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Environmental innovation across Sweden:

The role of related variety in regional knowledgebases

by

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Abstract

Sustainable development has become a major goal of development policies across the globe and environmental innovation is commonly viewed as a means to fulfil this goal because it can create growth while simultaneously reducing environmental impact. Recent research in economic geography has provided evidence for a positive relationship between variety in local knowledgebases and innovativeness. Following this notion, the present study investigates Sweden's performance in environmental innovations and the effect from related variety in the regional green knowledge stock. Patent data is used to analyse the environmental innovation output in 20 Swedish regions during 2000 to 2015. The study finds that while present across the entire country, the majority of environmental innovation is concentrated in Stockholm, Västra Götaland and Skåne. These regions do not only have the most patent families in climate change mitigation technologies but did also increase their output the most. Moreover, innovation in most green technology fields is dispersed but innovation in green technologies related to ICT and climate change adaptation technologies are concentrated in few regions. Additionally, entropy indicators present evidence for limited but expanding related variety in the green knowledge base of most regions, with only the most innovative regions exhibiting large degrees of related variety. Lastly, a beneficial, albeit lagged effect from related variety on the number of green patent families in a region is confirmed by an econometric model, which is based on the regional knowledge production function (RKPF). Consequently, the study identifies the distribution of environmental innovation and the level of related variety in Sweden. It, additionally, finds evidence for a positive relationship between related variety and environmental innovation.

Keywords: Environmental innovation, related variety, variety, regional development, sustainable development.

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1 Introduction

As the anthropogenic climate change progresses, the need for changes in the way modern societies operate becomes unequivocal, yet society's strife for perpetual growth remains as crucial and persistent as ever. Growth has been unmistakably detrimental to the global ecosystem in the past. Recent developments, however, propelled notions of green growth, sustainable growth and environmental innovation (EI), which promise to fulfil the need for growth without doing harm to the environment, to the top of policymakers' agendas. In 2015 the UN General Assembly adopted the 2030 Agenda for Sustainable Development and later that year 196 parties ratified the Paris Agreement, pledging to combat global warming and foster sustainable development (UN, 2015; UNFCCC, 2015). Nevertheless, these goals and the notions of green growth cannot become reality without transitions towards sustainability. The vast research on this topic indicates that such a transition, which aims for sustainable growth, fundamentally relies on EI and is spatially sensitive (Smith, Voß & Grin, 2010; Coenen, Benneworth & Truffer, 2012; Truffer & Coenen, 2012).

EIs are crucial to sustainable growth because they create win-win situations where economic value is generated and negative externalities are abated (Rennings, 2000). Consequently, efforts to research the creation and diffusion of EIs have expanded. Multiple studies emphasize the benefits from including a spatial dimension when investigating EI's emergence (Rennings, 2000; Schiuma, Moustaghfir, de Marchi & Grandinetti, 2013; Ghisetti, Marzucchi & Montresor, 2015). Additionally, insights from economic geography and innovation theory highlight that recombinant innovation draws from locally available knowledge and points to firms, organisations, economic sectors and other entities in proximity that facilitate knowledge spillovers as determinants for regional innovation (Jacobs, 1969; Cooke, 2001; Asheim & Gertler, 2005; Howells & Bessant, 2012). Moreover, diversity in the economic composition and the knowledge base within a region was found to have a profound impact on its development and innovativeness (Frenken, van Oort & Verburg, 2007; Boschma & Immarino, 2009; Content & Frenken, 2016).

To address the challenge of sustainable regional development, more research on the relationship between regional diversity, EI and the transition towards sustainability is needed. Not only do endowments, institutions, and other spatial particularities raise the question of how this relationship unfolds in different localities, they also undermine the validity of "one size fits all" approaches. Therefore, a better understanding of variety in this context can support regions to find a suitable strategy that guides their development. The European Commission has, for example, tasked regional policy makers to conceive a strategy for their region's economic development based on the Research and Innovation Strategy for Smart Specialisation (RIS3) (European Commission, 2014). RIS 3 is a place-based approach that aims to enhance regional innovativeness and competitiveness by building on the existing regional economy, capabilities, and knowledge. It, additionally, encourages multidisciplinary collaboration and knowledge transfer between multiple agents. Thus, a better understanding of the role of variety as a determinant of EI can help policymakers to improve their strategies for their region's and Europe's development.

Hence, this study uses concepts from economic geography to investigate whether variety in the regional knowledge stock contributes to regional sustainable development through recombinant innovation. Inspired by Castaldi, Frenken and Los (2015), and Barbieri, Perruchas and Consoli's (2020) approaches, I use patent data to investigate whether Swedish regions' EI output is positively affected by related variety amongst green technologies in their knowledgebases. Thus, a contribution to the research on sustainability transitions is made by analysing how regional knowledge of climate mitigation can be utilised to spur EI and, ultimately, lead to sustainable growth. Moreover, the study adds to the literature on the relationship between RV and regional innovation. It provides new insights in how this relationship appears for the subset of EI and in the Swedish spatial context.

The next section contains a literature review of the relevant concepts and theories, it concludes by elaborating on the theoretical framework and introducing the research questions for this study. Section 3 presents the data that is used to conduct the analysis and discusses limitations. Thereafter, the entropy method, which forms the basis to measure variety in green technologies, and the econometric model are provided in Section 4. Subsequently, Section 5 presents the results of the data analysis and the econometric model. A discussion of the results and how they fit with the literature follows. Lastly, Section 6 summarises the study, presents conclusions and suggests further research.

2 Literature review and theoretical framework

2.1 Environmental innovation

Technological change in the form of environmental innovation (EI) is crucial to achieve the climate goals put forward by the 2030 Paris Climate Accord and the EU Commission. Nevertheless, EI is a common concept that deals with climate change and environmental impact reduction and, as such, is often filled with different implications. In the literature, EI usually refers to an environmentally friendlier form of recombinant innovation (Weitzman, 1998). The Oslo-Manual (OECD, 2019) defines innovation on the basis of this notion as a different form of invention that is based on knowledge recombination and yields products or services that are introduced to the market. Rennings (2000), however, acknowledges that this technology based notion of EI is too narrow and that innovation with the aim of sustainability can also be of organisational, social and institutional nature. This critique is repeated by the sustainability transitions literature that emphasises the need for deep social, cultural, and normative changes that exceed firm boundaries and are based on social and institutional innovations (Rotmans, Kemp & van Asselt, 2001; Markard, Raven & Truffer, 2012; Loorbach et al., 2017; Schaile & Urmetzer, 2019).

This notwithstanding, technological EI is necessary and beneficial, although not satisfactory by itself, to reduce environmental impacts and create a sustainable economy because it possesses the potential to combine economic growth and environmental sustainability (Ghisetti, Gilli, Marin & Nicolli, 2016). Rennings (2000) highlights this by elaborating on technological EI’s ability to reduce negative externalities and create knowledge spillovers that benefit multiple actors. Thus, EI can lead to win-win situations that facilitate expanding economic activity and its decoupling from emissions and other negative environmental impacts (Ekins, 2010). However, Rennings (2000) emphasises that this “double externality” of environmental impact reduction and spillovers must be supported by congruent innovation and environmental policy to incentivise firms to invest in technological EI. If EI is not supported by policy, he argues that their high investment costs and the benefits for competitors from knowledge spillovers can prevent firms from investing in them.

Based on an innovation’s ability to create “double externality”, a distinction between “environmental innovation” and “eco-innovation” is made (Ekins, 2010). Where eco-innovation is defined by the ECODRIVE project as “[…] a change in economic activities that improves both the economic performance and the environmental performance of society” (Huppes, Kleijn, Huele, Ekins, Shaw, Esders & Schaltegger, 2008, p.29). Hence, eco-innovations are innovations that always fulfil the double externality and reduce environmental impacts, while simultaneously creating economic benefits. Environmental innovation (EI), on the other hand, was defined by the MEI European Framework as "[…] *the production, assimilation or exploitation of a product, production process, service or management or business method that is* ***novel to the organisation*** *(developing or adopting it) and which results, throughout its live cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use)* ***compared to relevant alternatives****"* (Kemp & Pearson, 2007, p.7). Thus, the notion of environmental innovation (EI) is broader and includes eco-innovations, just as other innovations that aim to reduce environmental impacts but do not fulfil the double externality. Ultimately, environmental innovation (EI) is an umbrella term that refers to non-technological, just as to technological innovation and can further be differentiated between such technological environmental innovations (EI) that contribute to economic growth and reduce negative externalities, and such that reduce negative externalities but do not generate growth. For the purpose of this study, environmental innovation (EI) explicitly follows the definition by the MEI European Framework and, thus, contains all technological innovations that reduce environmental impacts, whether they contribute to growth or not.

Since EI is necessary for sustainable growth, much research was conducted to illuminate how EIs are created and how their creation can be supported. The literature shows that the determinants of EI can be grouped into "Market-pull", "Technology-push", "Regulation" and "Firm-specific factors" (Horbach, 2008; Horbach, Rammer & Rennings, 2012; Barbieri, Ghisetti, Gilli, Marin &Nicolli, 2016). "Market-pull" refers to market conditions, for example future ROI, turnover or consumer preferences, that demand EI from firms. Similarly, determinants in the "Technology-push" category point to technological conditions on the firm or organisation side, like the available knowledge base, R&D or organisational investments or activities, and other capabilities that make EI more desirable for firms because they create comparative advantages. Moreover, environmental policy and regulation can boost EI because such innovations may be necessary to comply with environmental protection standards. Lastly, "Firm-specific factors" encompass all characteristics that belong to the individual firm or organisation and influence its innovativeness. These include sector, location, size, human capital, firm internal knowledge pool and capabilities, and so on. Hence, a broad set of factors from within a firm or an organisation and from its environment affects the creation of EI and provides many opportunities for support.

Furthermore, detailed analysis on smaller sets or individual determinants indicates that they vary not only between different sectors but also between types of EI. Cainelli and Mazzanti (2013) find, for example, that the regulation effect from stringent environmental policy for manufacturing in Italy does not induce expanded activities in EIs to the service sector. They, additionally, show that EIs in energy efficiency and carbon abatement technologies benefit from different drivers. Likewise, Demirel and Kesidou (2011) discover the EIs with varying technological complexity and environmental impacts are stimulated by different policy tools and firm level factors. Yet, Cainelli, Mazzanti and Montresor (2012), just as De Marchi (2012) suggest that EI is universally supported by cooperation in R&D and networking between firms. Schiuma et al. (2013) support this claim and emphasise that EI's high level of complexity requires more, and more interdisciplinary knowledge than other innovations, which in most cases exceeds the firm or organisation's available knowledge stock. Therefore, they conclude that cooperation in EI activities is highly effective because it grants access to outside knowledge. Additionally, Ghisetti et al. (2015) state that not only formalised R&D cooperation but also knowledge absorption from external sources of information are strong determinants of EI. Thus, the essential access to external knowledge emphasises the spatial dimension of EI. EI are a particular knowledge intensive sort of innovation and as innovators absorb new knowledge from their interactions with external entities, they are expected to benefit from being located in an area with an extensive and diverse knowledge stock.

2.2 Agglomeration economies and variety

The extend to which variety in the regional knowledge base is beneficial for firms and organisations' innovation and economic performance is a prevalent topic in economic geography. The concept of variety emerged as a construct to investigate externalities in agglomeration economies more precisely. In general, agglomeration economics are productivity, innovativeness and employment improving benefits like reduced transport costs, knowledge spillovers and labour market dynamics that arise from colocation in cities or clusters (Glaeser, 2010, pp.1-14). However, different types of agglomeration economies can be distinguished. Firstly, benefits that are typically associated with the size of regions and arise because of savings that are realised by a large urbanised locality's extensive infrastructure, labour and product markets, just as universities and other research facilities or associations are referred to as urbanisation externalities (Porter, 2003). Secondly, Marshall-Arrow-Romer (MAR) externalities describe externalities from spatial proximity within the same industry. They arise as a consequence of specialisation and spatial concentration of economic activities in a sector, which leads to labour market pooling, intra-industry spillovers and specialised suppliers and customers (Feser, 2002; Henderson, 2003). Lastly, Jacobs externalities emerge, contrary to MAR externalities, from diversified economic activity in spatial proximity (Jacobs, 1969). Jacobs externalities are akin to Schumpeter's (1911) notion of "new combinations" that growth generating innovations are created by recombination of existing knowledge, technologies and practices. Jacobs proposes that diversity in spatially concentrated economic activities provides extensive and diverse knowledge and, additionally, opportunities for interaction. Thus, multiple sectors in proximity of each other make recombination of knowledge and in consequence innovation much more likely to occur.

Naturally, these to some extent contrary sources for agglomeration economies led many scholars to empirically investigate whether spillovers occur when regions primarily house a large variety of sectors (Jacobs externalities), or are specialised in a few sectors (MAR externalities), or if agglomeration economies are foremost the result of size and density (urbanisation externalities). Following, Glaeser, Kallal, Scheinkman and Shleifer's (1992) seminal work and initial attempt to answer whether diversification or specialisation is most beneficial for regional development, De Groot, Poot and Smit (2016) reviewed the empirical literature on this subject. However, their results were inconclusive because almost as many studies that found evidence in favour of MAR externalities were found to disproof them. Moreover, they could show that a majority of studies found support for Jacobs externalities, but a considerable share also suggested no or an opposite effect, making a conclusion difficult. With no apparent trend and confirmation by the empirical literature, the question emerged, whether the concepts of specialisation and diversification are not sophisticated enough to capture the effects of economic composition on regional development (Content & Frenken, 2016).

Consequently, Frenken, van Oort and Verburg (2007) put forward the notion of related (RV) and unrelated variety (UV) to further investigate diversification in regional development. They draw on Jacobs' idea and acknowledge that diversification in related sectors benefits interaction, cooperation and the transmission or adoption of knowledge. Therefore, variety in related sectors improves the frequency of recombinant innovation because interaction with actors in the region creates more opportunities to absorb new knowledge which leads to knowledge spillovers and expands knowledge stocks. This, ultimately, enhances innovativeness, regional growth and employment. Moreover, Frenken et al. (2007) relate portfolio theory, a concept from business economics, to the regional economic composition. Portfolio theory is applied in the valuation and risk management of assets and states that the economic performance of a portfolio is determined by each of its elements individual performance (Montgomery, 1994). Thus, a wide variety between the elements reduces the risk of losses from the entire portfolio. Based on these insights, Frenken et al. (2007) suggest that a wide sector variety in the economic composition of a region makes the region's economy more robust against shocks, as bad performances in single sectors are not detrimental for the entire regional economy's performance. The less the sectors are related, the less are they affected if one suffers. Hence, they conclude that unrelated sector variety should protect the regional economy from large growth deficits and unemployment. In the next step, they test their hypothesis for the Netherlands and indeed find that RV is positively related to employment growth and UV is negatively related to unemployment growth.

RV has since Frenken et al.'s (2007) initial work become a useful addition to explain effects of the economy's composition. Many scholars conducted empirical studies to investigate the relationship between related sector variety, often proxied by export variety, and regional development. Saviotti and Frenken (2008) studied the effect of RV and UV on labour productivity and GDP per capita growth in OECD member states and found beneficial effects from RV on both but they could only find significant effects from UV with a substantial time lag. They explain this by suggesting that RV supports the recombination of knowledge that is similar and leads to incremental innovations with direct, albeit smaller, growth effects, whereas UV supports recombination of unrelated knowledge that is harder to achieve but yields radical innovations with higher and sustained growth benefits. In another empirical study, Boschma and Immarino (2009) indicated a positive relationship between RV and value-added growth in Italy but they did not receive distinct results when testing the relationship between RV and employment or labour productivity growth. However, studying the association between RV and productivity growth in Turkey, Falcioglu (2011) found a positive relationship. Moreover, Boschma, Minodo and Navarro (2012) provide support for this relationship and indicate that RV is related with value-added and regional growth in Spain.

While most studies find a significant relationship between one or multiple indicators of growth and RV, many results are opposing and unclear. Therefore, more detailed research was carried out. van Oort, de Geas and Dogaru (2015), for example, used pan-European data to unveil whether an urban region's size could explain the different findings of previous empirical studies. Their results indicate that small and medium urban regions benefit from higher RV, while no effect from UV occurred. Additionally, multiple studies recognized that different sectors could experience different effects from RV. Firstly, Bosma, Stam and Schutjens (2011) distinguish between manufacturing and services when exploring RV's effect on productivity growth in the Netherlands. Their results suggest that RV increases productivity in manufacturing and hampers it in services. On the contrary, Mameli, Immarino and Boschma (2012) find that regional employment is positively related with RV in services and UV in manufacturing in Italian labour markets. Moreover, Hartog, Boschma and Sotarauta's (2012) analysis shows no effect from overall RV on employment growth in Finland. When deconstructed into RV in high-technology and medium/low-technology sectors, however, RV in high-technology sectors benefitted employment growth. Bishop and Gripaios (2010) go even more into detail and distinguish between 23 sectors in the British economy. Their results are highly heterogenous between sectors and, surprisingly, RV only contributes to employment growth in three sectors, while UV is beneficial for eight.

In an effort to elaborate on the role of technology, Cortinovis and van Oort (2015) created a technology typology for European regions that depicts their technological progress and knowledge intensity. While they showed that high-technology regions experience increased employment growth and less unemployment from higher RV, just as improved productivity from higher UV, they could not find clear results for low and medium-technology regions. Finally, in a comprehensive study of 259 European regions and 15 sectors Caragliu, de Dominicis and de Groot (2016) show that Jacobs externalities are constituted by a diversity (RV) and a portfolio (UV) effect. Nevertheless, the authors could only find evidence for benefits from UV to regional growth. Similar to previous studies, the empirical work that focuses on sector effects and their knowledge intensity indicates that RV and UV play a significant role for regional development but find that their effect varies and is, likely, limited to only certain industries.

Many of the studies mentioned above recognise the supportive function of variety in successful innovation through knowledge recombination. Since innovation is commonly named as the crucial element in regional development, variety research shifted in recent years from analysing the effect of economic composition on employment or productivity growth to investigating how the variety in a region's knowledge base affects its innovativeness directly. Castaldi et al. (2015, p.769) justify the addition of the spatial dimension in innovation research by elaborating that "[…] *it follows from the notion of recombinant innovation that, to the extent that innovation processes draw on geographically localized knowledge, regions with a more diverse stock of knowledge would have a greater potential for innovation.*". Therefore, this branch of research focuses on the variety in the regional knowledge base and its effect on the region's innovativeness instead of the economy's sectorial composition's effect on employment or productivity. A major contribution is Asheim, Boschma and Cook's (2011) study, which elaborates on the construction of regional advantages through policies that support innovation by promoting a diversified, yet complementary knowledge stock. Moreover, Berlinat and Fujita (2011) show that innovations on the microlevel benefit from access to diverse knowledge and enhanced public knowledge transmission. Both factors are expected to increase with the extend of RV in the regional knowledgebase. Additionally, Tavassoli and Carbonara (2014) test the role of RV and UV in the knowledge base of Swedish regions for their innovation output. They confirm the positive effect of RV on regional innovation and cannot present evidence of an effect from UV. Similarly, Aarstad, Kvitastein and Jakobsen (2016) find that RV boosts innovation in regional enterprises and that a high level of RV and a low level of UV yields the best results.

Another approach is pioneered by Castaldi et al. (2015) and depicts the regional knowledge base by their patenting activity. They use patent data of US states to create an entropy indicator with different levels of aggregation that captures the relatedness of the patents. Analysing the variety in the regional knowledge base using this approach strays from the common approach to measure the variety based on a region's economic composition. This is not necessarily bad, it does, however, create variety indicators that are volatile with regards to time because innovation is an inherently uncertain process of varying length. Hence, the indicators might to some degree be volatile from year to year, which is conflicting with the slow rate of change that sector-based measures of the knowledge stock would expect. Even though the absolute values of these patent-based indicators might not represent the knowledge stock in that point of time accurately, the indicators are still appropriate to portray the long-term trends and variety in the knowledge base. Their analysis finds a positive relationship between RV and regional innovation in general but cannot impose an effect from UV on overall innovation. However, when studying "superstar" patents that represent radical or breakthrough innovations, Castaldi et al. (2015) show that UV significantly contributes to their creation.

2.3 Theoretical framework

Sustainable development and EI have not only been a popular subject amongst innovation scholars but they gained a commendable interest amongst economic geographers (Truffer and Coenen, 2012). While the literature agrees that purely technological EI are not satisfactory for sustainable development, it acknowledges that green technologies can create valuable comparative advantages and are crucial for successful sustainability transitions (Rennings, 2000; Markard et al., 2012; Barbieri et al., 2016; Loorbach et al., 2017). Moreover, spatial mechanisms, such as agglomeration externalities, localised knowledge spillovers and variety were shown to increase the likelihood for recombinant innovation to occur in a region. (Frenken et al., 2007; Asheim et al., 2011; Castaldi et al., 2015; Content & Frenken, 2016). Likewise, Cainelli and Iacobucci (2012), just as Antonioli, Borghesi and Mazzanti (2016) present evidence that these spatial mechanisms matter greatly in the development of EI. Furthermore, Tanner (2014) and Santoalha and Boschma (2019) show that the presence of environment-related knowledge in the regional knowledge stock functions as a positive predictor of EI and sustainable development. Additionally, Corrandini (2019) and Barbieri et al. (2020) use pan-European patent data to study whether technological relatedness in the regional knowledgebase supports EI. Corradini (2019) presents evidence that higher RV in green technologies supports entrepreneurship and innovation in this area but too much relatedness can cause lock-ins. On the other hand, Barbieri et al. (2020) find that high UV in the local knowledge stock is beneficial for EI, especially for those innovations in early life-cycle stages, while RV increases EI output when the technology reaches maturity. Ultimately, the literature suggests that EI enable regional sustainable development and benefit from variety in the regional knowledgebase through agglomeration externalities.

Connecting to this strand of literature, I draw inspiration from Castaldi et al. (2015) and analyse how RV affects innovation output in Swedish regions. I use geolocated patent data from 2000 to 2015 to construct a measure of innovativeness and of diversity in the local knowledge stock. This data is then employed to answer the following questions within the theoretical frame of variety and EI:

(1) Which regions were most successful in creating environmental innovation and which improved their performance the most?
(2) How much cognitive variety, in the form of related variety, and spatial dispersion do innovation activities in green technologies exhibit across Sweden?

Additionally, I construct an econometric model to investigate if and to which extend RV contributes to EI activities in Swedish regions. This is represented by the hypothesis:

(3) Related variety is positively associated with the number of patents in green technology families.

Answering these questions lays out the extend of Swedish EI, how different regions compare to the rest of Sweden and how diversified or specialised the regions’ knowledge base is with regards to green technologies and EI. Furthermore, the answers identify which regions, with their diversified or specialised knowledge stock, perform the best and can present a basis to deeper investigate the mechanisms and determinants in these successful regions. It does, additionally, show trends in the EI activity during the observed period from 2000 to 2015.

3 Data

This study relies on patent data as a proxy of technological EI and to derive the explanatory variables semi-related variety (SRV) and RV, which measure the variety in the knowledgebase at different aggregation levels. Furthermore, socio-economic data is used to create a range of variables that describe the development in the regions and serve as controls in the econometric model. The patent data originates from PATSTAT, the European Patent Office's (EPO) statistical database for patents, and includes patent families that were classified as green patents according to the CPC/EPO's Y02-tag classification scheme. The patent families are geolocated and each patent is supplied with a code that refers to their nomenclature of territorial units for statistics (NUTS: Eurostat, 2011; see Appendix A) code, based on their inventor's address, and can be associated to a Swedish region. In the case, where multiple inventors from multiple countries or regions file the patent, only the fraction that is represented by the proportion of Swedish inventors is counted and allocated to the respective region. For example, if a patent that classifies as a green technology with two inventors, one from Sweden and one form another country, is applied for at the EPO, the patent is only considered as 0.5 patents in the dataset. Similarly, if two inventors from different Swedish regions would file a patent application, the patent would be allocated as 0.5 patents to each region. Therefore, overcounting is avoided. Because inventors often apply patents at different offices across the globe, counting patent applications can also lead to overcounting. To avoid this, the data set uses patent families, which gather all patent applications for the same invention into an unique identifier.

The retrieved data base contains 4.271 patent families belonging to green technologies that are distributed over 20 Swedish NUTS 3 regions during the period from 2000 until 2015. No patents were applied for with their inventor in Gotland (SE214). Nevertheless, every other NUTS 3 region in Sweden had a patent application from a local inventor in at least one year between 2000 and 2015. After applying the fractional counting technique, a total of 2.796 green patent families could be associated with Swedish regions. This reduction in the patent family number suggests that Swedish EI efforts in green technologies are substantially collaborative and international. In that case it is important to note that the literature indicates that collaboration can facilitate knowledge spillovers (Amin & Cohendet, 2005; Boschma, 2005). Therefore, one must be aware that the extra regional influence can substitute for or enhance the regional knowledge base and, as such, influence the innovation process.

As mentioned above, not only are the patent families geocoded, they are additionally classified as green technologies according to the CPC/EPO Y02-tag scheme (EPO, 2020). The Y02-tagging scheme was created by the EPO together with UN organisations, the OECD, NGOs, business and industry associations and academics under the Cooperative Patent Classification (CPC) to provide a way to distinctly classify green technologies, which often are technologically complex and, thus, are scattered across multiple categories in traditional classification schemes like the IPC codes (Veefkind, Hurtado-Albir, Angelucci, Karachalios & Thumm, 2012). Y02-tags identify "technologies or applications for mitigation or adaptation against climate change" (EPO, 2020). Hence, the classification contains climate change mitigation technologies that have a potential to reduce anthropogenic greenhouse gas (GHG) emissions, limit natural resource use or improve the adaptation to changing environments. The criteria for the existence of such potential in a technology are defined by a "Green Inventory", which is based on IPCC reports, policy document from the European Commission, UNFCCC inventories and expert's feedback (Veefkind et al., 2012). Ultimately, the Y02-tag scheme consists of eight green technology classes. Namely, "technologies for adaptation to climate change" (Y02A), "climate change mitigation technologies related to buildings" (Y02B), "capture, storage, sequestration or disposal of GHG" (Y02C), "climate change mitigation technologies in ICT" (Y02D), "reduction of GHG emissions, related to energy generation, transmission or distribution" (Y02E), "climate change mitigation technologies in the production or processing of goods" (Y02P), "climate change mitigation technologies related to transportation" (Y02T) and "climate change mitigation technologies related to wastewater treatment or waste management (Y02W). Each class is further divided into multiple sub-classes. The full arrangement is presented in Appendix B.

The Y02-tagging scheme is a cooperative initiative of multiple supra-national institutions, industry, business and research actors to distinctly identify and classify green technologies without overlap between technology classes. Nevertheless, Veefkind et al. (2012) emphasise that the scheme suffers from the shortcomings of the general definition of green technologies. Green technologies are notoriously hard to define because their environment friendly nature may be contested depending on the circumstances and their application. This dependence on the context makes it difficult to assess if detrimental effects from the technology can be ruled out. Despite this limitation, Y02-tags provide an efficient and reliable way to identify and find green technologies because they in general correctly identify and return more patents than other classifications (Kapoor, Karvonen, Ranaei & Kässi, 2015).

Patent data is a popular proxy for innovation in economic geography (Crescenzi, Rodriguez-Pose & Storper, 2007; Castaldi et al., 2015; Montresor & Quatraro, 2017; Barbieri et al., 2020). Patents are an attractive resource to measure and classify inventive output because they meet formal novelty requirements and they are classified and grouped together by their technological content (Pavitt, 1985; Smith, 2005). Moreover, patent data contains a wealth of information about underlying knowledge bases and the applicant of an invention (Barbieri et al., 2020). Hence, inventive activities can be linked to their geographical origin, just as their technological affiliation and relatedness can be established, which are critical properties for this study. Nevertheless, patent data comes with its own limitations (Acs, Anselin & Varga, 2002). Firstly, not all innovations are patented or patentable because their application was not filed for or they do not have a technological component. Secondly, patent data selects for large, resourceful firms because the patenting process is expensive and often prevents small firms from protecting their innovations. Lastly, some sectors might not prefer to patent their inventions because their innovation cycles are noticeably short, which would incur high costs from frequent patenting and makes reproduction by competitors less dangerous. Direct counts of innovation, for example through surveys, present a non-selective alternative to patent data that can capture non-technological innovations (Acs et al., 2002; Barbieri et al., 2016). However, direct innovation counts lack formalised identification and allocation criteria because they mostly rely on the self-assessment from the survey participants. This introduces a degree of uncertainty and takes much of the richness of patent data away. Ultimately, Acs et al. (2002) and Popp (2005) argue that patent data are adequate for detailed analysis of knowledge fields at the lowest possible geographical aggregation level.

The socio-economic data comes form Statistics Sweden, Sweden's central statistical bureau. Educational attainment data are publicly available through their website (www.scb.se). In this study, human capital (HC) is defined as the share of the employed population in a region with three or more years of tertiary education, which usually represents a bachelor's degree. It is used as a measure innovativeness. Hence, HC is constructed by dividing the absolute number of employed people with three or more years of tertiary education by the number of all employed people in the region. The remaining data is from SCB's Longitudinal integrated database for health insurance and labour market studies (LISA). LISA is an anonymised integrated labour market, health, and educational database with the individual as its primary object (SCB, 2020). It contains rich information about employees, employers and their connection. Amongst these is individual level data, such as, education, employment, earnings, age, place of residence, and company level data like type of sector, employees, location and basic economic data. Such a high-quality dataset makes it possible to retrieve information about regional economic composition and employment.

To indicate regional competitiveness and innovativeness, the share of regional employment in high-tech manufacturing (HT_{manu}) is retrieved by dividing the sum of employed personnel in high and medium-high-technology manufacturing by the total number of employed people in the region. High and medium-high-technology manufacturing sectors are defined by the EU's Statistical classification of economic activities in the European community (NACE) and include NACE Rev. 2 sectors 20, 21, 26-30 (Eurostat, 2016). The share of knowledge intensive services (KI_{serv}) is obtained in the same fashion and for the same reason. It captures employment in NACE Rev. 2 sectors 50, 51, 58-66, 69-75, 78, 80, 84-93. Additionally, the employment growth (Emp) corresponds to the relative change of the total number of employed in a region during a year (percent change in employment) and serves as an economic control variable. Lastly, the region and sector specific employment data is used to construct variables for the level of educational attainment (HC_{nb}) and the economic composition (HT_{manu_nb}, KI_{serv_nb}) in neighbouring regions. These facilitate inter-regional knowledge in- and outflow and, thus, serve as another determinant for innovativeness and competitiveness. HC_{nb} is calculated by dividing the sum of people with a bachelor's degree in regions that share a border with the region in question by the sum of all employed people in the neighbouring regions:

$$HC_{nb_{i,t}} = \frac{\sum_r employed\ population\ with\ bachelor's\ degree_{r,t}}{\sum_r employed\ population_{r,t}} \quad (1)$$

Where *i* refers to the region that the measure of external knowledge in- and outflow is calculated for and *r* represents all regions that share a border with region i. Subsequently, HT_{manu_nb} and KI_{serv_nb} are calculated in the same manner.

4 Methodology

4.1 Measuring green knowledge base variety

The study relies on entropy indicators to quantify the variety in the regional green knowledge base. Entropy indicators were used in Frenken et al.'s (2007) seminal work to quantify the variety and relatedness in the regional economic composition. Moreover, Castaldi et al. (2015) adapted this method to create a measure of variety in US states' knowledge bases. The entropy method is a useful tool to measure variety because the indicators can be decomposed to different levels of aggregation, which makes analysis of relatedness possible and prevents collinearity issues (Theil, 1972; Grupp, 1990; Frenken et al., 2007; Castaldi et al., 2015). Variety is captured through the uncertainty of probability distributions of sets with varying aggregation. The process is as follows. Let E_f be the event that a patent in a given technological field (f) is applied for in a region, with $f = 1, \dots, F$ and let the probability for this event be denoted by p_f, then the entropy level H is defined as:

$$H = \sum_{\mathrm{f}=1}^{F} p_f \ln\left(\frac{1}{p_f}\right) \tag{2}$$

with:

$$p_f \ln\left(\frac{1}{p_f}\right) = 0 \ \text{ if } \ p_f = 0 \tag{3}$$

H's maximum value is $\ln(F)$ and its minimum is 0. H reaches its minimum if there is patent activity for only one technology field g ($g \in f$) present ($p_g = 1$ & $p_{f \setminus g} = 0$). In this case, uncertainty about the field to which the patent belongs is non-existent. Its maximum is reached when all patent activity is equally spread out over all technology fields. Here, the probability p_f for a patent application to belong to a specific technology class f is the exact same for all patent application events E_f and uncertainty about its technological association is the highest.

Applying Theil's (1972) decomposition theory, the entropy at the level of events H can be decomposed into the entropy at the level of sets with higher aggregation H_0 plus the weighted average of the entropy within groups in a set H_m. Sets refer to grouped together events. Hence, all events E_f are assigned to a smaller number of sets S_m where $m = 1, \dots, M$. The probability that the event E_f happens in the set S_m is found by summation of the probability p_f of each element that belongs to S_m:

$$P_m = \sum_{f \in m} p_f \tag{4}$$

Therefore, the “between-group entropy” at the level of sets can be obtained through:

$$H_0 = \sum_{\mathrm{m}=1}^{M} P_m \ln\left(\frac{1}{P_m}\right) \tag{5}$$

The entropy decomposition theorem then defines the relationship between the entropy at the lowest level of events H and the level of sets with higher aggregation H_0 as:

$$H = H_0 + \sum_{m=1}^{M} P_m H_m \tag{6}$$

In the context of technological relatedness equation (6) implies that minimally aggregated technological variety can be represented by the sum of variety in technological classes with higher aggregation and the variety between those classes (Castaldi et al., 2015). Considering that this study uses patent data of green technologies, whose technological affiliation is denoted by their Y02-tag classification and that this classification distinguishes between technology classes at broad and narrow levels, entropy indicators for the different aggregation levels of Y02-tags can be created (see Appendix B for an overview of Y02-tags and Y02-tag subclasses). Since this study aims to investigate the effect of variety in the local green technology knowledgebase, all technologies are related to some degree because they all aim to reduce environmental impacts. This is the main criteria that must be fulfilled to be included in the Y02-tag patent data. Hence, the highest level of aggregation in the patent data set possesses some degree of relatedness. This semi-relatedness is captured by the entropy indicator s*emi-related variety* (SRV) that is constituted by the entropy within the distribution of patents over the eight Y02-tag main classes (Y02A-E, Y02P, Y02T, Y02W):

$$SRV_{i,t} = \sum_{k=1}^{8} s_{k,it}\, ln\left(\frac{1}{s_{k,it}}\right) \tag{7}$$

Here *k* refers to the Y02-tag main classes, *i* denotes the region and *t* the year for which the indicator is calculated. Moreover, $s_{k,it}$ is the share of all patents in year *i* and region *t* that belong to the technology group that is depicted by Y02-tag main class *k*. Next, Y02-tag sub-classes present the lower level of aggregation. Equation (6) shows that the within-group entropy levels for the lower aggregation level, which indicate variety in technologies in Y02-tag subclasses and as such are a measure of *related variety* (RV), can be found by:

$$RV_{i,t} = \sum_{l=1}^{35} s_{l,it} \, ln\left(\frac{1}{s_{l,it}}\right) - \sum_{k=1}^{8} s_{k,it} \, ln\left(\frac{1}{s_{k,it}}\right) \tag{8}$$

Where $s_{l,it}$ presents the share of patents in Y02-tag subclass *l*. As there are patent families belonging to 35 different Y02-tag subclasses in the dataset, *l* can reach a maximum of 35. The SRV and RV indicators quantify how diversified the knowledge base in green technologies is through the variety in Y02-tag main classes (SRV) and in Y02-tag subclasses (RV). It is important to recognise that both indicators are not opposites but capture variety between broad and narrow technology groups. For example, a region can be diversified in climate mitigation technologies, meaning the there are many patent applications across different Y02-tag main classes, and it can at the same time be diversified in a single climate mitigation technology group, which would be indicated by a large number of patent families in one or more Y02-tag subclasses. The former is captured by a large SRV value and the latter leads to a high RV value.

Lastly, the treatment of "zero observations" should be discussed. The instances where there is no green patent filing activity in a region in a particular year or where there is not more than one per technology class will lead the variety indicators to become zero. These zero values for SRV and RV are problematic because of two reasons. Firstly, green patenting activity is highly concentrated in Sweden and relatively small in volume. Therefore, many regions did not experience any or only a small number of patent filings in many years, leading to 220 zero values for RV. Secondly, these zero values assign the effect form the absence of variety to the indicator that is designed to capture the effect from existing variety. Hence, zero values do per definition not capture variety but its absence, which is not what this study aims to do. The entropy indicators are specifically designed to investigate the effect that emerges when there is variety present in the regional green technology knowledge base. To keep the zero values would, thus, capture a different effect, namely the negative effect that arises if variety is absent, and would lead to a substantial bias, given that they are more than twice the number of zero values than non-zero values. Consequently, I drop all observations where RV = 0 or SRV = 0, which leaves 100 observations with non-zero RV values that are used for the regression.

4.2 Econometric model

This section elaborates on the econometric model that is created to provide empirical evidence for the positive relationship between RV and EI. The dependent variable “number of green patent families“ (GP) is a typical count variable. It has many observations with a low count of green patent applications and only a few with a high count (Figure 1). Hence, GP is not

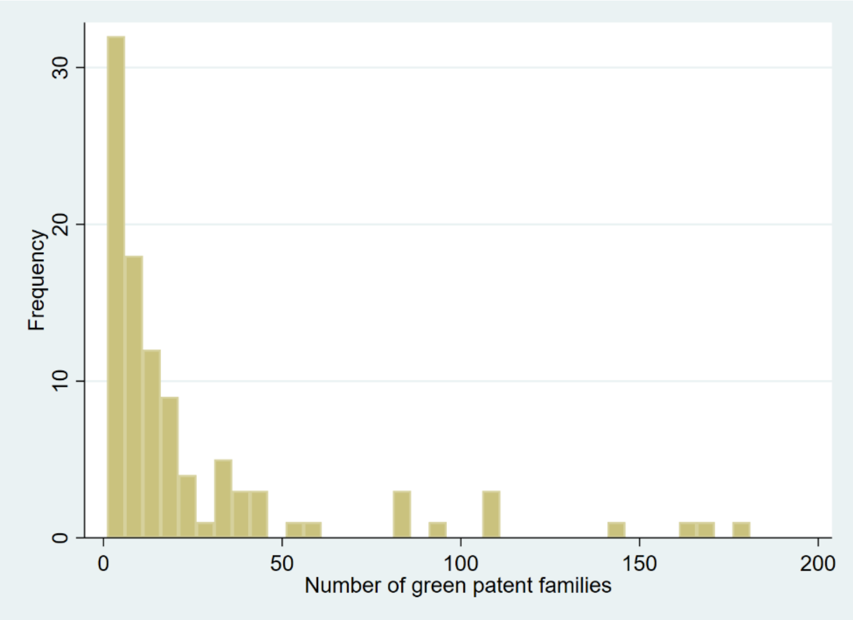

Figure 1: Histogram GP. Frequency of the number of green patent families per state and year.

normally distributed and does not fulfil the requirements of the OLS estimator. Even in a log-lin model, or the log-log specification that is popular in regional studies, the OLS estimator is significantly biased and produces inefficient and incorrect standard errors (Cameron & Trivedi, 2013, pp.29-40). Instead a generalized linear model like the Poission model should be used. While Figure 1 suggests that GP could possess a Poission distribution, the sample variance and mean (Table 1) reveals that Poission regression is not appropriate either. That is because the sample’s variance is greater than twice its mean, indicating overdispersion and falsifying the Poission regression’s assumption that the conditional mean equals the conditional variance (Cameron & Trivedi, 2013, pp.71-79). In such a case, the use of negative binomial (NB) regression is recommended as it produces consistent estimators and standard errors with over dispersed count data (Cameron & Trivedi, 2013, pp.79-91).

Table 1: Summary of GP

GP (Number of green patent families)				
	Percentiles	Smallest		
1%	1	1		
5%	2	1		
10%	3	1	Obs	100
25%	4.5	1	Sum of Wgt.	100
50%	10.5		**Mean**	**25.07**
		Largest	Std. Dev.	37.61615
75%	27	143		
90%	83.5	165	**Variance**	**1414.975**
95%	109.5	170	Skewness	2.520449
99%	173.5	177	Kurtosis	8.997214

The model for this study is based on Griliches' (1979) seminal concept of the knowledge production function (KPF) that set out an agenda to create an empirical model to describe the innovation process. Subsequent contributions highlighting the links between economic geography and innovation theory has led to increased interest in the geography of innovation (Howells & Bessant, 2012). For instance, human capital is fundamentally linked with the ability of a local economy to create and absorb new knowledge, exploit ideas and technologies, and translate them into new products and processes (Faggian & McCann, 2009; Gennaioli, La Porta, Lopez-de-Silanes, & Shleifer, 2013). Consequently, scholars modified Griliches' KPF to capture regional mechanisms, spatial spillovers and agglomeration effects (Ó hUallacháin & Leslie, 2007). The resulting regional knowledge production function (RKPF) is widely used in empirical literature to capture the role of geography when quantifying the innovation process. It mainly uses measures of R&D, specialised knowledge flows and human capital in a region and in its surroundings to model regional innovation processes (Bode, 2004; Ó hUallacháin & Leslie, 2007; Marrocu, Paci & Usai, 2011; Charlot, Crescenzi & Musolesi, 2015). However, the innovation process also depends on many unobservable characteristics that are related to social, economic, cultural and institutional settings, organisational properties and networks (Bode, 2004; Bathelt, Malmberg & Maskell, 2004; Malecki, 2010; Content & Frenken, 2016). These unobservable properties are allocated to the error-term in a regression model, which creates endogeneity problems as these unobservable factors can be correlated with the inputs of the innovation process (independent variables) (Charlot, Crescenzi, Musolesi, 2015). To limit the endogeneity risk that arises from such unobservable factors, I include individual and time fixed effects. Individual, region fixed effects capture region specific properties and events, like stringent environmental policies, while time fixed effects select for time-varying characteristics, like, for example, technological progress.

Moreover, I include the two entropy indicators as independent variables that capture variety in the local green knowledge base (see section 4.1) (Grupp, 1990; Frenken, 2007; Castaldi, Frenken & Los, 2015). These variables do not only contribute to answer this study's research questions but do also reduce the risk of endogeneity by reducing the correlation between the error term and the independent variables. Furthermore, I lag the independent variables to account for the time intensive process of innovation that disperses the inputs and outputs in time. Finally, the negative binomial model specification is as follows:

$$GP_{i,t} = \exp\Big(\beta_0 + \beta_1 SRV_{i,t-n} + \beta_2 RV_{i,t-n} + \beta_3 HC_{i,t-n} + \beta_4 {HC_{nb}}_{i,t-n} + \beta_5 {HT_{manu}}_{i,t-n} + \beta_6 {HT_{manu_{nb}}}_{i,t-n} + \beta_7 {KI_{serv}}_{i,t-n} + \beta_8 {KI_{serv_{nb}}}_{i,t-n} + \beta_9 Emp_{i,t-n} + \gamma_{i,t-n} + \varepsilon\Big) \qquad (9)$$

Where the dependent variable $GP_{i,t}$ is the number of patent families in green technologies in region *i* and year *t*. *SRV* is an indicator of the regional green knowledge base diversification at the highest aggregation of green technology groups (Y02-Tags). Similarly, *RV* indicates related variety of the regional green knowledgebase at lower aggregation of green technology groups (Y02-Tag sub-classes). *HC* refers to human capital as the share of highly educated population. Likewise, HT_{manu} displays the share of high-tech manufacturing in the regional industry and KI_{serv} represents the share of knowledge intensive services. These variables are included to form a proxy for the regional level of R&D. Knowledge intensive industry and firms have a high R&D intensity that makes their presence or absence in a region a suitable indicator for the region's innovation and R&D capabilities (Crescenzi, Pietrobelli, & Rabellotti, 2014). The variables HT_{manu_nb} and KI_{serv_nb} describe the share of high-tech manufacturing and knowledge intensive services in neighbouring regions. *EMP* is a control variable that captures the economic development. Additionally, γ is a vector that includes time and region fixed effects. Lastly, the error term ε denotes the remaining variation.

5 Empirical Analysis

5.1 Descriptive statistics and analysis of the patent data

The combination of the EPO's green patent data and corresponding location data provides a rich database of innovation activities in green technologies and their spatial attributes. The dataset employed in this study contains 2.796 patent families classified by EPO's Y02-tag scheme with their location of application in Sweden in the period from 2000 until 2015. Figure 2 displays the development of green patenting volume in total and in distinct Y02-tag classes during 2000 – 2015.

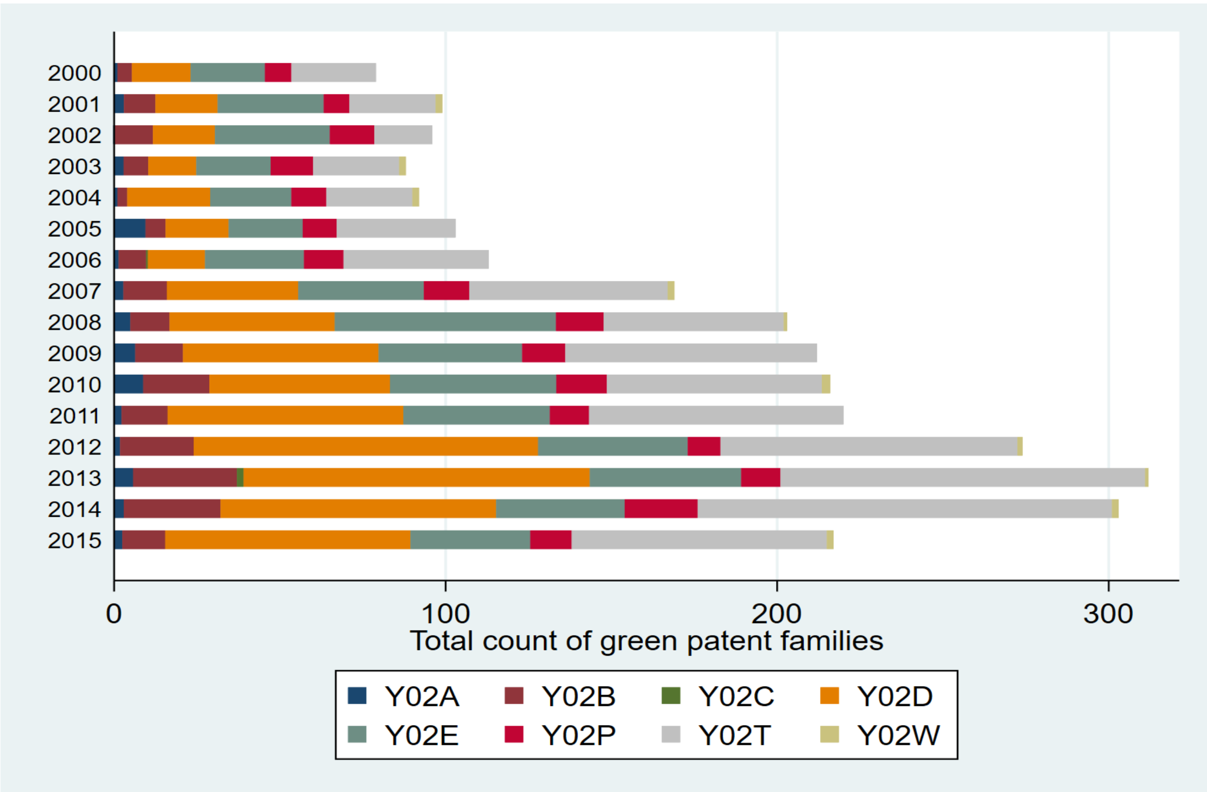

Figure 2: Yearly count of green patent families by Y02-Tag for Sweden during 2000 - 2015.

It shows that the patenting volume and the share of the individual technology groups vary through time. The major innovation efforts in green technologies are in climate change mitigation technologies related to ICT (Y02D), transport (Y02T) and energy (Y02E). While green patent application volume in Y02-tag classes more than tripled between 2000 and 2013, it experienced a short reduction in 2003 and 2004 and receded in 2014 and 2015. This data reflects the increasing interest in and the necessity of EI as a tool to create sustainable development. Keeping this in mind, the reduction of green patents in 2014 and 2015 is surprising. It might be the result of changing incentives and interests or, more likely, the absolute number decreased because many green technologies reached a later life-cycle state, where the amount of innovation and research declines (Andersen, 1999; Haupt, Kloyer & Lange, 2007; Barbieri et al., 2020).

An overview of green patent activity in Sweden's NUTS 3 regions is given in figure 3. It is apparent that the intensity of innovation in green technologies varies significantly across space. Stockholm (SE110), for example, accounts for almost half of all applications in Sweden during the observed period. Other regions with high patenting volume are Västra

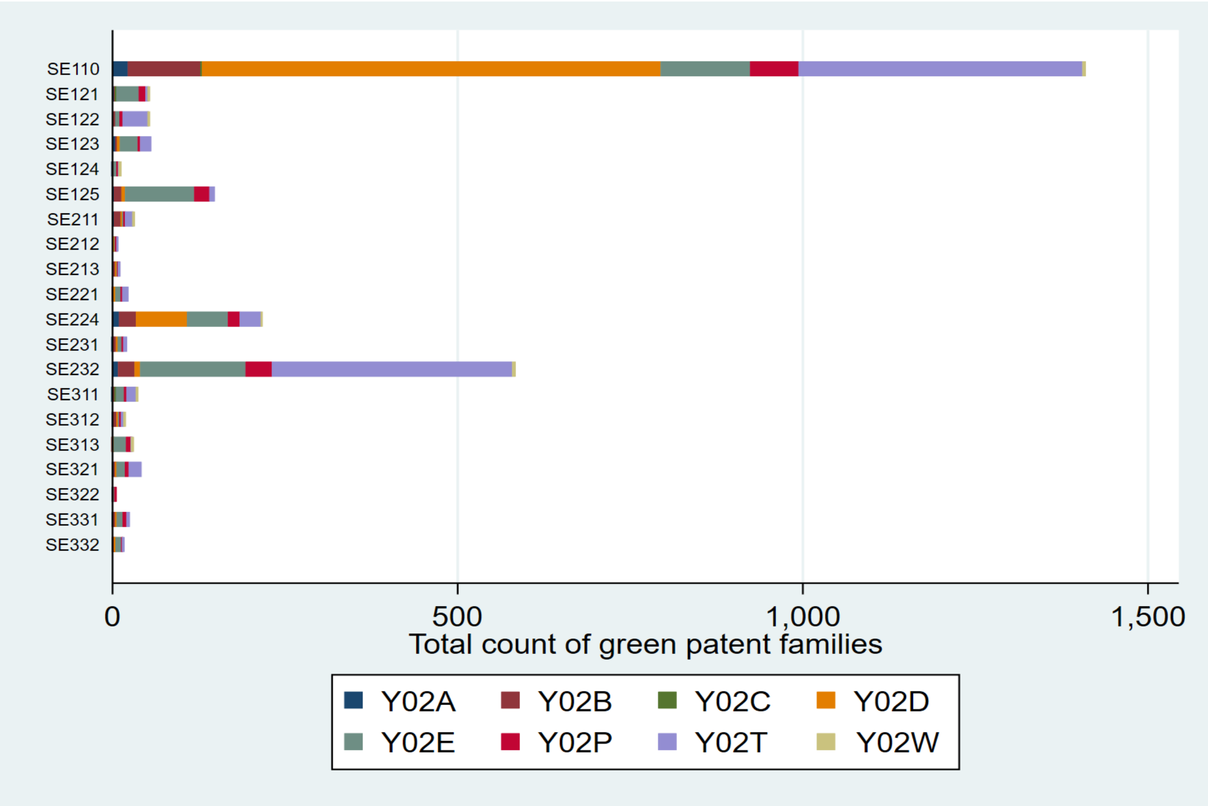

Figure 3: Total count of green patent families by NUTS 3 regions during 2000-2015.

Götaland (SE232), Skåne (SE242) and Västmanland (SE125). This regional concentration traces the accumulation of economic activity in Sweden. As more innovation is conducted where more economic activity is present.

Furthermore, figure 4 illustrates the development of green patent volume in regions with more than five years of patenting activity. The figure shows the volatility and uncertainty of creating innovations, as some regions increase their patenting volume in one year and apply no patents at all in the next. However, a sustained expanding innovation effort is depicted for Stockholm and Västra Götaland, which both increased their number of green patent families almost six fold between 2000 and 2013. Skåne does double its green patenting volume

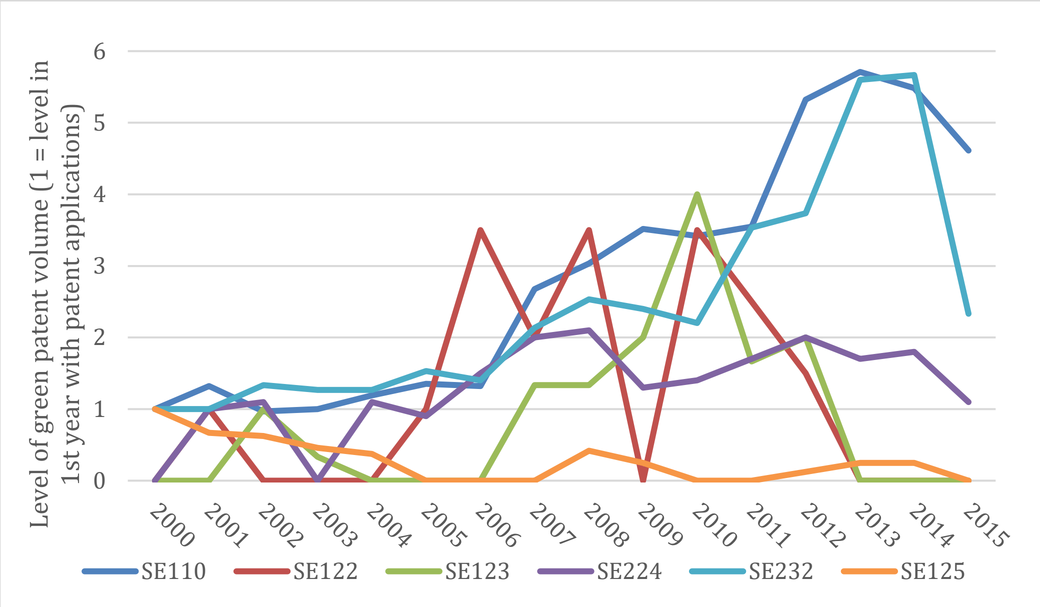

Figure 4: Evolution of green patent volume. 2000-2015. Regions with five or more years of patenting activity. 1 = patenting volume in 2000 (SE110, SE232, SE125), 2001 (SE122, SE224) or 2002 (SE123).

between 2001 and 2008 but does not fully sustain that level afterwards. Västmanland had its highest number of green patent families in 2000 and reduced its patenting activity during the observation period. Lastly, Södermanland (SE122) engaged in innovation in green technologies during 2005 – 2012, where it had double to more than triple the number of green patent families than in its first year of patent application (2002), for most years. Yet, innovation in green technologies was all but abandoned after 2012 in the region. Taking the absolute numbers of green patent families, shown in figure 2 into account, it is safe to conclude that Stockholm, Västra Götaland and Skåne are Sweden's most innovative regions in EI when quantity is analysed. Not only do these regions have the greatest number of patent families, they also increased their patenting volume the most.

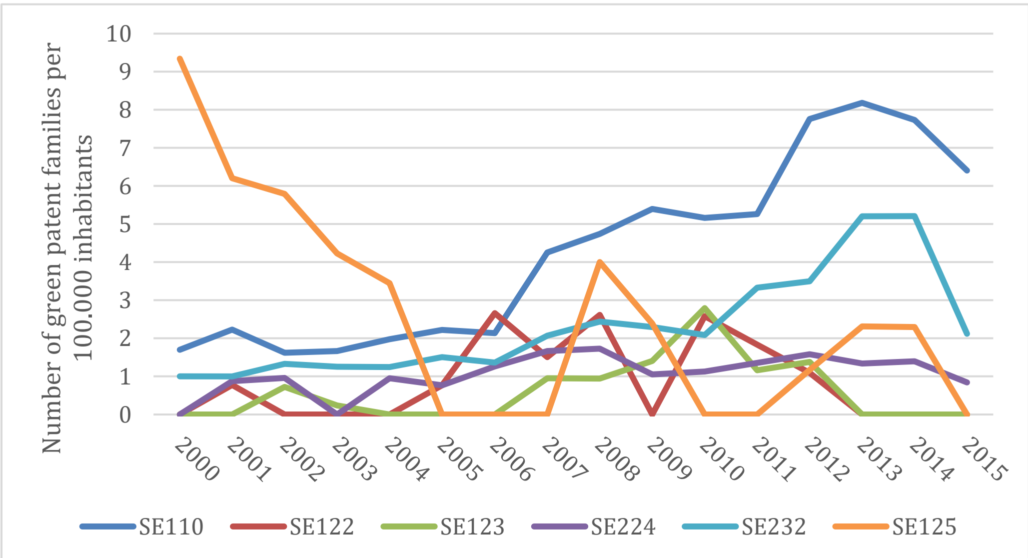

Figure 5: Green patent families relative to population. 2000-2015. Regions with five or more years of patenting activity

Another way to analyse innovation performance is to put the patent output in relation to the region's population. Figure 5 shows the number of green patent families per 100.000 inhabitants for the regions with five or more yeas of patenting activity. It is evident that Stockholm and Västra Götaland have substantially increased their relative patenting volume and are more innovative per inhabitant than the remaining regions. Surprisingly, Västmanland (SE125) had an extraordinarily high number of green patent families in comparison to the rest of Sweden in the beginning of the observed period but experienced receding EI activities until 2005. From 2005 on Västmanland exhibited only occasional green patent applications and had by the end of the period fallen behind Stockholm and Västra Götaland. The early patent activity in Västmanland could have been driven by the surge of EI in the energy sector, as most patents in Västmanland belong to that category (see figure 3) and as Sweden made significant progress in its energy transition during the period. Västmandland's industry is characterised by a large energy sector and the multinational power and electrical technology company ABB is one of the largest employers in the region. Additionally, the region's labour market is knowledge-intensive, which leads to a high share of the population that possesses tertiary education (European Commission, 2019). The advanced state of Sweden's energy transition and many climate change mitigation technologies related to energy reaching maturity may facilitate the reduction in green patent families in the region. In any case, Västmanland's development is interesting but to uncover the precise events and reasons for it requires more detailed inquiry than this study can deliver without losing its focus. Nevertheless, this evolution in Västmanland emphasises the importance of the spatial dimension in EI as innovation is decidedly heterogenous across Sweden.

Moreover, the dataset makes it possible to study how EI in various regions is compounded. Figure 3 indicates how diversified research in green technologies is in different regions and figure 6 displays each region's dominant Y02-tag class. Innovation in green technologies is predominately related to ICT (SE110, SE242) or Transport (SE232) in Sweden's most innovative regions. The remaining regions most frequently patent green technologies with relation to energy or transport, while Kalmar (SE213), Kronoberg (SE212) and Jämtland (SE322) apply most patents for technologies aimed at improving buildings' emission impact. These research areas mostly correspond to the region's major knowledge producing industries and highlights the contingency of green innovations on the local knowledgebase.

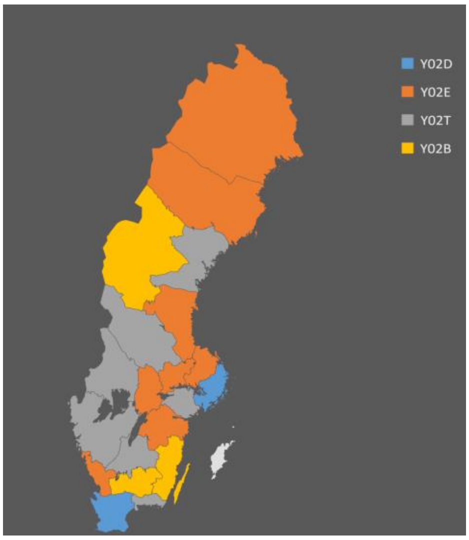

Figure 6: Dominant EI areas across Sweden. Y02-tag class with most patent families in NUTS 3 regions during 2000-2015.

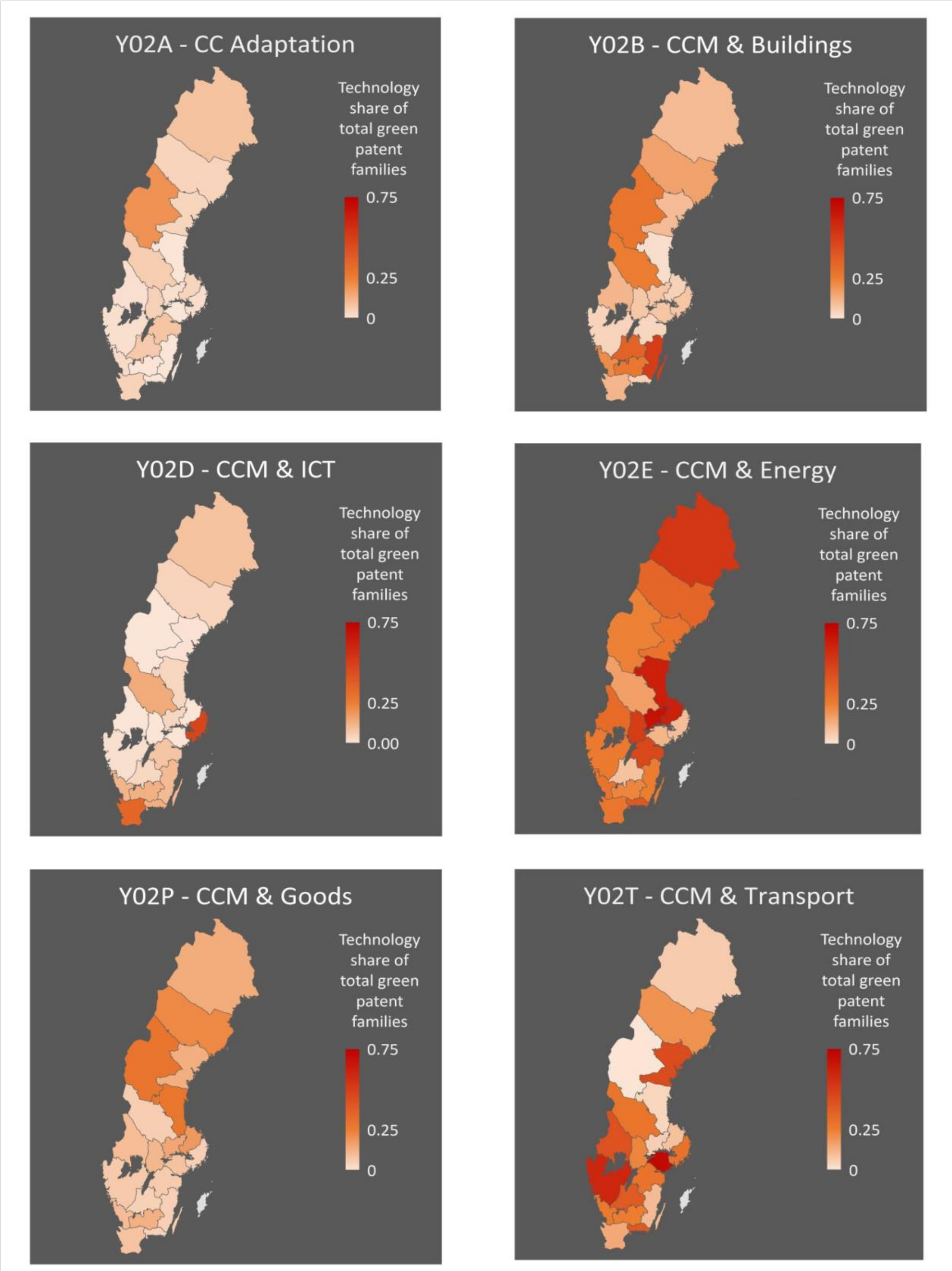

Figure 7: Share of patent families belonging to individual Y02-tag technology class of region's total patent family count in Y02 technologies. Y02C & Y02W have less than 20 patent families and are not displayed. (NUTS 3 regions, 2000-2015)

A measure of diversity can be created by calculating each technology class' share of all present patent families in each of Sweden's regions. This data is presented in figure 7. It is apparent that innovation in climate change adaptation (Y02A) and mitigation technologies in ICT (Y02D) are concentrated within in few places, while innovation in the remaining green technology areas is fairly spread out. Additionally, patenting activity in climate change adaptation (Y02A) and the mitigation of emissions by the production of goods (Y02P) are minor research areas. Research related to climate change mitigation in energy (Y02E), transport (Y02T) and buildings (Y02B) makes up 20% or more of the total patenting in Y02-tags in most regions, indicating a country wide preference for advances in these areas. Moreover, figure 7 gives an indication of how diversified research in each region is. For example, Skåne and Stockholm have a higher than average share for most technology classes, suggesting that their research is more diversified and their knowledge bases possess rich cognitive variety. Västra Götaland and Östergötland (SE123), on the other hand, show a very high share of patents in Y02T, suggesting that they are specialised in climate change mitigation technologies related to transport.

Similarly, related variety (RV) can provide insights into regional technological capabilities. RV is obtained by comparing the technological diversity and relatedness of green patent families. Thus, a high RV value indicates that the region's green patenting activities are diversified across multiple technology groups and are at the same time closely technologically related. This wide knowledgebase provides an extensive basis for recombination and is, thus, supposed to benefit the innovation process (Castaldi et al., 2015). Two variables for RV are distinguished in this study. Firstly, SRV, which captures broad relatedness within green technologies at the level of Y02-tags. Secondly, RV itself marks technological relatedness on a level with less aggregation, between sub-classes in Y02-tag technology groups. Figure 8 illustrates the evolution of these variables during 2000-2015 for Sweden's most innovative

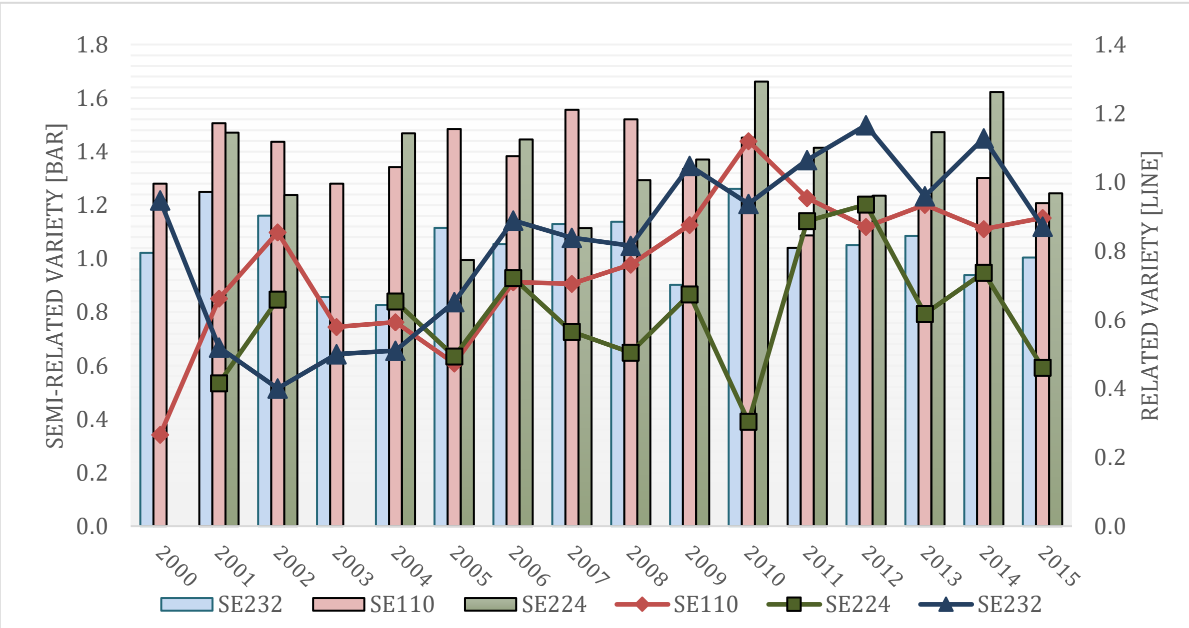

Figure 8: Semi-related and related variety in Skåne (SE224), Västra Götaland (SE232) and Stockholm (SE110). 2000-2015.

regions in green technologies (Stockholm, Skåne and Västra Götaland). As indicated by the lack of values for Skåne in 2000 and 2003, the data is somewhat patchy because there needs to be a significant volume of patenting activities between green technologies in a region to create the SRV and RV variables, which is rarely the case for new research fields like green technologies or for regions with little technological capabilities. Therefore, green patent applications are often confined to one technology group (Y02-tag or Y02 subclass) and RV in green technologies does not exist.

Additionally, figure 8 reveals the dynamic nature of this measure of RV and suggests that the innovative regions expanded their RV in total during the observation period. The observed fluctuation should, however, be regarded critically. Castaldi et al.'s (2015) method to determine RV does not follow the classical sector based measure of variety. Instead it takes all patents that occur in a region in a given period, creates groups by the patent's technological relatedness and relates them to each other. Since patenting represents research and innovation processes, which are inherently uncertain and encompass varying timeframes, patenting volumes are not distributed equally over time or space. Such unequal distribution can lead to high fluctuations in patenting volume that are unrelated to the region's existing knowledgebase, which, in the literature on this subject, is only expected to change significantly over longer timeframes than this patent derived measure might suggest (Content & Frenken, 2016). Furthermore, the graph shows that SRV and RV develop independently of each other and do not always follow the same trends, although both capture technological relatedness. This is due to the different level of aggregation. If a state would apply one patent in each Y02 class it would display the maximum SRV value but minimum RV, as there is no diversity within each Y02 class.

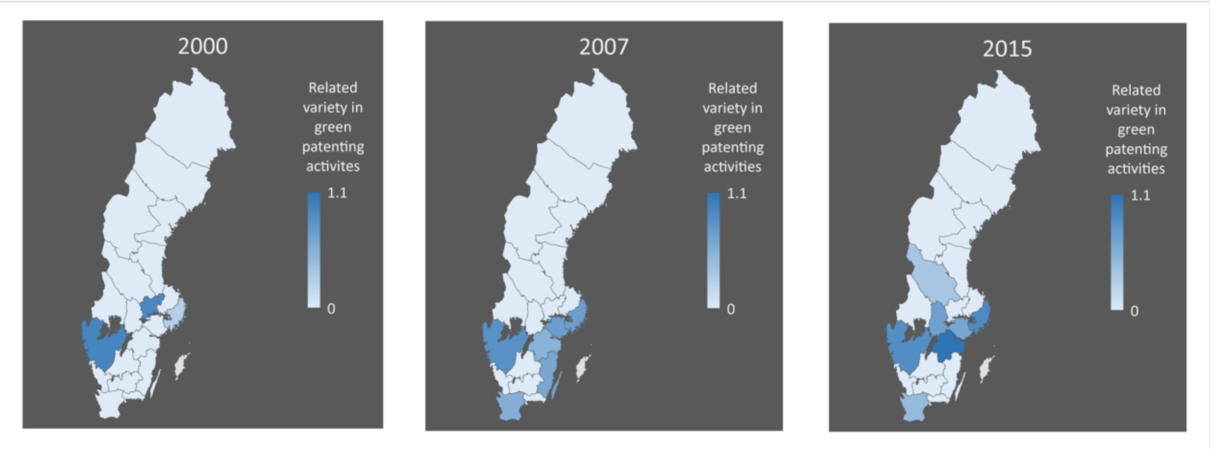

Figure 9: Related variety in green patenting activities across Sweden. NUTS 3 regions, 2000-2015.

To better illustrate the variations in RV across space and time, figure 9 presents the data in a map. The map depicts the fluctuations in the observation period. Precisely, Västmanland (SE125) had extremely high related variety in green technologies in 2000 but severely lost variety in the following years. Stockholm, Skåne, Östergötland and Södermansland (SE122), on the other hand, started with limited variety in their green technology innovation and increased it greatly during the next 15 years. Furthermore, Västra Götaland exhibited a steady, high level of RV during the entire period. The figure, additionally, highlights that Sweden's remote or economically weaker regions lack related variety in green technological innovation and cannot benefit from local, diversified knowledge related to climate change mitigation.

The evidence presented in this section leads to the conclusion that Stockholm (SE110), Västra Götaland (SE232) and Skåne (SE224) are the most successful in creating EI during the observed period. Stockholm and Västra Götaland did, moreover, improve their EI activities the most, while Skåne's fluctuated around its initial level. Sadly, Västmanland's (SE125) dominant position in the early 2000 eroded over time. Additionally, high levels of related variety are only present in a few regions. The same is true for high volumes of EI activities, which makes them highly spatially concentrated. Although, some peripheral and less developed regions slowly pick up pace and contribute to dispersion across space. Analysis of innovation activities in different technologies unveils that efforts in Y02A and Y02D are confined to a small number of regions, while those in Y02B, Y02E, Y02P and Y02T are dispersed across most Swedish regions.

Lastly, figure 10 is plotted to analyse the relationship between green patent volume, RV and SRV. It indicates positive correlation between patenting volume and RV, just as between

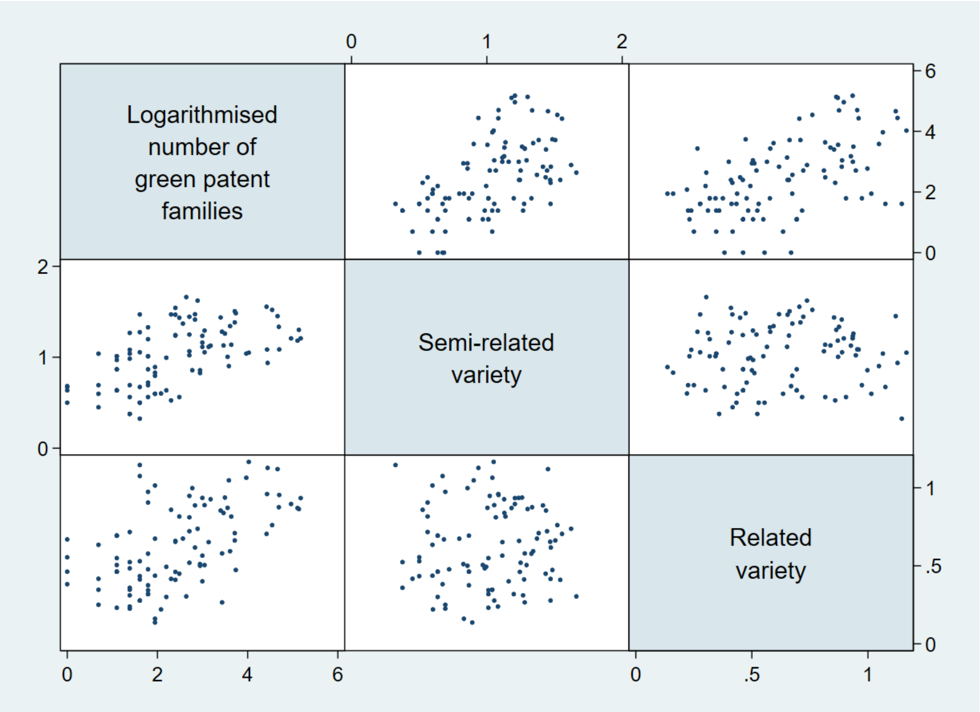

Figure 10: Scatterplot patenting volume, semi-related variety and related variety. Contains: 100 observations during 2000-2015.

patenting volume and SRV. Thus, suggesting that related variety at both aggregation levels contributes to more innovation and patenting activities in green technologies. Additionally, no apparent correlation between RV and SRV is observed. Tables that contain the RV and SRV data that is discussed in this section can be found in Appendix C.

5.2 Descriptive statistics and analysis of the socio-economic data

A range of socio-economic data is used to proxy inventive activities and for control variables in the regression. Table 2 gives an overview. There are 320 observations for the control variables, one per region for each year. Moreover, there are only 238 observations for the number of green patent families as there were 82 instances where no green patent applications were recorded in a state. The full arrangement of tables that contain the data that is illustrated and discussed in this section is displayed in appendix D.

Table 2: Description of variables for green patent families and socio-economic controls

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
GP	*Number of green patent families*	238	11.748	26.87	1	177
lnGP	Logarithmised number of green patent families	238	1.323	1.32	0	5.176
HC	*Share of employed population with bachelor's degree or higher*	320	0.252	0.069	0.134	0.481
HC_nb	*Share of employed population with bachelor's degree or higher in neighbouring regions*	320	0.266	0.051	0.167	0.398
HT manufacturing	*Share of regional employment in high-tech manufacturing*	320	0.068	0.03	0.016	0.139
HT manufacturing_nb	*Share of regional employment in high-tech manufacturing in neighbouring regions*	320	0.07	0.021	0.027	0.12
KI services	*Share of regional employment in knowledge intensive services*	320	0.450	0.041	0.347	0.552
KI services_nb	*Share of regional employment in knowledge intensive services in neighbouring regions*	320	0.456	0.031	0.389	0.534
Employment growth	*Yearly employment growth [%]*	320	0.006	0.017	-0.058	0.058

Coverage: 20 NUTS 3 regions, 2000-2015.

I will limit the discussion of the control variable's development during the observation period to Sweden's three most and least innovative regions in EI. Namely, Stockholm (SE110), Västra Götaland (SE232), Skåne (SE224), Kronoberg (SE212), Örebro (SE124) and Jämtland (SE322). This comparison will shed light on the differences between high and poorly performing states and is likely the most appropriate way to unveil how the different control variables affect patenting volume using descriptive statistics. Additionally, the trends in variables that are associated with the development in neighbouring regions will not be discussed in detail as these are entirely a product of the respective variables for a singular region and, as such, respond to the same events or trends in the same fashion.

Figure 11 shows that Sweden's most and least innovative regions in green technologies follow similar trends in both their share of highly educated population and employment

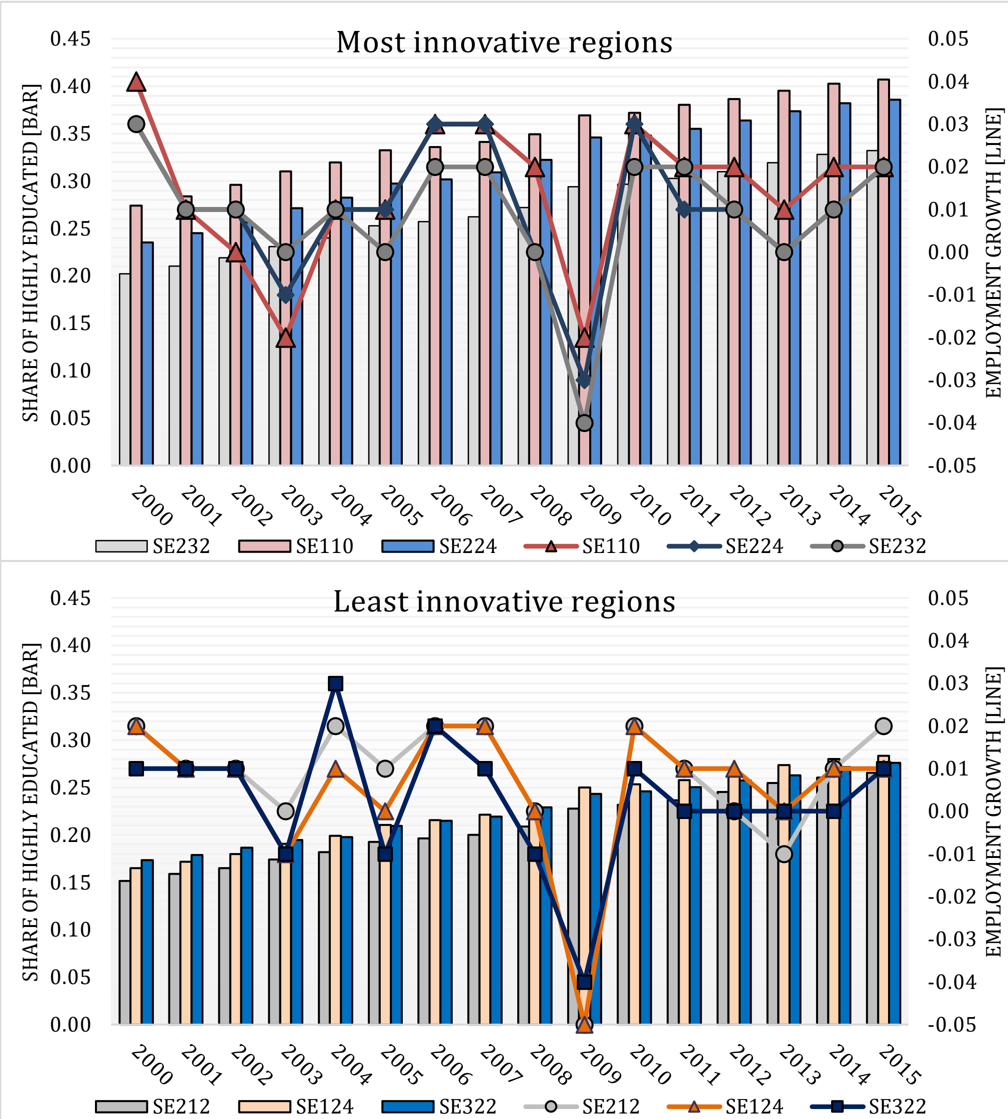

Figure 11: Development of human capital and employment in Sweden's most and least innovative regions in green technologies. 2000-2015

growth. Albeit, the highly innovative regions start from and end with higher levels of human capital and employment growth. The share of highly educated persons increases fairly constantly in all regions, while employment growth is more volatile and sensitive to economic developments. This is apparent by the drops in employment growth in the beginning of the century when Sweden's economy was laggard and during 2007-2009 when the global financial crisis hampered the economic system.

A similar picture emerges from the analysis of high-tech manufacturing and knowledge intensive service shares between 2000 and 2015 in Sweden's most and least innovative regions in EI. Figure 12 demonstrates that all regions reduce their high-tech manufacturing share and increase their share of knowledge intensive services during the

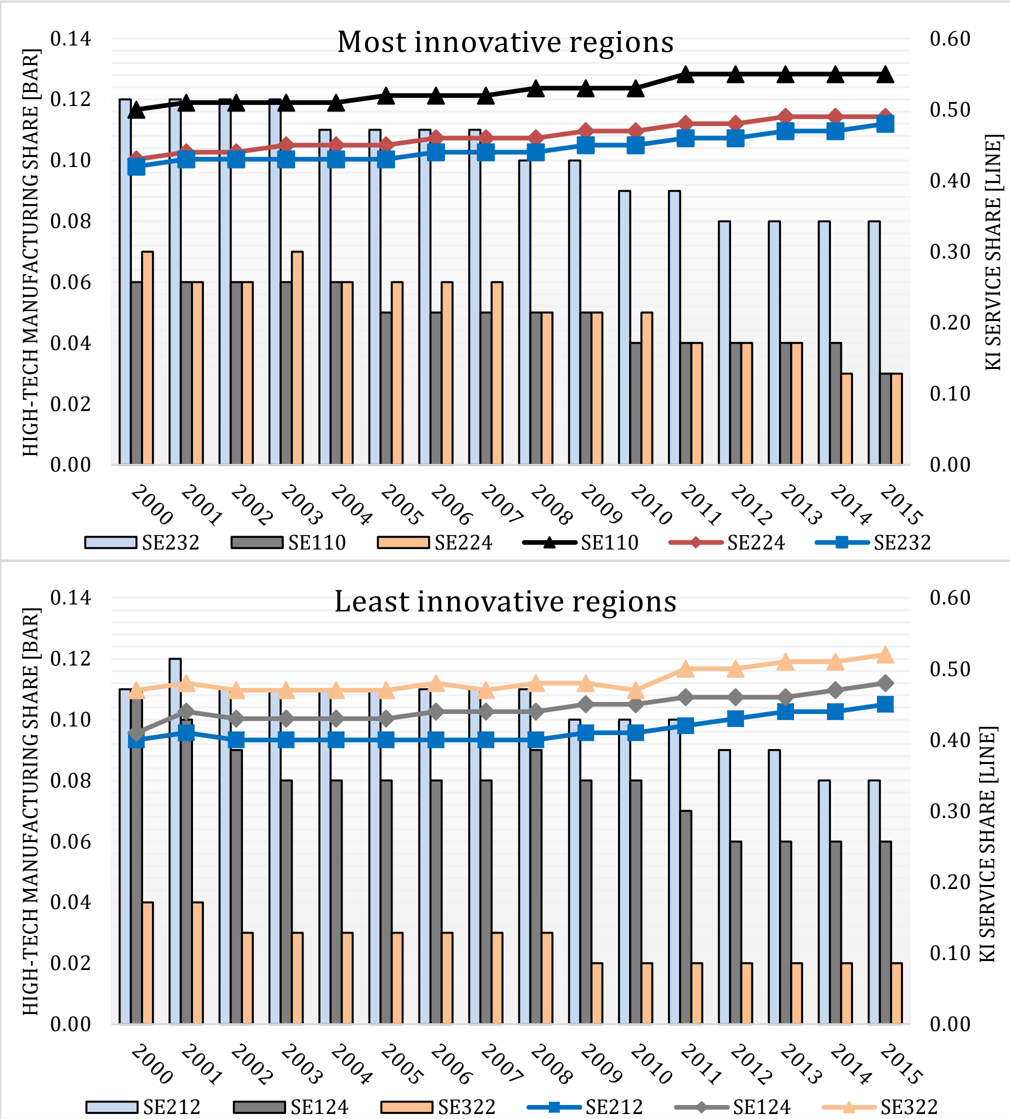

Figure 12: Development of high-tech manufacturing and knowledge intensive services in Sweden's most and least innovative regions in green technologies. 2000-2015

observed period. In contrast to figure 11, significant differences are found between regions in the most or least innovative group. Stockholm and Skåne's high-tech manufacturing share, for example, is half of Västra Götaland's in 2000 and almost a third of Västra Götaland's in 2015. This is likely because of Västra Götalands prosperous automotive, maritime and life science sectors and their corresponding value chains. Nevertheless, Västra Götaland's knowledge intensive service share is on par with Skåne's, indicating that Västra Götaland posses a broad economic foundation that should provide a diversified knowledge base. Regarding the least innovative regions, their knowledge intensive service share is only slightly below that of the most innovative regions. By 2015 they are moslty on the same level. Their high-tech manufacturing share, however, is on average larger. Although Jämtland has the smalles high-tech manufacturing share of the six analysed states. Overall, figure 12 shows no apparent link between high or low high-tech manufacturing or knowledge intensive services shares that is unique to highly innovative regions in green technologies.

Next, I analyse the correlation between green patenting volume, human capital, high-tech manufacturing share and knowledge intensive services share. A scatterplot is provided with figure 13.

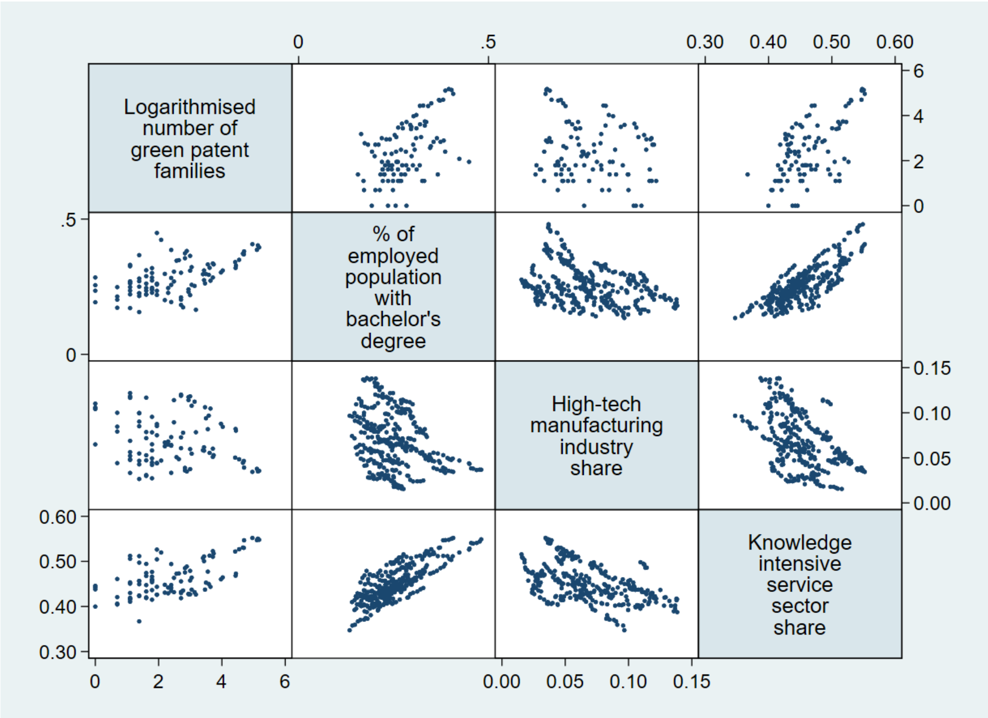

Figure 13: Scatterplot of lnGP, HC, HT manufacturing and KI services. Contains: 238 Observations, during 2000-2015.

The scatterplot indicates a positive correlation between the share of the highly educated population and green patenting volume, just as between the knowledge intensive service sector share and green patenting volume. Since both a highly educated population and knowledge intensive services enlarge the regional knowledge base and improve its innovation capabilities, this relationship appears justified (Griliches, 1979; Charlot, Crescenzi & Musolesi, 2015). On the other hand, negative correlation is suggested for the relationship between green patenting volume and high-tech manufacturing industry. Such a relationship is surprising, as high-tech manufacturing is considered knowledge intensive and should contribute to regional innovation capabilities (Hartog, Boschma & Sotarauta, 2012). A possible explanation is that most of its technological content is unrelated to green technologies. Given the often detrimental environmental impact of intensive manufacturing and its large-scale resource-intensive nature, its knowledgebase could lack effectiveness in the generation of green innovation and technologies. Such unrelated variety is beneficial in creating radical innovations but does contribute little to incremental innovations, which make up the bulk of all innovations and patents (Castaldi et al., 2015; Barbieri et al., 2020). Additionally, other channels can be at play. High environmental standards and environmentally friendly manufacturing are in most cases more expensive and difficult. Therefore, significant opposition to “green adventures” could be constituted the high-tech manufacturing sector and hinder the development of green technologies.

Furthermore, the scatterplots in figure 14 present similar correlations between green patenting volume and the variables that describe the region's surroundings. The population share with tertiary education and the share of knowledge intensive services in neighbouring states are overall positively correlated with the number of green patents, just like their counterparts in the region. Although the relationship appears not as distinct as it does for the within region

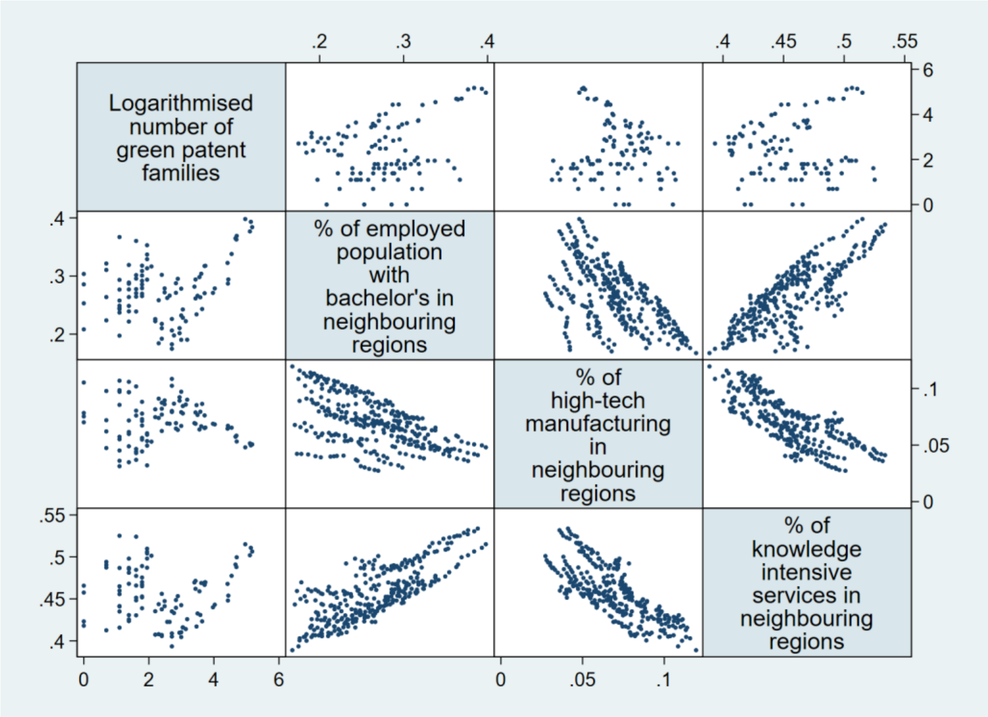

Figure 14: Scatterplot of lnGP, HC_nb, HT manufacturing_nb, KI services_nb. Contains: 238 observations during 2000-2015

variables. A large part of the observations clearly depicts the positive correlation, while another seems uncorrelated. Discovering the true relationship, hence, requires further investigation, which is undertaken in the following section. Likewise, the share of high-tech manufacturing in neighbouring regions is negatively correlated with green patent volume and displays the same ambivalent properties.

5.3 Regression results

Table 3 provides an overview of the regression data. As discussed in section 4.1, only 100 observations from the original dataset are used to run the regression to prevent bias and definition issues.

Table 3: Descriptive statistics of regression variables

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
GP	*Number of green patent families*	100	25.07	37.62	1.00	177.00
Semi-related variety	*Semi-related variety at Y02-tag classes*	100	1.019	0.333	0.325	1.662
Related variety	*Related variety at Y02-tab sub-classes*	100	0.623	0.262	0.136	1.166
HC	*Share of employed population with bachelor's degree or higher*	100	0.281	0.064	0.156	0.449
HC_nb	*Share of employed population with bachelor's degree or higher in neighbouring regions*	100	0.275	0.051	0.175	0.398
HT manu	*Share of regional employment in high-tech manufacturing*	100	0.069	0.027	0.027	0.122
HT manu_nb	*Share of regional employment in high-tech manufacturing in neighbouring regions*	100	0.071	0.018	0.031	0.108
KI serv	*Share of regional employment in knowledge intensive services*	100	0.462	0.040	0.367	0.552
KI serv_nb	*Share of regional employment in knowledge intensive services in neighbouring regions*	100	0.455	0.032	0.393	0.525
Employment growth	*Yearly employment growth [%]*	100	0.006	0.018	-0.051	0.039

The scatterplots that are presented in section 5.2 suggest that there is significant correlation between the independent variables that serve as proxies for R&D and innovativeness in a region (HC, $HC_{\_nb}$, HT_{manu}, HT_{manu_nb}, KI_{serv}, KI_{serv_nb}). Therefore, I run an OLS regression with the specification that is introduced in section 4.2 on this data and test for multicollinearity amongst the independent variables by calculating the variance inflation factor (VIF). As the entropy decomposition method predicts, there exists no multicollinearity for RV (VIF = 3.13) and SRV (VIF = 4.51). However, all VIFs for the R&D proxies are larger than ten and, thus, exhibit multicollinearity. The presence of multicollinearity in these variables reduces their statistical significance and makes the results for their coefficients unreliable (Kennedy, 2008, pp.192-197). Nevertheless, the literature around the RKPF provides good reason to include the variables as they capture different unique types of R&D and innovation. Moreover, the explanatory power of the model, just as the RV and the SRV indicator are not affected, which makes the specified model useful to test the hypothesis whether RV is positively associated with the number of patents in green technology families.

Estimation of the negative binomial model, specified in section 4.2, yields the results presented in table 4. Eight models were regressed in total. Model (3) – (8) represent the full specification with different or no time lags and supra-regional influences. Similarly, Model

Table 4: Regression results

Dependent variable	(1) GP	(2) GP	(3) GP	(4) GP	(5) GP	(6) GP	(7) GP	(8) GP
SRV	0.419	0.221	0.213	-0.0628	-0.254	-0.445*	0.100	0.282
	(0.420)	(0.217)	(0.209)	(0.434)	(0.182)	(0.227)	(0.171)	(0.341)
RV	1.104**	1.099***	0.920***	0.389	1.176***	0.544*	0.294***	0.296
	(0.471)	(0.212)	(0.169)	(0.290)	(0.182)	(0.327)	(0.111)	(0.225)
HC		1.970	4.406	-9.309	-16.55	-2.048	-62.68***	5.486
		(27.69)	(24.04)	(34.32)	(20.71)	(28.29)	(7.268)	(88.13)
HC_nb			47.00**	32.31*	-4.023	24.99	21.14***	5.139
			(21.00)	(17.23)	(8.813)	(27.25)	(7.069)	(30.37)
HT manu		31.54	14.72	16.37	21.79	-6.931	-42.75***	-37.11
		(23.33)	(23.21)	(23.55)	(13.30)	(14.98)	(7.767)	(64.94)
HT manu_nb			-10.28	-22.38	-15.48	-13.42	77.20***	79.61
			(35.08)	(27.74)	(16.37)	(22.53)	(10.46)	(56.41)
KI serv		38.48**	34.37**	48.66***	36.12**	27.90	94.12***	-12.10
		(17.42)	(15.94)	(18.13)	(14.70)	(23.35)	(9.878)	(92.62)
KI serv_nb			1.024	0.185	-32.91***	-12.54	26.63***	34.54
			(14.89)	(19.73)	(6.620)	(14.71)	(6.648)	(46.76)
Employment growth		10.59*	8.581	15.03	10.14***	10.04	4.473**	4.775
		(5.895)	(5.318)	(10.95)	(2.336)	(11.11)	(2.138)	(22.37)
Observations	100	100	100	68	57	50	48	45
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Time dummies	Y	Y	Y	Y	Y	Y	Y	Y
Time lag	X	X	X	1 year	2 years	3 years	4 years	5 years
Pseudo R^2	0.303	0.334	0.341	0.342	0.394	0.349	0.456	0.388

Notes: Analysis covers 20 Swedish NUTS 3 regions and the timeframe is 2000-2015. Robust to heteroskedasticity and spatial correlation. Standard errors in parentheses.

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

(2) excludes supra-regional effects. Lastly, Model (1) regresses just the variety indicators on GP. All models except (4) and (8) indicate a statistically significant and positive effect from RV on the number of green patent families. On the other hand, only model (6) finds a statistically significant negative effect from SRV. However, the estimator only has a significance level of 10%, none of the other models find influence from SRV on GP and a negative influence is surprising, when the literature on this subject is taken into account. Therefore, this finding should not be taken at face value, as there is a high probability of a false positive. Nevertheless, the results for the RV indicator suggest that there is a benefit from cognitive relatedness, in the form of related variety, in the green knowledge base. Since, no influence from SRV is found, only evidence for an effect of variety in closely related disciplines with a low level of aggregation is presented. Such a decline of benefits from variety with increasing cognitive distance is natural because the technologies in Y02 classes might have in common that they mitigate climate change and emissions, but the techniques

used to achieve this vary substantially between the classes. Possessing the knowledge and capabilities to innovate in the field of efficient water supply/use (Y02A-20) is unlikely to ease knowledge adoption and capability building to create EIs in reducing the energy consumption in communication networks (Y02D-50). It does, however, proof beneficial when creating technologies that adopt infrastructure to or protect it from climate change (Y02A-30), as supplying water is a critical infrastructure function and knowledge about it is likely to be applicable during the innovation process.

Moreover, the statistically significant and positive relationship between RV and GP that most models find indicates that EI output of Swedish regions is enhanced when the regional knowledge base is diverse in related environmentally friendly technologies. This resonates well with previous findings in the literature. For example, Barbieri et al.'s (2020) study comes to the same conclusion for RV and green patents in the US. Furthermore, Berlinat and Fujita (2011) expect enhanced knowledge transmission to increase with RV and since Schiuma et al. (2013) found that EI are particularly knowledge and collaboration intensive, RV is expected to aid in their creation. Similarly, Aarstad et al. (2016) provide evidence that high levels of RV are ideal for regional innovation, just as Tavassoli and Carbonara (2014) found an overall positive effect from RV for Swedish regional innovation. Additionally, Castaldi et al. (2015) state that RV contributes to incremental, rather than radical innovation, which occurs more frequently and, thus, is significant for the volume of innovation and patents. Barbieri et al. (2020) suggest a similar role for RV in the creation of incremental innovation based on their life-cycle analysis. Such mechanisms likely underly the present results.

Models (5) to (7) provide evidence for the existence of a time lag and a reduction of magnitude over time, when it comes to RV affecting EI. Considering that recombinant innovation is a time intensive process it is sensible to assume that RV affects the EI output with a significant delay. Additionally, models (1) to (3) suggest an immediate influence from RV. Nevertheless, the immediate effect from RV, that is presented in the models without time lag, is not fully congruent with the theory, where most scholars agree that RV affects regional development and innovation only over time, and not all incremental innovations have short development times. Similar studies to the present one from Tavassoli and Carbonara (2013), and Castaldi et al. (2015) also find a delayed effect from RV in Sweden and the United States. The insignificance of the RV indicator in model (4) further supports the notion that the relationship between RV and EI is characterised by delayed influence. This seems also plausible from a theoretical standpoint as most EI are complex, research intensive and, hence, take a longer period to develop (Schiuma et al., 2013). Although, Barbieri et al.'s (2020) study shows similar results for their model without time lags, the significance of RV in the first three models should be interpreted with this caveat in mind. Yet, even if the literature points to a delayed effect, models (1) to (3) do provide additional robustness for the overall beneficial relationship from RV on EI. Model (8) then suggests that this relationship fades away in the long-term. In summary, the results of the model confirm the hypothesis that RV is positively associated with the number of patents in green technology families and suggest that this relationship is characterised by a significant time-lag.

It is noticeable that the share of knowledge-intensive services in neighbouring regions is found to have significant negative effect in model (5). This finding is not necessarily spurious because it is within the RKPF's notion of extra regional knowledge flow. The negative effect could be explained by the concentration of EI in a small number of locations in Sweden. Namely, Stockholm, Västra Götaland and Skåne concentrate the vast majority of green patent families on themselves. The agglomeration economies that are present in these locations, just as their more intensive green knowledge bases can provide a strong incentive for other environmental innovators to locate in those regions, instead of locating in the less developed regions. Thus, the innovative regions drain innovation potential from the other regions, leading to the negative effect. Similarly, the negative indicator of HT_{manu} in model (7) could capture the opposition from high-tech manufacturing that was hinted at in section 5.2. Overall, the results for the variables that proxy research and innovation effort should not be relied on because, as discussed above, these likely suffer from multicollinearity.

Nevertheless, in the case that a drain of knowledge does exist, it does not need to be a final process that condemns peripheral regions to stagnation. Interactive learning and knowledge spillovers can also be facilitated by collaboration, alliances or cooperation in networks with distant actors (Amin & Cohendet, 2005). This notion is prominently supported by Boschma (2005), who argues that the geographical proximity can be substituted through other dimensions of proximity. Hence, cognitive or organisational proximities that are created by collaboration or networking, for example, can substitute for the effect of local RV and allow peripheral innovators to be successful in creating EIs. Grillitsch and Nilsson (2015) even provide empirical evidence for this theory from Sweden and reiterate that knowledge spillovers and recombinant innovation are not purely regional. Consequently, the inclusion of cross-regional knowledge flows would enhance the accurateness of RV's effect on EI and should be an object of future research.

Finally, it should be mentioned that the dispersion parameter, which serves as an indication that the data is over-dispersed and that the model fits, is positive and different from zero for all models. However, the parameter approaches zero, especially for the models with time lag. This is in any case not necessary an indication that the models do not fit because the negative binomial regressor fails to reliability assess the dispersion of the dataset, when only a small number of observations is used. Although the analysis of the dataset's distribution itself (see section 4.2) and the results of the regression, which are plausible from a theoretical standpoint, support the applicability of the model, this caveat must be acknowledged. Ultimately, a more extensive dataset would be desirable to deal with this problem.

6 Conclusion

The aim of this study is to investigate EI and how it is affected by RV across Sweden during 2000-2015. The study adds to both the literature on EI and that on RV. Furthermore, it can be used to give policy recommendations for successful sustainable development. Initially, the literature, central concepts, and theories with regards to EI and variety in regional knowledge bases were laid out. Previous studies on the subject were discussed thereafter. Then, the theoretical framing for the study was derived and concrete research questions were formulated. Moreover, the data was introduced, its fit and limitations were elaborated. The application and definition of entropy indicators was presented and an econometric model to test the study's hypothesis that RV is positively associated with the number of green patent families and, consequently, with EI is derived. Descriptive analysis of the data is conducted. Lastly, its findings and that of the econometric model are discussed.

Analysis of the patent data showed that EI activity is strongly concentrated in Sweden. Stockholm, Västra Götaland and Skåne combined account for the vast majority of patent filings. Moreover, the three regions do not only create the most EI in absolute numbers, they also improved their EI output the most. Hence, providing an answer for the first research question. It should be noted that Västmanland had the highest EI per inhabitant ratio in Sweden in the first four years but fell behind the other tree regions thereafter. While Stockholm, Västra Götaland, and Skåne are the most innovative regions, the remaining Swedish regions contribution cannot be neglected, especially when considering climate change mitigation technologies related to energy and transport. Furthermore, the analysis presented evidence that EI in climate change adaptation technologies and mitigation technologies related to ICT are concentrated in a few regions and are sparsely present in others. On the other hand, EI in climate change mitigation technologies related to energy, transport, buildings, and the production of goods are dispersed across Sweden and make up a significant share of most regions' green patent families. The entropy indicators shed light on the variety in regional green knowledge bases and indicated that RV is limited for most regions but has expanded substantially during the observed period. Thereby, answering the second research question. Lastly, the results of the econometric model confirmed the hypothesis that RV is positively associated with the number of patents in green technology families. Thus, providing evidence that RV in the regional green knowledge base is indeed beneficial for EI. This relationship is, additionally, characterised by a significant time lag and the strength of RV's influence is shown to fade over time.

Further research should investigate if the effect from RV remains stable in varying geographic, institutional and cultural circumstances. Moreover, expansion of the database to include more regions on the one hand and more patents on the other would improve the robustness of the results and could unveil additional spatial variation. However, since innovation in green technologies and research in climate change mitigation technologies are contemporary phenomena, extending the observation period in the past will likely yield marginal benefits. Another useful addition would be the quantification and inclusion of extra-regional effects from collaboration, cooperation and alliances. These are expected to facilitate knowledge spillovers and increase interaction, which are essential to recombinant innovation.

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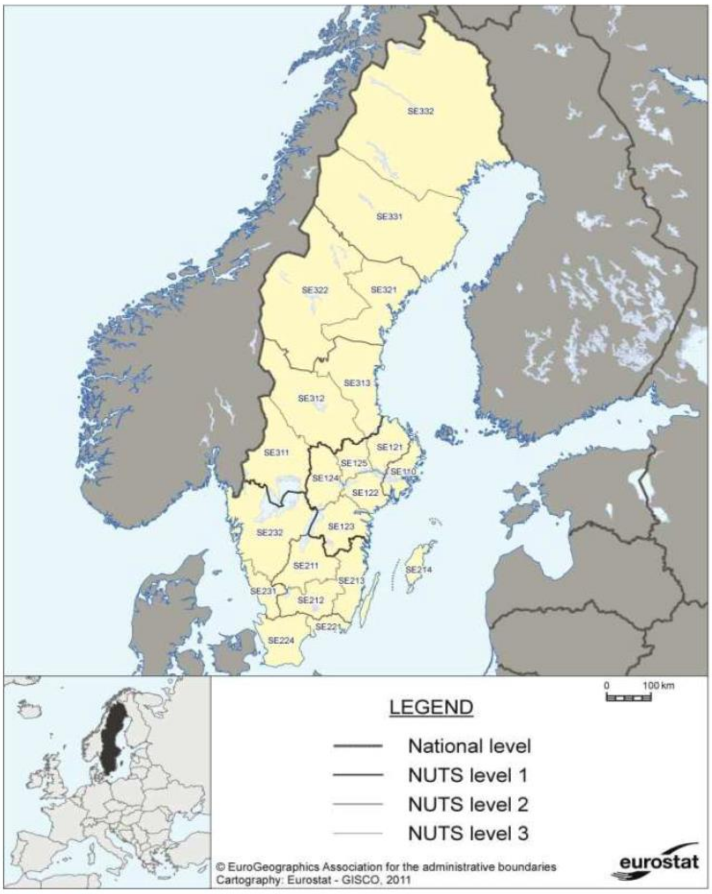
Appendix A – Swedish NUTS3 Regions

European nomenclature of territorial units for statistics (NUTS). Swedish territorial units three-digit level (Eurostat, 2011).

Nomenclature of territorial units (NUTS) for statistics - level 3

Code	NUTS3
SE110	Stockholms län
SE121	Uppsala län
SE122	Södermanlands län
SE123	Östergötlands län
SE124	Örebro län
SE125	Västmanlands län
SE211	Jönköpings län
SE212	Kronobergs län
SE213	Kalmar län
SE214	Gotlands län
SE221	Blekinge län
SE224	Skåne län
SE231	Hallands län
SE232	Västra Götalands län
SE311	Värmlands län
SE312	Dalarnas län
SE313	Gävleborgs län
SE321	Västernorrlands län
SE322	Jämtlands län
SE331	Västerbottens län
SE332	Norrbottens län



Appendix B – Green technology classes: CPC Y02-Tags (EPO, 2020)

Y02- Technologies or applications for mitigation or adaptation against climate change

Y02A - Technologies for adaptation to climate change (CC ADAPTATION)	**Y02B** - Climate change mitigation technologies related to buildings (CCM & BUILDINGS)	**Y02C** - Capture, storage, sequestration or disposal of GHG (CCS & GHG)	**Y02D** - Climate change mitigation technologies in ICT, i.e. aiming at the reductio nof their own energy use (CCM & ICT)	**Y02E** - Reduction of GHG emissions, related to energy generation, transmission or distribution (CCM & ENERGY)	**Y02P**- Climate change mitigation technologies in the production or processing of goods (CCM & GOODS)	**Y02T**- Climate change mitigation technologies related to transportation (CCM & TRANSPORT)	**Y02W**- climate change mitigation technologies related to wastewater treatment or wate management (CCM & WASTE)
10 at coastal zones; at river basins	**10** integration of renewable energy sources in buildings	**10** CO2 capture or storage	**10** energy efficient computing	**10** energy generation through renewable energy sources	**10** technologies related to metal processing	**10** road transport of goods or passengers	**10** technologies for wastewater treatment
20 water conservation; efficient water supply/use	**20** energy efficient lighting technologies	**20** capture or disposal of GHG other than CO2	**30** high level techniques for reducing energy consumption in communication networks	**20** combustion technologies with mitigation potential	**20** technologies related to chemical industry	**30** transportation of goods or passengers via railways	**30** technologies for solid waste management
30 adapting or protecting infrastructure	**30** energy efficient heating, ventilation or air conditioning		**50** techniques for reducing energy consumption in wire-line communication networks	**30** energy generation of nuclear origin	**30** technologies related to oil refining and petrochemical industry	**50** aeronautics or air transport	**90** enabling technologies or technologies with a potential or indirect öcontribution to GHG emissions mitigation
40 adaptation technologies in agriculture, forestry, livestock or agroalimentary production	**40** technologies aiming at improving the efficiency of home appliances		**70** techniques for reducing energy consumption in wireless communication networks	**40** technologies for an efficient electrical power generation, transmission or distribution	**40** technologies relating to the processing of minerals	**70** maritime or waterways transport	
50 in human health protection	**50** energy efficient technologies in elevators, escalators and moving walkways			**50** technologies for the production of fuel of non-fossil origin	**60** technologies relationg to agriculture, livestock or agroalimentary industries	**90** enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation	
90 technologies having an indirect contribution ot adaptation to climate change	**70** technologies for an efficient end-user side electric power management and consumption			**60** enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation	**70** climate change mitigation technologies in the production process for final industrial or consumer products		
	80 architectural or constructional elements improving the thermal performance of buildings			**70** other energy conversion or management systems reducing GHG emissions	**80** climate change mitigation technologies for sectorwide applicatoins		
	90 enabling technologies or technologies with a potential or indirect contribution to GHG emission mitigation				**90** enabling technologies with a potential contribution to GHG emissions mitigation		

Appendix C

Related variety and semi-related variety results for each NUTS 3 region and year, constructed by Castaldi, Frenken, & Los' (2015) enthropy method. Described in detail in section 4.1.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
SE110	1.3	1.5	1.4	1.3	1.3	1.5	1.4	1.6	1.5	1.3	1.5	1.1	1.2	1.2	1.3	1.2	
SE121			0.4						0.6	0.8							
SE122		0.7				0.5	0.6	0.6	0.6		0.8	0.5	0.6				
SE123			0.6	0.5				0.4	0.7	1.0	1.4	0.7	1.0				
SE211				1.1											0.7		
SE212						0.6											
SE213								0.6							0.7		
SE221																	
SE224		1.5	1.2		1.5	1.0	1.4	1.1	1.3	1.4	1.7	1.4	1.2	1.5	1.6	1.2	
SE231									1.0		1.5						
SE232	1.0	1.2	1.2	0.9	0.8	1.1	1.1	1.1	1.1	0.9	1.3	1.0	1.1	1.1	0.9	1.0	**Semi-related variety**
SE125	1.1	0.9	1.1	1.5	0.6				0.5	1.3			0.9	0.6	0.7		
SE124																	
SE311						1.1	0.9		1.0	0.6				0.7			
SE312																1.0	
SE313					0.6					1.0		0.3					
SE321										0.5	1.2	1.3	1.3		0.9		
SE322																	
SE331											1.0	0.9					
SE332						1.0	0.9										
SE110	0.3	0.7	0.9	0.6	0.6	0.5	0.7	0.7	0.8	0.9	1.1	1.0	0.9	0.9	0.9	0.9	
SE121			0.4						0.2	0.2							
SE122		0.3				0.4	1.0	0.7	0.4		0.7	0.5	0.7				
SE123			0.7	0.6				0.5	0.2	0.3	0.4	1.1	0.3				
SE211				0.2											1.0		
SE212						0.5											
SE213								0.6							0.7		
SE221																	
SE224		0.4	0.7		0.7	0.5	0.7	0.6	0.5	0.7	0.3	0.9	0.9	0.6	0.7	0.5	
SE231									0.5		0.3						
SE232	0.9	0.5	0.4	0.5	0.5	0.7	0.9	0.8	0.8	1.0	0.9	1.1	1.2	1.0	1.1	0.9	**Related variety**
SE125	0.9	1.0	0.8	0.4	0.3				0.9	0.6			0.5	0.9	0.5		
SE124																	
SE311						0.3	0.7		0.5	0.8				0.4			
SE312																0.3	
SE313					0.5					0.3		1.1					
SE321										0.4	0.3	0.4	0.3		0.1		
SE322																	
SE331											0.2	0.5					
SE332						0.5	0.4										
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	

Appendix D

Control variable base data for each NUTS 3 region and year.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
SE110	0.27	0.28	0.3	0.31	0.32	0.33	0.34	0.34	0.35	0.37	0.37	0.38	0.39	0.4	0.4	0.41	**Share of employed population with bachelor's degree or higher**
SE121	0.34	0.36	0.37	0.38	0.39	0.41	0.4	0.4	0.42	0.45	0.45	0.45	0.46	0.47	0.48	0.48	
SE122	0.17	0.17	0.18	0.19	0.2	0.21	0.22	0.23	0.24	0.26	0.26	0.26	0.27	0.27	0.28	0.29	
SE123	0.2	0.21	0.22	0.24	0.25	0.26	0.26	0.27	0.28	0.3	0.31	0.31	0.32	0.33	0.33	0.34	
SE211	0.13	0.14	0.15	0.16	0.16	0.17	0.18	0.18	0.19	0.21	0.21	0.22	0.22	0.23	0.24	0.24	
SE212	0.15	0.16	0.16	0.17	0.18	0.19	0.2	0.2	0.21	0.23	0.23	0.24	0.25	0.25	0.26	0.27	
SE213	0.15	0.15	0.16	0.17	0.18	0.19	0.2	0.2	0.21	0.23	0.23	0.23	0.24	0.25	0.26	0.26	
SE221	0.17	0.18	0.19	0.2	0.21	0.22	0.22	0.23	0.24	0.26	0.27	0.27	0.28	0.28	0.29	0.3	
SE224	0.24	0.24	0.26	0.27	0.28	0.3	0.3	0.31	0.32	0.35	0.35	0.36	0.36	0.37	0.38	0.39	
SE231	0.2	0.21	0.21	0.22	0.23	0.25	0.25	0.26	0.27	0.29	0.29	0.29	0.3	0.31	0.32	0.33	
SE232	0.2	0.21	0.22	0.23	0.24	0.25	0.26	0.26	0.27	0.29	0.3	0.3	0.31	0.32	0.33	0.33	
SE125	0.16	0.17	0.18	0.19	0.2	0.21	0.21	0.22	0.23	0.25	0.25	0.25	0.26	0.27	0.28	0.29	
SE124	0.17	0.17	0.18	0.19	0.2	0.21	0.22	0.22	0.23	0.25	0.25	0.26	0.27	0.27	0.28	0.28	
SE311	0.17	0.18	0.19	0.2	0.21	0.22	0.24	0.24	0.25	0.27	0.27	0.27	0.28	0.28	0.29	0.29	
SE312	0.15	0.15	0.16	0.17	0.18	0.19	0.19	0.19	0.2	0.22	0.22	0.22	0.23	0.24	0.24	0.25	
SE313	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.19	0.2	0.22	0.22	0.22	0.23	0.24	0.24	0.25	
SE321	0.16	0.17	0.17	0.18	0.19	0.2	0.21	0.21	0.22	0.24	0.24	0.25	0.25	0.26	0.26	0.26	
SE322	0.17	0.18	0.19	0.19	0.2	0.21	0.21	0.22	0.23	0.24	0.25	0.25	0.26	0.26	0.27	0.28	
SE331	0.23	0.24	0.25	0.27	0.27	0.29	0.29	0.3	0.3	0.33	0.33	0.33	0.33	0.34	0.35	0.36	
SE332	0.18	0.19	0.2	0.21	0.21	0.23	0.23	0.23	0.24	0.25	0.25	0.25	0.25	0.26	0.27	0.27	
SE110	0.04	0.01	0.00	-0.02	0.01	0.01	0.03	0.03	0.02	-0.02	0.03	0.02	0.02	0.01	0.02	0.02	**Employment growth per year**
SE121	0.03	0.03	0.02	0.00	0.00	0.00	0.06	0.02	-0.02	-0.02	0.03	0.02	0.02	0.01	0.01	0.02	
SE122	0.02	0.01	0.00	0.00	0.01	0.00	0.02	0.02	0.00	-0.05	0.02	0.02	0.00	0.01	0.00	0.01	
SE123	0.02	0.01	0.02	-0.01	0.00	-0.01	0.02	0.02	0.00	-0.03	0.02	0.01	0.01	0.01	0.01	0.02	
SE211	0.04	0.00	0.01	-0.01	0.01	0.00	0.02	0.02	-0.01	-0.06	0.03	0.01	0.00	0.00	0.01	0.02	
SE212	0.02	0.01	0.01	0.00	0.02	0.01	0.02	0.02	0.00	-0.05	0.02	0.01	0.00	-0.01	0.01	0.02	
SE213	0.02	0.01	0.00	-0.01	0.00	-0.01	0.02	0.02	-0.01	-0.04	0.02	0.00	-0.01	0.00	0.00	0.01	
SE221	0.01	0.00	0.00	0.00	0.02	0.00	0.02	0.01	-0.02	-0.05	0.01	0.00	-0.01	0.00	0.00	0.01	
SE224	0.03	0.01	0.01	-0.01	0.01	0.01	0.03	0.03	0.00	-0.03	0.03	0.01	0.01	0.00	0.01	0.02	
SE231	0.03	0.02	0.03	0.01	0.02	0.01	0.03	0.03	0.00	-0.03	0.03	0.02	0.01	0.00	0.01	0.01	
SE232	0.03	0.01	0.01	0.00	0.01	0.00	0.02	0.02	0.00	-0.04	0.02	0.02	0.01	0.00	0.01	0.02	
SE125	0.01	0.00	0.01	-0.01	0.02	0.00	0.02	0.01	-0.01	-0.05	0.02	0.01	0.00	-0.01	0.00	0.01	
SE124	0.02	0.01	0.01	-0.01	0.01	0.00	0.02	0.02	0.00	-0.05	0.02	0.01	0.01	0.00	0.01	0.01	
SE311	0.02	0.00	0.01	-0.01	0.01	0.00	-0.02	0.02	0.00	-0.05	0.02	0.02	0.01	0.01	0.00	0.01	
SE312	0.01	0.01	0.02	0.00	0.02	0.00	0.01	0.01	-0.01	-0.04	0.02	0.00	0.00	0.00	0.00	0.01	
SE313	0.01	0.00	0.00	-0.01	0.01	-0.01	0.02	0.02	0.00	-0.05	0.02	0.00	-0.01	0.00	0.00	0.00	
SE321	0.01	0.01	0.01	-0.01	0.01	0.00	0.01	0.00	-0.01	-0.04	0.00	0.00	0.01	0.00	0.00	0.01	
SE322	0.01	0.01	0.01	-0.01	0.03	-0.01	0.02	0.01	-0.01	-0.04	0.01	0.00	0.00	0.00	0.00	0.01	
SE331	0.01	0.00	0.02	-0.01	0.03	0.00	0.02	0.02	0.00	-0.04	0.02	0.01	0.01	0.00	0.00	0.01	
SE332	0.01	0.00	0.01	-0.01	0.02	0.00	0.03	0.02	-0.01	-0.04	0.02	0.01	0.01	0.01	0.00	0.00	
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
SE110	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.03	
SE121	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
SE122	0.11	0.10	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.08	0.08	0.07	0.07	0.07	0.07	0.06	
SE123	0.14	0.13	0.12	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.09	0.08	0.08	0.08	0.08	0.07	
SE211	0.10	0.10	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.06	
SE212	0.11	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.09	0.09	0.08	0.08	
SE213	0.10	0.10	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07	0.06	0.06	0.07	
SE221	0.14	0.14	0.14	0.13	0.13	0.13	0.12	0.12	0.12	0.10	0.10	0.11	0.11	0.11	0.11	0.11	
SE224	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	
SE231	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	**High-tech manufacturing share**
SE232	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.10	0.10	0.09	0.09	0.08	0.08	0.08	0.08	
SE125	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.05	0.05	0.04	0.04	0.04	
SE124	0.11	0.10	0.09	0.08	0.08	0.08	0.08	0.08	0.09	0.08	0.08	0.07	0.06	0.06	0.06	0.06	
SE311	0.14	0.14	0.14	0.13	0.13	0.12	0.12	0.12	0.12	0.11	0.11	0.10	0.10	0.10	0.10	0.10	
SE312	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.04	
SE313	0.07	0.07	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.03	0.03	0.03	0.03	0.02	
SE321	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.04	0.04	
SE322	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	
SE331	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.05	0.05	0.05	0.05	0.05	
SE332	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	
SE110	0.50	0.51	0.51	0.51	0.51	0.52	0.52	0.52	0.53	0.53	0.53	0.55	0.55	0.55	0.55	0.55	
SE121	0.51	0.52	0.51	0.51	0.51	0.51	0.51	0.50	0.52	0.53	0.53	0.54	0.54	0.54	0.54	0.55	
SE122	0.40	0.40	0.42	0.42	0.42	0.42	0.43	0.42	0.43	0.44	0.44	0.45	0.45	0.46	0.47	0.47	
SE123	0.42	0.44	0.43	0.44	0.44	0.44	0.45	0.45	0.46	0.46	0.46	0.47	0.48	0.48	0.49	0.49	
SE211	0.35	0.36	0.36	0.37	0.37	0.37	0.37	0.37	0.38	0.39	0.39	0.40	0.40	0.41	0.41	0.42	
SE212	0.40	0.41	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.41	0.41	0.42	0.43	0.44	0.44	0.45	
SE213	0.39	0.40	0.40	0.40	0.40	0.40	0.41	0.41	0.41	0.42	0.42	0.43	0.44	0.44	0.44	0.45	
SE221	0.40	0.42	0.41	0.42	0.41	0.42	0.42	0.43	0.44	0.44	0.44	0.49	0.49	0.49	0.49	0.50	
SE224	0.43	0.44	0.44	0.45	0.45	0.45	0.46	0.46	0.46	0.47	0.47	0.48	0.48	0.49	0.49	0.49	
SE231	0.40	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.42	0.42	0.42	0.43	0.43	0.43	0.44	0.44	
SE232	0.42	0.43	0.43	0.43	0.43	0.43	0.44	0.44	0.44	0.45	0.45	0.46	0.46	0.47	0.47	0.48	**Knowledge intensive services share**
SE125	0.43	0.44	0.43	0.43	0.43	0.43	0.43	0.42	0.43	0.44	0.44	0.45	0.45	0.45	0.46	0.46	
SE124	0.41	0.44	0.43	0.43	0.43	0.43	0.44	0.44	0.44	0.45	0.45	0.46	0.46	0.46	0.47	0.48	
SE311	0.39	0.39	0.40	0.40	0.40	0.42	0.41	0.41	0.42	0.43	0.43	0.44	0.44	0.45	0.45	0.46	
SE312	0.42	0.43	0.43	0.43	0.42	0.42	0.42	0.42	0.42	0.43	0.43	0.44	0.45	0.45	0.46	0.46	
SE313	0.41	0.41	0.42	0.42	0.42	0.42	0.41	0.41	0.42	0.42	0.42	0.43	0.44	0.44	0.45	0.46	
SE321	0.45	0.46	0.45	0.45	0.45	0.45	0.44	0.45	0.46	0.47	0.47	0.49	0.50	0.50	0.50	0.51	
SE322	0.47	0.48	0.47	0.47	0.47	0.47	0.48	0.47	0.48	0.48	0.47	0.50	0.50	0.51	0.51	0.52	
SE331	0.49	0.50	0.50	0.50	0.49	0.49	0.49	0.49	0.49	0.50	0.51	0.51	0.52	0.52	0.52	0.52	
SE332	0.46	0.47	0.47	0.47	0.46	0.46	0.46	0.45	0.45	0.45	0.45	0.47	0.48	0.48	0.48	0.49	
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
SE110	377.8	386.7	399	409.8	435.4	452.3	468.2	498.2	505.5	509.9	520.9	542.9	544	548.3	572.7	606.1	
SE121	241.1	270.3	278.1	293	295.5	309.2	314.7	317	333.6	321.9	335.7	349.6	353.3	369.6	377.4	392.8	
SE122	211.6	218.8	224.3	229.6	245.8	253	265	288.3	294.5	261.8	298.8	307.1	307.6	295.8	296.5	303.9	
SE123	234	244.4	256.5	258.4	266.8	277.4	290.5	313.3	313.2	314.6	328.4	338.5	338.4	345.2	356.2	372.2	
SE211	245.7	253.9	263	270.4	283.1	276.2	301.6	325.8	332	300.6	316.2	335.9	335.2	339.6	350.7	367.7	
SE212	244.1	251.9	260.3	268.1	286	271.9	309.2	335	342.2	308.9	337.3	349.1	352.4	361.8	365.3	396.9	
SE213	223.8	232.3	243.4	256.6	257.9	267.3	285.4	288.3	307.5	277.3	305.4	310.8	302.6	309.4	314	328.4	
SE221	249.2	233.8	249.2	267.4	284.7	292.8	298.9	318.8	316.5	293.9	312.1	307.2	298.5	314.6	322.7	334.8	
SE224	241.7	251.1	262.4	267	274.1	283.5	298.8	329.6	318.9	302.6	321	326.2	327.4	332.6	345.7	366.1	
SE231	204.6	228.8	238.4	254.7	256.7	260.9	284.6	288.1	310.1	287.8	315.4	317	308.9	316.6	317.4	323.9	**GRDP per**
SE232	268.3	279.8	283.7	302.2	309.3	319	340.8	357.4	366.4	346.1	367	379.6	376.4	386.2	402.4	432.4	**capita**
SE125	233.4	232.2	241.5	246.8	253.9	258.9	294.9	312.9	316.6	298.4	321.2	330.4	326.6	332.3	334.7	363.4	
SE124	227.1	230.4	244.1	257.4	274.2	277.5	303.1	313.6	311.8	300.1	323	338.2	345.2	340.5	347.9	356.6	
SE311	218.8	232.2	241	248.2	254.2	258	272.9	280.7	288.6	262.2	289.4	299.9	305.1	308.6	311.4	326.6	
SE312	228	236.6	244.8	260.2	275.6	287.8	304.9	320.4	321.2	297.9	318.1	334.8	329.1	328.5	335.8	349.3	
SE313	235.8	221.8	238.1	247	262.7	272	287.7	291.4	302.7	294.5	313.5	303.1	310	312.3	324.1	334.2	
SE321	250.2	274.9	273.3	273.9	286.8	297.7	305.4	312.8	326.7	325.7	345.7	352.4	351.9	351.2	358	372.7	
SE322	215.8	247.6	242.7	253.9	261.3	274.3	288.7	281	312.9	298.5	349.5	325.5	320.6	322.5	331.6	335.1	
SE331	214.8	231	238.6	252.5	269.7	278.6	304.5	302.4	312.1	297.1	324.3	328.6	336.7	333.8	339.2	361.1	
SE332	237.2	249.5	259.9	268.7	286.1	306.1	337.7	341.8	378.6	315.3	414.9	423.6	410.6	406.3	403.8	404.6	