4. Finally, section 5 will conclude with some final remarks and possible directions for future research.

3.2 Literature review

In economics, agglomerations have long been the topic of discussion (Arrow, 1962b; Marshall, 1920; Romer, 1990). Concentrations of economic activity enables for labour market pooling, the use of common suppliers, and knowledge spillovers. Firms benefit from these localisation externalities when they locate in close geographical proximity to agglomerations of firms operating in the same sector. In contrast, firms may also benefit from Jacobs externalities by being located close to agglomerations with a diversified variety of economic activity (Jacobs, 1969), as such an environment would promote intersectoral knowledge spillovers. The literature, however, is inconclusive in terms of which type of these agglomeration externalities is most accurate, and expects that depending on the circumstances in which they are tested, both can be right (Beaudry & Schiffauerova, 2009; de Groot et al., 2016). More recently, scholars have also emphasised that for knowledge spillovers to be effective geographic proximity is not the only prerequisite, other forms like cognitive proximity should be taken into the equation as well (Boschma, 2005; Nooteboom, 2000). When the knowledge or capabilities possessed by local firms is cognitively proximate or related, this would enable them to effectively communicate and understand each other, increasing the likelihood of recombining their knowledge (Breschi et al., 2003). In the next section we explain and summarise the recent empirical findings on industry relatedness.

3.2.1 Industry relatedness

Industries can be described as collections of economic activities that share technologies, capabilities, knowledge, and are operating within common markets. The technologies, capabilities, and knowledge required or obtained by the economic activities within

a certain industry can, to varying degrees, be similar to the technologies, capabilities, and knowledge shared in other industries. The presence of particular firms can enhance likelihood of entry and growth of related firms (and on aggregate industries), because they can draw on the already obtained capabilities and knowledge making knowledge spillovers easier and more likely. As a consequence, economies tend to branch-out into new activities that are related to pre-existing activities (Frenken & Boschma, 2007).

Hidalgo et al. (2007) were the first to empirically assess this logic and found that in general countries indeed tend to become specialised in products that are related to the products it already produces. Following, Neffke et al. (2011) were able to measure co-production of products in Swedish plants, and subsequently showed that as for countries, regions also have a higher probability to branch-out into industries related to already present industries, relative to unrelated industries. These findings suggest that the relatedness of knowledge and capabilities required by firms and on aggregate by industries, determines the direction of diversification in economies. These results[1] were later underlined by studies done for Spanish regions (Boschma et al., 2013) and metropolitan areas in U.S.A. the (Essletzbichler, 2015). Drawing on the above-mentioned findings and theoretical considerations, we formulate our first hypothesis as follows:

> *Hypothesis 1: The probability of an industry entering a region is positively associated with the degree of relatedness to already present local economic activity.*

3.2.2 Unrelated diversification

While less common and left unexplained by the former reasoning, economies occasionally diversify into unrelated industries relative to their current base of activities. This gives rise to the question of whether certain economies might be better equipped to diversify into unrelated industries and what underlying factors are determining this capability. Building upon the arguments of Hall and Soskice (2001), Boschma and Capone (2015) found that liberal-market economies are more likely to diversify into unrelated industries, relative to coordinated-market economies. This finding is explained by liberal-markets being more flexibly in reallocating capital from one sector to another (un)related sector. In contrast, coordinated-market economies tend to diversify into related industries as to maximally leverage existing knowledge, institutional arrangements, and collaborative relationships. This suggest that national institutions seem to condition whether some countries are better capable in diversifying into unrelated activities relatively to others. On the regional level, Cortinovis et al. (2017) found that it is not so much formal institu-

[1] For a more comprehensive review we suggest Content and Frenken (2016) and Boschma (2017).

tions but rather informal institutions, particularly bridging social capital, that matter to diversify into new activities. The effect of informal institutions was found to be strongest in regions with weak formal institutions. Another study has looked at the innovation capacity of regions proxied by its knowledge-intensiveness Xiao et al. (2018) and found regions with weaker innovation capacity were more reliant on the already existing portfolio of competences in developing new industries. The authors interpret from this finding that innovation capacity enables a region to break with path-dependence and makes it better able in developing unrelated industries. Yet another study, by Petralia et al. (2017), has found that a countries' income-level has predicative power over the probability whether it will diversify in related or unrelated directions. They show that with increasing levels economic development, countries become less reliant on existing competences in the development of new activities. Similar to the previous studies, Zhu et al. (2017) look into whether certain factors increase a regions capability to develop new industrial specialisations in general and whether these factors are to some degree influencing the probability of whether this will be in related or unrelated activities. They find that non-local linkages, as proxied by the share of a region's output produced by foreign-owned firms, to reduce a region's reliability on local related capabilities. In addition, Neffke et al. (2018) show that incumbent firms are expected to reinforce the current industrial profile of a region, whereas unrelated diversification of a region can mostly be expected from entrepreneurs, particularly those with non-local roots.

The results presented in these studies is important for at least two issues concerning long-term prosperity and resilience. First, as global advancements of technology or changes in demand, might render certain capabilities or knowledge irrelevant. And second, solely relying on related diversification as a means of economic development might in the long-term create technological lock-ins. It is therefore important to gain unrelated knowledge and promote structural change. To sum up, ensuring long-term prosperity requires a certain level resilience and unrelated diversification. The resilience of a region in this context should not be seen as a stable end point but rather as a means to install a cycle of continues structural renewal (Boschma, 2015; Simmie & Martin, 2010). Foregoing studies have presented that innovation capacity, liberal-market institutions, bridging social capital, high-income levels, extra-regional linkages, and non-local entrepreneurs are conditions that increase regional resilience by supporting diversification into less related activities (Boschma & Capone, 2015; Cortinovis et al., 2017; Neffke et al., 2018; Petralia et al., 2017; Xiao et al., 2018).

3.2.3 Bridging unrelated sectors and inflow of foreign knowledge

According to the literature on industrial diversification discussed above, regions are expected to branch-out their economic activity into related activities. Moreover, the literature on regional resilience seems to have focussed mainly on economies' ability to resist and recover from shocks. Knowledge about how regional economies can structurally renew their industrial landscapes is limited but necessary in light of, for instance, shifts in global demand or technology. In the framework for evolutionary regional resilience proposed by Boschma (2015), economies depend in their ability to achieve structural change on their adaption and adaptability. Here, we look at three conditions that may increase regions' adaptability without necessarily weakening adaptation: the presence of Knowledge-Intensive Business Services (KIBS), the participation in Global-Value-Chains (GVCs), and investment in Research & Development (R&D). These factors might provide the generic competences of running business, managing global chains, and increase innovation capacity, respectively, which can be used in many different – and unrelated – industry contexts.

Knowledge Intensive Business Services (KIBS)

We propose that the presence of firms offering KIBS may in some cases support unrelated diversification. KIBS, usually offered by private firms, are intermediate services and knowledge-based. Due to the high adaptability and customisation the production of these services requires close collaboration and interaction with their customers (Den Hertog, 2000). Globalisation and an increasing rate of technological change have made it increasingly risk and cost intensive for firms to acquire the knowledge and capabilities necessary to stay competitive. KIBS form a source of these external assets and support firms to develop them and stay competitive by taking over non-core tasks (Hipp, 1999; Muller & Zenker, 2001; Wood, 2006). Frequently these services are supplied as an interactive learning process in which knowledge of the client firm is combined with the knowledge of the KIBS firm (Den Hertog, 2002; Tomlinson, 1999). KIBS firms in turn gather their knowledge not only from their clientele but from other sources such as R&D organisations, networks, and universities as well (Czarnitzki & Spielkamp, 2003). For this reason, firms in KIBS industries are often described as nodes or bridges between clients, universities, public institutions, and R&D organisations in systems or networks of knowledge and innovation (Czarnitzki & Spielkamp, 2003; Toivonen, 2004). Within these systems KIBS play an important role in the creation, recombination, and diffusion of knowledge. Some research has identified KIBS as stimulators of innovation in other firms and industries (Aslesen & Isaksen, 2007; Rodriguez, 2013), national gross output and productivity (Muller & Zenker, 2001), and regional growth in employment in the long-term (Brenner, Capasso,

Duschl, Frenken & Treibich, 2017). Moreover, KIBS are found to increase a client's absorptive capacity, specifically by increasing their capability to acquire new knowledge (Lau & Lo, 2015).

As KIBS get inspired by knowledge from their clients, some of this knowledge is able to spill over efficiently across different firms making use of the same KIBS firm (Czarnitzki & Spielkamp, 2003; Wood, 2006). In consequence, KIBS not only function as a node or bridge between different types of actors within systems of innovation but can also act as a bridging platform between their clients and facilitate knowledge spillovers between them. KIBS firms supply these intermediate services to a variety of clients in many different – and unrelated – industry contexts, possibly enabling knowledge spillovers between unrelated firms and industries.

Considering that KIBS play an important part in the knowledge dynamics of an economy, increase their client's absorptive capacity and innovation performance, and as a consequence increase the competitiveness of local firms and industries, the presence of KIBS is likely to foster an economy's ability to develop new industrial specialisation as well. Additionally, the presence of KIBS might render the demand for having related economic activity in the development of new economic activity less important, as KIBS in some cases are able to facilitate knowledge spillovers between both related and unrelated firms and industries. This leads us to formulate the following hypotheses:

> *Hypothesis 2a: The presence of KIBS is positively associated with the probability of a region to develop new industrial specialisations.*
>
> *Hypothesis 2b: The presence of KIBS negatively moderates the relation of relatedness and the probability of a region to develop new industries.*

Global Value Chains (GVCs)

In addition to KIBS, we propose that the participation in GVCs in some cases might support unrelated diversification. Due to the great advancements made in information, communication, and transportation technologies, individual activities of production chains do not necessarily have to be carried out within geographical proximity of each other anymore. As a consequence, not only are production chains getting increasingly fragmented globally (Baldwin & Lopez-Gonzalez, 2015), the comparative advantage of a country or region does not so much determine what kinds of goods are being produced anymore, rather it determines what tasks within those production chains are be-

ing performed (Baldwin & Lopez-Gonzalez, 2015; Baldwin & Robert-Nicoud, 2014; Los, Lankhuizen & Thissen, 2017; Timmer, Los, Stehrer & de Vries, 2013).

Participation in GVCs has potential benefits for firms and industries: it provides access to new global markets, creates access to external knowledge, opportunities to develop new capabilities, and subsequent local learning and innovation (Giuliani, Pietrobelli & Rabellotti, 2005; Humphrey & Schmitz, 2002b; Pietrobelli & Rabellotti, 2011; Saliola & Zanfei, 2009; Tajoli & Felice, 2018). Learning can support firms and industries to improve their comparative advantage and their position in the value chain (Gereffi, 1999). Although participation in GVCs is not a sufficient condition for the acquisition of new knowledge and capabilities, it does complement local innovation efforts (Fu, Pietrobelli & Soete, 2011; Morrison, Pietrobelli & Rabellotti, 2008). The inflow of new knowledge together with local innovation competences makes that participation in GVCs functional to local development and upgrading.

The mechanisms and potential for learning can vary greatly, however, depending on the mode of governance practiced in the GVC and the local absorptive capacity (Humphrey & Schmitz, 2002a). Learning of local firms can be the result of increased pressure to comply with certain standards, deliberate knowledge transfer from buyers, or unintended knowledge spillovers (Altenburg, 2006). In addition, depending on the mode of GVC governance and local context, firms and industries have different possibilities for upgrading. Firms can move-up in the value chain into more complex or higher value-added activities or use the acquired knowledge and capabilities to supply similar goods in different value chains (Chaminade & Vang, 2008; Gereffi et al., 2001; Humphrey & Schmitz, 2002b). A firm specialised in the production of particular intermediate parts, at some point might have accumulated the capabilities for more complicated tasks such as designing or logistics. On the other hand, it might deepen its capabilities in a particular task to serve multiple (un)related value chains (Morrison et al., 2008). As a consequence, learning opportunities can arise from multiple (un)related sectors and industries as well.

Considering that involvement in GVCs offers firms and industries the opportunity to acquire new knowledge and capabilities, we expect that on average an economy's ability to develop new industrial specialisations to increase with the level of participation in GVCs. In addition, the involvement in multiple GVCs increases the probability of unrelated knowledge spillovers flowing in, making the rise of new unrelated specialisations more likely as well. This leads us to formulate the following hypotheses:

Hypothesis 3a: Participation in GVCs is positively associated with the probability of a region developing new industrial specialisations.

Hypothesis 3b: Participation in GVCs negatively moderates the relation of relatedness and the probability of a region to develop new industries.

Research & Development (R&D)

Along with KIBS and GVC, we propose that investment in R&D has the potential to support unrelated diversification in some cases. Since economic growth theory incorporated knowledge as endogenous driver of innovation and technological change (Romer, 1986, 1990), R&D and its spillovers as catalysts of economic development have been a common topic of research. Overall, it has been found that R&D investment has beneficial effects on the productivity and innovative activity of firms and industries, and on aggregate economies as well (Griliches, 1991; Jaffe, Trajtenberg & Henderson, 1993). Due to the non-rival nature of knowledge, the knowledge created by R&D investments in particular firms or research institutes spills over for third-parties to exploit. However, despite considerable advancements made in information and communication technologies, still geographical proximity to the places of R&D explains the intensity of knowledge spillovers by significant extent (Bottazzi & Peri, 2003). As a consequence, innovative activity concentrates geographically (Audretsch & Feldman, 1996; Simmie, 2003) and local learning, search routines, and utilisation of resources can sometimes converge into path dependent processes (Ahuja & Katila, 2004; Maskell & Malmberg, 2007; Neffke et al., 2011).

One way to avoid technological lock-in due to path-dependent development is to ensure an inflow of external knowledge (Asheim & Isaksen, 2002; Binz et al., 2016). This can change the interpretation and perceived potentialities of local knowledge (Bathelt et al., 2004), possibly leading to new and original recombination of local and non-local knowledge. Sometimes referred to as 'global pipelines' (Maskell, Bathelt & Malmberg, 2006), collaborative linkages in R&D with distant firms and research institutes form the basis for the inflow of new and complementary knowledge, which can initiate new diversification paths due to the development of new activities within an economy (Grillitsch & Trippl, 2014; Tanner, 2014; Trippl et al., 2017).

Globalisation of production has made knowledge as a resource central in sustaining or increasing competitiveness (Lundvall & Johnson, 1994; Maskell & Malmberg, 1999), as such, investment in R&D and innovation have become crucially important. Besides, production processes often draw on a multitude of different disciplines and knowledge bases, resulting in firms needing to have specialised knowledge about a varying degree

of technologies. Parts of (knowledge) production are therefore often outsourced (Hipp, 1999), however in order to be able to accommodate the production process timely in the event of technological change in a particular component of production, firms keep developing knowledge about more than they actually produce. The boundary of firms' knowledge is often wider than the boundary of its production, making them better able to act upon innovation. Put differently, R&D-intensive firms can be said to 'know more than they do' (Brusoni, Prencipe & Pavitt, 2001).

Considering the discussion above, the following hypotheses are formulated:

Hypothesis 4a: Investment in R&D is positively associated with the probability of a region developing new industrial specialisations.

Hypothesis 4b: Investment in R&D negatively moderates the relation of relatedness and the probability of a region to develop new industries.

3.3 Data and methodology

In order to examine these hypotheses we construct a new dataset that combines data derived from Bureau van Dijk with data provided by Eurostat and information on the intensity of GVCs activities in regions across Europe. The resulting dataset covers 269 NUTS-2 regions spread over 28 countries across Europe[2] and contains annual information for each of these regions for the period 2008 until 2013. The information gathered from Bureau van Dijk is supplied by the Orbis dataset, which among other variables, contains annual information on firm's employment figures, revenues, and geographical location. Importantly, we also know for each firm its primary industrial classification according to the NACE classification system at the 4-digit level. Using this information, we can aggregate employment in each 4-digit level to our spatial unit of analysis (NUTS-2). At the 4-digit level the NACE classification distinguishes about 600 different industries. In this exercise we exclude all non-tradable activities, which means that in our dataset contains 554 different 4-digit industries.

3.3.1 Industry specialisation and relatedness

A common approach to estimating inter-industry relatedness is by using a proximity index, originally developed by Hidalgo et al. (2007). By using international trade data, the authors could calculate whether a country has a comparative advantage in exporting a

[2]This includes 27 EU countries (excluding Malta) including Norway

good and the probability that this good is exported with comparative advantage simultaneously with another good. With rising probability of a country exporting a set of goods with a comparative advantage simultaneously, relatedness is assumed to rise as well. The argument for this approach is that related industries or goods would require similar capabilities. In contrast to Hidalgo et al. (2007), a number of studies have replicated this approach not on the national level but on the regional level (Boschma et al., 2013; Cortinovis et al., 2017; Essletzbichler, 2015; Neffke et al., 2011). Instead of using trade data to establish a comparative advantage in a good or industry, these studies have used employment data to establish whether regions are relatively to other regions in the sample more or less specialised in an industry. We follow those studies and use the location quotient to determine whether a region is specialised in a certain industry using

$$LC_{ir} = \left(\frac{E_{ir}/E_r}{E_i/E}\right) \tag{3.1}$$

where i and r index industries and regions, respectively. E represents the sum of employment in either all industries of all regions, one industry but all regions, one region but all industries, or one industry in one region. When LC_{ir} is equal to 1, it means the share of that industry is the same as the average of other regions in our sample. Not specialised ranges from 0 to 1, and specialised ranges from above 1 to infinity. This means that the values on both sides of 1 (or unity) cannot be compared. Moreover, if this measure would enter a regressions equation much more weight would be given to values above 1 compared to values below 1 (the variable is skewed towards values above 1) and it is therefore likely to violate the normality assumption. Laursen (2015) therefore proposes a symmetrical index, such that the measure ranges from -1 to 1, given by

$$SLQ_{ir} = \left(\frac{LC_{ir} - 1}{LC_{ir} + 1}\right) \tag{3.2}$$

A region is specialised in a certain industry when its SLQ is above 0. Meaning that the share of employment of industry i in region r is higher than the share of that industry in our sample as a whole, i.e. it measures the relative specialisation of a region in a certain industry. Once we know in which industries what regions are specialised we can go further and calculate inter-industry relatedness based on the co-occurrence of specialisations. We follow Hidalgo et al. (2007)) and assume that when the probability of being specialised rises, so does relatedness. Accordingly, we define our proximity index as

$$\varphi_{ij} = min\{P(BLQ_i|BLQ_j), P(BLQ_j|BLQ_i)\} \tag{3.3}$$

The result of this transformation is a 554 x 554 matrix, in which each cell refers to the minimum conditional probability of a region being specialised in industry i given that it is specialised in industry j. BLQ is our binary location quotient, which is 1 if region r is specialised in industry i and 0 otherwise. Proximity between a set of industries is higher when regions are more often specialised in them together because they require similar capabilities, technologies, social networks, institutions, infrastructure, et cetera. Following Hausmann and Klinger (2007), the next step is to calculate industry density as

$$d_{ir} = \left(\frac{\Sigma_j \varphi_{ij} BLQ_{jr}}{\Sigma_j \varphi_{ij}}\right) \tag{3.4}$$

where φ represents proximity as shown in eq. 3.3, between industry i and j. Again, BLQ is our binary location quotient, just as in eq. 3.3. The resulting density measure, d_{ir}, gives an indication in how much of the related industries a region is specialised relative to a certain reference industry i. It ranges from 0 to 1, where 0 indicates a region is not specialised in any of the related industries and 1 indicates it is specialised in all of the related industries.

3.3.2 KIBS, GVCs, and R&D

As we are able to distinguish industry employment at the 4 digit-level for most NUTS-2 regions in Europe, we measure the presence of KIBS in regions as a share in certain 4-digit industries that are typically described as primarily hosting KIBS. Following Schnabl and Zenker (2013) we define KIBS as economic activity proxied by the amount of employment in the following industries: (J62) Computer programming, consultancy and related activities, (J63) Information services activities, (J69) Professional, scientific and technical activities, (M70.2) Management consultancy activities, (M71) Architectural and engineering activities; technical testing and analysis, (M72) Scientific research and development, and (M73) Advertising and market research.[3]

In order to be able to measure the degree to which a region is involved or earns its income by tasks performed within GVCs we make use of a newly constructed dataset,

[3] For other ways of classifying KIBS; see table 2 of Zieba (2003)

which measures the share of Gross Regional Product (GRP) generated in GVCs at the regional level in Europe (Los et al., 2017). This data is generated by disaggregating national input-output tables to the NUTS-2 level for most countries in Europe[4]. From Eurostat we derive annual data on the R&D-intensity of NUTS-2 regions. Specifically, we calculate the share of R&D expenditure in GRP.

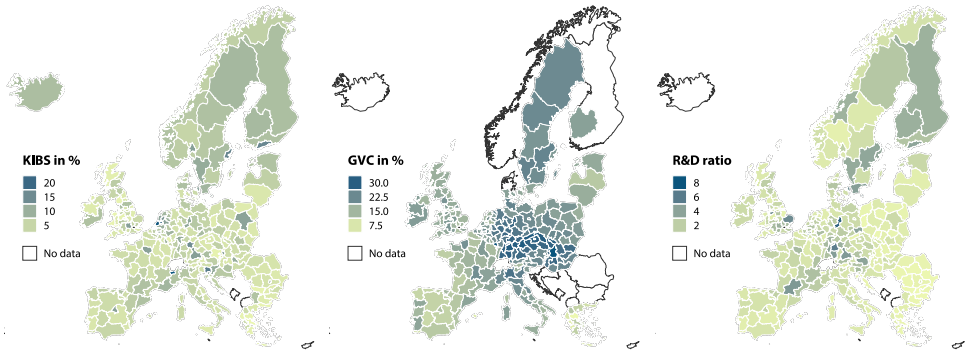


Figure 3.1: *Geographic distribution of KIBS, GVCs, and R&D*

Figure 3.1 presents the geographic distribution of our main explanatory variables. We clearly see that KIBS seem to spatially cluster in urban regions. When looking at the map in the middle, representing our data on GVCs, we notice a band of regions in the core of Europe that generates high shares of their income with activities in GVCs. Especially, regions in the Southern Germany, Czechia, and Hungary. The R&D shares appear to be clustering in urban regions as well, although to a lesser extent than KIBS do.

3.3.3 Estimation strategy

After establishing what regions are specialised in which industries, the next step is to estimate both the direct and moderating effect of the presence of KIBS, participation in GVCs, or investment in R&D on a region's ability to specialise in new industries. In other words, we want to analyse whether regions with high economic activity in one these factors have a higher propensity to specialise in new industries and whether this helps regions to diversify into less related industries.

[4] The GVCs data covers all EU28 countries, except: Bulgaria, Cyprus, Croatia, Slovenia, and Romania.

Regional-level specification

First, we start by estimating a model at the regional level, meaning that we aggregate our data by summing industry-level variables to the NUTS-2 level. As we know in which industries regions are specialised, we can for each region sum the number of specialisations and examine how this changes over time. We measure the number of industries a region is specialised twice, once in 2008 and once in 2013. Our independent variables are measured in 2008. The model takes the form of

$$\begin{aligned} y_r = \alpha &+ \beta_1 d_r + \beta_2 KIBS_r + \beta_3 GVC_r + \beta_4 R\&D_r \\ &+ (\beta_5 KIBS_r + \beta_6 GVC_r + \beta_7 R\&D_r) * d_r \\ &+' \delta' Control_r + \vartheta C_r + \varepsilon_r \end{aligned} \tag{3.5}$$

where r indexes regions. The dependent variable, y, either refers to the net change in the number of specialisations ($dBLQ$), the gross increase in the number of specialisations ($Gain$), or the sum of the absolute increase and decrease in the number of specialisations ($Turbulence$). Our industry density indicator, d_r, here represents the sum of densities around all industries, as

$$d_r = \sum_{i=1}^{I} d_{ir} \tag{3.6}$$

where I represent all industries in the sample. Higher values indicate a region is specialised in a greater number of the related industries, whereas lower values indicate that a region is specialised in a limited number of related industries. The variables $KIBS$, GVC, and $R\&D$ are interacted with industry density d_r, to estimate the moderating effect these variables might have on relatedness. A positive moderating effect would indicate that, for instance investment in R&D, increases the probability that new specialisations are more related to existing industries. By contrast, a negative moderating effect would indicate that investment in R&D leads to less related new specialisations, suggesting that R&D reduces a region's reliance on path-dependent diversification.

Ideally, we would like to control for NUTS2-specific effects to control for unobserved heterogeneity between regions. However, as this is a cross-sectional regression that means we would lose the variation of our explanatory variables $KIBS$, GVC, and $R\&D$. We

therefore control for country specific effects by including a dummy for each country and cluster our standard errors at the regional level, as our errors might be correlated (i.e. not independently and identically distributed) within each region. The control variables, captured in the vector ‘C, will be discussed more elaborately in the next section.

Figure 3.2 shows the spatial distribution of the dependent variables. We see that, especially in Southern and Eastern Europe turbulence in the number of specialisations has been high over the 5-year period starting in 2008. Particularly the countries Spain, Italy, Romania, and Slovakia have seen high numbers of lost and gained specialisations compared with regions in the more Northern and Western parts of Europe. Looking at for instance Spain or Germany, we clearly see that within country variation is substantial as well.

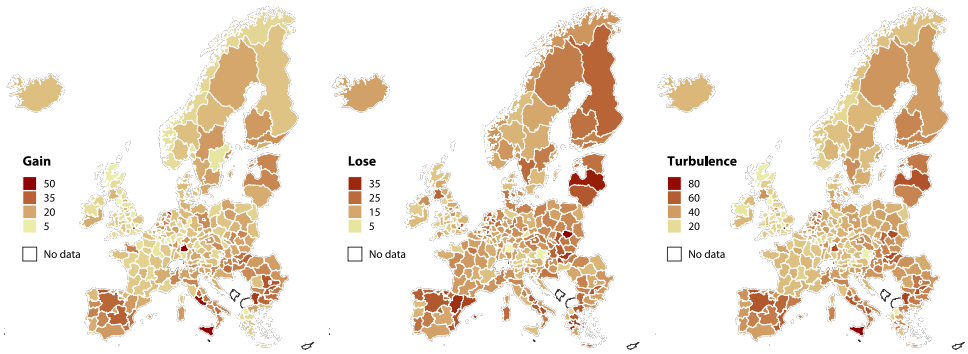


Figure 3.2: *Geographic distribution of gains, losses, and turbulence of specialisations*

Industry-level specification

Our second model is estimated at the industry level with each observation representing a 4-digit industry of a NUTS2 region. We analyse a 5-year time period by measuring specialisations in 2008 and again in 2013. As we are interested in what factors are determining a region’s ability to develop new specialisations, we exclude those industries that regions were already specialised in 2008. The corresponding entry model takes the form of

$$
\begin{aligned}
BLQ13_{ir} = \alpha + \beta_1 d_r + \beta_2 KIBS_r + \beta_3 GVC_r + \beta_4 R\&D_r \\
+ (\beta_5 KIBS_r + \beta_6 GVC_r + \beta_7 R\&D_r) * d_{ir} \\
+' \delta' Control_r + \theta_i + \vartheta C_r + \varepsilon_r
\end{aligned}
\tag{3.7}
$$

where i indexes industries and r indexes regions. Our dependent variable, $BLQ13$, is a binary variable, which is 1 if region r is specialised in industry i in 2013. Industry density, d_{ir}, indicates the density around each industry, i.e. the extent to which a region is specialised in related industries. The variables $KIBS$, GVC, and $R\&D$ are interacted with density to estimate the moderating effect. A significant moderation effect is interpreted as making a region more or less reliant on related diversification. The control variables, captured in the vector 'C, will be discussed more elaborately in the next section. For each country and 4-digit industry a dummy variable is included to control for both industry-specific and country-specific effects. The standard errors are clustered at the regional level, as they might be correlated (i.e. not independently and identically distributed) within each region.

3.3.4 Control variables

In order to account for other factors that might influence a region's propensity to develop new industrial specialisations, we include several control variables in our models. Earlier studies have shown that more developed and richer economies have a higher probability to develop new specialisations due to increased opportunities for recombination (Hidalgo & Hausmann, 2009). Therefore, to control for the overall level of economic development of regions we include the gross regional product per capita ($GRPPC$). To control for the overall level of urbanisation, we include population density ($PDEN$) and a dummy variable ($BCITY$), which is 1 if a region contains a city with more than 500,000 inhabitants. We include both these variables as some NUTS-2 regions contain such a city but spread over large stretches of rural land as well. As human and physical capital might support the development of new industry activities, gross capital formation ($CAPFRM$) and tertiary educational attainment (HC) are also included in the model. Information to construct these variables is retrieved from Eurostat at the NUTS-2 level for the year 2008. Except $BCITY$, all of these variables enter our specifications in logarithms.

3.4 Results

3.4.1 Regional-level results

First, we estimate eq. 3.5 with the net change in the number of specialisations from 2008 until 2013 for each region. The first column shows the results when only the number of specialisations in 2008 ($BLQ08$) and the sum of density around specialised industries are included. The initial number of specialisations is negatively related to the number of new specialisations, which could resemble that regions with an already high number of specialisations in 2008 are constraint by the available resources and increases the effort required to maintain those specialisations. Industry density is positively associated with the net change in number of specialisations, reflecting that regions with on average more related specialisations will develop more new ones as well. In the columns 2-4 we include our main explanatory variables, $KIBS$, GVC, and $R\&D$. Starting with column 2, in which we included both the KIBS variable and its interaction with density, we see that the direct effect of $KIBS$ is positive, however, not statistically significant, whereas the moderation effect is negative. Column 3, in which we include our GVC variable together with its interaction with density, we obtain a similar result. However, the parameter on GVC is now statistically significant and the participation in GVC moderates negatively the effect of industry density. In column 4, where we include $R\&D$, we do not find a statistically significant direct or indirect effect. Column 5a, present the results obtained when all of variables are included into the estimation. Apart from the effects being estimated slightly smaller, not much has changed. Column 5b present the standardised coefficients obtained from the estimation in column 5a, this enables us to directly compare the effect sizes of $KIBS$, GVC, and $R\&D$ with each other. We find that the strongest direct effect on the number of new specialisations is estimated for GVC, whereas the strongest interaction effect with industry density is estimated for $KIBS$.

	(1) dBLQ	(2) dBLQ	(3) dBLQ	(4) dBLQ	(5a) dBLQ	(5b) Std.
BLQ08	-0.534**	-0.584**	-0.534**	-0.515**	-0.562**	-1.709
	(0.128)	(0.129)	(0.117)	(0.125)	(0.122)	
Density	0.296**	0.418**	0.409**	0.327**	0.470**	1.659
	(0.110)	(0.121)	(0.128)	(0.111)	(0.135)	
KIBS		60.871			36.160	0.117
		(38.013)			(37.106)	
KIBS * Density		-1.404**			-1.181*	-0.527
		(0.489)			(0.512)	
GVC			130.798*		95.239*	0.520
			(54.346)		(44.125)	
GVC * Density			-0.696*		-0.515+	-0.494
			(0.313)		(0.300)	
R&D				455.487	129.534	0.147
				(351.945)	(329.479)	
R&D * Density				-3.437	-0.184	-0.027
				(2.619)	(2.547)	
Constant	47.537	14.002	48.132	47.882	16.282	-
	(33.993)	(39.583)	(37.627)	(34.687)	(43.057)	
Observations	268	268	238	268	238	238
R-squared	0.442	0.476	0.454	0.453	0.485	0.485
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Column 5b shows the standardised coefficients of column 5a. The control variables are included in all models: GRPPC, CAPFRM, and HC do not produce a significant coefficient in any of the models. PDEN produces a significant coefficient of about -1.25 in models 1 and 4. BCITY produces a significant coefficient of about 2.46 in model 2.*

Table 3.1: *Net change in the number of specialisations (dBLQ) from 2008-2013*

Instead of using the net change as dependent variable, table 3.2 presents the findings with the gross increase ($Gain$) in the number of specialisations. Taking a look at the first two rows reveals that the number of specialisations in 2008 has a negative impact in columns 2, 3 and 5a, whereas density impacts the gross increase positively in the same columns. $KIBS$, GVC, and $R\&D$ have a direct impact on the gross increase in the number of specialisations. The interaction effect with industry density is statistically significant and negative for all three variables. Column 5b, which shows the standardised coefficients of column 5a, reveals that both the direct and interaction effect is estimated to be the strongest for GVC, followed by $R\&D$ and then $KIBS$.

	(1) Gain	(2) Gain	(3) Gain	(4) Gain	(5a) Gain	(5b) Std.
BLQ08	-0.206	-0.253+	-0.199+	-0.187	-0.214+	-0.353
	(0.132)	(0.131)	(0.112)	(0.124)	(0.118)	
Density	0.099	0.212+	0.288*	0.145	0.336**	1.149
	(0.118)	(0.125)	(0.114)	(0.114)	(0.121)	
KIBS		58.987+			10.127	0.049
		(34.998)			(34.356)	
KIBS * Density		-1.314**			-0.816+	-0.229
		(0.417)			(0.430)	
GVC			142.179**		104.868**	0.551
			(45.803)		(36.698)	
GVC * Density			-1.095**		-0.909**	-0.954
			(0.261)		(0.246)	
R&D				575.726+	296.777	0.355
				(298.523)	(276.875)	
R&D * Density				-4.613*	-1.573	-0.390
				(2.204)	(2.091)	
Constant	54.889+	24.124	45.011	55.531+	19.273	-
	(28.864)	(33.631)	(31.694)	(29.638)	(36.223)	
Observations	268	268	238	268	238	238
R-squared	0.514	0.551	0.520	0.536	0.556	0.556
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Column 5b shows the standardised coefficients of column 5a. The control variables are included in all models: GRPPC, PDEN, and HC do not produce a significant coefficient in any of the models. CAPFRM produces a significant coefficient of about 2.96 in model 1, whereas BCITY produces a significant coefficient of about 2.30 in models 2, 4, and 5.*

Table 3.2: *Number of new specialisations (Gain) from 2008-2013*

Table 3.3 presents our findings with $Turbulence$ as the dependent variable, the sum of the gross increase and decrease in the number of specialisations. This measure reflects the extent to which movement in the number of specialisations takes place and, in some cases, can reflect structural change of the economy. In these estimations, we omit the initial number of specialisations[5]. The estimated parameters of industry density, presented in the first row, show that it is positive and significant only in columns 3,4 and 5. A higher number of related specialisations thus seems to result in a higher turbulence in the number of specialisations over time. The direct effect of GVC and $R\&D$ is positive and significant, with the strongest effect of $R\&D$. The interaction effects are significant

[5] As a robustness test, we estimated the models presented in table 3.3 including $BLQ08$ as control variable as well. $BLQ08$ did not have significant effect on Turbulence and although the coefficients of the other explanatory variables changed somewhat, no changes in terms of the significance can be reported.

for all three variables in columns 2, 3, and 4, however, when put together in column 5a, only the interaction of GVC with industry relatedness stays statistically significant.

	(1) Turbulence	(2) Turbulence	(3) Turbulence	(4) Turbulence	(5a) Turbulence	(5b) Std.
Density	0.024	0.087	0.303**	0.103+	0.336**	0.892
	(0.052)	(0.055)	(0.064)	(0.055)	(0.066)	
KIBS		58.397			-11.556	-0.018
		(47.875)			(45.997)	
KIBS * Density		-1.253**			-0.523	-0.377
		(0.479)			(0.481)	
GVC			153.394**		114.207**	0.239
			(45.569)		(42.500)	
GVC * Density			-1.493**		-1.298**	-0.637
			(0.287)		(0.309)	
R&D				679.918*	436.696	0.425
				(282.382)	(276.845)	
R&D * Density				-5.716**	-2.763	-0.571
				(2.155)	(2.220)	
Constant	75.906*	42.278	58.297+	78.795*	36.885	-
	(33.882)	(38.493)	(34.848)	(33.129)	(39.653)	
Observations	268	268	238	268	238	238
R-squared	0.588	0.607	0.607	0.607	0.628	0.628
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Column 5b shows the standardised coefficients of column 5a. The control variables are included in all models: GRPPC has an impact of about -7.90 in models 3 and 4. CAPFRM and HC do not have an impact. PDEN and BCITY have an impact of about 1.10 and 2.56, respectively in model 5.*

Table 3.3: *Sum of new and lost specialisations (Turbulence) from 2008-2013*

To sum up our findings so far. Overall, we find support for hypothesis 1 that industry density increases a region's propensity to develop new specialisations. We find that in all of the estimations so far, participation in GVCs increases the probability of a region to develop new or sustain industrial specialisations (supporting hypothesis 3a). Some of our results indicate that the presence of KIBS and investment in R&D increases a regions ability to develop new or sustain specialisations (partly supporting hypothesis 2a and 4a). In most our models, we find that the presence of KIBS and participation in GVCs negatively moderates the relationship of industry density with new specialisations (supporting

hypothesis 2b and 3b). With respect to R&D, we find this effect less frequently (partly supporting hypothesis 4b).

3.4.2 Industry-level results

In remainder of the analysis the unit of observation will be 4-digit industries within NUTS-2 regions. Recall that in the estimation of eq. 3.7 we have excluded those industries in which regions in 2008 were already specialised. Our dependent variable $BLQ13$, is a dummy variable that is 1 if a region becomes specialised in a particular industry during the period 2008 to 2013, which makes that we should interpret the estimated parameters as a probability that a region will gain a specialisation in a specific industry.

Table 3.4 presents the results from estimating the baseline model, i.e. we are interested in the effect of industry density and how this might change once we include our control variables. Column 1 shows that industry density has a positive and significant effect, reflecting that relative to a particular industry, with a rising level of related specialisations, the probability of a region becoming specialised in that particular industry rises as well. In columns 2, 3, and 4 we include $KIBS$, GVC, and $R\&D$ individually as well as their interaction terms with industry density. In column 5a we estimate the direct and interaction effects together. Regressions that include KIBS as explanatory variable have less observations, as we have excluded the KIBS industries from those estimations. We do not find a significant direct effect for $KIBS$ and GVC, whereas we do find a positive impact of $R\&D$. Only in column 4 do we find an interaction effect of $R\&D$ with industry density, where we do not find significant interaction effects of $KIBS$ and GVC.

	(1) BLQ13	(2) BLQ13	(3) BLQ13	(4) BLQ13	(5a) BLQ13	(5b) Std.
Density	0.310**	0.356**	0.481**	0.437**	0.508**	0.133
	(0.079)	(0.102)	(0.162)	(0.088)	(0.180)	
KIBS		0.067			-0.104	-0.018
		(0.231)			(0.282)	
KIBS * Density		-0.967			-0.255	-0.006
		(0.974)			(1.173)	
GVC			0.246		0.081	0.024
			(0.266)		(0.210)	
GVC * Density			-1.143		-0.709	-0.063
			(0.907)		(0.777)	
R&D				1.983+	1.721+	0.091
				(1.008)	(0.953)	
R&D * Density				-7.356*	-5.509	-0.075
				(3.687)	(3.628)	
Constant	0.047	0.005	0.032	0.063	0.019	-
	(0.115)	(0.138)	(0.134)	(0.115)	(0.155)	
Observations	85,992	81,999	75,766	85,992	72,225	72,225
R-squared	0.029	0.030	0.030	0.030	0.030	0.030
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Column 5b shows the standardised coefficients of column 5a. The control variables are included in all models: GRPPC, PDEN, and HC do not produce a significant effect. CAPFRM and BCITY have an impact of about -0.016 and 0.007, respectively in all models.*

Table 3.4: *Estimated impact of KIBS, GVCs, and R&D*

The estimations presented in table 3.4 are conditional on industry specific effects, as for each 4-digit industry a dummy variable is included in the model. However, the effects of $KIBS$, GVC, and $R\&D$ on a region's ability to develop new specialisations, as well as the interaction effect with industry density might depend on the type of industry. To further investigate this, we split up the sample into four broad industry groups: (1) industry and manufacturing, (2) distribution, (3) business services, and (4) personal services. Table 3.5 presents our findings when we estimate the model for each of these groups separately.

	Industry group	Density	Independent var.	Interaction with Density	Constant	R-sqr.
			KIBS	*KIBS * Density*		
(1)	Industry	0.326 (0.051)**	0.298 (0.153)+	-2.047 (0.692)**	0.025 (0.068)	0.029
(2)	Distribution	0.246 (0.079)**	-0.036 (0.226)	-1.201 (1.045)	-0.080 (0.101)	0.044
(3)	Business serv.	0.500 (0.120)**	-0.343 (0.351)	0.430 (1.570)	-0.378 (0.152)*	0.043
(4)	Personal serv.	0.355 (0.093)**	0.300 (0.277)	-1.203 (1.241)	0.266 (0.117)*	0.036
			GVC	*GVC * Density*		
(5)	Industry	0.296 (0.100)**	0.236 (0.124)+	-0.693 (0.486)	0.111 (0.071)	0.030
(6)	Distribution	0.683 (0.148)**	0.570 (0.181)**	-3.070 (0.720)**	-0.018 (0.102)	0.039
(7)	Business serv.	0.939 (0.177)**	0.505 (0.212)*	-2.746 (0.873)**	-0.420 (0.128)**	0.040
(8)	Personal serv.	0.290 (0.175)+	0.108 (0.212)	-0.390 (0.847)	0.277* (0.122)	0.040
			R&D	*R&D * Density*		
(9)	Industry	0.363 (0.075)**	2.254 (1.108)*	-8.912 (4.100)*	0.114 (0.102)	0.029
(10)	Distribution	0.290 (0.137)*	1.781 (1.343)	-6.115 (5.183)	0.065 (0.167)	0.044
(11)	Business serv.	0.622 (0.127)**	2.248 (1.240)+	-9.835 (4.924)*	-0.343 (0.165)*	0.040
(12)	Personal serv.	0.362 (0.175)*	1.243 (0.882)	-4.032 (3.709)	0.285 (0.206)	0.037

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Dependent variable: BLQ13. Control variables, country fixed effects, and industry fixed effects are included in all estimations presented in this table. A series of Wald-tests showed that the estimated coefficients differ signficantly across groups.*

Table 3.5: *Different effect of KIBS, GVC, and R&D across broad industry groups*

Starting with $KIBS$ we notice that although we do not find a statistically significant effect in the estimations presented in table 3.4, once we distinguish between broad industry groups we find that KIBS directly increase the probability of developing new specialisations in the industry/manufacturing group. Similarly, $KIBS$ substitutes the effect of relatedness in this group, suggesting that the presence of KIBS makes regions less reliant on having related specialisations in developing industry/manufacturing activities. By offering their services to a wide variety of clients, $KIBS$ appear to facilitate knowledge spillovers between their clients, making those clients less reliant on knowledge spillovers from related firms. The participation in GVCs mainly impact the probability of regions to develop new specialisations in distribution and business services. Moreover, we find that the negative moderation effect is particularly strong for these two groups. This may reflect that with a rising share of income that regions generate by performing tasks within GVCs, distribution and business services activities supporting this develop as well. Depending on the governance within the GVC, the knowledge and capabilities necessary for the development of these distribution and business services activities may originate from firms higher up in the value chain. Increased investment in R&D seems to benefit the rise of specialisations mainly in the industry/manufacturing group, while it

substitutes the effect of industry density both in the industry/manufacturing and business services group.

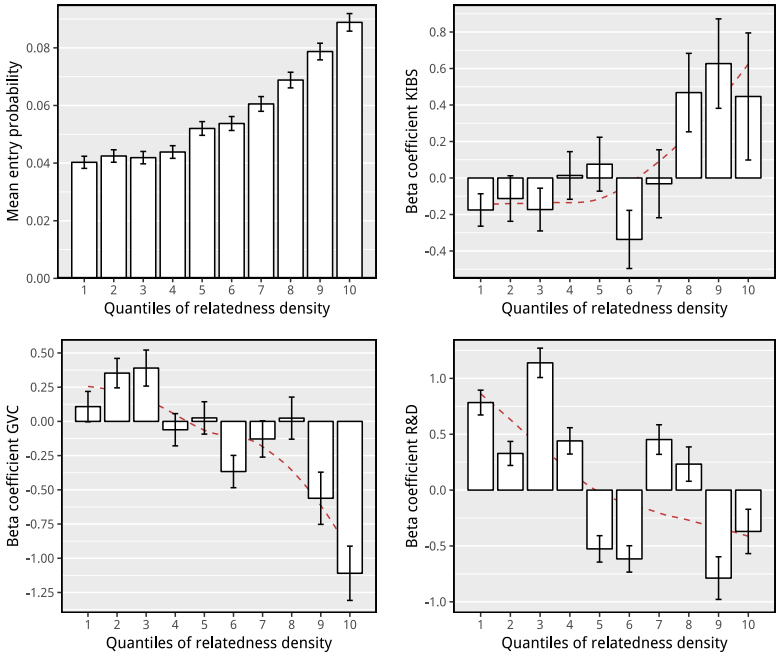


Figure 3.3: *Mean entry probability and effects of KIBS, GVC, and R&D across quantiles of relatedness density. The top left panel depicts the mean entry probability of an industry across quantiles of relatedness density. The top-right, bottom-left, and bottom-right panels, respectively depict the estimated beta coefficients of KIBS, GVC, and R&D across quantiles of relatedness density. The first quantile contains observations with an industry density between the 1st and 10th percentile, the second between 11th and 20th, and so forth to the tenth quantile, which contains observations between the 91st and 100th percentile.*

Besides industry groups, the effects of $KIBS$, GVC, and $R\&D$ might be heterogenous across levels of industry density. For instance, a region with a limited number of specialised activities also has a limited amount of capabilities and knowledge on which it can draw, and is therefore at a relative disadvantage to develop new specialisations. However, especially in such cases might the presence of KIBS, participation in GVC, and investment in R&D proof to be valuable, as these conditions can sometimes provide inflows of external knowledge. To further investigate whether the effects of $KIBS$, GVC,

and $R\&D$ are differentiated across levels of industry density, we divide the observations in the sample into ten quantiles of industry density. We then estimate the effect of $KIBS$, GVC, and $R\&D$ on the probability of a region to develop a new specialisation for each of these groups separately. The results of this exercise are presented in figure 3.3 and in table A.5 of the appendix.

The top-left panel of figure 3.3 depicts the mean entry probability across quantiles of relatedness density. With rising industry density, the mean entry probability clearly rises as well. The top-right, bottom-left, and bottom-right panels, depict the estimated beta coefficients of $KIBS$, GVC, and $R\&D$, respectively. Starting with $KIBS$, we notice that it has a strong and positive effect on the entry probability at high levels of industry density (quantiles 8, 9 and 10), whereas at medium levels we mostly observe insignificant effects. At low levels of relatedness density, the effect is smaller but negative and significant (quantiles 1 and 3). When we take GVC as explanatory variable instead, we notice a positive impact at low levels of industry density (quantiles 2 and 3) and a negative impact at high levels of industry density (quantiles 9 and 10). At medium levels of relatedness density, the effect is mostly insignificant. Taking $R\&D$ as the explanatory variable yields yet a different picture. $R\&D$ negatively impacts the mean entry probability at some medium levels (quantiles 5 and 6) of industry density, but positive in others (quantiles 4 and 7). At low and high levels, we clearly find a positive and negative effect, respectively.

The results depicted in figure 3.3 show that, despite a limited availability of local related knowledge and capabilities (as in quantiles 1-3), R&D investment and GVC participation can provide the competences to develop new industrial activities in such circumstances. We interpret these findings to likely indicate that, regions can acquire new knowledge through collaborative relationships of R&D institutions with non-local partners, or through the provision of new capabilities by value chain partners higher up in the value chain. The knowledge spillovers originating from such non-local linkages, could either be related or unrelated to the current knowledge and capability base. It is however likely, that in the case of limited availability of local related knowledge, R&D collaborations are initiated to gather new and unrelated knowledge, whereas in the case of GVC participation, firms higher up in the value support the initial development of new unrelated activities. At very high levels of relatedness density (as in quantiles 9 and 10), increased participation in GVCs, however, increase the changes of path-dependence, as the region might become locked-in a definite range of related tasks or industries.

In contrast, at high levels of relatedness density the presence of KIBS seems to foster the development of industrial activities, possibly by being able to indirectly connect yet

more (un)related firms and organisations. One explanation could be that KIBS, although they play an important role in connecting different and sometimes unrelated actors within the region, are especially capable in doing this when cognitive distances are not too high (as in quantiles 8-10). Another explanation holds true that the knowledge-intensive departments of KIBS themselves are subdivided into sections, impeding unrelated within-firm knowledge spillovers, that in turn impedes the efficiency by which KIBS can support unrelated knowledge spillovers within a region as well.

3.4.3 Robustness tests

In order to further scrutinise the main findings, two of the robustness analyses that have been carried out will be described in this paragraph. First, it could be that a substantial share of the observed industry entries is the result of regions being close to the specialisation threshold in 2008. If this is a large share of the entries, we might observe that regions gain or lose specialisations quite often. To control for this, we estimate all of the models using wider thresholds for a region to gain a specialisation. We include only those industries that had a SLQ of -0.1 or below in 2008 and 0.1 or above in 2013. Of the about 86,000 observations without such a wide threshold, about 5,000 observations fall within the threshold and are excluded from the estimations. The findings for the regional level model are mostly supported: the coefficients presented in table 3.1 are somewhat smaller but stay significant mostly at the same level, the effects of $R\&D$ disappear in table 3.2, whereas the effects of $R\&D$ in table 3.3 become smaller but stay significant. The findings for the industry level model are mostly supported as well: the coefficients of table 3.4 become smaller but stay significant at the same level, the coefficients of $KIBS$ and GVC in table 3.5 stay roughly the same, while the effects of $R\&D$ in table 3.5 disappear. This exercise was carried out using -0.05 to 0.05 and -0.15 to 0.15 as thresholds as well; higher thresholds seem to produce lower coefficients, and mostly, but not in all cases, lower significant levels.

	(1) Density	(2) Density	(3) Density	(4) Density
KIBS	-0.203*			-0.172*
	(0.080)			(0.084)
GVC		0.202*		0.175*
		(0.078)		(0.087)
R&D			-0.024	-0.119
			(0.165)	(0.198)
Constant	-0.020	0.064	0.027	0.008
	(0.100)	(0.101)	(0.101)	(0.105)
Observations	4,714	4,267	4,920	4,089
R-squared	0.722	0.721	0.715	0.726
Control vars.	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Dependent variable: industry density in 2013. Only industries with SLQ < 0 in 2008 and SLQ > 0 in 2013 are included.*

Table 3.6: *Regression of industry density in 2013 on KIBS, GVC, and R&D*

A second robustness test is shown in table 3.6. In order estimate the effect of $KIBS$, GVC, and $R\&D$ on the entry probability of less related industries more directly, we also estimated the effect of these variables on industry density directly. The dependent variable is industry density in 2013 and only those industries in which regions were not specialised in 2008 but were in 2013 are included. $KIBS$ has a negative coefficient, suggesting that with rising $KIBS$ industry entries become less related. The opposite is found for GVC, suggesting that GVC promote more related industry entries, opposing our findings earlier. We do not find a significant effect of $R\&D$.

3.5 Conclusion

In the long run, regional economic development is dependent on the development of new activities and associated jobs offered by more efficient firms that push out established firms and industries. Recent studies have persistently shown, that new activities are expected to branch-out of related and established activities (Boschma, 2017; Content & Frenken, 2016). This constrains regional diversification to a highly path-dependent dynamic, making it difficult for regions to explore unrelated territory and structurally renew their industrial profiles in order to attain sustainable growth and resilience. Recently, scholars have therefore paid attention to factors that might enable regions to structur-

ally renew their economies and diversify into unrelated areas (Boschma & Capone, 2015; Cortinovis et al., 2017; Neffke et al., 2018; Zhu et al., 2017). Although this has led to some new and important insights, more knowledge is needed to understand the dynamics of unrelated diversification.

Specially, we establish that two conditions that potentially enable economies to develop new unrelated knowledge and capabilities, markedly emerge from these new insights. On the hand, the presence of extra-regional linkages can be identified to provide an inflow of external knowledge (Asheim & Isaksen, 2002; Binz et al., 2016). While on the other hand, platforms or networks within an economy that connect both related and unrelated firms (but also universities, research institutes, and governments) can be identified as potential facilitators of knowledge spillovers between (un)related actors (Czarnitzki & Spielkamp, 2003; Wood, 2006).

In this study, we propose that the presence of KIBS, participation in GVCs, and investments in R&D may be such conditions. As KIBS supply intermediate services to a variety of firms in many different – and unrelated – industry contexts, KIBS can sometimes act as a bridging platform between these firms and facilitate knowledge spillovers. Similarly, the tasks performed in GVCs may act as a bridge for knowledge to spill over between unrelated sectors. As a region specialised in a particular task of a value chain can serve many different sectors and products possibly in other value chains. Investment in R&D, then, is expected to increases a region's capability to innovate and exploit new opportunities, which in the end should help to develop new economic activities as well. What these factors have in common is their ability to source knowledge and capabilities from non-local sources. For instance, KIBS in the form of multinational firms may provide extra-regional linkages, giving rise to cross-border knowledge spillovers. GVCs are by definition global, a region specialised in a certain task can sometimes acquire knowledge from actors higher up in the value-chain. R&D is typically done in knowledge institutions that often times enter in collaborative relationships or networks with distant research institutes or firms in order to gain knowledge not available locally.

We show that under some conditions, the presence of KIBS, participation in GVCs, and investment in R&D can indeed support the emergence of new specialisations as well as moderate the effects of relatedness – i.e. compensate for the lack of local related knowledge. Specifically, we find that the presence of KIBS promotes the emergence of (un)related manufacturing and industry activities, whereas the participation in GVCs does so for activities in distribution and business services. Investment in R&D mainly impacts the probability of (un)related activities emerging in manufacturing and business services.

Moreover, the substitution effects found for these factors are different across levels of relatedness density. At low levels of relatedness density (i.e. scarcity of local related knowledge and capabilities) increased participation in GVCs and investment in R&D, increases the probability of new industrial specialisations, whereas at high levels (i.e. abundance of local related knowledge and capabilities), increased presence of KIBS and participation in GVCs might decrease the probability of new industrial specialisations.

These findings further our knowledge and understanding of how regions can acquire new unrelated and non-local knowledge and capabilities to foster economic development. Furthermore, these findings bare important implications for policy makers as well. As for instance emphasised by the Smart Specialisation Strategy of the European Commission, policy makers should acknowledge that regions cannot do everything but instead to enhance the effectiveness of their policy efforts, should build upon the assets and resources readily available to the region. Smart Specialisation highlights the role of an entrepreneurial discovery process, in which entrepreneurs (defined in a broad sense to include, besides individual inventors, also firms, higher education institutions, and innovators in general) are key to the discovery of potential domains for development, as they are able to combine scientific and technological knowledge with knowledge about market growth potential and potential competitors (Foray, David & Hall, 2009). Hence, not all regions should focus on the invention of new General-Purpose Technologies (GPTs), but rather the majority of the R&D and innovation efforts should focus on new applications of such GPTs in other parts of the economy.

Although the Smart Specialisation Strategy emphasises the importance to build upon the assets and resources readily available to the region, with respect to industrial diversification present and preceding studies (Boschma, 2015; Simmie & Martin, 2010) highlight the importance of making regions less reliant on already existing (related) knowledge and capabilities in the development of new economic activities. New activities within a region are expected to arise from the recombination of already existing local (related) knowledge, which makes the process of industrial diversification a highly path-dependant process that sometimes results in technological lock-ins. Policies mainly aiming at reinforcing a regions' assets and resources in the long-term thus increase the regions' exposure to such technological lock-ins and dependency on related knowledge, potentially with detrimental effects for employment and growth. Rather, policy makers are advised to take into account such a long-term perspective by finding the right balance between exploiting less risky related diversification options and focusing on what conditions are available or can be developed that can compensate for lacking related

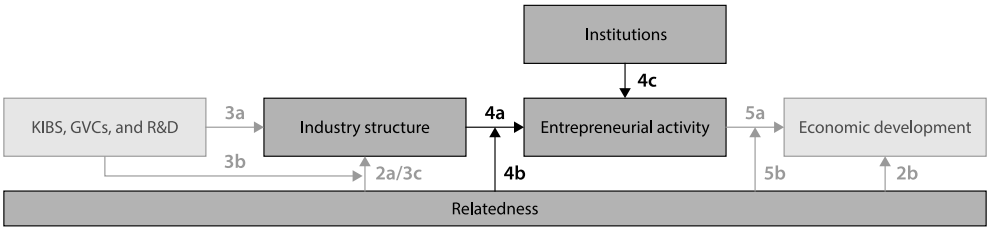
capabilities. With respect to the latter, two conditions enable regional economies to acquire new unrelated knowledge and capabilities: (1) conditions that provide external linkages for the inflow of knowledge, and (2) conditions that act as a bridging platform between unrelated actors, facilitating knowledge spillovers between them. Besides the presence of KIBS, participation in GVC, and investment in R&D, other conditions might offer such channels to acquire new unrelated knowledge as well.

The function of KIBS as external sources of knowledge enables them to facilitate knowledge spillovers between a diverse and sometimes unrelated and non-local set of actors (such as firms, governments, or research institutes). Due to their central position between these actors and ability to combine and transfer knowledge, KIBS can bring together different types of knowledge (e.g. about technology, markets, or regulation), fostering an entrepreneurial discovery process as intended with the Smart Specialisation Strategy. In addition, KIBS play an important role in the diffusion of GPTs, as by combining their client's knowledge with knowledge about the GPTs can enable the development of new applications. Involving KIBS in the development of Smart Specialisation Strategies may therefore help to identify more efficiently possible directions for specialisation. In addition, making KIBS more accessible likely benefits an entrepreneurial discovery process in the sense that it might reduce barriers for entry, by increasing recombination and transmission of knowledge about technology, markets, or regulation across a diverse set of actors.

Especially in cases with limited availability of local related knowledge and capabilities can the participation in GVCs support a region to develop new activities. From a Smart Specialisation perspective, supporting initial participation or location decisions of GVC leaders in these specific cases may assist the development of new unrelated activities. In later stages, upgrading of local activities after the initial participation or the promotion of technological diversification to related sectors or industries should become more important. Furthermore, firms' investment in R&D often results in firms purposefully having more knowledge than what is required for production, as such a situation allows them to timely act upon new innovations in related knowledge domains (Brusoni et al., 2001). Besides, generic R&D subsidies are in general expected to support the development of related innovation domains (Frenken, 2017). Subsidising those R&D efforts that specifically focus on the development of new applications of GPTs may therefore increase the additionality of these policies and benefit aggregate productivity and development of the region more.

Chapter 4

Does related variety foster regional entrepreneurship? Evidence from European regions[1]



[1]This chapter is based on Content, Frenken, and Jordaan (Forthcoming), Does related variety foster regional entrepreneurship? Evidence from European regions, Regional Studies.

4.1 Introduction

The investigation of the effects of different types of agglomeration externalities on the development of regional economies has motivated a vast expanding body of research ever since the seminal contributions of Glaeser et al. (1992) and Henderson, Kuncoro and Turner (1995). Particular interest has been devoted to the question whether variety ('Jacobs externalities') or specialisation ('MAR externalities') promotes regional growth. To date, however, the empirical evidence has been inconclusive (Beaudry & Schiffauerova, 2009; de Groot et al., 2016). Frenken et al. (2007) distinguish between related and unrelated variety, and argue that related variety can be expected to generate most of the spillovers between sectors, as knowledge from related sectors is more easily understood and recombined compared to knowledge from unrelated sectors. A recent review by Content and Frenken (2016) concludes that, although the evidence base is still rather small, the majority of studies on related variety support the hypothesis that related variety is a significant driver of regional employment growth.

Although studies that associate related variety with regional growth are suggestive of processes where inter-industry spillovers lead to new business opportunities, the exact mechanisms through which such opportunities are recognised and exploited remain underexplored. In this study, we analyse whether related variety spurs entrepreneurship - assuming that entrepreneurship, in turn, leads to employment growth. Access to knowledge spillovers can cause individuals to recognise new business opportunities and act upon them by becoming entrepreneurial (Acs et al., 2013; Audretsch, 1995; Audretsch & Lehmann, 2005). If we assume that related varieties are technologically proximate so that the knowledge necessary for these activities has similarities, it will be easier for individuals to learn and discover new ways of combining knowledge with related activities. Hence, familiarity with one knowledge area enables individuals to identify entrepreneurial opportunities in related knowledge areas (Shane, 2000). In turn, as many studies have shown, entrepreneurship is then expected to promote regional employment growth (Acs & Armington, 2004; Audretsch, Keilbach & Lehmann, 2006; Carree & Thurik, 2010; Fritsch & Mueller, 2004, 2007).

Our study is not the first to test whether related variety increases regional entrepreneurship. Previous studies have identified positive associations between these key variables for regions in Great Britain, Italy, China and Sweden (Bishop, 2012; Colombelli, 2016; Guo et al., 2016; Tavassoli & Jienwatcharamongkhol, 2016). Another study by Fritsch and Kublina (2017) on West-Germany, however, finds that unrelated variety positively moderates the effect of the start-up rate of new firms on employment growth.

The present study extends upon these studies in two ways. First, rather than using the start-up rate or the level of new firm formation as indicator of entrepreneurship, we measure entrepreneurship using survey data that distinguishes between necessity and opportunity-driven entrepreneurship. This distinction is important, as it is likely that the drivers of necessity and opportunity-driven entrepreneurship differ. Also, regional policy focuses primarily on stimulating opportunity-driven entrepreneurship given its expected larger positive impact on regional employment growth (Block & Wagner, 2010; Vivarelli, 2004). Second, we use a novel regional pan-European dataset covering many more regions than previous country studies have analysed. This also allows us to control for institutional effects at the national level, as we hypothesise that different 'Varieties of Capitalism' (VoC) (Hall & Soskice, 2001) influence levels and types of entrepreneurship. In particular, we distinguish between Liberal Market Economies (LMEs), Coordinated Market Economies (CMEs), Mediterranean Market Economies (MMEs), and Dependent Market Economies (DMEs).

The paper is organised as follows. Section two provides a literature review that we use to develop our hypotheses. Section three describes the data and methodology. Section four presents the main findings from our study and section five summarises and concludes.

4.2 Theoretical framework

Building on the early work of Marshall (1920), scholars have argued that firms benefit from being located near other firms operating in the same sector (Arrow, 1962b; Romer, 1990). This type of agglomeration externalities is usually referred to as localisation externalities. Relative high concentrations of economic activity in a sector create efficiency-enhancing opportunities, caused by labour market pooling and the use of common suppliers (Henderson, 2003). Furthermore, the co-location of firms in the same sector creates opportunities for knowledge spillovers, as firms operating in the same sector can easily understand and adopt each other's knowledge and innovations. In contrast, scholars have also argued that firms benefit from being located in agglomerations containing a variety of economic activities (Jacobs, 1969). The geographical proximity of firms in different sectors improves opportunities for exchanging and recombining ideas between sectors, benefitting the development of the local economy overall. Such externalities are usually referred to as Jacobs externalities. Following the seminal contributions by Glaeser et al. (1992) and Henderson et al. (1995), the empirical investigation of the effects of these different types of agglomeration externalities has fostered a vast expanding literature.

This literature, however, is inconclusive in terms of which type of these agglomeration externalities is more important as driver of regional growth. Depending on the circumstances in which they are tested, both can generate positive economic effects. To a large degree, the disparity in the findings can be explained by measurement and methodological differences, as well as differences in the levels of geographical and industrial agglomeration (Beaudry & Schiffauerova, 2009; de Groot et al., 2016).

Frenken et al. (2007) agree with Jacobs that innovation constitutes a recombinant process, in which different pieces of knowledge are recombined to develop new innovations. However, they also point out that some pieces of knowledge might be easier recombined than others. By making a distinction between related and unrelated variety, Frenken et al. (2007) propose a new interpretation of Jacobs externalities by arguing that for these externalities to be effective, some form of proximity should exist in order for inter-sectoral knowledge spillovers to occur. Regions with more related varieties - economic activity in cognitive proximate sectors - would therefore experience more employment growth as a result of new re-combinations that form new products and services, which in turn create new jobs. Having economic activity in cognitive distant sectors – unrelated variety - would make regions more resilient to sector specific shocks and in the long-run experience lower unemployment growth.

Frenken et al. (2007) present evidence for Dutch regions in support of their argument that related variety increases the rate of employment growth and unrelated variety decreases the rate of unemployment growth. Following these findings, a number of studies have tried to replicate the variety hypothesis for regions in other countries. In their review of these studies, Content and Frenken (2016) conclude that, although the evidence base is still rather small, the majority of studies present findings that support the hypothesis that related variety acts as a driver for regional employment growth, especially concerning knowledge-intensive activities. Mixed evidence, however, is found for the auxiliary hypotheses that related variety would also spur regional productivity growth and that unrelated variety would dampen unemployment growth. With respect to unrelated variety, some authors have argued that, although the opportunities for recombination occur less frequently, if successful, are more likely to produce radical innovations (Castaldi et al., 2015).

Although the evidence so far is suggestive of the workings of recombinant mechanisms that exploit related variety among a region's activities into new business opportunities, the question of which channels play a role in these processes remains unanswered. Entrepreneurship may well be such a channel, as entrepreneurs are typically actors that

recognise new business opportunities by associating knowledge from one domain with the context of other domains (Shane, 2000). This reasoning is consistent with the Knowledge Spillover Theory of Entrepreneurship (KSTE), which highlights the role of entrepreneurs in seizing opportunities generated by regional knowledge spillovers (Acs et al., 2013; Audretsch, 1995). At this point, it is important to distinguish between two types of entrepreneurship that both result in new firm formation, but are driven by different motives (Reynolds, Camp, Bygrave, Autio & Hay, 2001). First, there is 'opportunity-driven' entrepreneurship where individuals start new firms to exploit business opportunities unrecognised by fellow market participants. This type of entrepreneurship is likely to generate employment growth as such new businesses usually are better informed about untapped market opportunities created by spillovers (Vivarelli, 2004). Second, there is 'necessity-driven' entrepreneurship, referring to self-employed individuals who set up firms due to lack of other employment opportunities. These firms are often less productive (Vivarelli, 2004) and typically remain small without creating any additional new employment.

Audretsch (1995) represents a first attempt to connect regionally bounded knowledge spillovers to entrepreneurship, theorising that the knowledge generated by incumbent firms is not fully appropriated, leaving opportunities for new firms to exploit. Audretsch and Lehmann (2005) test for this by examining whether there is an association between regional investment in knowledge by universities and entrepreneurial activity. Their findings show that the number of firms located around universities is positively associated with the knowledge capacity and knowledge output of those universities. Acs, Braunerhjelm, Audretsch and Carlsson (2009) propose a more general model of 'the knowledge filter', linking the stock of knowledge and the efficiency of incumbents in commercialising their R&D efforts to the level of entrepreneurial activity. They argue that the stock of knowledge positively affects entrepreneurial activity, while the efficiency of incumbents regarding the appropriation of new knowledge exercises a negative effect on entrepreneurial activity (as fewer opportunities are left to exploit for entrepreneurs). Hence, both the characteristics of the actors and the environment in which the actors operate influence the probability that the knowledge filter is penetrated.

Turning to inter-industry spillovers between related sectors as a source of knowledge, one can analogously theorise that related variety positively affects entrepreneurship. The possession of proximate knowledge increases the absorptive capacity of economic agents and enables them to identify new entrepreneurial opportunities (Shane, 2000; Shane & Venkataraman, 2000). A high degree of related variety implies that economic

agents possess proximate knowledge allowing them to recognise new entrepreneurial opportunities if these were to occur. Following Acs et al. (2009), the extent to which such opportunities lead to the creation of new firms would then depend on the ability and efficiency of incumbent firms to exploit spillovers among related industries. Combining the Knowledge Spillover Theory of Entrepreneurship with the notion of related variety leads us to suggest that related variety in a region promotes knowledge spillovers, resulting in higher rates of opportunity entrepreneurship. Regarding the effect of unrelated variety, the literature is more ambiguous. On the hand, it could be argued that the opportunities stemming from the recombination of unrelated knowledge might be perceived as too risky by incumbent firms, thereby leaving more knowledge unappropriated and thus more opportunities for entrepreneurs to exploit. On the other hand, it could also be argued that nascent entrepreneurs are less likely to have the resources to bridge large cognitive distances or be able to raise the funding necessary to setup such a risky businesses.

One way to investigate this is to examine the link between (un)related variety and opportunity entrepreneurship directly. Another way is to look at the effect of (un)related variety on the ratio of opportunity over necessity entrepreneurship, capturing the overall quality of regional entrepreneurship given that opportunity entrepreneurship is more likely to create further employment growth. However, considering the ambiguity about the direction of impact of unrelated variety, no specific expectations can be formulated, which leads us to the following two hypotheses:

> *Hypothesis 1a: Related variety positively impacts the level of opportunity-driven entrepreneurial activity.*
>
> *Hypothesis 1b: Related variety positively impacts the ratio of opportunity-driven entrepreneurship over necessity-driven entrepreneurship.*

Important to note is that in our empirical analysis we also control for the effect of unrelated variety on entrepreneurship. We do not specify concrete hypotheses on the effect of unrelated variety on opportunity entrepreneurship however, as it is not clear what the nature of this effect is. Whereas our discussion of the Knowledge Spillover Theory of Entrepreneurship and the concept of related variety produces a clear prediction that related variety fosters entrepreneurship, no such clear relationship can be derived regarding unrelated variety. Also, whereas most studies find positive effects of related variety on employment growth, the effect of unrelated variety is much less uniform (Con-

tent & Frenken, 2016). In similar fashion, findings on the effect of unrelated variety on entrepreneurship from country studies are also heterogeneous, ranging from positve (Colombelli, 2016) to insignificant (Tavassoli & Jienwatcharamongkhol, 2016) or negative (Guo et al., 2016).

The innovation strategy of an incumbent firm relates to the institutional environment it operates in (Freeman, 1987). In this context, two major 'varieties of capitalism' are generally distinguished (Hall & Soskice, 2001): Coordinated Market Economies (CMEs), of which Germany is the most illustrative example, and Liberal Market Economies (LMEs), of which the UK is the most prominent example in Europe. The most important difference between these two varieties of capitalism is the extent to which institutions promote either cooperation or competition between economic actors. In CMEs, patient capital, labour protection and high levels of trust in suppliers and clients all promote long-term collaborations in a complementary fashion. This lends itself for continuous innovation along the supply chain as well as for informal knowledge exchange and collaborative projects among firms in related sectors. Given the high level of training and long-term commitment of a firm's employees, entrepreneurial opportunities will be relatively often exploited within incumbent firms rather than by new firms poaching ideas and labour from established firms. At the same time, given the strong labour protection and social security in CMEs, on average fewer people will be forced into necessity-driven entrepreneurship. In LMEs by contrast, relations are more transactional, opportunistic and volatile, while labour is less protected and committed. At the same time, compared to CMEs, employees are less restricted by non-compete clauses in setting up their own business and more venture capital and tax relief for start-ups is available. Compared to CMEs, then, entrepreneurial opportunities in LMEs are more likely to be exploited by opportunity-driven entrepreneurs setting up their own firms. And, as labour protection and social security in LMEs are relatively weak, necessity-driven entrepreneurship is also expected to be higher in LMEs than in CMEs.

> *Hypothesis 2a: LMEs have higher rates of opportunity-driven entrepreneurial activity compared to CMEs.*
>
> *Hypothesis 2b: LMEs have higher rates of necessity-driven entrepreneurial activity compared to CMEs.*

In addition to these two varieties of capitalism, we also control for the effects of Mediterranean Market Economies (MMEs) and Dependent Market Economies (DMEs). Hall and

Soskice (2001) refer to the Mediterranean group of economies as not fitting into either the CME group or the LME group. These countries have more intensive government intervention, bureaucracy and regulation compared to CMEs and LMEs. Social security is reasonably developed for selected professions and state organizations, but welfare and unemployment benefits are generally lower than in CMEs. Their economies are further characterised by significant agrarian and tourism sectors as well as lower levels of educational attainment (Amable, 2003; Schmidt, 2016).

East-European countries have been considered as a fourth variety of capitalism with a history of socialism. Between East-European economies, important institutional differences exist as well, as some have developed more into the direction of LMEs and others more into the direction of CMEs (Lane & Myant, 2007). In particular, the Baltic States have introduced drastic liberal reforms and low tax rates, and are now commonly classified as LMEs (Feldmann, 2006; Schmidt, 2016). The other Eastern European countries have reformed at a slower pace and can be considered to constitute a fourth variety of capitalism known as Dependent Market Economies (Nölke & Vliegenthart, 2009). Their financial institutions remain underdeveloped and their development strategies mostly rest on the attraction of foreign direct investment combined with an educated, but relatively cheap labour. The exception has been Slovenia, which has very similar institutions to neighbouring Austria, and is commonly considered a CME. Additionally, the social security systems in these economies are typically less developed in comparison with countries classified under one of the other varieties of capitalism, resulting in the following hypotheses.

Hypothesis 3: MMEs have the lowest rates of opportunity-driven entrepreneurial activity.

Hypothesis 4: DMEs have the highest rates of necessity-driven entrepreneurial activity.

4.3 Data and methodology

4.3.1 Entrepreneurship

Our study is not the first to analyse the relationship between related variety and regional rates of entrepreneurship. For instance, Bishop (2012) investigates how the rate of new firm formation in British regions is affected by diversity of the regional knowledge stock. The findings show that related and unrelated variety of the regional stock of knowledge

positively impact the rate of new firm formation. Using data on Chinese regions, Guo et al. (2016) examine whether related variety, relative to unrelated variety, has a larger positive effect on new firm formation. They find support for this hypothesis for the manufacturing industry at the city level. Colombelli (2016) also finds that a knowledge base that is characterised by a high level of related variety promotes entrepreneurial activity in Italian regions. Tavassoli and Jienwatcharamongkhol (2016) look at related variety and survival rates of newly established firms in Sweden. As previous survival studies neglect regional characteristics, the authors investigate the role of different types of agglomeration externalities. They find that the survival rate of Swedish entrepreneurial firms operating in knowledge intensive business sectors is positively influenced by related variety.

These studies all use new firm formation as a proxy for regional entrepreneurship. However, as already argued, this indicator ignores the difference between firms created for opportunity reasons and firms created for necessity reasons. In the present study we are especially interested in opportunity-driven entrepreneurship to test the hypothesis that related variety fosters business opportunities through inter-industry spillovers. Importantly, entrepreneurship, does not start with the creation of a new firm. Rather, it is the discovery of opportunities that is key, which (often much later) results in the creation of new firms (Shane, 2000). Therefore, indicators of entrepreneurship should not only focus on the level of new firm creation, they should be able to distinguish between firms that are created to exploit new opportunities and firms that are created for other reasons.

Since 2001, the Global Entrepreneurship Monitor (GEM) distinguishes between opportunity-driven entrepreneurs and necessity-driven entrepreneurs (Reynolds et al., 2001). The difference between these types of entrepreneurs lies within their underlying motivation. Opportunity-driven entrepreneurs start a new business to pursue new opportunities, whereas necessity-driven entrepreneurs start a business out a lack of other employment options. Empirically, this distinction has proven to be relevant from the macro perspective, as opportunity-driven entrepreneurs are over-represented in developed and under-represented in less-developed regions, while for necessity-driven entrepreneurs it is the other way around (Wennekers et al., 2005). From a policy perspective this distinction is also relevant, as opportunity-driven entrepreneurs have a higher probability of entry and also tend to setup more profitable firms than necessity-driven entrepreneurs (Block & Wagner, 2010; Vivarelli, 2004).

Using survey-based data provided by the GEM, we are able to explicitly distinguish between necessity and opportunity entrepreneurship. Each year, the GEM conducts an adult population survey on a representative sample containing at least 2000 individuals per coun-

try, who are different each year. Using this data, total entrepreneurial activity is measured as the share of the working age population (from 18 until 64) involved in the creation of a new business at the time the survey was conducted. A respondent is classified as an entrepreneur when he or she is either engaged in any activity to start a new business or has been running a new business for less than 3.5 years at the time of being interviewed. Therefore, our data also contains individuals who, whilst having identified an entrepreneurial opportunity, have not formally started a firm yet.[2]

Since we are interested in regional entrepreneurship, we pool the respondents into NUTS-2 and NUTS-1 regions. The annual survey-waves are not representative at these regional levels, as they contain 2000 individuals sampled at the national level. For this reason, we pool regional data over multiple waves and then take the average over these waves, which of course comes at the cost of losing time variation. In this process we take into account the composition of the populations in the regions in terms of age and sex and weigh the respondents' contribution to the mean accordingly. This approach is similar to other studies that have used the GEM data to calculate regional entrepreneurship indicators for EU regions (e.g. Bosma & Sternberg, 2014; F. G. Van Oort & Bosma, 2013; **?**). Following this approach, we extract regional data on entrepreneurs at the NUTS-2 level for 24 European countries[3] (184 regions) and at the NUTS-1 level for 2 European countries[4] (20 regions). With this information, we calculate indicators of average entrepreneurship for the period 2007 - 2014.

Figure 4.1 depicts the average rates of opportunity and necessity-driven entrepreneurship for this period. As some countries do not participate in the GEM survey or do not have enough observations to produce reliable measures at the NUTS-2 or NUTS-1 level[5], some regions in figure 4.1 appear grey. These regions are not included in the analysis of this study. We see that opportunity-driven entrepreneurship is rather scattered and especially high in Eastern Europe and in a limited number of regions outside Eastern Europe, while the lowest levels of opportunity-driven entrepreneurship are found in Belgium, France, Germany and Italy. Necessity entrepreneurship displays a more pronounced core-periphery pattern with the highest levels in Eastern Europe, Greece, Spain and Ireland and the lowest levels in Scandinavia. Finally note from the correlation mat-

[2] A detailed description on the GEM methodology can be found in the 'GEM Manual' by (Bosma, Coduras, Litvosky & Seaman, 2012).

[3] Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, and Sweden.

[4] France and United Kingdom.

[5] There is no data for the following countries: Bulgaria, Switzerland, Cyprus, Iceland, Liechtenstein, and Montenegro.

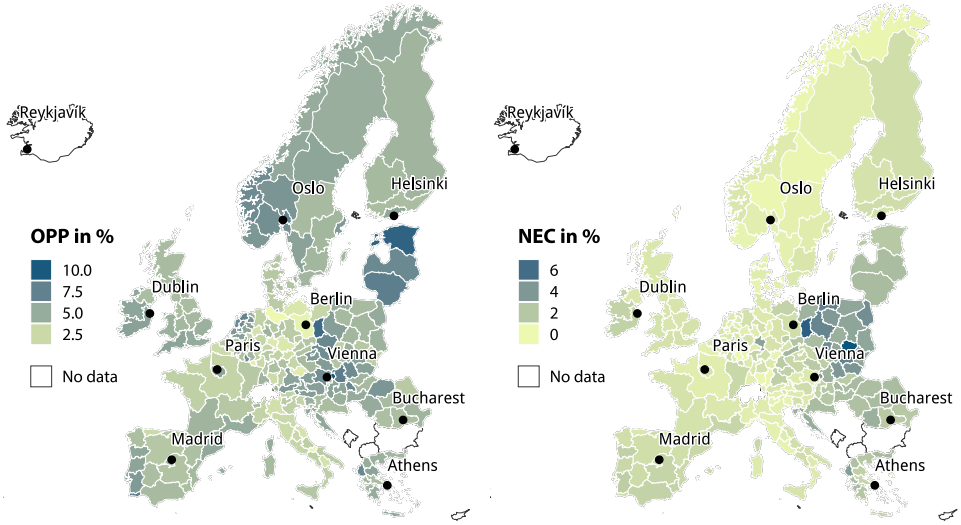


Figure 4.1: *Opportunity-(left) and necessity-driven entrepreneurship (right)*

rix in table B.2 of the appendix that the correlation between opportunity and necessity-driven entrepreneurship is rather low (0.23).

4.3.2 Related and Unrelated Variety

In line with the approach of Frenken et al. (2007) we calculate entropy measures for related and unrelated variety using employment shares at different levels of industry aggregation. Following an earlier study by Cortinovis and Van Oort (2015), we use the ORBIS database provided by Bureau van Dijk, which contains annual individual firm level data that can be aggregated to our spatial unit of analysis (NUTS-1 and NUTS-2). Information on the type of industry using the NACE classification scheme is available at the 4-digit level. This allows us to construct the related variety measure at a detailed 4-digit level for the regions, in contrast to other European data sources which have much less detail (de Groot et al., 2016). A disadvantage in using this data, however, is that the distribution of firms in terms of size is not representative as only those firms that provide sufficient information through annual reports are included, which tend to be on average larger firms. This biases the shares towards industries with a larger firm size. In order to ensure a sufficient time-lag we calculate the indicators of related and unrelated variety using the ORBIS data from 2006.

To calculate unrelated variety, we assume that firms belonging to different 2-digit sectors are unrelated. To calculate related variety we assume that firms belonging to different 4-digit sectors are related within each of their 2-digit sectors. The 4-digit shares pi are summed to derive the 2-digit shares P_g:

$$P_g = \sum_{i \epsilon S_g} p_i \tag{4.1}$$

Unrelated variety (UV), i.e. the entropy between the 2-digit sectors, is then calculated as:

$$UV = \sum_{g=1}^{G} P_g log_2\Big(\frac{1}{P_g}\Big) \tag{4.2}$$

Entropy within each 2-digit sector, H_g, is given by:

$$H_g = \sum_{i \epsilon S_g} \frac{p_i}{P_g} log_2\Big(\frac{1}{p_i/P_g}\Big) \tag{4.3}$$

Related variety (RV), then, is given by the sum of entropy within each 2-digit sector (4.3), weighted by employment shares (4.1):

$$RV = \sum_{g=1}^{G} P_g H_g \tag{4.4}$$

The maps in figure 4.2 depict the related and unrelated variety measures for the year 2006. The left map represents related variety, whereas the map on the right represents unrelated variety.
There are some spatial patterns observable in the levels of related variety. In particular, most regions in Spain, France and Northern Italy have high levels of related variety, while regions in the UK and Ireland have relative low levels. Regional levels of unrelated variety are more diffuse. Interestingly, the correlation between related and unrelated variety is quite high (0.55).[6]

[6] Note that some South-East European countries are not included in the maps (i.e. Bosnia and Herzegovina, Serbia, Albania, Macedonia, and Montenegro). This is because the ORBIS dataset does not contain sufficient

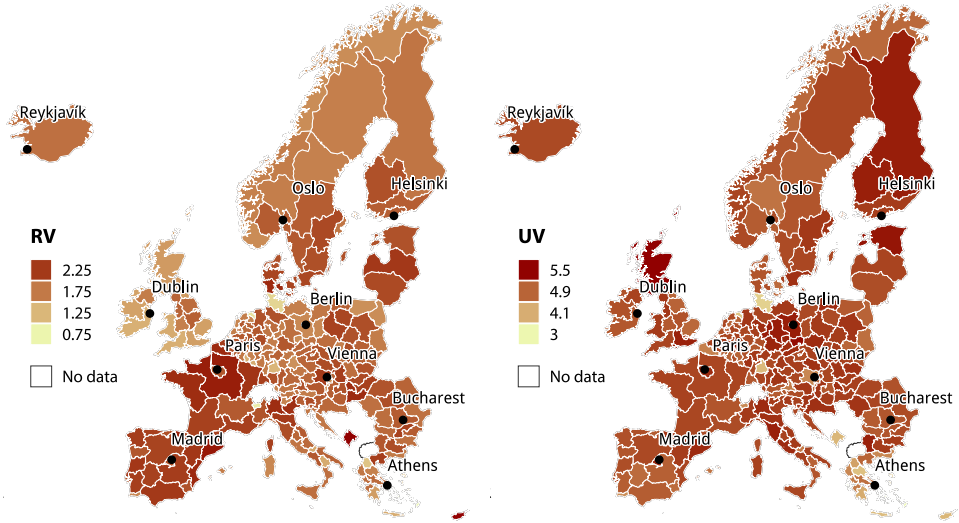


Figure 4.2: *Related (left) and unrelated variety (right) in 2006*

4.3.3 Estimation method

To test the hypotheses, we estimate a cross-sectional regression model. The model is estimated with Ordinary Least Squares at the NUTS-1 and NUTS-2 level and is specified as:

$$y_i = \alpha_i + \lambda W y_i + \beta_1 UV_i + \beta_2 RV_i +' X_i' \phi +' VOC_i' \vartheta + \rho W u_i + \varepsilon_i \tag{4.5}$$

where y_i is either total entrepreneurial activity, opportunity-driven entrepreneurial activity, necessity-driven entrepreneurial activity, or the ratio of opportunity over necessity-driven entrepreneurial activity in region i. The primary explanatory variables in our model are related variety RV_i and unrelated variety UV_i. The different varieties of capitalism are captured by dummy variables labelled LME_i, CME_i, MME_i, and DME_i and are represented by the vector 'VOC_i. Figure 4.3 shows the different varieties of capitalism in Europe. It shows that CMEs are clustered more to the north of Europe, whereas DMEs are mainly present in the east. Apart from the Baltic States, most East-European countries are classified as DME.

information about these countries to calculate the variety indicators. There is also no information available to calculate the dependent variables for these countries.

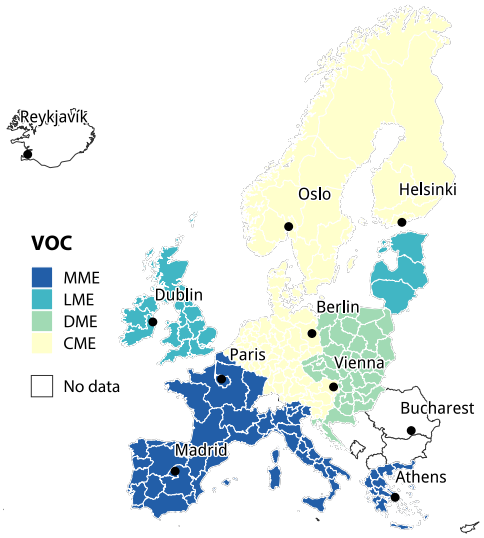


Figure 4.3: *Varieties of capitalism*

The other control variables, captured in the vector 'X_i, will be discussed more elaborately in the next section. Two spatial terms are included; the first term $\lambda W y_i$ accounts for the spatial autoregressive process of the dependent variable; including only this term would result in a spatial error model (SEM). The second term $\rho W u_i$ captures the spatial correlation in residuals of neighbouring regions; including only this term would result in a spatial lag model (SAR). Including both spatial terms results in a spatial autoregressive model with autoregressive disturbances (SARAR).

To test and, if necessary, control for spatial correlation in the residuals and/or dependent variable, we follow Hendry's methodology (Florax, Folmer & Rey, 2003). We start with the restricted and unrestricted models (SARAR and SEM) using a maximum likelihood estimator and subsequently test the common factor restriction using a likelihood ratio test. If spatial autocorrelation seems to be present, the result of this test will then determine whether we should make use of a spatial error model or a spatial lag model. We use an inverse distance spatial weight matrix to account for potential geographical dependencies. Regions will be classified as neighbours when the distance between them is smaller than 750 kilometres, using the inverse of the distance between the regions as weight. If the distance between regions is larger than 750 kilometres, this weight is set to zero.

The distance matrix is row-standardised such that the impact of neighbouring regions is equalised.

4.3.4 Control variables

We control for several factors that are likely to influence regional entrepreneurial activity. Table 4.1 gives an overview of all the variables used in the analysis, while summary statistics and a correlation matrix are provided in the . We control for the effect of income by including Gross Regional Product per capita (GRP), as the overall level of development of a region is likely to influence the amount of entrepreneurial opportunities available. More densely populated regions are also expected to produce more entrepreneurs due to urbanisation economies and specialised demand. We control for population density by including two variables: the average number of inhabitants per square kilometre and a dummy variable capturing whether a region has a city with more than half a million inhabitants. The level of human capital is likely to influence potential entrepreneurs' ability and skills to identify opportunities and consequently act upon them. To control for this, we include the percentage of the working age population having completed a tertiary education in the model. Finally, we control for the rate of unemployment as it is expected to act as push mechanism for individuals to create a firm. In particular, unemployment is expected to motivate individuals to engage in necessity-driven entrepreneurship.

Variable	Description	Source
TEA	Average percentage of the working age population involved in entrepreneurship over the period 2007-2014.	GEM
TEA_OPP	Average percentage of the working age population involved in opportunity-driven entrepreneurship over the period 2007-2014.	GEM
TEA_NEC	Average percentage of the working age population involved in necessity-driven entrepreneurship over the period 2007-2014.	GEM
OPP/NEC	Share of TEA_OPP / TEA_NEC	GEM
UV	Unrelated variety in 2006.	BvD
RV	Related variety in 2006.	BvD
LNGRPPC	Logarithm of Gross Regional Product per/capita in 2006 (log).	Eurostat
LNPDEN	Logarithm of population density in 2006 (log).	Eurostat
HC	Percentage points of working age population who completed tertiary education in 2006.	Eurostat
CITY	Presence of a city with >500,000 inhabitants in 2006.	Eurostat
UNEMP	Average rate of unemployment over the period 2007 until 2014.	Eurostat
VOC	LME (Estonia, Ireland, Latvia, Lithuania, United Kingdom), CME (Austria, Belgium, Denmark, Finland, Germany, Luxembourg, Netherlands, Norway, Slovenia, Sweden), MME (France, Greece, Italy, Portugal, Spain), DME (Croatia, Czech Republic, Hungary, Poland, Slovakia)	

Table 4.1: *Variables description*

4.4 Results

Table 4.2 presents the findings from the estimation of our model in which we look at what the effect of unrelated and related variety is on different types of entrepreneurship. Model (1) in table 4.1 shows no association between related and unrelated variety and total regional entrepreneurship when we omit the other control variables. When the other control variables are included in Model (2), the estimated coefficient of related variety persists to be insignificant. Unrelated variety now carries a significant negative coefficient, indicating that unrelated variety lowers the degree of total regional entrepreneurship. A possible interpretation holds that unrelated variety within an economy renders it more difficult for entrepreneurs to identify possible inter-industry spillovers. As such, this finding is in line with Guo et al. (2016), who identify a negative effect of unrelated variety on the level of entrepreneurship in Chinese cities, while it opposes the findings by Bishop (2012) and Colombelli (2016), who identify a positive effect of unrelated variety in knowledge on entrepreneurship.

	(1) TEA	(2)TEA	(3) TEA_OPP	(4) TEA_NEC	(5) OPP/NEC
UV	-0.286 (0.379)	-1.632** (0.413)	-1.243** (0.361)	-0.412** (0.156)	-0.061 (0.156)
RV	-0.301 (0.499)	0.562 (0.485)	0.815* (0.401)	-0.215 (0.178)	0.374* (0.172)
LNGRPPC		1.322* (0.572)	1.939** (0.435)	-0.701** (0.211)	0.997** (0.155)
CITY		0.705* (0.298)	0.346 (0.233)	0.340** (0.120)	-0.153 (0.099)
LNPDEN		-0.294** (0.108)	-0.233** (0.084)	-0.045 (0.038)	-0.092+ (0.048)
UNEMP		0.074* (0.033)	0.037 (0.025)	0.044** (0.013)	-0.034** (0.010)
HC		0.022 (0.022)	0.006 (0.018)	0.016* (0.007)	-0.013* (0.006)
VOC_LME		-	-	-	-
VOC_CME		-1.131* (0.522)	-1.142** (0.423)	-0.007 (0.148)	-0.052 (0.132)
VOC_MME		-1.826** (0.657)	-1.690** (0.529)	-0.049 (0.187)	-0.300* (0.135)
VOC_DME		2.785** (0.738)	1.183* (0.586)	1.652** (0.240)	-0.646** (0.140)
Constant	8.259** (1.534)	0.560 (6.190)	-8.875+ (4.757)	9.859** (2.301)	-7.557** (1.448)
Observations	204	204	204	204	204
R-squared	0.007	0.407	0.274	0.652	0.583

*Robust standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table 4.2: *General estimation results*

Once we split total entrepreneurship into opportunity-driven entrepreneurship (model 3) and necessity-driven entrepreneurship (model 4), we observe that unrelated variety persists to exercise a negative impact on both types of entrepreneurship, while related variety only increases regional opportunity-driven entrepreneurship. This finding provides support for our hypothesis 1a. In Model (5), we use the ratio of opportunity over necessity entrepreneurship as dependent variable, reflecting the relative quality of regional entrepreneurship. The importance of related variety as suggested in hypothesis 1b is confirmed, as the estimation produces a significant positive effect. Unrelated variety does not significantly influence this indicator of regional entrepreneurship.

Regarding the effects of the other control variables, we find that GRP per capita increases the rate of opportunity-driven entrepreneurship, whereas it decreases the rate of necessity-driven entrepreneurship. This result is likely to reflect that more developed economies on average offer better opportunities for entrepreneurship, while individuals in less developed economies are by contrast more often pushed into starting up a firm due to limited employment options. As expected, unemployment seems to act as push mechanism for individuals to become entrepreneurial by necessity, while no effect is observed in the case of opportunity-driven entrepreneurs. Perhaps surprisingly, the control variables population density, presence of a large city and human capital do not support opportunity-driven entrepreneurship, while some effect of these variables on necessity-driven entrepreneurship is observable.

The dummy variables with the prefix VOC represent the different varieties of capitalism; VOC_LME is the reference category against which the other VoC dummies are interpreted. From model (2) we can infer that regions in DMEs have substantially higher rates of total entrepreneurial activity. Regions in CMEs and MMEs have significantly lower levels of entrepreneurial activity. Moving on to Models (3) and (4), we can observe that opportunity-driven entrepreneurship is significantly lower in regions in CMEs, supporting hypothesis 2a. This type of entrepreneurship, however, is also found to be significantly higher in regions in DMEs. Moreover, it is found to be lower in MMEs compared to LMEs and CMEs[7], which supports hypothesis 3. Necessity-driven entrepreneurship does not seem to differ significantly between regions in CMEs and LMEs, contrasting our expectations expressed in hypothesis 2b. This finding suggests on average equal levels of necessity-driven entrepreneurs in these groups, while we expected higher levels in LMEs. This finding might be explained by policies adopted by Germany and other countries (Caliendo & Kritikos, 2010; Caliendo & Künn, 2014) to motivate unemployed people to become an entrepreneur. These policies have induced substantial numbers of individuals to start a firm and thus become necessity-driven entrepreneurs (Dvouletý & Lukeš, 2016). This in turn would have decreased the ratio of opportunity over necessity entrepreneurs as well, possibly explaining the insignificant coefficient for the CME dummy in model (5). Finally, we find that regions in DMEs have the highest level of necessity-driven entrepreneurship, while regions in MMEs do not differ significantly with regions in LMEs and CMEs[8]. This finding supports hypothesis 4.

It is important to stress that the findings on the effects of the VoC variables need to be interpreted with the necessary caution. One issue is that for some countries it is not entirely clear which VoC category is most appropriate. To examine whether this affects our findings, we re-estimate the model with France classified as CME instead of MME and the Baltic states as a separate VoC category. The reclassification of France does not impact our findings as presented in table 4.2. The estimated effect of the additional VoC variable for the Baltic States is significant in some estimations, suggesting that these states contain VoC elements that are distinctly different from the other groups of countries.[9]

Second, although the distinction between the different VoC categories at the national level is useful, it does not capture the feature that, within countries, regions may exhibit substantial deviations from national institutional arrangements (Gertler, 2010; Rafiqui,

[7] A Wald-test on the equality of the coefficients on CME and MME returned a test value of 2.75, which is significant at the 10% level.

[8] A Wald-test on the equality of the coefficients on MME and CME returned an insignificant test value (0.11).

[9] Due to space constraints we do not present the full findings here but note that they are available upon request.

2010; Sternberg, Kiese & Stockinger, 2010). It also does not cover the effects that informal regional institutions may generate on regional industry dynamics and growth (e.g. Cortinovis et al., 2017; Tabellini, 2010). Furthermore, it is important to recognise that VoC institutional characteristics are subject to continuous change (Bathelt & Gertler, 2005), changes that may materialise and impact in different ways at subnational levels, an aspect which we cannot address in our cross-sectional analysis.

Having said this, the nature of the estimated effect of most of the VoC dummies in table 4.2 is broadly in line with our expectations, reflecting their general importance for regional entrepreneurship. Table 4.3 shows the findings from estimating the models omitting the VoC dummies. The R2-values of the models that include the VoC dummies are much higher than the values in the corresponding models excluding these dummies. Also, the significance of the estimated effect of related variety in the model with opportunity entrepreneurship is affected when the estimations do not control for the varieties of capitalism. This indicates that regional entrepreneurship patterns are to an important extent structured by national factors, including institutions, underlying the notion of VoC. Further research is required to assess more accurately whether and how subnational deviations from country-level VoC institutional frameworks may influence the different types of regional entrepreneurship.

	(1) TEA	(2)TEA	(3) TEA_OPP	(4) TEA_NEC	(5) OPP/NEC
UV	-0.286 (0.379)	-0.717 (0.497)	-0.607 (0.393)	-0.152 (0.190)	-0.070 (0.151)
RV	-0.301 (0.499)	-0.574 (0.556)	-0.089 (0.414)	-0.415* (0.192)	0.307* (0.149)
LNGRPPC		-2.078** (0.496)	-0.226 (0.346)	-1.932** (0.234)	1.289** (0.112)
CITY		0.965** (0.366)	0.567* (0.267)	0.399** (0.142)	-0.2* (0.096)
LNPDEN		-0.115 (0.121)	-0.134 (0.096)	0.033 (0.040)	-0.112* (0.045)
UNEMP		-0.053+ (0.03)	-0.049* (0.02)	0.007 (0.013)	-0.037** (0.009)
HC		0.037 (0.023)	0.022 (0.018)	0.012+ (0.007)	-0.005 (0.006)
Constant	8.259** (1.534)	31.632** (5.608)	10.477** (3.949)	21.615** (2.657)	-10.588** (1.290)
Observations	204	204	204	204	204
R-squared	0.007	0.126	0.058	0.480	0.544

*Robust standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table 4.3: *Estimation results without VOC dummies*

To further scrutinise our main finding that related variety fosters opportunity-driven entrepreneurship, we re-estimate the model with controls for spatial effects. The results are

presented in table 4.4. Following Hendry's method (Florax et al., 2003), we start by estimating a restricted spatial model (SARAR), using a maximum likelihood estimator and assuming a priori that spatial correlation among our independent and dependent variables exists, as shown in column (1). Next, we estimate an unrestricted spatial model (SEM) using a maximum likelihood estimator, shown in column (2), and test whether the model can be simplified. Using a likelihood ratio test, the common factor restriction (with its null hypothesis that $\lambda\beta = -\lambda\beta$), is not rejected. Subsequently, the next step is to test for the significance of ρ. As it is insignificant in column (2), our final specification is a spatial independence model.

	(1) SARAR 750	**(2) SEM 750**	**(3) SARAR 500**	**(4) SARAR 250**
UV	-1.204** (0.371)	-1.238** (0.335)	-1.149** (0.356)	-1.094** (0.353)
RV	0.788+ (0.426)	0.819* (0.417)	0.757+ (0.419)	0.705+ (0.417)
LNGRPPC	1.942** (0.537)	1.943** (0.401)	1.956** (0.439)	1.886** (0.424)
CITY	0.362 (0.241)	0.351 (0.242)	0.374 (0.240)	0.376 (0.237)
LNPDEN	-0.236** (0.087)	-0.232** (0.083)	-0.233** (0.084)	-0.225** (0.083)
UNEMP	0.033 (0.029)	0.036 (0.028)	0.027 (0.028)	0.018 (0.028)
HC	0.005 (0.018)	0.006 (0.016)	0.003 (0.016)	0.005 (0.016)
VOC_LME	-	-	-	-
VOC_CME	-1.174** (0.411)	-1.164** (0.400)	-1.291** (0.402)	-1.400** (0.404)
VOC_MME	-1.736** (0.507)	-1.721** (0.483)	-1.865** (0.476)	-1.949** (0.472)
VOC_DME	1.129* (0.456)	1.158* (0.454)	0.994* (0.457)	0.865+ (0.458)
λ	-0.073 (0.492)	0.097 (0.442)	0.053 (0.491)	0.237 (0.415)
ρ	0.34 (0.725)	-	0.581 (0.428)	0.647* (0.329)
σ^2	1.599** (0.159)	1.602** (0.159)	1.582** (0.157)	1.560** (0.155)
Constant	-8.607 (5.824)	-9.356* (4.719)	-9.325+ (4.817)	-9.531* (4.668)
Log likelihood	-337.474	-337.569	-336.669	-335.502
Observations	204	204	204	204

*Dependent variable: TEA_OPP. Column (1) and (2) use 750km as cut-off. Column (3) 500km and column (4) 250km. Standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table 4.4: *Spatial autocorrelation.*

As a further robustness test, we also estimate the model using shorter cut-off points for the spatial weight matrix. Models (3) and (4) are SARAR models similar to Model (1), but with spatial cut-off points of 500 and 250 kilometres respectively. The coefficient on λ becomes larger with these smaller cut-off points but remains insignificant, suggesting that at these shorter distances the level of opportunity-driven entrepreneurship in neighbouring regions has no predictive power regarding regional entrepreneurship. The

coefficient on ρ is not significant when cut-off points of 750 and 500 kilometres are used, while in the case with 250 kilometres as cut-off point it becomes positive and significant. This suggest that within this distance spatial correlation among the residuals exists. Looking at the coefficient of related variety in models (1), (3), and (4), we notice that it is similar to the estimated coefficient from the model without spatial terms, although the effect is estimated somewhat less precisely.[10] Unrelated variety persists to exercise a negative effect on entrepreneurship in all the estimations.

4.5 Conclusion

Recent studies report positive effects of related variety on regional employment growth. However, how related variety leads to employment growth has remained implicit (Content & Frenken, 2016). This study examines whether related variety fosters entrepreneurship, motivated by the Knowledge Spillover Theory of Entrepreneurship which posits that regions endowed with more knowledge spillovers can expect more entrepreneurial activity (Acs et al., 2009), and, in turn, more employment growth. The present study is the first that analyses the effect of related variety on regional entrepreneurial activity across Europe. Importantly, we distinguish between necessity-driven and opportunity-driven entrepreneurship, as spillovers from related industries are expected to foster the latter type of entrepreneurship in particular. Elaborating on Hall and Soskice (2001), we further hypothesise that different 'varieties of capitalism' show different rates of opportunity-driven and necessity-driven entrepreneurship.

As hypothesised, related variety has a positive impact both on the level of opportunity-driven entrepreneurship as well as on the ratio of opportunity over necessity-driven entrepreneurship. Also, the estimations show no effect of related variety on the level of necessity-driven entrepreneurship. We interpret this result as reflecting that necessity-driven entrepreneurs start a business out of a lack of employment options, rather than out of opportunities from knowledge spillovers stemming from related variety. This interpretation is further supported by a robust positive association between regional unemployment and necessity-driven entrepreneurship. Opportunity-driven entrepreneurs, by contrast, leverage opportunities stemming from knowledge spillovers caused by related variety. Furthermore, we also identify a persistent negative effect of unrelated variety on the various indicators of regional entrepreneurship. This might reflect that the ab-

[10] We estimated the SARAR-750 model with different dependent variables as well, i.e. total entrepreneurial activity (TEA), necessity-driven entrepreneurship (TEA_NEC), and the share of opportunity over necessity-driven entrepreneurship. The results, shown in table B.3 of the appendix, are similar to those of 4.2.

sence of cognitive proximity increases the difficulty for individuals to identify or exploit opportunities for entrepreneurship. Our primary focus in this paper lies with the identification of entrepreneurship as a possible mechanism that transmits positive growth effects from related variety. Our finding that unrelated variety lowers entrepreneurship in European regions is clearly also important and further research will benefit from a further examination of this negative effect.

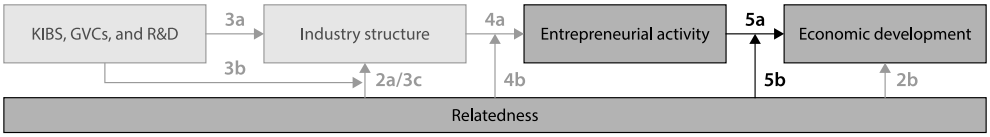
Varieties of capitalism also explain part of the regional variation in entrepreneurship. Regions in countries classified as Liberal Market Economies host more opportunity-driven entrepreneurs compared to regions in Coordinated Market Economies. Entrepreneurial opportunities in LMEs are more often exploited by new ventures (especially spinoffs), while such opportunities in CMEs are captured more often by incumbent firms and their employees. Unexpectedly, regions in Dependent Market Economies display even higher rates of opportunity-driven entrepreneurship than regions in LMEs, despite the commonly held notion that their institutions are less supportive for new ventures. Although the data on entrepreneurial activity provided by GEM is carefully weighted for the age and gender composition of the regional populations and has a questionnaire design that has been developed and improved for quite some years, the usual limitations that come with using survey data do apply to the present study as well. For instance, questions may be vulnerable to misinterpretation and there may be respondents that do not feel encouraged or comfortable to provide accurate answers. Another limitation of this study concerns the use of the ORBIS dataset to calculate the variety measures. In this dataset, large firms are overrepresented, which means that sectors with mostly large firms are overrepresented in the variety measures. Lastly, our unit of analysis (NUTS-1 and NUTS-2) is arguably not the most meaningful spatial level to capture knowledge spillovers. Instead, labour market regions (NUTS-3) may constitute the more appropriate spatial unit of analysis. In this respect, the challenge will be to develop comparable data across Europe at the level of local labour markets.

Our study represents a first attempt to unpack the channels through which related variety among a region's industries supports regional employment growth. We suggest that opportunity-driven entrepreneurship may well be one such channel, as spillovers create business opportunities that entrepreneurs aim to exploit. This leaves open the question what other channels exist. For example, one can expect that related variety increases social networking as well as labour mobility across industries (Breschi & Lissoni, 2009). Furthermore, relatedness in a region's industrial structure provides a platform for specific actors with recombinant capabilities such as knowledge-intensive business services

and applied research organizations (Asheim, Boschma & Cooke, 2011). As a second line of research, we advocate a further theoretical and empirical deepening of the research field's understanding of how national institutions influence entrepreneurship. In particular, an interesting question remains to what extent institutions – and their complementarities – relevant to entrepreneurship map onto the existing varieties of capitalism that have been distinguished so far. Furthermore, significant differences are likely to exist between institutions or cultures across regions within countries (Charron, Dijkstra & Lapuente, 2014; Rodriguez-Pose & Di Cataldo, 2015). It will therefore be worthwhile to develop methods to disaggregate the VoC framework at a sub-national level to clarify its relation with regional entrepreneurship. A third question that future research may wish to examine is whether opportunity-driven entrepreneurship, as well as the other aforementioned spillover channels, indeed foster employment growth. A fully-fledged model of related variety, then, would analyse both the direct effect of related variety on employment growth and its indirect effects mediated by various spillover channels. Although such an analysis is more demanding in terms of empirical data, it is certainly worthwhile for the related variety literature to 'come full circle'.

Chapter 5

Entrepreneurial ecosystems, entrepreneurship and economic growth: New evidence from European regions



5.1 Introduction

There is a growing recognition of the role of entrepreneurship as important driver of economic growth and development (Bjørnskov & Foss, 2016; Block et al., 2017; Van Praag & Versloot, 2007). Several studies report positive effects of new firm creation on employ-

ment growth or productivity growth (Acs & Armington, 2004; Audretsch & Fritsch, 2002; Carree & Thurik, 2008). Other studies present corroborating evidence that rates of entrepreneurship are positively associated with output, productivity, and employment growth (see e.g. Castaño-Martínez, Méndez-Picazo & Galindo-Martín, 2015; Urbano & Aparicio, 2016).

These findings, however, do not imply that policies that focus only on the promotion of entrepreneurship will be successful in the promotion of economic growth. In particular, effective policies need to be built around the recognition that relationships between entrepreneurship and economic performance are embedded in (regional) entrepreneurial ecosystems (e.g. Stam, 2015). In order to fully understand differences in the relationship between entrepreneurship and growth between countries and regions, more research is urgently required into how the ecosystem conditions this relationship. Stam (2015) defines the concept of the entrepreneurial ecosystem as "a set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship" (p. 1785). Levels and types of entrepreneurship in such ecosystems are both the result and the prime mediator of the relationship between institutions and aggregate economic growth (Bosma, Content, Sanders & Stam, 2018).

The purpose of this paper is to conduct an empirical analysis on the question whether and how entrepreneurial ecosystems affect the relationship between entrepreneurship and regional economic growth. Although becoming increasingly popular as a concept, both academically and among policy makers (Isenberg, 2010; Stam & Spigel, 2017), approaches that focus on entrepreneurial ecosystems suffer from being relatively undertheorized Stam (2015) and not yet being adequately measured (Stam, 2018). In this context, our paper aims to provide much needed novel empirical evidence on whether and how entrepreneurial ecosystems matter for the positive impact of entrepreneurship on economic growth.

To do so, we use newly assembled data for EU regions. We combine information from the Global Entrepreneurship Monitor (GEM) survey with data from Eurostat for 169 NUTS-1 and NUTS-2 regions. We first estimate the general relation between entrepreneurship and economic growth within a neo-classical growth framework for the full set of regions. Applying a multi-level structure reveals the results change quite significantly. Then we examine whether the relationship is different for groups of EU regions. Importantly, rather than choosing arbitrary cut-off points to allocate regions into groups, we estimate a latent regression model that allows us to endogenise the sorting of regions according to a specific set of observed variables that capture the internal context of the regions

Bruns et al. (2017). Following this, we compare sets of variables that are linked to underlying entrepreneurial ecosystems between the groups of regions and examine whether they provide explanations for structural differences in the relationship between entrepreneurship and growth that we identify for the groups of EU regions.

The paper is structured as follows. Section two provides a selective literature review to position our work in the literature. Section three discusses the data and presents our empirical strategies. Section four presents the main findings from our analysis. Cross-sectional ordinary least squares (OLS) estimations of neo-classical growth models on our full sample of regions produce significant positive effects of various indicators of regional entrepreneurship, but these results disappear in a multilevel specification that is statistically preferred. Further examination of the relationship based on the latent class model produces clear indications that the relationship between entrepreneurial activity and growth does not uniformly apply to all regions. Whereas a relatively large group of European regions seems to have an ecosystem in which a positive growth effect from entrepreneurship arises, typically smaller groups of regions experience no positive or even negative growth effects from regional entrepreneurship. An exploratory comparison of a large list of regional characteristics reveals clear differences between the various groups of regions, suggesting that the quality of the regional entrepreneurial ecosystem drives the relationship between entrepreneurship and economic growth across the groups of regions. Section five summarises, discusses policy implications and provides suggestions for future research.

5.2 Literature review

Regional entrepreneurship is increasingly linked to a variety of positive economic effects (Block et al., 2017; Carree & Thurik, 2010; Van Praag & Versloot, 2007). Scholars have empirically investigated entrepreneurship in various ways, considering different levels of spatial aggregation, different proxies for entrepreneurship, as well as different outcome variables. Several studies examine the effect of new firm creation and find positive associations with regional employment growth (Acs & Armington, 2004; Audretsch & Fritsch, 2002; Stuetzer et al., 2018; Van Stel & Suddle, 2008). Other studies have taken growth in gross output or productivity of states or regions as their dependent variable. For instance, Robbins, Pantuosco, Parker and Fuller (2000) find that entrepreneurial activity, proxied by the share of small business employment, has a positive impact on both the growth in Gross State Product and productivity in US states. Another example is Bosma

et al. (2011), who find that firm entry fosters total factor productivity growth in Dutch regions.

Instead of using new firm births or the prevalence of small business as a proxy for entrepreneurial activity, another strand of the literature uses measures provided by the Global Entrepreneurship Monitor adult population survey (Reynolds et al., 2005). One indicator that this survey provides is total early-stage entrepreneurial activity (TEA), capturing the share of all respondents in the working-age population that can be classified as either a nascent entrepreneur or an owner-manager of a new business existing up to 42 months. Recent studies that relate this measure to growth in income and/or productivity levels tend to find positive effects. For instance, Urbano and Aparicio (2016) construct a panel of 43 countries covering the period from 2002 to 2012 and find that total entrepreneurial activity exercises a positive effect on GDP. Using a structural equation model approach covering 13 European countries in 2012, Castaño-Martínez et al. (2015) find that entrepreneurial activity promotes economic performance in terms of GDP per capita. Findings on the effect on per GDP per capita growth are less clear, however (e.g. Hessels & Van Stel, 2011; Prieger, Bampoky, Blanco & Liu, 2016).

The evidence that indicates that regional entrepreneurship generates positive economic effects does not warrant the conclusion that policies that focus only on the promotion of entrepreneurship will be successful in the promotion of economic growth. Essentially, empirical studies on direct economic effects from entrepreneurship do not take into account that the relationship between entrepreneurship and growth is embedded in entrepreneurial ecosystems. Among policymakers and publicly minded entrepreneurs, the importance of such ecosystems is increasingly recognised (Feld, 2012; Isenberg, 2010; Stam & Spigel, 2017). In contrast to its popularity, the approach was until recently highly undertheorized (Stam, 2015; Stam & Spigel, 2017), not yet adequately measured (Stam, 2018) and empirical evidence on the effects of these ecosystems is lacking.

The entrepreneurial ecosystem is defined by Stam (2015) as "a set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship" (p. 1765). Entrepreneurship in such an ecosystem is both a result and a mediator of the relationship between institutions (interdependent actors) and aggregate economic values. The extent to which the ecosystem generates productive entrepreneurship, i.e. the type of entrepreneurship that is expected to contribute to growth (Baumol, 1993), is dependent on the quality and interdependence of the various ecosystem elements, their interactions as well as aggregate economic outcomes. Differences in entrepreneurial ecosystems will thus engender different kinds of entrepreneurial activity, which in turn

determine the degree to which these kinds of entrepreneurial activities can become productive in terms of economic benefits.

The different elements of the entrepreneurial ecosystem can be divided into systemic conditions - networks, leadership, finance, talent, knowledge, and intermediate services - and framework conditions - formal and informal institutions, physical infrastructure, and demand. Institutions, both formal and informal, play an important role both for the prevalence of different types of entrepreneurship and for economic development (Baumol, 1990; North, 1990). Physical infrastructure can enhance human interactions, connectivity, and reduce costs, which helps not only individuals to recognise entrepreneurial opportunities (Audretsch, Heger & Veith, 2015), but more general, economic activity as well. The level and variety in demand for goods and services acts as pull mechanism for entrepreneurship, whereas active networks of entrepreneurs provide information flows, enabling opportunity recognition and resource allocation (Aldrich & Zimmer, 1986).

Entrepreneurs are put centre stage in the ecosystem approach, not only as an output of the system but also as creators (or leaders) of the system (Feld, 2012). Leadership within the entrepreneurial ecosystem approach should be seen as having certain role models or otherwise visible entrepreneurs (Stam, 2018). Accessible financing for entrepreneurs is an important condition for their ability to grow and to sustain competitive, and ultimately for economic development as well (Kerr & Nanda, 2009; King & Levine, 1993). The supply of talent or human capital in the form of high skilled and creative individuals is important for entrepreneurial activity and economic development (Acs & Armington, 2004; Lee, Hong & Sun, 2013). The creation and the growing stock of knowledge form important sources of spillovers for entrepreneurial opportunities (Audretsch, 1995; Audretsch & Lehmann, 2005). Lastly, the presence of intermediate and support services is important to assist new entrepreneurs and increase the efficiency of the economy.

Despite the growing acceptance of the importance of the entrepreneurial ecosystem for the effects of entrepreneurship, most studies have focused mainly on identifying the effects of the ecosystem on the level and types of entrepreneurship. Several studies find that regional ecosystems play a role in the degree that regions are characterised by the creation of high growth new firms (Mason & Brown, 2013). Others look at the rate of new firm creation in the EU and present evidence that several components of regional entrepreneurial ecosystems foster the start-up rate of new firms in EU cities (see e.g. Audretsch & Belitski, 2017). For a selection of countries and using data for a large number of years, Hechavarría and Ingram (2018) examine data from the Global Entrepreneurship Monitor

and produce corroborating evidence that elements of entrepreneurial ecosystems are positively associated with rates of both female and male entrepreneurship.

Turning to the question whether the entrepreneurial ecosystem influences the economic impact of entrepreneurship, some studies examine the effect of a national or regional entrepreneurship development index on productivity. These indices capture a variety of factors related to entrepreneurial characteristics and regional inputs. Overall, these studies find significant positive effects on productivity (Acs, Estrin, Mickiewicz & Szerb, 2018; Acs & Szerb, 2009). However, it is not clear how and to what extent these indices capture the effect of the interrelatedness of the underlying factors. Another approach consists of using a system of equations, where the effect of institutions on growth is mediated by entrepreneurship (Aparicio, Urbano & Audretsch, 2016). The drawback of this approach is that institutions represent only one – be it central - factor of the underlying entrepreneurial ecosystem, leaving out possible effects of a range of other elements of the ecosystem.

In order to overcome the measurement issue of the various elements of an entrepreneurial ecosystem and to encompass the complexity of the interrelatedness of the different ecosystem elements, Bruns et al. (2017) propose the use of a latent class model. This approach allows the estimated relationship between entrepreneurial activity and economic growth in their study to be heterogeneous across a finite number of clusters of regions. Without explicitly measuring the entrepreneurial ecosystem, Bruns et al. (2017) do capture whether similarities exist in the extent to which entrepreneurial activity contributes to growth. Subsequently, indicators on the institutional quality of the regions in their sample can be used to predict cluster membership probabilities, in order to assess whether ecosystems impact upon the economic value of entrepreneurship. Using this approach, the authors find no evidence that entrepreneurial ecosystems determine variation in the effect of entrepreneurship on regional growth, suggesting that the relationship between entrepreneurship and growth applies in a uniform way to all the regions in their sample of EU regions.

Summary and research questions

Summing up, there is increasing evidence that entrepreneurship can act as an important driver of economic performance. There is also a growing recognition of the importance of entrepreneurial ecosystems as underlying contextual frameworks that influence both levels and types of entrepreneurship as well as the economic effects from observed entrepreneurial activity. However, empirical evidence on the effects of these ecosystems is still limited and has focused primarily on examining their impact on rates of new firm

creation and other indicators of entrepreneurship, indicating the scope for new research on the effects of entrepreneurial ecosystems on the economic effects from entrepreneurship.

Within the context sketched above, we aim to examine whether and how entrepreneurial ecosystems matter for the economic growth effect of entrepreneurial activity. To do so, we conduct an empirical analysis addressing the following research questions. First, we examine whether entrepreneurial activity positively contributes to economic growth on average. Second, we look at the degree that the relationship between entrepreneurship and economic growth is non-uniform across countries in our research sample. Any evidence that this relationship is characterised by heterogeneity across the countries is likely to be related to differences in national elements of the regional entrepreneurial ecosystems. Third, we examine whether a range of characteristics of regions in our research sample are in line with the heterogeneity of the relationship between entrepreneurship and regional growth, in order to explore whether a limited set of entrepreneurial ecosystem types might provide an explanation for our findings.

5.3 Data & methodology

5.3.1 Entrepreneurial activity

For the analysis we rely on various sources to assemble a new dataset, consisting of 169 regions spread over 25 countries across Europe. Our regional level data on entrepreneurial activity is provided by GEM, by aggregating annual individual level survey data for the 169 regions. In order to make the entrepreneurial activity measures reliable at the subnational level, we pooled the data for the years 2006 - 2014 to construct average measures of regional entrepreneurial activity for that period. For most countries, we are able to calculate reliable indicators at the NUTS-2 level; for five countries however, we were forced to adopt the NUTS-1 level.[1]

The advantage of using the GEM data to calculate proxies for regional entrepreneurship is that they capture the share of the working age population (from 18 until 64) that is involved in the creation of a business at the time of the survey. A person is classified as an entrepreneur when he or she is engaged in any activity to start a business or has been

[1] NUTS level between parentheses: Austria (2), Belgium (2), Czech Republic (2), Germany (1), Denmark (2), Estonia (2), Greece (2), Spain (2), Finland (2), France (1), Croatia (2), Hungary (2), Ireland (2), Italy (1), Lithuania (2), Luxembourg (2), Latvia (2), Netherlands (2), Norway (2), Poland (1), Portugal (2), Romania (2), Sweden (2), Slovenia (2), Slovakia (2), and United Kingdom (1).

running a new business that exists less than 42 months at the time of being interviewed.[2] We use three indicators of regional entrepreneurial activity. Total early stage entrepreneurial activity (TEA) captures the share of the working age population that is actively involved in setting up a new firm or owns and manages a new business. Opportunity-driven entrepreneurship (OPP) is the share of the working age population that is involved in early-stage entrepreneurial activity for reasons including taking advantage of new market opportunities or the desire to be their own boss.[3] The third type of entrepreneurial activity (JOB) is measured as the percentage of the working age population that is classified as early-stage entrepreneur and expects to be creating at least 5 new jobs in the next five years.

Figure 5.1 depicts the prevalence rates of the different types used in this study. The countries that are not covered by the GEM survey are shaded white. The figure shows that all three types of entrepreneurship are especially high in Eastern Europe, while only a select number of regions in West and Central Europe appear to have substantial rates of early-stage entrepreneurial activity.[4] As OPP and JOB are subcategories of TEA, the correlation among them is positive by construction. It ranges from 0.56 of TEA with JOB to 0.90 of TEA with OPP.

5.3.2 Estimation methodology

The aim of this study is to obtain indications of whether and how entrepreneurial ecosystems can impact upon the relationship between entrepreneurial activity and regional economic performance. Our empirical approach consists of three key steps. In the first step we estimate a standard neo-classical cross-sectional regional growth model. In the second step we use the residuals from the first estimation in a latent class regression model to see whether there are latent groups of regions that differ in their relationship between entrepreneurship and regional growth. In the third step, we compare these groups of regions according to a set of regional characteristics that are direct elements of or closely related to their entrepreneurial ecosystems.

Following Mankiw, Romer and Weil (1992), we start by specifying our baseline model as:

[2] See Reynolds et al. (2005) and Bosma (2013) for a detailed explanation of the methodology underlying the GEM survey.

[3] The opposite category to opportunity entrepreneurship is necessity entrepreneurship, which refers to entrepreneurs that report that they do not see other viable options.

[4] These figures indicate that the GEM-measures do not strongly correlate with productivity levels or GDP per capita. The GEM measures of entrepreneurial activity therefore do not necessarily correspond closely to productive or effective entrepreneurship. We use the prevalence of certain types of activity (starting up a business) to see if such activity contributes to economic growth in different ways across entrepreneurial ecosystems of different quality.

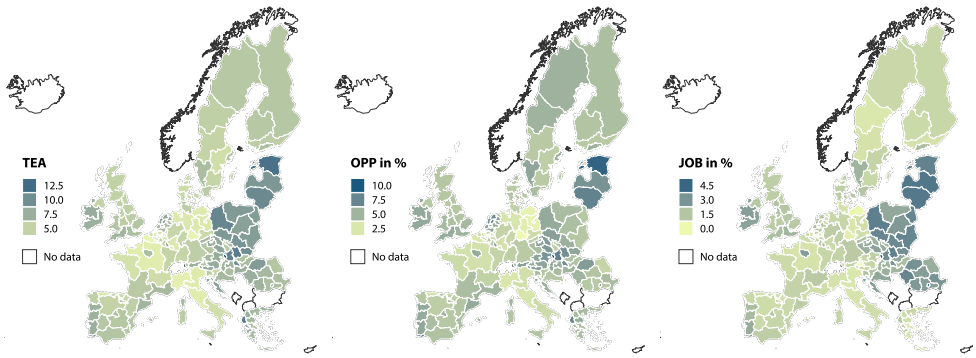


Figure 5.1: *Maps of entrepreneurship in Europe (left = TEA, middle = OPP, right = JOB)*

$$g_i = \frac{y_{it} - y_{it-1}}{T} = \beta_0 + \beta_1 y_i + \beta_2 k_i + \beta_3 h_i + \beta_4 n_i + \varepsilon_i \tag{5.1}$$

where i denotes regions, g_i is the average annual growth rate of Gross Regional Product (GRP) per capita for the period 2006-2014, y_i is the natural logarithm of GRP per capita at the start of the period, k_i and h_i are the share of income invested in physical and human capital, and n_i is the average growth rate of the population. As proxy for physical capital, k_i, we take the average of gross fixed capital formation divided by GRP for the period 2006 -2014. Mankiw et al. (1992) proxy human capital by the share of the population aged 12-17 participating in secondary school multiplied by the share of the population that is of school age (15-19). As nearly all European countries, to a considerable degree at least, have education systems in which secondary school education is mandatory, we foresee limited variation between countries regarding their level of secondary education. Therefore we use tertiary education to capture human capital. We take the share of the working-age population aged 20-24 multiplied by tertiary education participation among the population aged 20-24 (see Bruns et al., 2017). To control for population growth, n_i, we include the average annual rate of population growth for 2006-2014.

The specification as in equation 5.1 does not take into account productivity differences between countries and regions. When between-country differences are not considered, distinct marginal effects of the factors of production between countries are not observed and therefore end up in the error term. The resulting bias that may arise can be minim-

ised by estimating equation 5.1 with country-specific effects using a multilevel model, specified as:

$$g_{ij} = \beta_0 + \beta_1 y_{ij} + \beta_2 k_{ij} + \beta_3 h_{ij} + \beta_4 n_{ij} + \delta_j + \varepsilon_{ij} \tag{5.2}$$

where i denotes regions, j denotes countries and the dummy variables δ_j allow for country-specific intercepts.

Next, we add some variables to capture regional growth effects related to economic geography. We include population density P_i to control for urbanisation economies (Puga, 2002). This variable is measured as total population divided by the squared kilometres of the region, averaged for the period 2006-2014. We also include controls for related variety R_i and unrelated variety U_i, given recent findings that show that the composition of regional economic structures may influence regional growth (Content & Frenken, 2016). We follow Frenken et al. (2007) in the calculation of these two variables. Table 5.1 gives an overview of all the variables and their descriptive statistics.

Variable		**Source**	**Mean**	**SD**	**Min**	**Max**
GRP p/c growth	*g*	Eurostat	0.013	0.020	-0.035	0.065
Initial GRP p/c	*y*	Eurostat	24220	9310	6016	64236
Share of gross capital formation	*k*	Eurostat	-0.024	0.034	-0.116	0.058
Human capital	*h*	Eurostat	6.49	3.352	0.593	23.858
Population growth	*n*	Eurostat	0.002	0.007	-0.016	0.028
Population density	*P*	Eurostat	4.973	1.256	1.126	8.829
Related variety	*R*	BvD	1.917	0.311	0.728	2.455
Unrelated variety	*U*	BvD	5.045	0.401	2.773	5.574
Total early-stage entrepreneurship	E^{TEA}	GEM	6.354	2.003	2.521	14.358
Opportunity entrepreneurship	E^{OPP}	GEM	4.689	1.476	1.608	10.241
Job growth expecting entrepreneurship	E^{JOB}	GEM	1.527	0.940	0.000	5.116

Table 5.1: *Descriptive statistics*

The cross-sectional growth impact of entrepreneurship can be estimated by adding indicators of entrepreneurial activity directly to the model. The factors of production, as mentioned in equation 5.1 and 5.2, as well as the additional regional variables are now captured in vector 'X_i to shorten the notation to:

$$g_i = \beta_0 + \beta_1 E_i + \beta' X_i + \epsilon_i \tag{5.3}$$

$$g_{ij} = \beta_0 + \beta_1 E_{ij} + \beta' X_{ij} + \epsilon_{ij} \tag{5.4}$$

where E represents the indicators of regional entrepreneurial activity.

Estimating equations 5.3 and 5.4 for the whole sample of regions estimates a single β_1 across all regions. Consequently, the relationship between entrepreneurial activity and regional economic growth is estimated to be the same for all regions in our sample by construction of the model. Given different entrepreneurial ecosystems, however, regional economies are likely to be heterogeneous in their relationship between entrepreneurship and growth. In equations 5.3 and 5.4, the regional variation in the quality of the ecosystem that causes variation in the degree to which entrepreneurship is able to contribute to economic growth of the region instead ends up in the error term that is then no longer random, causing bias in our estimations.

One approach to deal with this is to group regions according to factors that influence growth patterns such as population density (Noseleit, 2013; Scott & Storper, 2003), income (Hessels & Van Stel, 2011; Prieger et al., 2016), institutions (Hall & Gingerich, 2009), or geographic location (Redding & Venables, 2004). Subsequently running separate regressions for each group yields varying coefficients over the groups. However, such an approach relies on the use of arbitrary cut-off points and allows for all parameters in the model to differ, but only between pre-defined groups of regions. Furthermore, given the multidimensionality of entrepreneurial ecosystems, the separation of regions based on individual components of these ecosystems is likely to produce relatively uninformative results.

Therefore, in this paper we use an alternative approach in line with Bruns et al. (2017). This involves the application of a latent class regression, which allows us to endogenise the sorting of regions into unobserved/latent groups, without having to make a priori assumptions about what may distinguish different groups of regions.[5] An important differ-

[5] Bosma et al. (2018) use a different approach in their analysis of the impact of entrepreneurship on growth at the EU country level, by positing entrepreneurship as a mediator of the effect of institutions on economic growth. The drawback of this approach is that they examine only one element of the underlying entrepreneurial ecosystem as influencing the growth impact of entrepreneurship.

ence between the present study and Bruns et al. (2017) is that the latter study examines the effect of regional entrepreneurship averaged for 2001-2006, whereas we look at the impact of entrepreneurship measured for the period 2006-2014, giving us observations for 169 regions, whereas their sample contains 107 regions.

In order to do the latent class regression, we first re-estimate equations 5.3 and 5.4 without the entrepreneurship variables. We then take the residuals[6] from these regressions and regress them on our different measures of entrepreneurship using:

$$\hat{\epsilon}_{i|k} = \alpha_{0|k} + \alpha_i E_{i|k} + \varepsilon_{i|k} \tag{5.5}$$

where $k = 1, \ldots, K$ denotes the groups, and K indicates the optimal number of groups. This can be rewritten into a latent class regression model (DeSarbo & Cron, 1988; Leisch, 2004), given by:

$$f(\hat{\epsilon}|E, \theta) = \sum_{k=1}^{K} \pi_k f(\hat{\epsilon}|E, \theta_k) \tag{5.6}$$
$$where\ \pi_k > 0,\ and\ \sum_{k=1}^{K} \pi_k = 1$$

The dependent variable $\hat{\epsilon}$, represents the residuals from equations 5.3 and 5.4, re-estimated without E. E is again the independent variable entrepreneurship and π_k is the prior probability (or unconditional probability) of any region belonging to cluster k. The prior probabilities are larger than zero and add up to one, and $\theta = (\pi_1, \ldots, \pi_K, \theta_1, \ldots, \theta_K)$ is the vector of all parameters (in our case only a slope coefficient and a constant). Each density function f_k has its own cluster specific parameters θ_k.

The next step is to classify regions into homogenous groups based on their effect of entrepreneurship on (residual) growth. To do so, we calculate the posterior probability that observation $(E, \hat{\epsilon})$ belongs to class j, given by

[6] Strictly speaking, one could also estimate the entire growth model in latent class specification. Our implicit assumption in this two-step procedure, is that the output elasticities and other parameters in model 5.1 are stable across regions in Europe. By regressing entrepreneurial activity on the residual, we force the clustering to take place on the relation between entrepreneurial activity and growth. See Bruns et al. (2017) for more details.

$$P(j|\hat{\epsilon}, E, \theta) = \frac{\pi_i f(\hat{\epsilon}_i|E_i, \theta_k)}{\sum_k \pi_k f_k(\hat{\epsilon}_i|E_i, \theta_k)} \tag{5.7}$$

Each region is then assigned to the group for which its posterior probability is the highest. Before we can classify regions into groups and estimate equation 5.5, we need to establish the appropriate value for K. We first estimate the equation with $K = 1$ and then re-estimate the equation, each time adding an additional group. The maximum number of groups is theoretically only limited by the number of observations in the sample; however, overfitting the data (when for instance the estimated parameters of 2 classes are statistically indistinguishable) restricts the number of classes in practice. We obtain the appropriate number for K by selecting the configuration with the lowest Bayesian Information Criterion (BIC) value.

5.4 Results

We start our analysis by estimating the regression model without country effects on our whole sample of 169 regions. The results of these OLS growth regressions are shown in table 5.2. In model 1, representing the standard Mankiw et al. (1992) specification, we find a negative and significant coefficient for the initial level of GRP per capita, indicating the presence of conditional growth convergence among European regions during the period. Investment in physical capital is positively associated with economic growth. The estimated insignificant coefficient on human capital investment may be explained by the limited variation across Europe in the rate of human capital or the high mobility of well-educated individuals. The rate of population growth is negatively associated with growth in income per capita.

In model 2, we augment the standard Mankiw et al. (1992) specification by adding the economic geography variables to the model. The estimated effect of population density is positive, suggesting the presence of urbanisation advantages. In line with Frenken et al. (2007), who hypothesise that unrelated variety can act as a portfolio against economic shocks, we find that regions with higher rates of unrelated variety seem to have outperformed the others in the crisis and recovery period of our sample 2006-2014. In contrast, related variety does not have a significant impact on a regions' growth rate.

g	**(1)**	**(2)**	**(3a)**	**(3b)**	**(3c)**
y^{2006}	-0.019** (0.003)	-0.021** (0.003)	-0.017** (0.003)	-0.020** (0.003)	-0.009** (0.003)
k	0.388** (0.029)	0.293** (0.031)	0.298** (0.029)	0.293** (0.029)	0.271** (0.025)
h	0.001 (0.002)	-0.001 (0.002)	-0.003* (0.002)	-0.003 (0.002)	-0.005** (0.002)
n	-0.544** (0.191)	-0.657** (0.176)	-0.715** (0.164)	-0.710** (0.166)	-0.810** (0.146)
P		0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.002** (0.001)
R		-0.003 (0.004)	-0.001 (0.003)	-0.002 (0.003)	0.001 (0.003)
U		0.014** (0.003)	0.014** (0.003)	0.014** (0.003)	0.009** (0.003)
E^{TEA}			0.224** (0.044)		
E^{OPP}				0.264** (0.057)	
E^{JOB}					0.831** (0.094)
Constant	0.214** (0.031)	0.149** (0.032)	0.097** (0.031)	0.132** (0.030)	0.048+ (0.028)
Observations	169	169	169	169	169
R^2	0.629	0.707	0.748	0.742	0.803

*Clustered standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table 5.2: *OLS growth regressions*

Models 3a-3c add the indicators of the different types of regional entrepreneurial activity. The findings indicate that the estimated positive effect becomes larger when moving from generic to more specific types of entrepreneurship. In particular, the estimated growth effect of JOB is statistically significantly larger than the effect of TEA and OPP. These findings provide evidence that entrepreneurship is important for economic growth at the regional level in the EU. However, the results presented in table 5.2 should be interpreted with care. As the estimated models do not control for country specific effects, the estimated coefficients might be biased due to systematic country level variation not explicitly modelled in these estimations.

g	(1)	(2)	(3a)	(3b)	(3c)
y^{2006}	0.003 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.0004 (0.002)
k	0.074** (0.027)	0.073** (0.027)	0.073** (0.027)	0.073** (0.027)	0.074** (0.027)
h	0.00004 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
n	-0.497** (0.120)	-0.508** (0.134)	-0.494** (0.138)	-0.527** (0.139)	-0.552** (0.136)
P		0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
R		-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
U		0.005* (0.002)	0.005* (0.002)	0.005* (0.002)	0.005* (0.002)
E^{TEA}			−0.016 (0.044)		
E^{OPP}				0.025 (0.051)	
E^{JOB}					0.187 (0.114)
Constant	-0.005 (0.023)	-0.015 (0.024)	-0.016 (0.024)	-0.013 (0.024)	-0.008 (0.024)
Observations	169	169	169	169	169
Log Likelihood	576.45	563.18	561.02	561.23	562.98
BIC	-1,116.9	-1,075.1	-1,065.6	-1,066.1	-1,069.5

*Standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table 5.3: *Multilevel regression with random country effects*

To clean out these effects, we re-estimate model 5.2, adding country dummies. We tested our OLS specification from table 5.2 against random country effects and fixed country effects specifications. Hausman tests reveal that the OLS specification is rejected in favour of a random country effects specification, which in turn is preferred over the fixed country effects specification for all models.[7]

Table 5.3 presents the findings from estimating the models with random country effects. The results show that after controlling for these country effects, the estimated positive effect of the three types of entrepreneurship turns insignificant. Controlling for unobserved heterogeneity between countries absorbs the growth effects of regional entrepreneurship. This implies that between country variation is important for explaining regional differences. But taking that variation out, leaves too little variation within countries to precisely estimate the effect at the regional level.[8] On the other hand, this method still estimates a single coefficient for regional entrepreneurial activity across all regions in a country.[9]

[7] At the 5% significance level, a Hausman specification test of OLS vs random effects rejects OLS in favour of random effects (1327.78, df = 7). A random effects specification is not rejected in favour of fixed effects specification (8.48, df = 7).

[8] Also, several countries consist of only a few NUTS-2/1 regions, such that we effectively lose these observations in a multilevel specification.

[9] Which is a problem if for example urban regions differ systematically from rural areas, but all countries have urban and rural regions.

To assess whether the full sample of regions can be classified into distinct groups of regions, we turn to the latent class analysis. We take the residuals from the growth regressions that do not contain the entrepreneurship indicators and regress these on the different indicators of regional entrepreneurship using a latent class regression. For this, we first need to determine whether a configuration with more than one cluster is indeed preferred. That would indicate that some groups of regions are distinct in the relationship of entrepreneurial activity to growth. The results of this exercise are shown in table 5.4.

k	TEA	OPP	JOB
1	-849.92	-841.66	**-918.52**
2	-853.41	-832.69	-908,00
3	-847.48	-812.18	-889.31
4	-826.96	**-853.34**	-891.22
5	**-856.85**	-835.93	-885.73
6	-848.45	-760.50	-867.46
7	-844.35	-818.76	-864.79

Table 5.4: *Model fit comparison (BIC criterion)*

The findings show that, for total entrepreneurial activity or opportunity-driven entrepreneurial activity, the highest BIC values are obtained in a 5-cluster and 4-cluster configuration, respectively. In the case of job growth expecting entrepreneurial activity, we do not observe a better model fit when more than one cluster is used. This suggests that, overall, job growth expecting entrepreneurial activity contributes equally to residual regional growth across the regions and years in our sample.[10] Therefore, we focus in our latent class analysis on the relationship between TEA and OPP with economic growth. In order to avoid overfitting the data, we estimate the model with the restriction that the minimal prior weights are > 0.05 (approximately 10 regions). In the case of TEA, this means that one cluster is removed during the estimation process. For both TEA and OPP, we then end up with four clusters of regions. In contrast to Bruns et al. (2017), the

[10] Note, one would expect this to happen first to the more specific measures of entrepreneurial activity, with on the one extreme entrepreneurship very strictly defined as e.g. only those activities that contribute proportionally to GRP-growth and on the other very inclusive measures and proxies that include all kinds of "entrepreneurial" activity such as self-employment, new firm-formation, corporate entre- and intrapreneurship etc. etc. As explained in detail in Bosma et al. (2018) TEA is more inclusive and therefore also noisier than OPP and JOB.

present findings do suggest that a configuration with more than one cluster is to be preferred to identify the growth effect from entrepreneurship. We think that the difference between our findings and those of Bruns et al. (2017) are related to our sample. Bruns et al. (2017) estimate the impact of average entrepreneurial activity on residual growth during the years 2001-2006, whereas we use the years 2006-2014, years that were heavily affected by the crisis. In those years, the relationship between entrepreneurial activity and growth is perhaps trumped by demand side shocks and depression. Our use of more recent indicators of entrepreneurship and the larger number of regions in the sample may explain why we do find clusters with the same method. In any case, our results indicate that the relationship between entrepreneurship and growth is not uniform across all the regions in the sample.

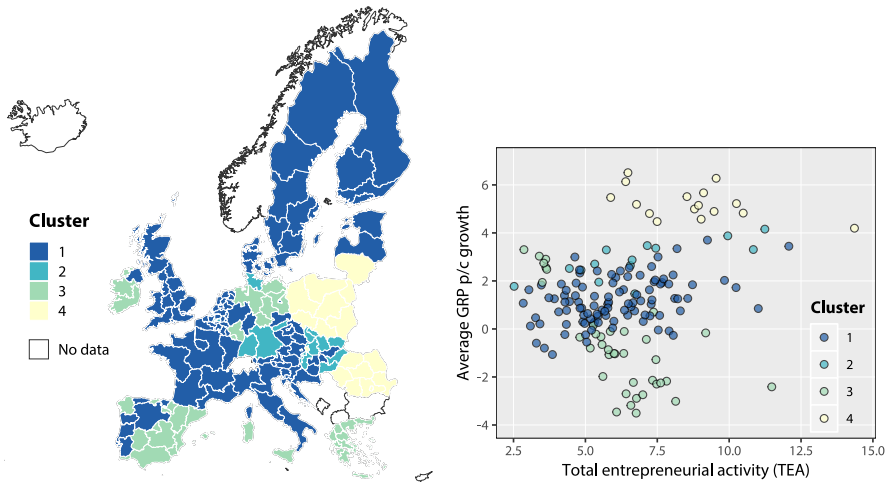
Tables 5.5 and 5.6 present the result of the latent class regressions with TEA and OPP as explanatory variables. The dependent variable in these regressions is the residual obtained from the multilevel growth regression excluding entrepreneurship (equation 5.4). In the case we use TEA as our proxy for entrepreneurship, the regions get sorted into two small groups (16 and 14 regions), one medium sized group (38 regions), and one large group (101 regions). Group 1 is significantly larger than the rest of the groups and is spread over Scandinavia and west and central Europe. Group 2 contains some southern regions of Germany and some regions of Slovakia, Austria, and Hungary. Group 3 mostly consists of regions in southern Europe, Ireland, and some regions in the north of Germany. Group 4 contains eastern European regions. The rate of total entrepreneurial activity seems to have a positive impact in regions sorted into clusters 1 and 2, whereas it appears to have a negative impact in regions sorted into clusters 3 and 4.

Figures 5.2 (a) and (b) show the clustering on the map and the corresponding scatterplot showing residual growth and TEA.

	1	**2**	**3**	**4**
E^{TEA}	0.222 (0.051)**	0.265 (0.007)**	-0.719 (0.112)**	-0.161 (0.026)**
Constant	-0.001 (0.003)	0.009 (0.000)**	0.04 (0.007)**	0.066 (0.002)**
Prior	0.527	0.064	0.317	0.092
Size	101	14	38	16

*Dependent variable: Residual model (2) table 5.3. Std. errors in parentheses (** p<0.01, * p<0.05, + p<0.1) Log likelihood: 477.707 (df=15). BIC criterion: -878.465.*

Table 5.5: *Latent class regression (total entrepreneurial activity)*



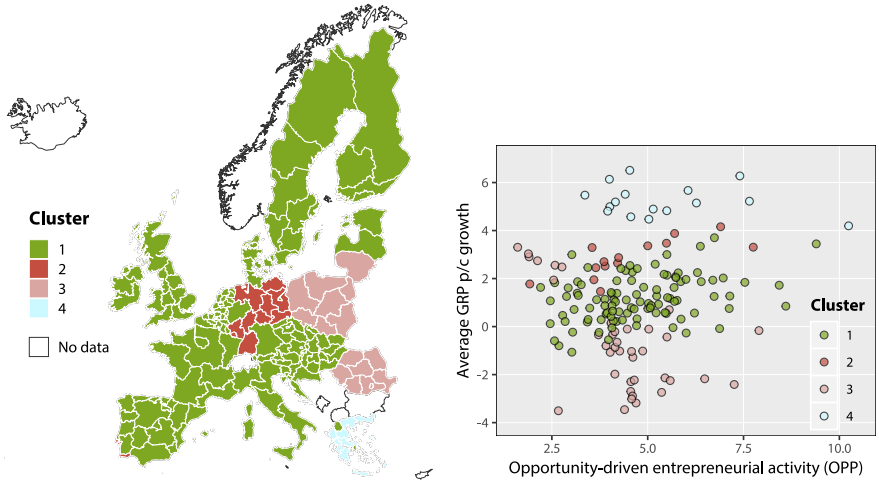
(a) *Cluster map* ***(b)*** *Scatterplot*

Figure 5.2: *Map (a) and scatterplot (b) of Latent Class Clusters for TEA*

The scatterplot in figure 5.2 (b) corresponds to the regression results in table 5.5, where we clearly observe the cluster of regions in Eastern member states that recovered quickly from the crisis, more or less independent of TEA, whereas sluggish growth persisted in Ireland and big parts of Spain and Greece and the relation to TEA was negative. A mild positive slope can be distinguished in groups 1 and 2, covering most of Europe, whereas the latter group experienced on average a higher growth (residual). The little cluster of regions to the left and above the big cloud, is formed by the north- and eastern German regions that had relatively high growth at very low levels of TEA. Our latent class method suggests these regions therefore belong to a cluster where more TEA contributes negatively to growth, which could be explained by an ecosystem in which formal sector employment is more productive in the aggregate.

Moving on to table 5.6, which depicts the results when opportunity-driven entrepreneurial activity is used as measure for entrepreneurial activity, we see that there are three smaller clusters with 15, 13, and 11 regions and one big cluster containing 130 regions. Group 1 contains regions spread over Scandinavia, West and South Europe, with the exception of Greece. Group 2 contains regions located in eastern European countries. Group 3 includes regions mostly from Germany, and group 4 contains the regions of Greece. In groups 3 and 4 we do not observe a significant association of opportunity-

driven entrepreneurship with the growth residual, whereas in group 1 and group 2 we observe a positive and negative association, respectively.



(a) *Cluster map* ***(b)*** *Scatterplot*

Figure 5.3: *Map (a) and scatterplot (b) of Latent Class Clusters for OPP*

	1	2	3	4
E^{OPP}	0.329 (0.078)**	-0.505 (0.052)**	-0.113 (0.055)	0.085 (0.063)
Constant	-0.005 (0.004)	0.036 (0.002)**	0.058 (0.003)**	-0.031 (0.003)**
Prior	0.674	0.175	0.088	0.063
Size	130	13	15	11

*Dependent variable: Residual model (2) table 5.3. Std. errors in parentheses (** p<0.01, * p<0.05, + p<0.1) Log likelihood: 465.145 (df=15). BIC criterion: -853.341.*

Table 5.6: *Latent class regression (opportunity-driven entrepreneurial activity)*

Table 5.6 reveals that the small groups 3 and 4 seem clustered together primarily because of a high, and low average level of residual growth, respectively. The latter is undoubtedly related to the fact that Greece has been in a severe recession and experienced

a slow recovery due to macroeconomic instability in the period under study, whereas in group 3 the recession was only mild and/or the recovery was relatively quick. For group 1 there is a significant positive effect of opportunity-driven entrepreneurial activity, whereas for the German regions (again) this relationship seems less pronounced, given that residual growth is high in the East, where also OPP is lowest. Tentatively, one can conclude that the German entrepreneurial ecosystem is less effective in turning entrepreneurial activity into growth and/or other engines of growth are more important in the former East-German Länder.

The findings from the latent class analysis suggest that the relation between entrepreneurial activity and regional growth is not uniform across all the regions. The hypothesis that now remains to be tested is that the cluster differences in the growth impact of entrepreneurial activity are related to characteristics of the underlying entrepreneurial ecosystems of the regions.

As a first attempt at showing how clusters regarding the relationship between entrepreneurial activity and economic growth are related to their entrepreneurial ecosystems, we compare cluster means of a selection of regional characteristics that are direct components of or closely related to these ecosystems. There is still a strong debate on the exact components of these ecosystems and their inter-relationships. Our selection of variables should therefore be seen as preliminary and explorative. We are guided in our choice of variables by other studies that have analysed various components of entrepreneurial ecosystems (Audretsch & Belitski, 2017; Auerswald & Dani, 2017; Bell-Masterson & Stangler, 2015; Horváth & Rabetino, 2018; Spigel, 2017; Stam, 2018; Stam & Spigel, 2017). Of course, we are also confined in our selection by the availability of relevant indicators at the NUTS-2 and NUTS-1 levels. Some elements could therefore not be measured. For other elements we use multiple variables as those ecosystem elements in turn consist of different dimensions[11].

Tables 5.7 and 5.9 present cluster mean values of the selected regional characteristics (reflecting or closely related elements of entrepreneurial ecosystems), together with t-test statistics that indicate whether the means are significantly different between pairs of clusters. Tables 5.8 and 5.10 also present cluster mean values; however, these characteristics reflect the industry structure and dynamics of industrial specialisations of regions.

[11] The variables presented in tables 5.7-5.10 are gathered from various sources: Formal institutions (EQI: Charron et al., 2014), entrepreneurship culture (GEM), physical infrastructure (RCI: Annoni, Dijkstra & Gargano, 2017), demand (Eurostat), SMEs with innovation co-operation (RCI), know some that started a firm (GEM), human capital (Eurostat), creative class employment & knowledge workers (RCI), and knowledge (RCI).

Tables 5.7 and 5.9 presents the results for the clusters obtained with TEA as explanatory variable and tables 5.8 and 5.10 with OPP as explanatory variable. For both cases, we compare cluster 1, the biggest cluster of regions where entrepreneurship is significantly and positively associated with growth, against the other clusters.

	Cluster mean			T-test cluster a,b		
	1	**2**	**3** *(3+4)*	**1,2**	**1,3**	**2,3**
Formal institutions						
Corruption	0.54	-0.35	-0.57	3.67**	7.77**	0.80
Quality of government	0.53	-0.12	-0.66	3.05*	8.69**	2.05*
Impartiality	0.53	-0.24	-0.58	3.47**	8.25**	1.32
Entrepreneurship culture						
Entrepreneurship is a good career choice	0.58	0.54	0.62	1.28	-2.52*	-4.19**
Successful entrepreneurs have status	0.68	0.65	0.67	0.90	0.97	-0.44
Fear of failure	0.41	0.44	0.53	-2.01*	-11.0**	-4.04**
Physical infrastructure						
Household access to internet	84.78	79.04	72.84	2.40*	7.99**	2.22*
Accessibility of motorways	99.60	78.28	42.23	0.98	5.05**	2.36*
Accessibility of railways	94.80	79.47	50.45	0.92	4.80**	2.17*
Accessibility of passenger flights	1083.1	890.52	271.11	0.36	3.03*	2.27*
Demand						
GRP p/c	27214	18558	20088	3.38**	4.89**	-0.65
Population	3925.1	2931.8	2743.7	0.52	1.20	0.23
Networks						
SMEs with innovation co-operation	0.44	0.31	0.22	2.67*	8.27**	2.31*
Know someone that started a firm	0.33	0.30	0.32	1.38	0.61	-1.40
Talent						
Human capital	6.44	4.49	7.10	2.45*	-1.14	-2.29*
Creative class employment	9.70	6.72	6.84	4.09**	7.21**	-0.23
Knowledge workers	42.18	34.75	31.26	3.79**	8.87**	1.44
New knowledge						
R&D ratio	1.93	1.50	0.94	1.42	6.49**	2.30*
Patent applications p/mil. inhabitants	175.91	340.1	46.54	-1.84+	4.65**	2.63*

Clusters 1 and 2 have a positive growth effect from entrepreneurship; clusters 3 & 4 have a negative growth effect.

Table 5.7: *Cluster means and t-tests total entrepreneurial activity*

Table 5.7 shows the comparison of clusters obtained from the latent class regression with TEA as explanatory variable. We group together the regions from clusters 3 and 4, as both these clusters are characterised by an estimated negative impact of entrepreneurship on growth and we want to examine in particular whether elements of the entre-

preneurial ecosystems elements may explain differences between clusters with a positive or a negative growth impact from entrepreneurship.

Looking at formal institutions, there are clear differences between the clusters. Cluster 1 (3) has the highest (lowest) perceived freeness of corruption, quality of government, and impartiality of institutions. These differences are highly significant when cluster 1 is compared to clusters 2 and 3. Clusters 2 and 3 differ much less in their scores on institutions.

A culture that is conducive for entrepreneurship as measured by whether entrepreneurship is perceived as a good career choice, whether successful entrepreneurs enjoy status, or how important the fear of failure is seems to differ less across clusters. Perhaps surprisingly, the differences that exists suggest that higher values that are conducive to entrepreneurship are observed in the cluster characterised by a negative growth impact of entrepreneurship. Regarding the different indicators used to measure the physical infrastructure of a region, we again notice the strongest and most significant differences between clusters 1 and 3. Especially, the differences in the accessibility of flights are high, whereas the accessibility of motorways, internet, and railways, although significantly different, seem to be somewhat smaller.

Demand, measured by the GRP per capita, is significantly higher in cluster 1, relatively to clusters 2 and 3. Population is not significantly different between any pair of clusters, which likely reflects the fact that the size of NUTS regions is based upon the number of inhabitants (EU, 2015) and variation is thus small. Our proxy for networks, the share of SMEs that are co-operating on innovation activities, is significantly different between the clusters. The table reports higher average values for cluster 1 compared to 2, and in turn higher values for cluster 2 compared to cluster 3.

Talent is measured using variables for human capital, creative class employment, and knowledge workers. We can observe significantly higher average levels of creative class employment and knowledge workers in cluster 1 compared to clusters 2 and 3. Human capital, however, is higher in cluster 3 compared to cluster 2. The generation of new knowledge is measured using the R&D ratio and the number of patent applications per million inhabitants. The cluster means of both these variables are significantly higher in cluster 1 with respect to cluster 3. The number of patent applications in cluster 2, however, is substantially higher than it is in cluster 1.

	Cluster mean			T-test cluster a,b		
	1	2	3	1,2	1,3	2,3
Industry structure						
Related variety	1.94	2.01	1.86	-0.97	1.45	1.47
Unrelated variety	5.11	5.21	4.87	-1.36	3.60**	2.09*
Relatedness density	191.82	204.37	141.04	-0.29	2.33*	1.64
Industrial specialisations						
Change in total	0.01	6.21	-1.76	-1.55	0.80	1.87+
Gained	28.30	33.36	24.57	-0.69	1.00	1.40
Turbulence	56.58	60.50	50.91	-0.30	0.84	0.88
KIBS, GVC, and R&D						
KIBS	7.14	5.30	4.45	1.70+	4.55**	1.03
GVC	19.25	26.21	14.66	-5.29**	4.71**	6.10**
R&D ratio	1.89	1.57	0.88	0.84	5.08**	1.93+

Clusters 1 and 2 have a positive growth effect from entrepreneurship; clusters 3 & 4 have a negative growth effect.

Table 5.8: *Cluster means and t-tests total entrepreneurial activity*

In the case that TEA is our indicator of entrepreneurship, table 5.8 depicts additional differences across clusters with respect to the industry structure of the region as well as changes in the number of specialisations and the presence of KIBS, participation in GVCs, and investment intensity in R&D. Although related variety is lowest in the group 3, this is not significantly different from groups 1 and 2. Unrelated variety, however is significantly higher in groups 1 and 2, relative to group 3. Relatedness density (reflecting here the average related specialisations in a group), is significantly higher in group 1, as compared to group 3. No significant differences are found with respect to the dynamics in the number of specialisations, while we do find quite substantial differences regarding KIBS, GVC, and R&D.

Table 5.9 presents the comparison of clusters obtained from the latent class regression in which OPP is the explanatory variable. As we are interested in whether differences in the underlying ecosystems elements exist between clusters with a positive and negative or no association, we again group together regions from clusters 3 and 4. In these two clusters entrepreneurship is not significantly associated with the growth residual. Overall, the most significant differences exist between clusters 1 and 3 and between clusters 2 and 3. The means of cluster 1 and 2 are similar, despite the fact that the growth impact of entrepreneurial activity is positive in cluster 1 and negative in cluster 2. This is probably due to the fact that group 2 is almost exclusively regions from Germany, that on the

variables compared here, do not differ significantly from say Belgium, the Netherlands, France and Sweden.

	Cluster mean			T-test cluster a,b		
	1	2	3	1,2	1,3	2,3
Formal institutions						
Corruption	0.31	0.78	-1.16	-1.85+	7.90**	12.8**
Quality of government	0.34	0.44	-1.27	-0.44	9.39**	8.06**
Impartiality	0.32	0.63	-1.15	-1.33	8.58**	12.42**
Entrepreneurship culture						
Entrepreneurship is a good career choice	0.58	0.54	0.66	1.60	-3.41**	-7.79**
Successful entrepreneurs have status	0.67	0.75	0.67	-2.96*	0.13	4.72**
Fear of failure	0.42	0.48	0.57	-3.22*	-9.67**	-3.24*
Physical infrastructure						
Household access to internet	82.69	86.46	66.48	-1.51	8.92**	8.13**
Accessibility of motorways	87.19	120.19	20.72	-1.56	4.52**	8.76**
Accessibility of railways	85.29	121.69	28.53	-2.20*	4.94**	9.57**
Accessibility of passenger flights	909.42	1242.52	81.52	-0.66	2.37*	4.15**
Demand						
GRP p/c	25981	25420	14813	0.22	6.07**	5.19**
Population	3601.0	3788.8	2625.2	-0.11	0.77	1.30
Networks						
SMEs with innovation co-operation	0.40	0.33	0.17	1.37	5.85**	3.38*
Know someone that started a firm	0.33	0.27	0.34	3.09*	-0.50	-5.67**
Talent						
Human capital	6.30	5.10	8.12	1.41	-2.50*	-2.17*
Creative class employment	9.03	8.15	6.26	1.14	4.95**	3.71**
Knowledge workers	39.94	41.00	27.32	-0.48	7.48**	6.11**
New knowledge						
R&D ratio	1.71	2.22	0.59	-1.74+	5.56**	7.92**
Patent applications p/mil. inhabitants	156.70	341.97	9.26	-2.18*	2.71*	3.33*

Clusters 1 and 2 have a positive growth effect from entrepreneurship; clusters 3 & 4 have a negative growth effect.

Table 5.9: *Cluster means and t-tests opportunity-driven entrepreneurial activity*

With respect to formal institutions we see the highest (lowest) values in cluster 2 (3). The differences between clusters 1 and 2 are not statistically significant. We see lower values of fear of failure in cluster 1 with respect clusters 2 and 3; however, we can also observe lower values on the issue whether entrepreneurship is perceived as a good career choice.

Apart from the accessibility of railroads, which is higher in cluster 2 compared to cluster 1, no other differences exist between these clusters when it comes to physical infrastruc-

ture. Overall it seems that the physical infrastructure of regions in cluster 3 (Eastern Europe and Greece) is significantly lower, compared to the rest of Europe.

Demand, measured by GRP per capita and population, is similar in clusters 1 and 2, but substantially lower in cluster 3, which are of course the poorer parts of the European Union. As might be expected, networks, measured by the ratio of SMEs collaborating on innovation activities is the highest in clusters 1 and 2, and much lower in cluster 3. When proxied by the share of entrepreneurs that know someone that started a firm, we see a different picture. Clusters 1 and 3 are now similar and different from cluster 2 (Germany). Looking at talent, we do not observe significant differences between cluster 1 and 2. The higher values of human capital are observed in regions within cluster 3, whereas creative class employment and knowledge workers are more prevalent in clusters 1 and 2. Generation of new knowledge is proxied using the R&D expenditure ratio and the number of patent applications. For both these measured we see higher values in cluster 2, compared to clusters 1 and 3, while cluster 1 has significantly higher means relative to cluster 3.

	Cluster mean			**T-test cluster a,b**		
	1	**2**	**3**	**1,2**	**1,3**	**2,3**
Industry structure						
Related variety	1.96	1.79	1.79	1.95+	2.55*	0.04
Unrelated variety	5.11	5.18	4.68	-0.92	5.32**	2.33*
Relatedness density	181.13	217.80	133.57	-0.89	1.62	1.93+
Industrial specialisations						
Change in total	0.34	3.15	-3.54	-0.69	1.40	1.29
Gained	27.56	33.62	24.31	-0.86	0.66	1.36
Turbulence	54.79	64.08	52.15	-0.75	0.29	0.97
KIBS, GVC, and R&D						
KIBS	6.69	6.41	3.19	0.26	4.59**	4.24**
GVC	18.82	23.65	12.69	-2.94**	4.35**	4.80**
R&D ratio	1.65	2.56	0.48	-2.41*	4.91**	5.21**

Clusters 1 and 2 have a positive growth effect from entrepreneurship; clusters 3 & 4 have a negative growth effect.

Table 5.10: *Cluster means and t-tests opportunity-driven entrepreneurial activity*

Table 5.10 depicts additional differences across clusters, in the case that opportunity-driven entrepreneurship is taken as our indicator for entrepreneurship. We observe a significantly higher value of related variety for regions where entrepreneurship contrib-

utes positively to growth, while unrelated variety shows the highest value in the cluster with a negative association of entrepreneurship with growth. Relatedness density and changes in the number of industrial specialisations do not seem to be significantly different across clusters in this case. Regarding the presence of KIBS, participation in GVCs, and investment intensity in R&D, we observe high rates in both clusters 1 and 2, in which entrepreneurship is positively and negatively associated, respectively.

Overall, the findings show that there are marked differences between the clusters for several of the regional characteristics that relate to their entrepreneurial ecosystems. The findings in tables 5.7-5.10 show that regions in the cluster with the largest positive growth impact of total entrepreneurship outperform all other regions especially in the areas of: formal institutions; elements related to networks; talent; and certain characteristics of the industry structure. As for regional characteristics influencing the growth impact of opportunity entrepreneurship, a comparison of the regions that experience positive growth effects with regions in the cluster where this effect does not materialise shows that the first group of regions outperforms the other regions mostly in the areas of: formal institutions; physical infrastructure; talent; and related and unrelated variety. The different results in this table, however, are significantly driven by group 2 and group 4 clustering almost exclusively German and Greek regions, respectively. The entrepreneurial ecosystem of the former seems to operate under different rules (see also Herrmann, 2018; Sanders et al., 2018), while the Greek situation is exceptional in 2006-2014 for well-known reasons.

Of course, the findings in tables 5.7-5.10 provide general indications that the clusters of regions are structurally different according to their regional characteristics, and further research is necessary to identify the relative importance of the differences of these characteristics for the different growth impact of entrepreneurship in the groups of regions. Furthermore, the cluster means do not shed light on how regional characteristics may interact and create systemic differences between the groups of regions. Having said this, we do find it reassuring that we find many characteristics differ significantly between the clusters. This clearly suggests that entrepreneurial ecosystems are linked to the heterogeneity of the growth impact of entrepreneurial activity across the groups of regions in the sample, as the entrepreneurial ecosystems literature would predict if ecosystems are expected to differ.

5.5 Summary and policy recommendations

Entrepreneurship is increasingly seen as an important driver of economic growth and development. Existing evidence indicates that entrepreneurship is linked to a variety of positive economic effects at the regional and country level. However, there is much less evidence on the influence of underlying frameworks of institutional, social, and economic factors on the relationship between entrepreneurship and economic growth. Recently, the concept of the entrepreneurial ecosystem has gained rapid popularity as a key framework that conceptualises this relationship. The contribution of the present paper is that we estimate the effect of entrepreneurial activity on (residual) economic growth for groups of NUTS-1 and NUTS-2 EU regions. Moreover, we estimate how the relationship between entrepreneurial activity and economic growth differs between groups of regions and explore whether these differences are related to regional characteristics that are components of or directly related to the quality of their entrepreneurial ecosystems.

First, adopting standard growth regressions for the full sample of regions, we find significant positive effects of our three indicators of regional entrepreneurship. When we include random country effects, however, the estimated effect of entrepreneurship turns insignificant. The drawback of the latter approach is that the inclusion of country random effects masks the presence of differences in the relationship between entrepreneurship and growth between groups of regions that are related to the characteristics of the entrepreneurial ecosystem in these regions.

To assess whether regions differ in their relationship between entrepreneurship and growth, we apply a latent class analysis, which allows for an endogenous sorting of regions into groups. For both total regional entrepreneurial activity and opportunity-driven entrepreneurial activity, we find that the sample of regions can be divided into four groups that differ markedly in their relationship between entrepreneurial activity and growth. Next to core groups that are characterised by significant positive effects of total and opportunity entrepreneurial activity on economic growth, there are smaller groups of regions where the positive effects are smaller, insignificant, or even negative. These groupings correspond in an intuitively plausible way with groupings across country borders. Within the context of the literature that argues that entrepreneurial ecosystems underlie structural relationships between entrepreneurship and economic outcomes, we take these findings as supporting the notion that ecosystems exercise an important influence on the growth impact of entrepreneurship.

As an exploratory analysis, we compare the groups of regions according to a range of regional characteristics that are components of, or closely linked to, entrepreneurial ecosystems. Looking at total early-stage entrepreneurial activity, the group of regions that is characterised by the largest positive impact of entrepreneurship on growth tend to perform well on indicators of formal and informal institutions. It also outperforms the other groups of regions when looking at: physical infrastructure; networks; talent; new knowledge; and certain characteristics of the industry structure. For opportunity entrepreneurship, similar differences between the core group and the other groups exist, although the differences are understandably weaker. Another interesting feature of the findings is that the comparison of the non-core groups shows much more variability in the differences of the various individual components of the entrepreneurial ecosystems. This suggests that differences in the relationship between entrepreneurship and economic growth are also likely to be related to different combinations of the various components. This is something which we intend to explore in future research.

Finally, we tentatively distil the following three policy recommendations from our empirical findings. First, the current policy climate in the EU is characterised by a strong emphasis on the implementation of a variety of policies designed to promote entrepreneurial activity. As our findings show, there is no guarantee that such policies will lead to higher growth. Depending on the characteristics of the underlying regional entrepreneurial ecosystem, additional policy measures may be required to allow the expected positive effects to materialise. Also, although our findings do show that in particular groups of regions positive growth effects can be found, this cannot be taken as evidence that this relationship is causal. Before drawing such conclusions, more, notably also qualitative research, will be necessary to uncover the exact causal links in given ecosystems. In general terms it is likely that all regions benefit from improving their entrepreneurial ecosystem, but what entails such improvements in a specific region requires more in-depth investigation than our data allow.

Second, we take our findings to indicate that governments need to adopt a place-based and holistic approach when examining the entrepreneurial ecosystem of their regional economy. In our analysis, we offer a first glance at how our groups of regions differ on a range of elements of entrepreneurial ecosystems. At a basic level, the findings from this analysis can be interpreted as indicating that governments need to try to improve all these indicators in order to facilitate the relationship between entrepreneurship and growth. However, such indicators need to be seen within the context of individual regional economies in order to understand their impact and to assess whether and how

they should be improved. Furthermore, these various elements are part of a structural framework that may operate in different ways in specific regional settings, something which we did not address in our analysis. Therefore, governments need to analyse both the individual elements and the unifying framework of the entrepreneurial ecosystem in their regional economies, whilst allowing for specific regional settings, in order to identify those policy areas and measures that are most important. Again, this calls for a clever combination of further quantitative and qualitative empirical research at the level of individual regional ecosystems, as proposed e.g. in Sanders et al. (2018).

Third, our findings also imply that regional governments need to adopt a more detailed cost-benefit approach when deciding on using entrepreneurship as a vehicle for economic growth. Governments of regions where the positive relationship between entrepreneurship and growth does not materialise may change this situation by improving their entrepreneurial ecosystem.

In making the assessment whether or not to do this, such governments need to compare the costs that improving the ecosystems will entail with the benefits that the region may enjoy when entrepreneurship leads to higher growth. This trade-off may turn out quite differently for such diverse regions as, for example, Bavaria, Attica and Eastern Poland. The differences in the relationship between entrepreneurship and growth that we have identified, together with the differences in characteristics between the groups of regions, may indicate that it is economically not feasible or unnecessary for some regions to establish a meaningful positive growth effect from entrepreneurship. Of course, regions may choose to promote entrepreneurship for a variety of reasons, but assuming that the ultimate goal of regional governments is to foster economic growth, it may be that for some regional governments policies to foster growth via other means than entrepreneurship are economically more viable.

Chapter 6

Conclusion

6.1 Introduction

The objective of this dissertation has been to examine the roles of industrial relatedness and entrepreneurship in the economic development of regions. Specifically, in light of constantly changing global competition and advances in technology, our analysis bears relevance for regional economies to develop new or maintain and strengthen existing competitive advantages in order to ensure long-term economic prosperity. For this objective, the introduction (**chapter 1**) has identified gaps in our knowledge about: (1) how regions acquire unrelated knowledge and capabilities to structurally renew their economies; (2) whether related and unrelated variety enhance entrepreneurship; and (3) to what extent the growth-enhancing effects of entrepreneurs depend on a region's entrepreneurial ecosystem. By combining recent empirical findings in the field of evolutionary economic geography with the literatures on entrepreneurship and regional economic development, this dissertation contributes to closings these gaps in our knowledge.

The point of departure is the emerging body of empirical research on the topic of relatedness within a region's industry structure and its effect on regional development. It has been suggested that related variety in a region's industry enhances knowledge spillovers, as firms in related activities benefit from opportunities for mutual learning. Alongside this, it has become evident that the opportunities and constraints for regional diversification are to a large extent determined by the industrial legacy of economies, as the knowledge and capabilities embedded in firms and individuals confines what future

activities a region feasibly can develop. Within this context, entrepreneurship constitutes an important mechanism for change, by introducing new and more productive activities that make redundant established and less productive activities. The extent to which entrepreneurship can become productive is dependent on the quality and interdependence of the various regional conditions, their interactions, as well as aggregate economic outcomes, i.e. the quality of the entrepreneurial ecosystem.

In this chapter we will provide an overview of the main findings (6.2), discuss their implications for policymaking (6.3), discuss the limitations of our analyses (6.4), and finally, we will offer some directions for a future research agenda (6.5).

6.2 Discussion of the main findings

This section summarises the findings for each chapter individually and concludes with a brief discussion of the general findings of this dissertation.

6.2.1 Relatedness and economic development (Chapter 2)

The related variety hypothesis has motivated a large number of scholars to empirically study the effects of related variety on economic development, as indicated by employment, income, or productivity. Consonantly, the product space concept has motivated a large number of empirical studies to analyse the industrial diversification of economies, measured by the relatedness of products or industries entering the export basket or economic landscape.

By reviewing these studies in **chapter 2**, we concluded that – although the evidence base is still rather small with 21 studies – most studies find support for the hypothesis proposed by Frenken et al. (2007) that related variety supports some form of regional growth. Those who also studied inter-industry differences, found that the effects of related variety on growth may be specific to certain industries only, especially manufacturing and knowledge-intensive industries (Bishop & Gripaios, 2010; Bosma et al., 2011; Cortinovis & Van Oort, 2015; Hartog et al., 2012). Regarding the hypothesised dampening effect of unrelated variety on unemployment growth, a more ambiguous picture arises from these studies. Moreover, some authors have argued that, granted the opportunities for recombination from unrelated varieties occur less frequently, if successful, are more likely to produce radical innovations (Castaldi et al., 2015).

Regarding the studies that examine how countries or regions develop new industries following Hidalgo et al. (2007), we concluded that if a region or country already hosts industries or exports products that are related to a specific industry or product, it is much more likely to become specialised in that industry or start exporting that product. By default, regional diversification for that reason can be seen as a path-dependent process, as new activities are expected to build upon existing knowledge and capabilities.

6.2.2 Industry relatedness and diversification (Chapter 3)

The majority of empirical studies analysing the product space concept in relation to diversification present evidence that economies diversify into related products and industries. Theoretically, there are many different reasons for this (Boschma & Frenken, 2011; Frenken & Boschma, 2007). However, it leaves unexplained under what conditions economies manage to develop seemingly unrelated new activities, as is occasionally is observed (Coniglio et al., 2018; Henning et al., 2013).

The development of new unrelated activities requires the development of new and unrelated knowledge and capabilities. In **chapter 3** we explore two local conditions that potentially enable regional economies to do so. First, the presence of extra-regional linkages may generate inflows of external knowledge, possibly unrelated to a region's existing knowledge base (Asheim & Isaksen, 2002; Binz et al., 2016). Second, we propose that platforms or networks within an economy that connect both related and unrelated firms (but also universities, research institutes, and governments) can be identified as potential facilitators of knowledge spillovers between unrelated actors (Czarnitzki & Spielkamp, 2003; Wood, 2006).

Our results of this study can be summarised as follows. First, we confirm that with rising industry density the mean entry probability of industries rises as well, corroborating the product space studies reviewed in chapter 2. Regarding non-local and bridging linkages, we find that the presence of KIBS, participation in GVCs, and investment in R&D may support the development of new specialisations, while also moderating the effect of relatedness density. We interpret from these findings that KIBS, GVCs, and R&D can indeed offer economies a channel through which non-local or unrelated knowledge and capabilities can be transmitted or developed allowing regions to diversify in more unrelated products compared to regions that lack such channels.

By zooming in on specific macro-industries, we further find that the presence of KIBS specifically promotes the emergence of both related and unrelated manufacturing and

industry activities, whereas the participation in GVCs does so for activities in distribution and business services. Investment in R&D mainly impacts the probability of related and unrelated activities to emerge in manufacturing and business services. Moreover, besides a differential impact across types of industries, a further nuance is made regarding the impact of these factors across levels of relatedness density. We find that KIBS *negatively (positively)* impacts on the entry probability at *low (high)* levels of relatedness density, GVC *positively (negatively)* impacts on the entry probability at *low (high)* levels of relatedness density, while R&D *negatively* impacts on the entry probability at *high* and *medium* levels of relatedness density, but *positively* at *low* to *medium* levels.

We infer from these results that, despite a low availability of local related knowledge and capabilities, collaborative relationships of R&D institutions with non-local partners or the value chain participation of firms can provide the knowledge and capabilities necessary to develop new industrial activities. At high levels of relatedness density, the presence of KIBS seems to foster the development of new activities, possibly by being able to indirectly connect yet more (un)related firms and organisations.

6.2.3 Related variety and entrepreneurship (Chapter 4)

The review in the second chapter shows that the majority of studies analysing the effects of related variety on employment growth report positive effects. However, the question remains through which channels such knowledge spillovers stemming from related variety eventually create jobs viz. employment growth.

Some channels such as patent applications have already been investigated and found to be positively associated with related variety (see e.g. Castaldi et al., 2015; Tavassoli & Carbonara, 2014). Motivated by the Knowledge Spillover Theory of Entrepreneurship that posits that regions endowed with more knowledge spillovers generate more entrepreneurial opportunities (Acs et al., 2009), we hypothesise in **chapter 4** that related variety fosters entrepreneurship.

In our research, we distinguish between necessity-driven and opportunity-driven entrepreneurship, as spillovers from related industries are expected to foster the latter type of entrepreneurship in particular. Additionally, by elaborating on Hall and Soskice (2001), we hypothesise that different varieties of capitalism exhibit different rates of opportunity-driven and necessity-driven entrepreneurship.

We find that related variety has a positive impact on both the level of opportunity-driven entrepreneurship and the ratio of opportunity-driven over necessity-driven entrepren-

eurship. We find no effect of related variety on the level of necessity-driven entrepreneurship. We interpret this result as corroborating the notion that necessity-driven entrepreneurs start a business out of a lack of other employment options, rather than in response to new opportunities from knowledge spillovers stemming from related variety. This interpretation is further supported by a robust positive association between regional unemployment and necessity-driven entrepreneurship. Opportunity-driven entrepreneurs leverage opportunities stemming from knowledge spillovers caused by related variety. Moreover, we also identify a persistent negative effect of unrelated variety on the various indicators of regional entrepreneurship. This might reflect that the absence of cognitive proximity increases the difficulty for individuals to identify opportunities for entrepreneurship.

Furthermore, the institutional context as measured by different varieties of capitalism, is found to explain regional variation in rates of entrepreneurship to a significant extent. Regions in countries classified as Liberal Market Economies (LMEs) host more opportunity-driven entrepreneurs compared to regions in Coordinated Market Economies (CMEs). We interpret from this finding that entrepreneurial opportunities in LMEs are more often exploited by new ventures (especially spinoffs), while such opportunities in CMEs are captured more often by incumbent firms and their employees. Unexpectedly, regions in Dependent Market Economies display even higher rates of opportunity-driven entrepreneurship than regions in LMEs, despite the commonly held notion that their institutions are less supportive for new ventures.

6.2.4 Entrepreneurial ecosystems (Chapter 5)

Although entrepreneurship is increasingly acknowledged to play an important role in the dynamics of economic development (Van Praag & Versloot, 2007; Wennekers & Thurik, 1999), there is little evidence on the effects of underlying structural factors (institutions, social structure, industrial structure, etc.) on the relationship between entrepreneurship and development (Bjørnskov & Foss, 2016). Recently, the concept of the entrepreneurial ecosystem has gained rapid popularity as a new approach that conceptualises this relationship (Stam, 2015).

In **chapter 5**, we attempt to include our insights gained from the findings of the preceding chapters into the entrepreneurial ecosystem approach. We start by estimating a standard growth model on our full sample of regions, and find that this produces significant positive effects of our three indicators of entrepreneurship (total entrepreneurial activity, opportunity-driven entrepreneurial activity, and job-creation-expecting entre-

preneurial activity). However, when we include random country effects in a multilevel specification, the estimated effect of entrepreneurship turns insignificant. While statistically preferred, the drawback of the latter approach holds that the inclusion of country random effects masks the presence of differences in the relationship between entrepreneurship and growth between groups of regions that are related to the characteristics of the entrepreneurial ecosystem in these regions.

A further examination of the relationship between entrepreneurship and economic growth using a latent class model, indicates that for both total regional entrepreneurial activity and opportunity-driven entrepreneurial activity the sample of regions can be divided into four groups of regions. These groups differ significantly in their relationship between entrepreneurial activity and development. Whereas a relatively large group of European regions seems to have an ecosystem in which a positive growth effect from entrepreneurship is present, there are some smaller groups of regions that experience no positive or even negative growth effects from regional entrepreneurship.

In an exploratory analysis, we compare the groups of regions according to a range of regional characteristics that are components of or closely linked to entrepreneurial ecosystems. With respect to total entrepreneurial activity, the groups of regions that are characterised by a positive impact of entrepreneurship on development have the best formal and informal institutions. Regarding the industrial structure, the groups of regions with a positive association of entrepreneurial activity with growth, have significantly higher levels of unrelated variety and industry relatedness density, as compared with the other groups of regions. Moreover, the group of regions with the largest positive effect, shows the highest number of new industrial specialisations, as well as the highest turbulence in the number of industrial specialisations.

For opportunity entrepreneurship, similar differences between the core group and the other groups exist, although the differences are weaker. Another interesting feature of the findings is that the comparison of the non-core groups shows much more variability in the differences of the various individual components of the entrepreneurial ecosystems. This suggests that differences in the relationship between entrepreneurship and economic development are also likely to be related to different combinations of the various components.

6.2.5 Discussion of the overall findings

The objective of this dissertation is to examine the roles of industrial relatedness and entrepreneurship in the economic development of regions. Overall, we find that the effect of relatedness on economic development is multi-faceted, generating direct effects as well as indirect effects through other channels. Figure 6.1 depicts the conceptual model as introduced in chapter 1, in which the numbers refer to the respective chapters. From the literature review it became apparent that past studies found that relatedness strongly influences the probability that certain activities will enter a region's economy (link *2a*), and also that related variety stimulates employment growth by fostering knowledge spillovers that facilitate innovations, which in turn introduce new goods and services in the economy (link *2b*). Moreover, related variety may also stimulate growth through entrepreneurship (links *4*), as related variety increases the probability that individuals discover new business opportunities by connecting related knowledge domains. The expected growth stimulus from entrepreneurship, in turn, is found to vary across levels of relatedness among an economy's activities (links *5*). Regions with higher relatedness density among an economy's industrial activity are found to benefit from a larger positive growth effect from entrepreneurial activity.

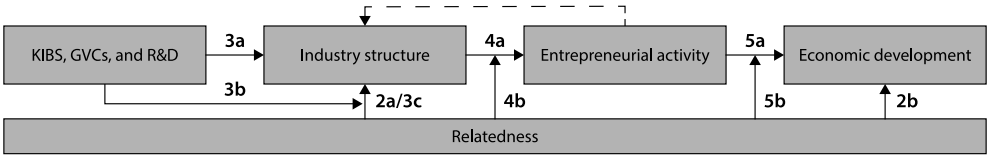


Figure 6.1: *Visualisation of the relationships investigated in this research*

The role of entrepreneurship in regional economic development is thus affected by the industry structure, as different compositions of industrial activity bring forth different types of entrepreneurship, while at the same time, certain types of entrepreneurship are found to play a significant part in the structural change of the industrial industry structure as well (Neffke et al., 2018). In chapter 4, we find that related variety increases opportunity-driven entrepreneurship whereas unrelated variety decreases opportunity-driven entrepreneurship. Although we do not specifically analyse the consequences that this may have for industrial diversification, it seems likely that it promotes a path-dependant or related type of diversification, as knowledge spillovers stemming from related variety imply a recombination of related knowledge domains. In this sense, the

introduction of new activities by entrepreneurs is expected to reinforce the industry structure of the economy. This is illustrated by dotted line in figure 6.1. In other words, the industry structure (in terms of diversity, maturity, density, etc.) determines the prevalence of entrepreneurial activity through factors such as knowledge spillovers, entry barriers, or competition, whilst at the same time, entrepreneurial activity impacts upon the industry structure by introducing new activities into the economy.

Industrial diversification of regional economies is persistently found to be highly path-dependent, which thus seems at least to some extent be explained by the finding that related variety is positively associated with the prevalence of entrepreneurship, while unrelated variety is so negatively. As a result, regional economies by default diversify into related products or industries. Such a development process can in some cases lead to technological lock-ins and may expose economies strongly to changes in global demand or competition. In other cases, however, such a development process might be preferred, for instance to reinforce young but promising new lines of industrial activity. In the long-term, a mix of related and unrelated diversification is therefore to be favoured, so that regions can benefit from the exploitation of existing knowledge and capabilities, whilst also sometimes diversifying into more risky unrelated territories to develop completely new knowledge and capabilities.

Although we found in chapter 3 that local conditions such as KIBS, GVCs, and R&D (links *3a* and *3b*) increase the probability that new development path emerge, it remains to be researched how significant the accompanying changes to the industry structure over time turn out to be. When discussing the path-dependence of institutions, Martin (2009) argues that incremental changes to the components of a system (in his example institutions, but this argument can be applied to regional economies consisting of industries as well), might not change the path-dependence of the system as a whole. In contrast, while path-dependence may prevent radical changes of the system, incremental changes of components of the system over time may cumulate into structural changes of the system. In addition, the extent to which entrepreneurial actions, by introducing new activities, reinforce path-dependent development or initiate new development paths is dependent on a multitude of conditions including competition, room for experimentation, or the maturity of technologies and industries. Regional development is therefore not only dependent on entrepreneurial activity and the entry of new unrelated activities, it is arguably equally important that entrepreneurial activity and the entry of new activities occasionally initiate a revitalisation of a region's development path.

6.3 Policy implications

The current policy climate in the European Union is characterised by a strong emphasis on the implementation of policies designed to promote entrepreneurial activity. Such policies can in theory be used to promote entrepreneurship for a variety of reasons, but assuming that the ultimate goal of governments is to foster economic development and prosperity, our findings indicate that policies that focus only on the promotion of the rate of entrepreneurship, do not warrant a de facto stimulus for economic development. The extent to which entrepreneurship is able to contribute to economic prosperity hinges upon the extent to which it introduces new productive activities that prevail for longer periods of time, upon which competitive advantages of an economy can be build.

With its Smart Specialisation Strategy, the European Commission emphasises that policymakers need to acknowledge that regions cannot do everything, but instead should build upon the assets and resources available to the region to enhance the effectiveness of their policy efforts. Smart Specialisation also highlights the role of an entrepreneurial discovery process, in which entrepreneurs (defined here in a broad sense to include, besides individual inventors, also firms, higher education institutions, and innovators in general) are key to the discovery of potential domains for development, as they are able to combine scientific and technological knowledge with knowledge about market growth potential and potential competitors (Foray et al., 2009). Furthermore, it stresses that not all regions should focus on the invention of fundamentals or new General-Purpose Technologies (GPTs). Rather, R&D and innovation efforts should focus on new applications of such GPTs in other parts of the economy. In this sense, Smart Specialisation is not only a strategy to enhance regional innovation and diversification, but also to enhance inter-regional diffusion within Europe (and beyond).

Although the Smart Specialisation Strategy accentuates the importance of building upon assets and resources readily available to a region, industrial diversification also relies on the presence of a place-based diversification and innovation strategy (Boschma, Coenen, Frenken & Truffer, 2017; Frenken, 2017; Simmie & Martin, 2010), one that does not only rely on related or unrelated diversification. For diversified economies, a related type of diversification might be preferred, as ample opportunities for recombination exists that ensure innovation dynamic and the development of new activities. For more specialised regions such opportunities might be more limited, and a related diversification strategy may enlarge the risk of these regions ending up in technological lock-ins and running the the risk of losing competitive advantages in the long-term. Additionally, new economic activities in general have a higher probability to be related to existing activities in

dense core regions, as there are more capabilities and knowledge to build upon, while in peripheral regions unrelated diversification strategies may be relatively riskier, as there are less knowledge and capabilities to support new activities. An unrelated diversification strategy may also be effective if supportive conditions are in place that enable the acquisition or development of new and unrelated capabilities, including universities and public research organization, R&D-intensive firms.

Although the Smart Specialisation Strategy promotes regions to develop new activities by building on locally available assets and resources, effectively promoting a related diversification strategy, we argue that depending on local circumstances either related, unrelated, or a mix of these regional diversification types is to be preferred. Also note that one may expect that related diversification, would often also occur without policy intervention. Hence, policy support for innovation or entrepreneurial activity that mostly relies on local related knowledge and capabilities, may have limited additionality (Frenken, 2017), as the new activities stemming from such support are expected to be developed regardless. Unrelated diversification, on the other hand, stems from breakthrough innovations (new-to-the-world) or inter-regional learning of unrelated knowledge (new-to-the-region), which would not frequently occur by itself, as the required innovation and entrepreneurial activity are considerably riskier. However, unrelated diversification potentially yields higher social returns compared to related diversification. Policies supporting such a type of diversification, if successful, therefore is expected to have a higher additionality.

The challenge for policymakers is twofold: to find the right balance between related and unrelated diversification in entrepreneurship and innovation policies and to benefit from those conditions that are available or can be developed without high risks providing a channel for the acquisition of new unrelated knowledge and capabilities. With respect to the latter, at least two conditions can be distinguished that provide regional economies with a channel through which new unrelated knowledge and capabilities can be acquired: (1) conditions that provide external linkages for the inflow of non-local knowledge, and (2) conditions that act as a bridging platform between unrelated actors, facilitating knowledge spillovers between them. Due to an inflow of new unrelated knowledge from outside of the region, the interpretation and perceived potentialities of local knowledge might change, possibly leading to new and original recombinations of local and non-local knowledge. Similarly, bridging platforms that act as intermediary between unrelated actors may shorten the cognitive distance between their knowledge domains, thereby increasing the potential for new and original recombinations of unrelated know-

ledge domains. In our analysis of chapter 3 we found that the presence of KIBS, participation in GVCs, and investment in R&D can offer such channels; however, other regional conditions might offer these channels as well, for instance migrant entrepreneurs or particular institutional frameworks (Boschma & Capone, 2015; Neffke et al., 2018).

The function of KIBS as external source of knowledge and supplier of intermediate services to a variety of clients in many – and unrelated – industrial and institutional contexts, enables them to facilitate knowledge spillovers across a diverse and sometimes non-local set of actors (such as firms, governments, or research institutes). Due to their central position between these actors and ability to combine and transfer knowledge, KIBS can bring together different types of knowledge (e.g. about technology, markets, or regulation), through which they can facilitate an entrepreneurial discovery process as intended with the Smart Specialisation Strategy. In addition, KIBS play an important role in the diffusion of GPTs, as by combining their client's knowledge with knowledge about GPTs, they can support the development of new applications. Involving KIBS in the development of Smart Specialisation Strategies, can therefore help to identify more efficiently, possible directions for regional specialisation. Making KIBS more accessible facilitates an entrepreneurial discovery process in the sense that it might reduce barriers for entry by increasing recombinations and transmissions of different types of knowledge such as technology, markets, or regulation across a diverse set of actors. Knowledge diffusion (e.g. knowledge about technological applications or organisational structures) from highly innovative and top tier firms to a broader group of SMEs could be supported by improving the presence and accessibility of KIBS. Making KIBS more accessible for SMEs can also accelerate the discovery of new applications of GPTs and help SMEs develop new knowledge and capabilities. Supporting innovation in such a way would fit a related diversification strategy. Our results indicate that this would be especially supportive for industrial diversification and ultimately economic development, in core regions with high industry relatedness density.

In more peripheral regions with limited related economic varieties there is also limited potential for recombinating related knowledge domains. For such regions, non-local linkages may foster inflows of new knowledge in the form of relationships of firms and organisations that cross regional or even national borders, increasing the potential for recombinations. Such relationships can be collaborative in nature, for instance research institutes that collaborate on temporary projects or on a more structural basis, but they may also exist in the form of trade relationships in global value-chains as well, which in turn can be governed in different ways.

Especially in cases with limited availability of local related knowledge and capabilities can the participation in GVCs support a region to develop new economic activities. The participation in value chains provides access to markets and an inflow of new knowledge that can support local development and upgrading. Firms that are active in trade relationships or value-chains can sometimes upgrade their activities and move-up in the value chain into more complex or higher value-added activities. Another possible diversification path is to use the developed knowledge and capabilities to supply similar goods in other (un)related value chains. Supporting the initial participation or location decisions of GVC leaders can therefore stimulate the development of new local capabilities and knowledge. Also, with respect to R&D activities, we find that they promote industrial diversification especially in regions with limited availability of local related knowledge and capabilities. Due to a higher level of innovation capacity that is associated with R&D activities, these regions can become less reliant on local knowledge and capabilities. For instance, due to non-local linkages associated with R&D efforts within local firms and research institutes, inflows of new and complementary knowledge can initiate new diversification paths. Local policymakers in regions with limited availability of local related knowledge and capabilities can try to stimulate this by encouraging such collaborative or trade relationships to promote unrelated diversification.

In cases where there is a limited amount of related economic varieties, an unrelated diversification strategy might be necessary for long-term economic prosperity, policymakers should be aware that this type of diversification strategy is, however, inherently riskier. Supporting or promoting unrelated activities in regions potentially yields the highest social returns, but if new activities are too unrelated the chances of failure might increase rapidly.

Regarding entrepreneurial activity, besides our finding that the industry structure of a region has important implications for the type of entrepreneurship, we find that the subsequent growth effect of entrepreneurship is dependent on the quality of the entrepreneurial ecosystem. From a Smart Specialisation Strategy perspective, on the one hand it would be beneficial if these activities are technologically related to each other, as this has advantageous effects on entrepreneurship, specifically the kind which is setting up firms to seize perceived market opportunities. On the other hand, it is advisable to have unrelated activities within an economy to increase a region's resilience against sector-specific shocks and breakthrough innovations. Too much unrelated varieties, however, seem to be harming entrepreneurial activity (chapter 4).

We take our findings to indicate that governments need to adopt a place-based and holistic approach when examining the roles of relatedness and entrepreneurship in their policy efforts. Regarding regional competitiveness, instead of entrepreneurial activity as key priority, regional governments should adopt an entrepreneurial ecosystems approach in which the focus of the policy differentiates across regional contexts. This means that given that not all regions benefit from a positive association of entrepreneurial activity with economic growth, in some cases particular elements of the ecosystem should be supported rather than entrepreneurial activity directly. Regions where a positive relationship between entrepreneurship and growth does exist whilst having a low prevalence of entrepreneurship are more likely to benefit from policies aimed at increasing the level of entrepreneurship. In contrast, regions where the positive relationship between entrepreneurship and development does not materialise may require policies directly aimed at improving their entrepreneurial ecosystem. In making the assessment whether or not to do this, regional governments need to compare the costs that improving the ecosystems will entail with the benefits that the region may enjoy when entrepreneurship leads to higher growth. This trade-off may turn out quite differently for such diverse regions as Bavaria, Attica, or East Poland. The differences in the relationship between entrepreneurship and growth that we have identified, together with the differences in characteristics between the groups of regions, may indicate that it is economically not feasible for some regions to engage in policymaking to try to establish a positive growth effect from entrepreneurship.

6.4 Limitations

The preceding sections discuss the main research findings and accordingly the implications for policymaking. As no analysis is perfect, the analyses done in this study are not without limitations as well. The following discussion will consider this, and in some cases discuss suggestions for future research on how to move beyond these issues.

The first limitation concerns the measurement of knowledge spillovers. Starting with chapter 3, we find that regions have a higher probability to develop related specialisations, as compared with their current industry portfolio. We argue that recombination, underlying the process of industrial diversification, is more efficiently accomplished with related sets of knowledge, i.e. we assume that knowledge spills over more easily between related firms and individuals, assuming in turn that, related firms and individuals have related sets of knowledge. Similarly, in chapter 4 we assume that the positive effect that we find of related variety on entrepreneurship is caused by knowledge spilling

over between individuals, from which they learn and recognise new business opportunities. However, precisely how these individuals learn new business opportunities from relating their knowledge with that of other individuals remains implicit. In both chapters we are unable to measure knowledge spillovers directly, i.e. the micro-level transmission of knowledge from one individual to another, but instead use indirect measures. In the case of related variety, we rely on an ex ante defined hierarchical classification scheme not intended to measure relatedness, while in the case of proximity we examine ex post the co-occurrence of specialisations. Resultantly, we cannot reject the possibility for different explanations besides the effects of knowledge spillovers underlying the mechanisms that we propose. A better understanding of the differences between micro-level transmissions of related and unrelated knowledge would support our empirical findings. Such an understanding can be developed through qualitive research, for instance in the form of case studies (see e.g. Binz et al., 2016; Dawley, 2014; Tanner, 2014).

Second, the data that is used in this study to measure the prevalence rates of regional entrepreneurship has some limitations that should be recognised. In the literature, entrepreneurship is operationalised and measured in various ways, including the share of small firms in the total the total number of firms, rates of new businesses and firm formation, or self-employment rates. In this study, we argue that entrepreneurship does not start with the creation of a new firm, rather, it is the discovery and exploitation of opportunities that is key (Shane, 2000), which (often much later) results in the creation of new firms. Indicators of entrepreneurship should therefore not only focus on the occasion of new firm formation, they should also be able to distinguish between the motives that underlie firm creation. For this reason, we use data provided by the Global Entrepreneurship Monitor (GEM), which distinguishes between different types of entrepreneurship based on, among other things, the motives of entrepreneurs to create new firms. Although this data is carefully weighted for the age and gender composition of the regional populations and has a questionnaire design that has been developed and improved for quite some years, the usual limitations that come with using survey data do apply to the present study as well. For instance, questions may be vulnerable to misinterpretation and there may be respondents that do not feel encouraged or comfortable to provide accurate answers.

Third, although the GEM data are primarily collected to be representative at the national level, by pooling several annual waves of data, we are able to measure entrepreneurial activity representative at the regional level. Mainly depending on the size of the country, we are able to measure different GEM indicators at the NUTS-1 or NUTS-2 levels. Arguably,

however, NUTS-1 and NUTS-2 regions are not the most meaningful spatial level to capture knowledge spillovers. Instead, labour market regions (NUTS-3) may constitute the more appropriate spatial unit of analysis.

A fourth limitation regards the time period of our analysis, especially when regional economic development is the subject of analysis in chapter 5. To study economic development, a sufficiently long time period should be used to eliminate the possible effects of short-term business cycles. In our specific case, although we measure growth and entrepreneurship as averages over the period 2006-2014, the great recession that started late 2007 might impact on our results.

Finally, the cross-sectional nature of the empirical analyses of chapters 3 and 5 creates some limitations. Mainly due to the limited availability of longitudinal data on entrepreneurship at the regional level, we were unable to estimate panel regressions. Although we have ensured a significant time lag between our dependent and independent variables, we are not able to fully rule-out the possibly of reverse causality. Specifically, in chapter 4 our dependent variable is entrepreneurship with related and unrelated variety as main explanatory variables. The positive and negative effect that we find for related variety and unrelated variety, respectively, on opportunity-driven entrepreneurship could potentially indicate that entrepreneurs are expected to setup related business, rather than unrelated business, and therefore add to the degree of related variety and lower the degree of unrelated variety. This explanation, however, we believe is rather implausible, seeing that the type of entrepreneurs we measure using the GEM data, concerns individuals and young start-ups, who arguably have a trivial part in shaping the industry structure. In the case of chapter 5, our dependent variable is economic growth and our main explanatory variables are different types of entrepreneurial activity. By creating employment and other external effects entrepreneurship causes an economy to grow, however, as an economy grows it also induces an increase in opportunity-driven entrepreneurial activity (in contrast, an economic recession might stimulate the prevalence of necessity-driven entrepreneurial activity). This makes that we should interpret our findings regarding the effects of entrepreneurship on growth with care. Although we take into account a substantial time lag, our findings are not indisputable due to the possibility of correlation over time of both the growth rate of regions and the prevalence rate of entrepreneurship.

Regarding the last three points, the urgent challenge is to create comparable data across Europe, at appropriate geographical levels, and with a sufficient longitudinal coverage, about the prevalence rates of different types entrepreneurial activity.

6.5 Future research

Where in the foregoing section some specific suggestions for future research are provided, this section will provide some more general directions for future lines of research.

First, in chapter 4 we find that opportunity-driven entrepreneurship may be a channel through which related variety leads to regional development, as spillovers create business opportunities that entrepreneurs aim to exploit. This leaves open the question what other channels exist. For example, one can expect that related variety increases social networking as well as labour mobility across industries (Breschi & Lissoni, 2009). Another example is intrapreneurship, i.e. individuals in wage employment that behave entrepreneurial on behalf of the organisation they work for. Besides identifying such potential channels, future research may wish to examine whether entrepreneurship, as well as other spillover channels indeed foster economic development in turn.

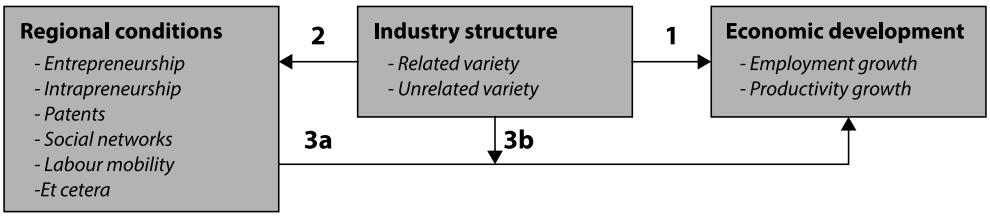


Figure 6.2: *Representation of various channels through which (un)related leads to growth*

Figure 6.2 shows a possible representation of such an analysis. A fully-fledged model of related variety would analyse the direct effects of related and unrelated on economic development (indicated by link 1 in figure 6.2), as well as the mediating (link 3a) and moderating (link 3b) effects of various spillover channels that are identified to be affected by related and/or unrelated variety (as indicated by link 2). Although such an analysis is more demanding in terms of empirical data, it is certainly worthwhile for the related variety literature to 'come full circle'.

As a second line of research, we advocate a further theoretical and empirical deepening of the research field's understanding of how institutions influence entrepreneurship. In particular, an interesting question remains to what extent institutions – and their complementarities – relevant to entrepreneurship map onto the existing varieties of cap-

italism that have been distinguished so far. As significant differences are likely to exist between institutions or cultures across regions within countries (Charron et al., 2014; Rodriguez-Pose & Di Cataldo, 2015), it will be worthwhile to develop methods to disaggregate the framework of Varieties of Capitalism at a sub-national level to clarify its relation with regional entrepreneurship, as well as other regional conditions identified to play an important role in economic development. Furthermore, these regional institutional differences are likely to not only explain variation in the prevalence rate of different types of entrepreneurship, but may also shape the relationship of entrepreneurship with regional development. The entrepreneurial ecosystem approach internalises this, but more empirical research is needed.

A third question, related to the entrepreneurial ecosystem approach, holds to what extent the industry structure of a region impacts upon or interacts with other elements of the ecosystem, and whether this matters for the extent that entrepreneurship can contribute to economic development. Currently, the literature on entrepreneurial ecosystems largely overlooks the industry structure as a factor of influence. However, relatedness in the industrial structure of a region affects the potential for knowledge spillovers significantly (chapter 4). Specifically, we find that knowledge spillovers stemming from related variety can explain variation in the level of productive entrepreneurship, as proxied by opportunity-driven entrepreneurship. In addition to these findings, it has been shown that other characteristics of the industry structure such as the size and age mix of existing firms affect the rate of new firm formation, as small and young firms for instance generate more spin-offs. Industry characteristics then also impact on the rate of entrepreneurship, as well as the probability that new firms will survive or drive structural transformations, as increased competition or entry barriers are expected in the case of mature industries for instance. Moreover, the composition of the industry structure in terms of the specific nature of the activities (e.g. manufacturing, business/consumer services, or distribution activities) that it consists of will affect how much entrepreneurship is expected, and whether it will contribute to economic development. The extent to which entrepreneurship truly contributes to development in response to knowledge spillovers from particular compositions of the industry structure, such as related variety as is highlighted by the first point in this section, has yet to be analysed. One possibility would be to incorporate the industry structure of a region as element into the entrepreneurial ecosystem approach.

A fourth suggestion for future research concerns the question why unrelated variety has a negative effect on entrepreneurship. Theoretically, unrelated variety can be associated

with either increased or decreased levels of entrepreneurial activity. The opportunities stemming from the recombination of unrelated knowledge might be perceived as too risky by incumbent firms, leaving them for entrepreneurs to exploit. In contrast, nascent entrepreneurs might be less likely to have the resources to bridge large cognitive distances or be able to raise the funding necessary to setup such a risky business. Existing evidence suggests that unrelated variety fosters entrepreneurship (Bishop, 2012; Colombelli, 2016; Guo et al., 2016) or that unrelated variety interacts positively with entrepreneurship (Fritsch & Kublina, 2017). More research is needed to investigate more precisely why and under which conditions unrelated variety impacts on the rate of entrepreneurship and in what direction. One suggestion would be to investigate whether the impact of unrelated variety is different across different levels of related variety, as an abundance of related variety within each unrelated variety could possibly alleviate the negative impact of unrelated variety.

A fifth question holds how entrepreneurial activity is associated with industrial diversification of regions in light of the product space concept. What role do different types of entrepreneurial activity play in the process of industrial diversification and is this different across types of industrial diversification. i.e. related or unrelated. Neffke et al. (2018) find that new establishments that do not belong to pre-existing firms, especially those with non-local geographical origin, are expected to bring the most structural change. This, however, leaves unexplained why these entrepreneurs start a new business and whether those with non-local origins do so in another region. Alternatively, different measures for entrepreneurship, such as provided by the GEM, could provide insight in for instance what type of entrepreneurship is expected to contribute the most to what type of industrial diversification. In addition, not only the motives of entrepreneurs are likely to influence the extent by which they can drive structural change, but also their traits, characteristics, and their previous experiences. Especially in the context of the Smart Specialisation Strategy, a better knowledge and understanding of the motives of different types of entrepreneurs paired with the extent to which each type is expected to drive structural change would provide a valuable instrument for policymakers.

Finally, in chapter 3 we find a positive effect of relatedness density on the entry probability of new industries. As relatedness density is based on the existing industries, the entry of an industry at a certain point in time can explain variation in future levels of relatedness density. Entry in the industry space makes entrants more related to existing industries, exactly because they enter. Therefore, the explanation that relatedness predicts entry is endogenous to some degree, giving rise to another question of why such a

large share of variation is left unexplained by relatedness? Or why the variation in entry probability that is explained by relatedness is not found to be higher than what is found now? One explanation is that certain place-based conditions make that the level of relatedness does not fully explain entry. This may reflect that the same level of proximity between a pair of products or industries corresponds to a different level of relatedness. Evidently, the learning experience of no individual is completely alike, tacit knowledge therefore is also never completely alike, and the same holds true for the collective learning experiences in firms and organisations. On aggregate, knowledge and capabilities of firms, industries, and regions, are therefore unequal as well: two firms producing the same product but residing in different places may be more or less related than what is assumed. Another question therefore holds; what makes that certain entities (e.g. patents, firms, industries, or products) are more or less related across particular environments. Or, what conditions make that certain industries are related in one particular context, but not in others.

Appendix A

Appendix to chapter 3

Variable	Obs.	Mean	Std. Dev.	Min	Max
BLQ08	269	134.796	30.818	44	231
BLQ13	269	134.777	31.330	45	219
dBLQ	269	-0.019	10.837	-46	62
Gain	269	18.290	9.349	3	70
Lose	269	18.309	6.840	2	54
Turbulence	269	36.599	12.285	11	81
Density	269	116.354	36.074	11.370	229.490
KIBS	269	0.057	0.035	0.007	0.229
GVC	238	0.188	0.058	0.048	0.317
R&D	269	0.015	0.012	0.001	0.080
GRPPC	269	10.085	0.404	8.916	11.262
CAPFRM	269	8.892	0.921	5.401	11.834
PDEN	269	4.951	1.228	1.125	9.139
BCITY	269	0.405	0.492	0	1
HC	269	24.148	8.260	6.8	48.3

Table A.1: *Summary statistics regional level*

		1	2	3	4	5	6	7	8
1	BLQ13	1							
2	dBLQ	0.15	1						
3	Gain	0.44	0.78	1					
4	Lose	0.36	-0.50	0.15	1				
5	Turbulence	0.53	0.32	0.84	0.66	1			
6	Density	0.91	-0.09	0.20	0.43	0.39	1		
7	KIBS	0.19	0.04	0.10	0.07	0.11	0.26	1	
8	GVC	0.28	0.18	0.12	-0.13	0.02	0.26	0.13	1
9	R&D	0.11	0.09	-0.04	-0.19	-0.13	0.19	0.44	0.29

Table A.2: *Correlation matrix regional level*

Variable	Obs.	Mean	Std. Dev.	Min	Max
BLQ08	86.133	0	0	45	0
BLQ13	86.133	0.057	0.232	0	1
Density	86.133	0.244	0.056	0	0.482

Table A.3: *Summary statistics industry level*

		1	2	3	4	5	6	7	8	9
1	BLQ13	1								
2	Density	0.06	1							
3	KIBS	0.00	0.15	1						
4	GVC	0.00	0.12	0.07	1					
5	R&D	-0.02	0.00	0.43	0.24	1				
6	GRPPC	-0.02	-0.07	0.54	0.01	0.46	1			
7	CAPFRM	-0.02	0.31	0.38	0.01	0.38	0.50	1		
8	PDEN	-0.03	-0.12	0.31	0.01	0.23	0.42	0.40	1	
9	BCITY	-0.01	0.19	0.30	0.00	0.16	0.19	0.55	0.44	1

Table A.4: *Correlation matrix industry level*

Quantiles	1	2	3	4	5	6	7	8	9	10
KIBS	-0.175	-0.113	-0.173	0.014	0.076	-0.337	-0.032	0.468	0.627	0.447
	(0.089)*	(0.125)	(0.117)	(0.131)	(0.148)	(0.159)*	(0.186)	(0.215)*	(0.245)*	(0.348)
R-sqr.	0.122	0.096	0.095	0.089	0.081	0.083	0.087	0.091	0.089	0.120
GVC	0.108	0.353	0.39	-0.061	0.025	-0.367	-0.128	0.024	-0.562	-1.110
	(0.111)	(0.108)**	(0.132)**	(0.118)	(0.118)	(0.118)**	(0.132)	(0.154)	(0.191)**	(0.198)**
R-sqr.	0.121	0.102	0.114	0.097	0.089	0.085	0.100	0.105	0.098	0.120
R&D	0.784	0.328	1.139	0.441	-0.526	-0.616	0.452	0.233	-0.788	-0.370
	(0.264)**	(0.288)	(0.313)**	(0.301)	(0.278)+	(0.296)*	(0.332)	(0.421)	(0.575)	(0.882)
R-sqr.	0.122	0.096	0.096	0.089	0.081	0.083	0.087	0.091	0.088	0.120

*Clustered standard errors in parentheses (** p<0.01, * p<0.05, + p<0.1). Depend variable: BLQ13. The results presented in this tabel were obtained afer dividing our sample into 10 different groups, based the level of relatedness density. For each main explanatory variable (KIBS, GVC, and R&D) and for each group, we estimated equation (7) seperatly to obtain the effects of KIBS, GVC, and R&D on entry proabiblity across different quantiles of relatedness density. Other control variables, country fixed effects, and industry fixed effects were included as well, however, due to space constrains not shown in this table.*

Table A.5: *Effects of KIBS, GVC, and R&D across different quantiles of relatedness density*

Appendix B

Appendix to chapter 4

Variable	Obs	Mean	Std. Dev.	Min	Max
TEA	204	6.245	2.104	2.332	14.358
TEA_OPP	204	4.577	1.489	1.187	10.241
TEA_NEC	204	1.352	1.103	0.08	7.145
OPP/NEC	204	1.469	0.805	-0.711	4.364
UV	204	5.044	0.38	3.04	5.547
RV	204	1.893	0.297	0.727	2.445
LNGRPPC	204	10.02	0.441	8.672	11.29
CITY	204	0.368	0.483	0	1
LNPDEN	204	4.945	1.233	1.194	8.759
UNEMP	204	9.231	4.857	2.463	27.375
HC	204	22.701	8.417	8	45.7
VOC_LME	204	0.083	0.277	0	1
VOC_CME	204	0.412	0.493	0	1
VOC_MME	204	0.289	0.455	0	1
VOC_DME	204	0.216	0.412	0	1

Table B.1: *Descriptive statistics*

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	TEA	1													
2	TEA_OPP	0.87	1												
3	TEA_NEC	0.67	0.23	1											
4	OPP/NEC	-0.27	0.16	-0.8	1										
5	UV	-0.08	-0.07	-0.07	0.03	1									
6	RV	-0.07	-0.08	0	-0.03	0.55	1								
7	LNGRPPC	-0.25	0.08	-0.65	0.65	0.01	-0.17	1							
8	CITY	0.07	0.1	-0.01	-0.03	0.26	0.08	0.27	1						
9	LNPDEN	-0.06	-0.03	-0.06	-0.06	0.13	-0.03	0.25	0.44	1					
10	UNEMP	0.05	-0.1	0.29	-0.43	-0.26	0.03	-0.32	0.06	-0.04	1				
11	HC	-0.08	0.11	-0.34	0.33	0.15	-0.05	0.62	0.28	0.22	-0.12	1			
12	VOC_LME	0.08	0.14	-0.05	0.04	0.07	-0.24	0.06	0.29	0.06	-0.05	0.23	1		
13	VOC_CME	-0.27	-0.07	-0.49	0.53	0.08	-0.08	0.51	-0.18	0.04	-0.51	0.41	-0.25	1	
14	VOC_MME	-0.22	-0.21	-0.08	-0.11	-0.28	0.13	0.02	0.12	-0.06	0.6	-0.19	-0.19	-0.53	1
15	VOC_DME	0.51	0.22	0.71	-0.54	0.17	0.12	-0.67	-0.1	-0.02	-0.03	-0.44	-0.16	-0.44	-0.33

Table B.2: *Correlation matrix*

	(1) TEA	(2) TEA_OPP	(3) TEA_NEC	(4) OPP/NEC
UV	-0.450 (0.439)	-1.200** (0.371)	-0.099 (0.168)	-0.131 (0.131)
RV	-0.003 (0.508)	0.788+ (0.426)	-0.257 (0.201)	0.376* (0.162)
LNGRPPC	1.869** (0.531)	1.942** (0.537)	-0.238 (0.213)	0.759** (0.173)
CITY	0.413 (0.279)	0.362 (0.241)	0.212+ (0.112)	-0.133 (0.096)
LNPDEN	-0.154 (0.134)	-0.240** (0.087)	-0.058 (0.05)	-0.067* (0.031)
UNEMP	0.019 (0.039)	0.033 (0.029)	0.036* (0.014)	-0.027* (0.011)
HC	0.034 (0.022)	0.005 (0.018)	0.017* (0.008)	-0.013* (0.006)
VOC_LME	-	-	-	
VOC_CME	-1.664* (0.677)	-1.170** (0.411)	0.019 (0.233)	-0.048 (0.137)
VOC_MME	-2.600** (0.888)	-1.74** (0.507)	0.094 (0.279)	-0.201 (0.17)
VOC_DME	1.655* (0.744)	1.129* (0.456)	1.367** (0.268)	-0.49** (0.168)
λ	0.326 (0.206)	-0.073 (0.492)	0.589** (0.126)	0.451** (0.148)
ρ	0.853** (0.101)	0.340 (0.725)	0.605** (0.173)	-0.351 (0.327)
σ^2	2.076** (0.209)	1.599** (0.159)	0.335** (0.034)	0.255** (0.026)
Constant	-11.32+ (5.837)	-8.607 (5.824)	3.103 (2.29)	-5.74** (1.723)
Log likelihood	-370.01	-336.54	-336.54	-151.79
Observations	204	204	204	204

*Inverse-distance matrix with 750km as cut-off. Standard errors in parentheses. Significance levels: ** p<0.01, * p<0.05, + p<0.1.*

Table B.3: *Spatial correlation; other types of entrepreneurship*

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Nederlandse samenvatting

Mondialisering betekent voor regio's binnen de Europese Unie een toenemende internationale concurrentiedruk doordat zij door handelsliberalisatie rechtstreeks worden blootgesteld aan de concurrentie van opkomende economieën elders in de wereld. Europese beleidsmakers hebben hier de laatste jaren op gereageerd door het nemen van maatregelen ter bevordering van ondernemerschap, innovatie en economische structuurversterking meer in het algemeen, om zodoende het welvaartsniveau van regionale economieën op pijl te houden of te verbeteren. De 'Smart Specialisation Strategy' speelt hierin een belangrijke rol als instrument voor het implementeren van plaats-afhankelijk beleid, waarin regio's worden gestimuleerd om hun eigen concurrentievoordelen te identificeren en vervolgens verder te ontwikkelen. Het uiteindelijke doel van deze strategie is het stimuleren van economische groei in Europese regio's. Binnen dit kader doen we in dit proefschrift onderzoek naar de rol van gerelateerde variëteit en ondernemerschap.

Een algemene bevinding van dit onderzoek is dat beleid dat slechts gericht is op het stimuleren van ondernemerschap en onderzoek & ontwikkeling, zonder de regionale context in acht te nemen, veelal minder effectief is in het creëren van nieuwe banen en uiteindelijk in economische welvaart. Deze bevinding bekrachtigt de onderliggende redenering van de 'Smart Specialisation Strategy'. Een tweede bevinding betreft de prominente rol van gerelateerdheid in allerhande facetten van economische ontwikkeling, suggererend dat de effectiviteit van regionaal beleid vergroot kan worden door de rol van gerelateerdheid op te nemen in beleid gericht op ondernemerschap en innovatie.

S.1 Economische ontwikkeling en agglomeraties

De theoretische onderbouwing van dit onderzoek stoelt op vroege beschrijvingen van economische ontwikkeling en ondernemerschap door onder meer Adam Smith (1776),

Joseph Schumpeter (1912) en Jane Jacobs (1969), alsook op meer recente bijdragen van met name Paul Romer (1986). Uit zijn werk blijkt onder andere de prominente rol van kennis als endogene productiefactor in economische ontwikkeling. Omdat kennis een niet-rivaliserend goed is, kan de kennis die wordt ontwikkeld binnen bepaalde bedrijven en onderzoeksinstellingen 'overspoelen' naar andere bedrijven om nogmaals gebruikt te worden. We spreken dan over 'kennis spillovers'. Ondanks aanzienlijke vooruitgang in de laatste decennia op het gebied van informatie- en communicatietechnologie, blijkt geografische nabijheid tot de plekken waar kennis wordt geproduceerd de intensiteit van die kennis spillovers in belangrijke mate te voorspellen. Als gevolg daarvan observeren we een disproportionele ruimtelijke concentratie van innovatie activiteit ten opzichte van de gehele economische activiteit.

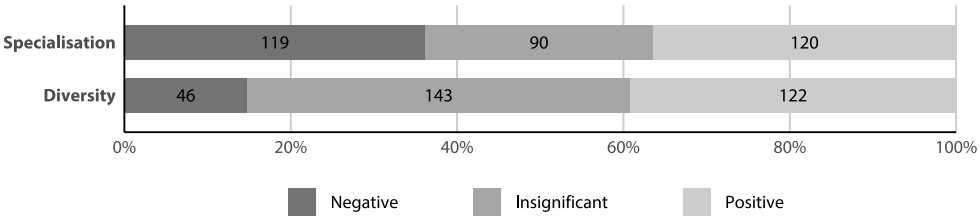
Naast kennis, en dan met name de kans op leren door kennis spillovers als agglomeratie externaliteit, onderscheidt de literatuur ook het ontstaan van een lokale poel van gespecialiseerde werknemers, lokale vraag en gespecialiseerde toeleveranciers als agglomeratie-externaliteiten. Deze ontstaan door de ruimtelijke concentratie van economische activiteiten uit dezelfde bedrijfstak en worden ook wel lokalisatievoordelen genoemd. Een andere vorm van agglomeratievoordelen ontstaat juist door de ruimtelijke concentratie van economische activiteiten uit diverse bedrijfstakken. Dit worden ook wel 'Jacobs externaliteiten' genoemd. Door een diversiteit aan economische activiteiten en daardoor een diversiteit aan kennis, ontstaat het potentieel om diverse soorten kennis te recombineren die zodoende tot kunnen innovaties leiden.

Hoewel de theoretische mechanismen van deze agglomeratie externaliteiten wel beschreven zijn, lijken de theorieën ogenschijnlijk onverenigbaar of zelfs tegenstrijdig. Dit komt voort uit een verschil in de uitleg van innovatie. In de theorie van lokalisatievoordelen wordt innovatie doorgaans als een incrementeel proces begrepen, waarin elke innovatie voortbouwt op een voorgaande. Daarentegen ziet Jacobs innovatie als een recombinant proces, waarin nieuwe innovaties niet noodzakelijk op nieuwe kennis gebaseerd hoeven te zijn, maar waarbij bestaande kennis ook op een nieuwe manier kan worden gerecombineerd en daarmee tot een nieuwe innovatie kan leiden.

Deze tegenstrijdigheid vindt zijn weerslag in de empirische literatuur naar agglomeratievoordelen. Het beeld dat wordt geschetst door de resultaten van de vele studies in navolging van Glaeser e.a. (1992) samen te vatten is sterk gemêleerd (zie ter illustratie figuur S.1). Voor zowel lokalisatie externaliteiten als Jacobs externaliteiten zijn ongeveer evenveel positieve resultaten gepubliceerd en alhoewel het aandeel negatieve resulta-

ten voor Jacobs externaliteiten relatief klein is, is de meerderheid van de resultaten met betrekking tot Jacobs externaliteiten niet significant.

Met deze heterogeniteit in onderzoeksresultaten als achtergrond, stellen enkele onderzoekers dat de theoretische noties van specialisatie en diversiteit te simplistisch zijn om de uiteenlopende effecten van de industriële compositie van economieën in relatie tot hun toekomstige ontwikkeling te vatten. Naast ruimtelijke nabijheid, zijn kennis spillovers afhankelijk van cognitieve nabijheid. Wanneer kennis cognitief gerelateerd is, maar niet hetzelfde, is het makkelijker voor betrokkenen om elkaar te begrijpen terwijl er nog ruimte over blijft om van elkaar te leren.



Figuur S.1: *Bevindingen van studies die agglomeratie externaliteiten onderzoeken. Bron: de Groot et al. (2016)*

S.2 Gerelateerde variëteit en ondernemerschap

Het concept gerelateerde en ongerelateerde variëteit (related- en unrelated variety) is door Frenken e.a. (2007) geïntroduceerd als nuancering in dit debat. De auteurs zijn het eens met Jacobs en Schumpeter die veronderstellen dat innovatie in essentie een recombinant proces is, maar stellen dat sommige kennis makkelijker is te recombineren dan andere. Een zekere mate van cognitieve nabijheid is nodig om een leerproces in gang te zetten en kennis spillovers te verwezenlijken. Variëteit van economische activiteit is dus vooral bevorderlijk voor innovatie en uiteindelijk economische ontwikkeling als het gerelateerd is.

Frenken e.a. (2007) veronderstellen dat gerelateerde variëteit bijdraagt aan de werkgelegenheid, gezien de verwachting dat de recombinatie van gerelateerde kennis leidt tot

nieuwe goederen en diensten wat uiteindelijk nieuwe banen creëert. Daarnaast veronderstellen zij dat ongerelateerde variëteit een dempend effect heeft op de werkloosheid gezien de verwachting dat de aanwezigheid van ongerelateerde sectoren als een portfolio fungeert tegen sectorspecifieke schokken. De bevindingen van de auteurs onderschrijven deze hypothesen voor regio's in Nederland. In hoofdstuk 2 van dit proefschrift constateren we dat de navolgende studies voor regio's in andere landen of zelfs op Europees niveau in het algemeen tot vergelijkbare resultaten komen wat betreft gerelateerde variëteit. Wat ongerelateerde variëteit betreft zijn de bevindingen wat minder eenduidig.

Hoewel deze bevindingen de indruk wekken dat recombinatiemechanismen, voortkomend uit gerelateerde variëteit binnen economieën, leiden tot innovatiekansen, blijft de vraag onbeantwoord via welke kanalen dit uiteindelijk in economische groei resulteert. In hoofdstuk 4 van dit proefschrift onderzoeken we of ondernemerschap een dergelijk kanaal zou kunnen zijn. De 'Knowledge Spillover Theory of Entrepreneurship' voorspelt dat ondernemers profiteren van de door andere partijen ontwikkelde, maar niet aangewende kennis, middels het opzetten van een bedrijf. De kans, dat ondernemers niet aangewende kennis als waardevol identificeren en benutten, neemt toe naarmate zij over meer gerelateerde kennis beschikken. Afhankelijk van lokale condities zullen de bedrijven, die als resultaat hiervan worden gestart, uiteindelijk banen scheppen en een stimulans vormen voor de regionale economie.

Door in hoofdstuk 4 onderscheid te maken tussen verschillende typen ondernemerschap, constateren we dat gerelateerde variëteit een positief effect heeft op kansgedreven ondernemerschap, maar niet op noodzaakgedreven ondernemerschap. We interpreteren dit resultaat als een bevestiging dat noodzaakgedreven ondernemers een bedrijf starten als laatste uitweg om werkloosheid te voorkomen in plaats van als reactie op kansen in de markt als gevolg van gerelateerde variëteit. Kansgedreven ondernemers daarentegen identificeren en benutten kansen die voortkomen uit kennis spillovers door gerelateerde variëteit. Bovendien constateren we een negatief effect van ongerelateerde variëteit op zowel kansgedreven als noodzaakgedreven ondernemerschap. Dit zou kunnen duiden op de toegenomen moeite die het kost om de cognitieve afstand die ongerelateerde variëteit suggereert te overbruggen.

Daarnaast blijkt de institutionele context, gemeten door onderscheid te maken tussen verschillende soorten kapitalisme (Varieties of Capitalism), een effect te hebben op de mate van ondernemerschap in een economie. Regio's in landen die zijn geclassificeerd als liberale markteconomie hebben een hoger percentage kansgedreven ondernemers, in vergelijking met regio's in landen die zijn geclassificeerd als gecoördineerde markt-

economie. Een mogelijke verklaring hiervoor is dat de kansen voor ondernemerschap in liberale markteconomieën vaker worden benut door het opstarten van een nieuw bedrijf. Terwijl in gecoördineerde markteconomieën dergelijke kansen vaker worden benut door gevestigde bedrijven en hun werknemers.

S.3 Diversificatie en de productruimte

Analoog aan de notie van gerelateerde variëteit is het concept van de 'product space'. Dit concept is geïntroduceerd door Hidalgo e.a. (2007) om aan te tonen dat economieën zich door de tijd heen ontwikkelen door zich te diversifiëren in producten die technologisch gerelateerd zijn aan de producten die het reeds exporteert. De nabijheid of gerelateerdheid van productparen in de product space wordt in deze methode bepaald door te kijken naar de frequentie waarmee productparen door economieën gelijktijdig met een comparatief voordeel worden geëxporteerd. De veronderstelling is dat deze frequentie indicatief is voor de mate waarin productparen vergelijkbare kennis en vaardigheden vereisen. Als een economie eenmaal de kennis en vaardigheden heeft ontwikkeld om een specifiek product met een comparatief voordeel te exporteren, zal het gemakkelijker zijn te diversifiëren naar producten die vergelijkbare kennis en vaardigheden vereisen, oftewel nabijgelegen producten in de product space. Deze bevindingen maken dat industriële diversificatie ook wel beschreven wordt als een vertakkingsproces, waarin nieuwe economische activiteiten vertakkingen of combinaties zijn van reeds aanwezige activiteiten in een land of regio.

Hoewel gerelateerde diversificatie de standaard lijkt en zonder sturing plaatsvindt, diversifiëren economieën zich zo nu en dan ook in willekeurige of ongerelateerde richting. Dit gegeven roept vragen op zoals, zijn sommige economieën beter in staat om in ongerelateerde richting te diversifiëren dan anderen, en als dat zo is, wat karakteriseert deze economieën dan? Dit zijn relevante vragen met het oog op bijvoorbeeld mondialisering, dat regio's blootstelt aan technologische vooruitgang, veranderingen in mondiale vraag of de intrede van opkomende economieën elders in de wereld. Door zulke ontwikkelingen kunnen specifieke kennis of vaardigheden waarop comparatieve voordelen van een economie berusten irrelevant raken, met een verlies van economische activiteit en werkloosheid als gevolg. Daarnaast bestaat het risico dat door langdurige gerelateerde diversificatie een economie in een situatie belandt met beperkte verdere diversificatiemogelijkheden, we spreken dan van een technologische 'lock-in'.

Om regio's minder kwetsbaar te maken voor dergelijke ontwikkelingen zou een zekere mate van en tijdige ongerelateerde diversificatie voor economische structuurversterking kunnen zorgen, waardoor technologische lock-ins vermeden kunnen worden. Om als economie echter in ongerelateerde richting te kunnen diversifiëren, dienen andere kennis en vaardigheden te worden ontwikkeld of verkregen dan de kennis en vaardigheden waarop reeds aanwezige economische activiteiten berusten.

In dit proefschrift onderzoeken we verschillende regionale condities of karakteristieken die hierin een rol zouden kunnen spelen. Eén conditie die ervoor zou kunnen zorgen dat nieuwe kennis of vaardigheden worden verkregen, zijn interregionale banden die voor een instroom van externe kennis kunnen zorgen. Zo'n instroom kan de interpretatie van de mogelijkheden van bestaande lokale kennis veranderen, wat vervolgens zou kunnen leiden tot nieuwe en originele recombinaties. Een andere conditie is de aanwezigheid van netwerken binnen de regio die zowel gerelateerde als ongerelateerde bedrijven (maar ook universiteiten, onderzoekscentra en overheden) verbinden. Zulke netwerken kunnen kennis spillovers bewerkstelligen tussen gerelateerde en ongerelateerde bedrijven, wat vervolgens zou kunnen leiden tot nieuwe en originele recombinaties.

Hoofstuk 3 van dit proefschrift onderzoekt of de aanwezigheid van kennisintensieve zakelijke dienstverlening (of Knowledge-Intensive Business Services, KIBS), de deelname aan mondiale waardeketens (of Global-Value-Chains, GVCs) en investeringen in onderzoek & ontwikkeling (of Research & Development, R&D), regio's kunnen voorzien in één of beide van deze condities. Hiervoor zijn verschillende redenen. Ten eerste omdat KIBS diensten leveren aan bedrijven die actief zijn in diverse – en ongerelateerde – bedrijfstakken, fungeren KIBS soms als overbruggingsplatform voor kennis spillovers tussen ongerelateerde bedrijfstakken. Ten tweede zou de verwikkeling in GVCs voor ongerelateerde kennis spillovers kunnen zorgen. Wanneer een regio eenmaal is gespecialiseerd in een specifieke taak, kan het die taak aanbieden in veel verschillende – en ongerelateerde – waardeketens. Ten derde gaan lokale bedrijven en onderzoeksinstituten die investeren in R&D, frequent samenwerkingsverbanden aan met bedrijven of onderzoeksinstituten gelegen in andere regio's of landen. Zodoende is de capaciteit van een regionale economie om ongerelateerde externe kennis aan te trekken en aan te wenden voor nieuwe innovaties gerelateerd aan de mate van investering in R&D.

Het onderzoek beschreven in hoofdstuk 3 vindt ondersteunend bewijs voor deze veronderstellingen. Daarnaast blijkt het effect van KIBS zich vooral te manifesteren op activiteiten in de maakindustrie, terwijl het effect van GVCs zich manifesteert op activiteiten in distributie en zakelijke dienstverlening, en vinden we voor wat R&D betreft voornamelijk

een effect op activiteiten in de maakindustrie en zakelijke dienstverlening. Een verdere nuancering wordt gemaakt met betrekking tot de impact over verschillende niveaus van gerelateerde bedrijfstakdichtheid (relatedness density).

S.4 Regionale ontwikkeling en entrepreneurial ecosystems

Ondernemerschap vormt een belangrijk mechanisme voor economische structuurverandering, doordat het door de introductie van meer productieve activiteiten, minder productieve activiteiten redundant maakt. Ondanks de overeenstemming onder economen dat geaggregeerde groei niet louter een functie van arbeid en kapitaal alleen is, is de rol van ondernemerschap hierin lange tijd genegeerd. Vanaf de late jaren 80 van de vorige eeuw kwam hier verandering in met studies die ondernemerschap als oorzaak van economische groei onder de loep namen. Inmiddels zijn de theoretische kanalen waardoor ondernemerschap economische groei kan stimuleren goed beschreven, en kunnen in de literatuur drie stromingen worden onderscheiden: innovatie creatie, innovatie diffusie en concurrentie. De innovatie creatie stroming legt de nadruk op de ondernemer als stimulator van structurele verandering, terwijl de innovatie diffusie stroming de ondernemer meer beschrijft als individu die kansen in marktimperfecties ziet. De neoklassieke kijk op ondernemerschap is voornamelijk gefocust op het concurrentie-effect van ondernemers.

In de empirische literatuur worden steeds meer onderzoeken gepubliceerd die de relatie van ondernemerschap en economische groei trachten te kwantificeren, desalniettemin kent deze literatuur beperkingen waarvan enkele in dit proefschrift worden benoemd. Zo is het meten en afbakenen van het begrip ondernemerschap een complex vraagstuk, aangezien dit op een dusdanige manier moet gebeuren dat het internationaal en door de tijd heen vergelijkbaar is en onderscheid moet kunnen maken tussen verschillende typen ondernemerschap. Daarnaast heeft economische groei ook invloed op het ondernemerschapspeil, er is dus sprake van omgekeerde causaliteit. Bovendien zou de relatie moeten worden bezien in de context van lokale condities (zoals instituties of compositie van de economische structuur).

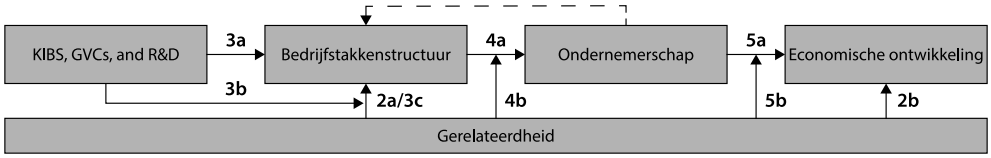
Met de 'entrepreneurial ecosystem' benadering worden sommige van deze zaken in acht genomen. Betreffende literatuur stelt dat voor een positieve relatie tussen ondernemerschap en economische groei, een effectief ecosysteem nodig is. Eén waarin verschillende condities dusdanig zijn geconfigureerd dat het productief ondernemerschap voortbrengt. Productief ondernemerschap in een dergelijk ecosysteem is zowel het re-

sultaat van instituties als mediërend in de relatie tussen instituties en geaggregeerde waarde creatie. De mate waarin ondernemers productief worden is vervolgens afhankelijk van de kwaliteit, de interdependentie en de interactie van de elementen van waaruit het ecosysteem is opgebouwd.

Hoofdstuk 5 van dit proefschrift neemt de entrepreneurial ecosystem benadering verder onder de loep door de inzichten uit voorgaande hoofdstukken mee te nemen in de analyse. De bevindingen zijn dat, zonder te controleren voor land specifieke effecten, verschillende typen van ondernemerschap een positieve bijdrage leveren aan economische ontwikkeling. Hoewel het statistisch gezien de voorkeur heeft om voor land specifieke effecten te controleren, heeft het als nadeel dat het de verschillen in de relatie tussen ondernemerschap en groei tussen groepen regio's maskeert. Deze verschillen zouden gerelateerd kunnen zijn aan de verschillen in de configuratie van ecosystemen. Een nader onderzoek van deze relatie middels een latente klasse model laat zien dat voor een optimale analyse, regio's in groepen moeten worden onderverdeeld. Deze groepen van regio's hebben een significant andere relatie tussen ondernemerschap en economische ontwikkeling. Vervolgens constateren we dat de groepen van regio's met een positieve associatie van ondernemerschap en economische ontwikkeling, de beste formele en informele instituties hebben. Zij scoren hoger wat betreft ongerelateerde variëteit en gerelateerde bedrijfstakdichtheid, en hebben de meeste nieuwe bedrijfstak specialisaties. Deze bevindingen zouden erop kunnen duiden dat verschillende configuraties van ecosystemen een andere relatie tussen ondernemerschap en economische ontwikkeling voortbrengen.

S.5 Algemene conclusie

De doelstelling van dit proefschrift is het onderzoeken van de rol van gerelateerdheid en van ondernemerschap in regionaal economische ontwikkeling. Al met al vinden we dat gerelateerdheid een veelzijdig effect heeft op economische ontwikkeling, zoals ook is geïllustreerd in figuur S.2. De verwachte groei stimuli van ondernemerschap zijn afhankelijk van onder meer de samenstelling van bedrijfstakken in de economie (pijlen **5**). Het literatuuronderzoek toont aan dat voorgaande studies concluderen dat gerelateerdheid invloed heeft op het diversificatieproces van regionale economieën (pijl **2b**) en dat gerelateerde variëteit groei in werkgelegenheid stimuleert (pijl **2a**). Bovendien stimuleert gerelateerde variëteit ondernemerschap (pijlen **4**) en daarmee mogelijk economische ontwikkeling.



Figuur S.2: *Figuur S.2 Visualisatie van de relaties die in dit onderzoek worden onderzocht*

De rol van ondernemerschap in regionaal economische ontwikkeling wordt beïnvloed door de compositie van de economie uit verschillende bedrijfstakken (bedrijfstakkenstructuur). Verschillende composities van een economie brengen verschillende typen ondernemerschap voort, die vervolgens in meer of mindere mate productieve activiteiten in de economie introduceren. Dat betekent dat ondernemerschap op de lange termijn ook een invloed heeft op de compositie van de economie zelf. In hoofdstuk 4 stellen we vast dat gerelateerde variëteit kansgedreven ondernemerschap bevordert, terwijl ongerelateerde variëteit dit juist hindert. Hoewel we niet direct analyseren wat voor effect dit heeft op het diversificatieproces, suggereren deze bevindingen dat het een pad-afhankelijke diversificatie stimuleert. Met andere woorden: de compositie van de economische structuur heeft een effect op de prevalentie van bepaalde typen ondernemerschap in de regio door factoren als kennis spillovers, toetredingsdrempels en concurrentie. Maar tegelijkertijd heeft de prevalentie van bepaalde typen ondernemerschap een effect op deze compositie door middel van het introduceren van nieuwe variëteiten in de economie.

Het diversificatieproces van economieën blijkt sterk pad-afhankelijk te zijn. Een deel hiervan lijkt dus verklaard te kunnen worden door de bevinding dat gerelateerde variëteit een stimulans is voor kansgedreven ondernemerschap, terwijl ongerelateerde variëteit dit juist hindert. Als gevolg hiervan diversifiëren economieën zich als vanzelf in gerelateerde producten of bedrijfstakken. Een dergelijk ontwikkelingsproces kan in sommige gevallen leiden tot een technologische lock-in en maakt economieën kwetsbaar voor veranderingen in mondiale vraag of concurrentie. Een gerelateerd diversificatieproces kan echter soms juist de voorkeur hebben, bijvoorbeeld om jonge maar veelbelovende nieuwe bedrijfstakken te versterken. Op de lange termijn is een mix van gerelateerde en ongerelateerde diversificatie waarschijnlijk te prefereren, aangezien regio's zodoende kunnen profiteren van reeds bestaande kennis en vaardigheden en soms kunnen diversifiëren in een meer risicovolle richting, maar potentieel met een hoog rendement.

Hoewel in hoofdstuk 3 wordt gevonden dat lokale condities zoals KIBS, GVCs en R&D (Pijlen **3a** en **3b**) de kans op het ontstaan van nieuwe ontwikkelingspaden doen toenemen, zal nader onderzoek moeten uitwijzen hoe significant deze effecten op de structurele verandering van economieën over tijd zullen zijn. De incrementele verandering van een systeem (in dit geval een economie bestaande uit bedrijfstakken) verandert de pad-afhankelijke ontwikkeling ervan slechts in geringe mate en voorkomt radicale verandering. Incrementele verandering in componenten van het systeem kan echter over tijd accumuleren in structurele veranderingen van het systeem. Daarnaast rest de vraag welke condities bepalen of ondernemers door het introduceren van productieve variëteiten, pad-afhankelijkheid versterken of juist nieuwe ontwikkelingspaden initiëren. Regionale economische ontwikkelingen zijn niet alleen afhankelijk van ondernemers en de toetreding van productievere activiteiten op de markt. Belangrijker is dat dit zo nu en dan zorgt voor nieuwe of een revitalisering van reeds bestaande ontwikkelingspaden.

S.6 Beperkingen en vervolgonderzoek

De analyses uitgevoerd in dit proefschrift kennen enkele beperkingen. Allereerst is er de kwestie van het meten van kennis spillovers. Aangezien deze in dit proefschrift niet direct worden gemeten, zijn we niet in staat om alternatieve verklaringen voor de werking van de door ons veronderstelde mechanismen te verwerpen. Dit geldt in het bijzonder voor de hoofdstukken 3 en 4, waarin we niet direct de kennis spillovers meten die voortkomen uit gerelateerde variëteit, respectievelijk de kennis spillovers tussen gerelateerde bedrijven of individuen.

De data over ondernemerschap kennen ook enkele beperkingen. Zo is ondernemerschap gemeten op de schaalniveaus NUTS-1 of NUTS-2. In de context van kennis spillovers zou een lager schaalniveau echter meer gepast zijn, bijvoorbeeld die van arbeidsmarktregio's (NUTS-3). Idealiter zou er daarnaast een langere tijdsperiode gebruikt zijn om mogelijke korte-termijneffecten van conjunctuurcycli en potentiele omgekeerde causaliteit van ondernemerschap en groei te elimineren.

Een eerste onderzoekslijn die voort zou kunnen vloeien uit de bevindingen van hoofdstuk 4 heeft betrekking op ondernemerschap als kanaal, waardoor kennis spillovers voortkomend uit gerelateerde variëteit, kunnen bijdrage aan economische groei. De vraag is nu welke andere kanalen er mogelijk nog meer zijn. Toekomstige studies zouden kunnen onderzoeken wat de rol van sociale netwerken, intrapreneurship of arbeidsmobiliteit zijn. Een volledig model van gerelateerde variëteit zou dan enerzijds het directe

effect van gerelateerde en ongerelateerde variëteit op economische ontwikkeling meten, en anderzijds de factoren die optreden als mediator in deze relatie.

Een tweede vraag gerelateerd aan de bevindingen in hoofdstuk 4 gaat over de substantiële institutionele en culturele verschillen tussen binnenlandse regio's. Een methode om het 'Varieties of Capitalism' raamwerk te disaggregeren naar regionaal niveau zou een waardevolle toevoeging zijn op de literatuur. Aangezien hiermee verschillen kunnen worden verklaard in de prevalentie van verschillende typen ondernemerschap, maar ook andere regionale condities die een rol spelen in regionaal economische ontwikkeling.

Een derde onderzoekslijn zou kunnen zijn, voortbouwend op de entrepreneurial ecosystem benadering, om het belang van de economische structuur als onderdeel van een ecosysteem verder onder de loep te nemen. Momenteel staat de compositie van de economische structuur binnen de literatuur van entrepreneurial ecosystems niet centraal. Zoals in hoofdstuk 4 echter wordt aangetoond, heeft dit in de vorm van gerelateerde en ongerelateerde variëteit verregaande gevolgen voor de prevalentie van verschillende typen ondernemerschap.

Een vierde suggestie voor vervolgonderzoek betreft de vraag waarom ongerelateerde variëteit een negatief effect heeft op ondernemerschap. Theoretisch gezien kan ongerelateerde variëteit zowel negatief als positief geassocieerd worden met ondernemerschap. Meer empirisch onderzoek is nodig om te weten waarom en onder welke omstandigheden dit effect positief of negatief is. Een mogelijke benadering is te onderzoeken of het effect van ongerelateerde variëteit op ondernemerschap varieert over verschillende niveaus van gerelateerde variëteit. Het is namelijk denkbaar dat een hoge mate van gerelateerde variëteit binnen ongerelateerde variëteiten het negatieve effect (gedeeltelijk) opheft.

Een vijfde onderzoekslijn betreft de vraag hoe ondernemerschap is gerelateerd aan economische diversificatie van regio's. Welke rol spelen verschillende typen ondernemers hierin en is dit anders voor gerelateerde of ongerelateerde diversificatie? Niet alleen het motief om ondernemer te worden, bijvoorbeeld uit noodzaak of om te profiteren van een kans in de markt, beïnvloedt waarschijnlijk de mate waarin ondernemers bijdragen aan structurele veranderingen van de economie. Maar ook zaken als hun persoonlijkheid, vaardigheden of eerdere werk- of ondernemerservaringen. Met name in de context van de Smart Specialisation Strategy kan kennis over deze zaken een waardevol instrument blijken voor beleidsmakers.

Curriculum Vitae

Jeroen Content was born on 15 August 1987 in Heemstede, the Netherlands. He holds a MSc in International Business and Economics from Utrecht University School of Economics (U.S.E, the Netherlands), where he became a PhD candidate in August 2015. His research focuses on entrepreneurship, industry relatedness, and regional economic development and he has published work on these topics in the journals of European Planning Studies (2016), Small Business Economics (2018), and Regional Science (2019). During his PhD, Jeroen has presented at several international conferences, including the European Regional Science Association Congress (2016), the DRUID Academy Conference (2017), the Regional Science Association Conference (2017), and the Geography of Innovation Conference (2018). He has participated in the DRUID PhD Course (2017) at the University of Southern Denmark (Odense, Denmark). After writing his dissertation, he will continue to do research at the Dutch Environmental Assessment Agency (PBL), where he currently is employed.

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