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TITLE:

A patent-based analysis of complex green technologies and the development of new green patents after the Paris Agreement in European regions.

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Summary

Climate change is high on the global political agenda and many of the world's developed countries have been refocusing their innovation efforts towards the development of new and complex green technologies. Certain European regions have a high output of novel technologies, and this paper investigates whether the Paris Agreement from 2015 has had any impact on the development of green technologies. One would expect a rise in patent activity related to green technologies given the urgency of the climate change issue. The results, however, show a surprising decline in recent years for the tested regions. In fact, innovations in green technologies were higher in the years leading up to the Paris Agreement. This suggests that there are policy implications, and different incentives may need to be offered to regions and economic actors.

This paper takes a closer look at green technologies as defined by the OECD in their ENV-TECH grouping (Haščič & Migotto, 2015). Recent research has found that the presence of non-green complex technologies can be a catalyst for the development of novel green technologies as well as a barrier (Montresor & Quatraro, 2020; Santoalha & Boschma, 2021). This paper seeks to find evidence of whether complex green technologies concentrate in space, as it is the related capabilities in a region that influence diversification into green technologies (Santoalha & Boschma, 2021). Connecting patent data to European regions for the years 2010, 2015 and 2019, the results indicate that complex green technologies concentrate in space. Ile-de-France, Oberbayern and Stuttgart have the highest density of complex green technologies, yet green patent development has a significant downward trend after 2015.

Using *"structural diversity"* (Broekel, 2019), the complexity of key enabling technologies (KETs) and green technologies are compared and the results indicate that green technologies are more complex than the already highly complex KETs. This result suggests that a presence of complex technologies makes it easier for regions to diversify into green technologies, and this can be one explanation for why novel green technologies concentrate in space.

Preface

As students of innovation at UiS Business School, we like to think that our specialization prepared us for disruption and shift in paradigms. That the world was to be disrupted so severely by a pandemic could not have been further from our minds when we embarked on the MSc program in business administration. Writing our thesis during the pandemic with its restrictions on physical collaboration, travel and a closed university campus has been challenging. The pandemic presented new obstacles to overcome, and along with everybody else, we had to adapt and find new ways. Left with the opportunities in digital communication, we shared our screens, chatted and conducted hour after hour of meetings on Teams.

We would like to thank the UiS Business School, our lecturers, and our supervisor for this thesis, Professor Tom Brökel. This has been an experience without comparison and if not for the helpful guidance of Professor Brökel, the challenge would have been daunting. We are especially grateful for the main dataset he provided to us for our research.

Due to the pandemic, this thesis has been produced cooped up with our nearest and dearest. For enduring us when yet another research gap was filled in by recent literature or when our R-programming did not produce any results, they truly deserve a warm and heartful thank you.

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1 Introduction

In 2009, an energy directive by the EU set a target that 20% of EU energy consumption should be from renewable sources by 2020 (Schöpe, 2008). By 2030, the target is set at 32% of overall energy consumption to be from renewable sources (EU, 2008). These targets have set a precedent that the EU and its member states need to diversify their technologies to meet these targets. To achieve the targets the EU has outlined a long-term strategy plan: “Energy Roadmap 2050”((EU), 2012). In the roadmap there are different scenarios in place for the growth of green energy after 2020. A critical finding in the report is that growth of green energy will slacken after 2020 unless there is further intervention to stimulate growth (European Comission, 2013). This creates a precedent that there needs to be increased focus on how EU regions can achieve more growth, where this is most feasible.

The European Commission has defined micro/nanoelectronics, photonics, nanotechnology, industrial biotechnology, advanced materials and advanced manufacturing systems as the six key enabling technologies (KET) for Europe (Foray et al., 2012). Montresor and Quatraro (2020) found that the presence of KETs had a significant impact on a region’s ability to create novel green technology. In their study they also found that regions with non-green technology could just as easily recombine their knowledge into novel green technology even without prior green experience. As such the possibility to create new green technology may not be so path dependent as one would expect. In fact, following the findings of Montresor and Quatraro (2020), one can expect that non-green regions with KET capabilities will have no problem turning green. The heterogeneous nature of the European economic and technological geography creates a challenge where the differences might have an impact on the different regions’ capability to become greener (González-López, Asheim, & Sánchez-Carreira, 2019). As research has shown, complex technologies often emerge from actors that have activities in related fields (Santoalha & Boschma, 2021). The significance that KETs have on the development of green technology implies that the regions without KETs, and that are generally less developed, will have a harder time diversifying and developing green technology.

It can be expected that non-green technologies are more diffused and might have lock-in effects, making it difficult for some regions to diversify into new green technologies (Arthur, 1989; Zeppini & van Den Bergh, 2011). Following Dosi (1982), a paradigm shift can arise from an innovation push that changes the dominant technologies (i.e., non-green). Technological relatedness makes it more likely that a specialization in new green technology can happen (Montresor & Quatraro, 2020), and regions seeking to diversify into green technology without pre-existing competences run a high risk of failing the attempt. A more likely scenario is that new green technology is created as a recombination and related to existing knowledge, competences and capabilities (Neffke, Henning, & Boschma, 2011). How the green and non-green technology overlap can be measured by their relatedness (Montresor & Quatraro, 2020). Cooke (2012) coined the term "*transversality*", reflecting that a region can contain a number of different clusters with related knowledge that diffuses among them to create new technologies. One such example is the North Jutland region in Denmark, where solar and wind power have been combined into new forms of green technologies (Cooke, 2012). Other recent examples of new green technology combinations include the hybrid car, re-combining combustion with an electric drivetrain (Zeppini & van Den Bergh, 2011).

In their article, Santoalha and Boschma (2021) investigate the greening of economies and found that it is the regions' related capabilities that influence diversification into green technology. Further, they found that new green technology is more likely to occur with related technologies. Interestingly they also found strong support for non-green technology possibly being a barrier for new specialization in green technology. This is in contrast to Montresor and Quatraro (2020), who found that regions could easily recombine existing technology into novel green technology. Given this gap between findings in recent literature, it could be interesting to further investigate this. Santoalha and Boschma (2021) studied the period 2000 – 2012 while Montresor and Quatraro (2020) looked at the period 1981 – 2013. However, both articles stopped short of possible effects from the Paris Agreement, a landmark for the climate change process signed in December 2015. The implications from the Paris Agreement could be increased speed in the greening of the economy and more novel green innovations. New green technology is complex and green patents have been found to be more complex and more novel than their non-green counterparts (Barbieri, Marzucchi, & Rizzo, 2020; Montresor & Quatraro, 2020).

Recent research has shown that regional vested companies may oppose the development of green technologies, which they see as a threat towards their type of specialized technology (Santoalha & Boschma, 2021). This can be attributed to a lack of incentives for non-green actors to transition towards cleaner production, as well as a lack of policy and incentives from the governmental side. The paper by Santoalha and Boschma (2021) used data from the time period

2000 – 2012. The Paris Agreement was agreed upon in 2015 and one of the main objectives for the agreement is that countries are committed to curbing their emissions by 2020 (United Nations, 2015). In the last five years there have been major changes in how governments both perceive and handle the transition towards greener economies. Balland et al. (2020) found that the patenting of complex technologies concentrates in US cities. In this research, we will check if complex green technology concentrates in space, and whether the Paris Agreement from 2015 has had any impact on the development of novel green technologies.

Based on this, the following two hypotheses will be tested:

1. Hypothesis: *Complex green technologies concentrate in space.*
2. Hypothesis: *The greening process in regions with KET capabilities increased after the Paris Agreement.*

The paper is structured as follows. The first section gives an introduction to the topic. The second section investigates and discusses recent background literature in related diversification, technological complexity, and innovation policies. The third section presents methods for measuring complexity, analysis using patent data, policy implications, as well as the datasets. The fourth section presents the empirical analysis and variables, and the results are presented using maps, plots, and tables. The fifth section discusses the results, concludes, and presents possible future research.

2 Literature review

Climate change is high on the global political agenda and many of the world's most developed countries have been refocusing their innovation efforts into the creation of novel green technologies. The European Union has created the Energy Roadmap 2050 and aims to have a totally transformed energy system by 2050 ((EU), 2012). Recent literature on the geography of innovation has focused on the specific knowledge base and how this base develops and transforms over time in countries and regions. The goal in this literature is often not to explain why some regions produce more new knowledge than others, but rather why complex technology is sometimes easier developed in some regions because of related pre-existing knowledge (Balland, 2016). In his article, Balland (2016) coins these types of studies as relatedness literature, and the flow of knowledge and how different technologies relate have been studied in great detail (Boschma, 2017; Neffke, Henning, & Boschma, 2012; Sorenson, Rivkin, & Fleming, 2006). Technological change is required if the green economy is to grow

(Barbieri et al., 2020). However, complex knowledge does not necessarily travel well, not even with advanced digital communication (Balland et al., 2020).

2.1 Related diversification

A region with a diversified portfolio of capabilities will not necessarily spark new technology if the capabilities and competences they possess are unrelated. For technological diversification, it has been found that the variety of capabilities and knowledge are far more likely to create new technology and products if they are somehow related (Frenken, Van Oort, & Verburg, 2007). Relatedness between technologies can spark new technologies and products when different types of knowledge are combined due to similarities in capabilities or by knowledge subsets (Balland, Boschma, Crespo, & Rigby, 2019). Hidalgo and Hausmann (2009) measured complexity and product diversity at a national aggregated level and found that different competences and capabilities play a crucial role when producing complex products. The competence and capabilities to produce complex products can be an indication for a nation's or region's possibility to create new complex technology. It has been found that regions with dense links between technology nodes can use their existing competencies to produce new combinations of existing technology (Balland & Rigby, 2017). Klepper and Simons (2000) found that companies with prior knowledge of radio production gained a competitive advantage from this knowledge when re-combining it into television production. Producers with experience from radio production were also found to be more innovative and had a longer survival rate. In the energy sector, where the oil segment in particular has been found to have minimal diversification (Teece, Rumelt, Dosi, & Winter, 1994), the situation today seems to be different, with a stronger focus and ongoing transitions into green and sustainable technologies. An example of this is Ørsted Energy, formerly Dong Energy (Danish Oil and Natural Gas). When the EU set their 2020 target of 20% renewable energy ((EU), 2012), Ørsted set a target goal that 85% of their production would be green by 2040 and partnered up with government institutions in their initial investments of wind farms. During the period 2012 to 2019, the cost of offshore wind production decreased by 66%, while at the same time the oil price collapsed in 2014. They sold their oil and gas production assets in 2017 and changed their name from Dong to Ørsted. By 2019 they hit their target goal of 85% energy generation from renewables, and at the same time their carbon emissions sunk by 86% while their operating profits doubled. Ørsted attributes much of their success to a supportive policy environment which allowed them to invest and innovate at scale, and this in turn led to a cycle of technology maturity and reduction of costs (Ørsted, 2020).

Following Marshall (1920) and Jacobs (1970), innovation is often described as either created from a varied urban scene (Jacobian) or from specialized clusters (Marshallian). Both scenarios depend on knowledge spillovers and capabilities that are related (Boschma, Balland, & Kogler, 2015). It is not hard to imagine that new technology will often be related to the existing knowledge and capabilities of a country or region. It has been found that industries in a region with related activities have a greater chance of creating new technologies than industries in an area with a poor selection of relatedness (Boschma, Minondo, & Navarro, 2013; Neffke et al., 2011). In the long run, however, Marshallian specialization might be a barrier for innovation, since in the end there will be nothing new to learn from each other and this can also be true for Jacobian clusters, as the serendipity with this theory might not be a valid explanation in the long run (Berge & Weterings, 2014). Neffke (2009) found that it is the specific knowledge and capabilities a region possesses that will help define what new technologies can be created. Those capabilities that help determine what new technologies can be created were also found on the national level by Hausman and Hidalgo (2010). Both Frenken and Boschma (2007) and Neffke (2009) found that technological relatedness plays a crucial role when determining the possibility for knowledge spillovers between different technologies and industries. Companies will use their existing capabilities and draw on related knowledge when they enter novel technology, and this can be described as a path-dependent process by the degree of relatedness (Boschma et al., 2015). Colombelli, Krafft and Quatraro (2014) found this to be true in their analysis on new nanotechnology that showed regions in Germany, France and Italy ahead of the curve in the emergence of new technology in general.

Relatedness and the geography of innovation is often explained as a network and knowledge space (Boschma et al., 2015; Rigby, 2015). In this knowledge space the nodes in the network can represent different patents and technological classes with the links between them representing the degree of relatedness (Balland, 2016). This network representation might seem very static, but it is this regular pattern that makes the technological setup of a region sustainable (Boschma et al., 2015). This path-dependent process can represent the dynamics of knowledge production and technological innovation (Balland, 2016). Collaboration between economic actors is required to create new technology out of related ones, and such collaborations are more likely to occur on a regional and local level due to issues with proximity, among other things

(Balland, De Vaan, & Boschma, 2013). One could imagine that with globalization and the internet, knowledge spillovers would flow easily to new areas of the world. However, this is unlikely to be significant even for codified knowledge like patents, as studies have found patents to have strong place dependent bias (Jaffe, Trajtenberg, & Henderson, 1993). This is a strong signal to countries and regions that related technology and capabilities are required if investments in innovation and new technologies are to be successful. Random jumps into new technological domains are seldom successful and literature tends to focus on the path-dependency (Balland, 2016). This is one of the reasons for why it is important to create knowledge networks and obtain the degree of relatedness so sustainable opportunities can be identified (Balland, 2016).

2.2 Technological complexity

Technological complexity has been studied from many different angles in recent innovation literature. When companies compete, they do so by expanding their knowledge space and adding new capabilities into this space (Balland et al., 2019). Kogut and Zander (2003) explain that transfer of knowledge can be difficult even within a company, and they also explain that tacit knowledge will often have complexity as a critical ingredient. As such, complexity can act as proxy for tacit knowledge (Kogut & Zander, 2003). In their study of knowledge complexity in US cities, Balland and Rigby (2017) found that only a few cities were able to produce highly complex technologies. It is the possibility for high earnings that pushes an economic agent to search for new complex knowledge, as it is the difficulty to imitate complex combinations that can give rise to new competitive advantage and capabilities (Teece, Pisano, & Shuen, 1997). Within a region's existing technological capacity, it is the degree of relatedness that can increase the possibility for complex new knowledge and technological opportunities (Balland et al., 2019). The best chance for innovation success may come from combinations of technology (i.e., components) that have a moderate degree of complexity (Fleming & Sorenson, 2001; Sorenson et al., 2006). Industries that can make use of moderate complex knowledge are also more prone to establish industrial clusters (Sorenson et al., 2006). Regions specializing in complex technologies related to their capabilities are more likely to gain technological growth and technological complexity, and this has been found to be a major factor in the economic growth of European regions (Balland et al., 2019; Mewes & Broekel, 2020). However, even though new complex technologies can receive high rents, complexity can also be an obstacle for the innovation and relatedness process (Juhász, Broekel, & Boschma, 2020; Yayavaram &

Chen, 2015). Transitioning into new green technology is a complex activity and green patents have been found to be more complex and more novel than non-green counterparts (Barbieri et al., 2020; Montresor & Quatraro, 2020). In their study, Barbieri et al. (2020) found that green technologies are more diverse and likely to contain more components than their non-green counterparts.

2.3 Innovation policies

The need for a knowledge base and the high costs of entry due to lack of technological maturity in the green technology sector can in many cases serve as a constraint for companies in related activities to enter the green business (Breschi, Lissoni, & Malerba, 2003). The co- existence of various industries with different knowledge and technology bases and their need of cluster, network and regional innovation systems requires a developed governance structure in order to diffuse and develop new and related technology (B. Asheim, Coenen, Moodysson, & Vang, 2005). The classical approach by governments to stimulate growth and innovation has been with the use of incentives and disincentives such as tax relief, R&D investment, subsidies, taxes, and in some cases co-ownership with the state (B. T. Asheim, 2019). However, the heterogeneity of the regional economies in Europe creates a challenge where policies need to be more specific.

A key challenge in terms of policy is to identify and build the foundations for complex activities that are related, so that they can combine processes to be further developed. This is supported by the finding that complex technologies tend to concentrate in space (Mewes & Broekel, 2020), although this creates challenges for policy makers. The main challenge is locating and identifying the regions with existing capabilities and competitive advantage in specific activities, and applying the needed policies (B. T. Asheim, 2019). This has been addressed by research and the EU, with innovation policies such as smart specialization. Smart specialization has been described as the single largest attempt to create a supernational innovation strategy to boost economic growth, through diversifying the regional economies into more technologically advanced activities and moving up the ladder of knowledge complexity compared to present levels in regions (B. T. Asheim, 2019). In terms of disincentivizing companies that pollute, governments have enforced carbon taxes to make it more expensive for companies to pollute and push them into developing solutions that makes their operations cleaner (European

Parliament and the Council of the European Union, 2018). Moreover, this creates an incentive for companies to develop fewer polluting solutions to avoid these taxes.

Regional policy in relation to innovation, and its importance in the diversification process is a topic that has seen an increase in interest over the last two decades (González-López et al., 2019), where the sentiment that "no size fits all" has been adopted as the approach to examine regional innovation in terms of policy (B. T. Asheim, 2019). The idea behind smart specialization is that countries should identify their existing or potential competitive advantages, where they can specialize and create capabilities in a different way than other countries or regions (B. T. Asheim, 2019). In the context of KETs and their perceived effect on regions' diversification into greener activities, policies need to be specialized to stimulate growth both for KETs and green technology. This will be a factor for motivating complex organizations with expertise to tune their portfolios to meet the emerging demands in these sectors, leading to an interplay of competitive advantage, expertise in core technologies and agile adaptation to these emerging demands. Smart specialization can play a pivotal role for regions to form policies that build upon existing capabilities and further develop them. Ørsted Energy has been mentioned earlier in this paper regarding how they used existing capabilities to develop new and better technology in the wind turbine energy sector, and showcases as a successful example of policy and the agility and willingness of a firm to diversify and transition toward greener activities.

3 Method

3.1 Measuring the complexity of technologies.

Complex technologies have been found to concentrate in space and the complexity has a tendency to increase over time (Balland & Rigby, 2017; Broekel, 2019). Different measures and evaluation methods have been created in recent literature. Fleming and Sorensen (2001) developed an approximation for knowledge complexity and Balland and Rigby (2017) developed an index for knowledge complexity based on Hidalgo and Hausmann (2009). However, as Broekel (2019) explains, knowledge complexity is not easy to measure objectively. Implementing measures from complexity and network science, Broekel (2019) creates *"structural diversity"* to determine the complexity of technology. Using *"structural diversity"*, Broekel (2019) investigates 655 technologies and finds that complexity increases with time. Concentration in space, however, is only significant within the sizeable technologies

(Broekel, 2019). This paper seeks to investigate the complexity of green technologies and will use the *"structural diversity"* method to do a comparison of green technologies as defined by OECD (ENV-TECH) and KETs.

3.2 Using patents for analysis.

Patents can give insight into the technological competencies a company possesses, and the co-occurrence of classification codes can be used to measure relatedness (Breschi et al., 2003). Technological relatedness between patents has been used to measure knowledge proximity and space (Rigby, 2015; Sorenson et al., 2006), while Boschma (2017) found that when two classes are named on the same patent this represents relatedness. It is possible to investigate how close two cooperative patent classifications (CPC)[1] are, by looking at the main and additional CPC (Ejermo, 2003). A method that can be used to measure relatedness between classes is weighted average relatedness (WARN). This measure only includes the strongest links in a network and thus excludes weak links that would be noise in an index. Using the WARN method, Ejermo (2003) calculated the technological diversity in Swedish regions. In his acclaimed article, Rigby (2015) uses patent classes to investigate technological relatedness, while Cook (2008) found that to create novel green technology, a complex system of pre-existing knowledge in a region is required. Combining patent data with geographical data, this paper will investigate how green technologies (ENV-TECH) concentrate in space and whether there has been an increase after the 2015 Paris Agreement.

3.3 Policy implications

The policy implications of complex green technology concentrating in a geographical space are the occurrence of clusters and the concentration of knowledge and technology. With complex knowledge and technology intensity, this often becomes the case. This is both positive and negative in terms of developing new technologies in regions. Clusters can be described as a collection of different activities in a geographical space, where there are linkages between different firms and institutions. This can allow regions and their companies to diffuse knowledge and technology that has linkages that are related to existing technologies, to develop new and related technologies (B. Asheim et al., 2005). Research by Montresor and Quatraro

[1] *"The Cooperative Patent Classification (CPC) is an extension of the IPC and is jointly managed by the EPO and the US Patent and Trademark Office. It is divided into nine sections, A-H and Y, which in turn are sub-divided into classes, sub-classes, groups and sub-groups. There are approximately 250 000 classification entries"*((EPO), 2021).

(2020) has found that relatedness to the preexisting knowledge base of a region plays a pivotal role in the acquisition of new green technologies. This supports the findings from the US which have shown that patents connected to complex technologies concentrate in a few urban areas, which is attributed to the requirement of division of knowledge that is distributed across many actors (Balland et al., 2020).

However, a downside of this centralization is the potentially uneven spatial distribution, where a few urban areas stand for most of the economic and technological development. There needs to be a balance act between regional social policy to stimulate research and growth in less developed regions, and regional innovation policy to avoid the loss of effectiveness when determining where to implement policies. This is the case for smart specialization, where a tradeoff between effectiveness and the need to stimulate less developed regions is necessary.

3.4 Data

This paper will use the OECD collection of environmental related patents ENV-TECH, which covers about 107 technological and related fields considered to be "green" technologies (Haščič & Migotto, 2015). The ENV-TECH categorization has been used in several recent articles on the very same topic and must be said to be valid for use in studying the topic of this paper. The paper will focus on European regions at the NUTS2 level and release year 2016. The NUTS2 dataset is obtained from the Eurostat database using the R-package EUROSTAT. Turkey and Iceland have been removed from the dataset to create a better visualization for the findings relating to hypothesis 1. The paper uses the CPC codes for ENV-TECH and KETs found in Tables A1 and A2 in the supplemental material for Montresor and Quatraro (2020).

The main dataset was provided by Professor Brökel and contains over 1 million observations from years 2000 to 2019. The dataset has information at CPC level 4 for all patents, which is also connected to the relevant NUTS2 code. In addition, it contains columns for patents found in the ENV-TECH and KET listings both on CPC level 4 and on CPC full where available. We are able to analyze the spatial concentration of green technologies in any given year between 2000 and 2019, when combining the total number of patents related to ENV-TECH and the NUTS2 code using this dataset.

For the complexity analysis, the dataset on technological complexity available from the homepage of Professor Brökel (Brökel, 2021) is used. This dataset contains 30879 observations with 7 variables, such as the structural diversity for patents at CPC4 level in the period of 1970 – 2016. These data make it possible to analyze how complex patents related to ENV-TECH and KETs are in the period from 2000 to 2016.

4 Empirical analysis and results

4.1 Comparing the complexity of green and KET technologies.

In the following we compare the complexity of patents categorized as ENV-TECH and KETs. Both categorizations have been deemed in recent literature to be complex and related. Remembering the findings from Montresor and Quatraro (2020), where preexisting knowledge was found to be important, it is interesting to check whether green technology is more complex than KETs. We have categorized at CPC level 1 to make a presentable plot. The CPC level 1 represents the nine sections, A-H and Y, by which the code is divided into at the very top level. Data representing section Y *"General tagging of new technological developments"* is only present when checking the complexity for ENV-TECH and as such is only displayed in Figure 1.

Comparing Figures 1 and 2, the structural diversity (y-axis) has a greater reach (above 12) for green technologies and only reaches above 10 for KETs in the same period. The structural diversity suggests that green technologies (ENV-TECH) are more complex than KETs, which is in line with the findings in recent literature. However, comparing section *E: Fixed construction*, green and KET are more or less equally complex. Indeed, this section also has the lowest structural diversity score. Another interesting observation is that section *F: Mechanical engineering, lighting, heating, weapons, blasting engines or pumps* displays a higher concentration in Figure 1 (Green) than in Figure 2 (KETs).

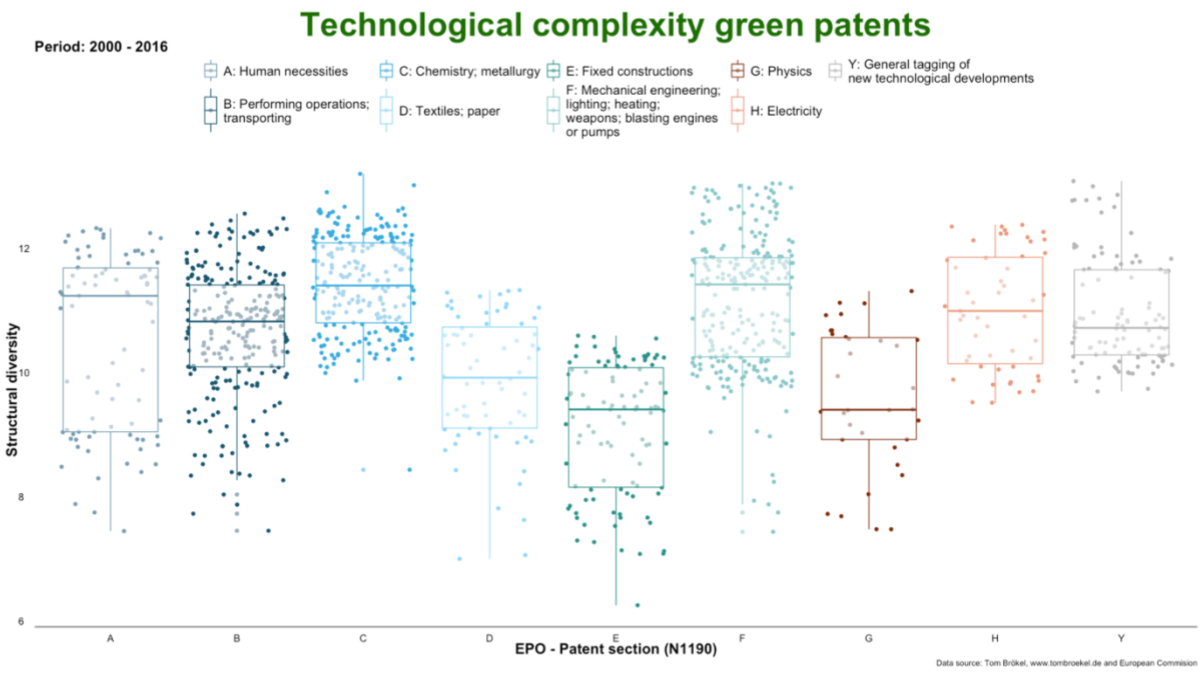

Figure 1 – Technological complexity green patents (ENV-TECH) 2000 – 2016.

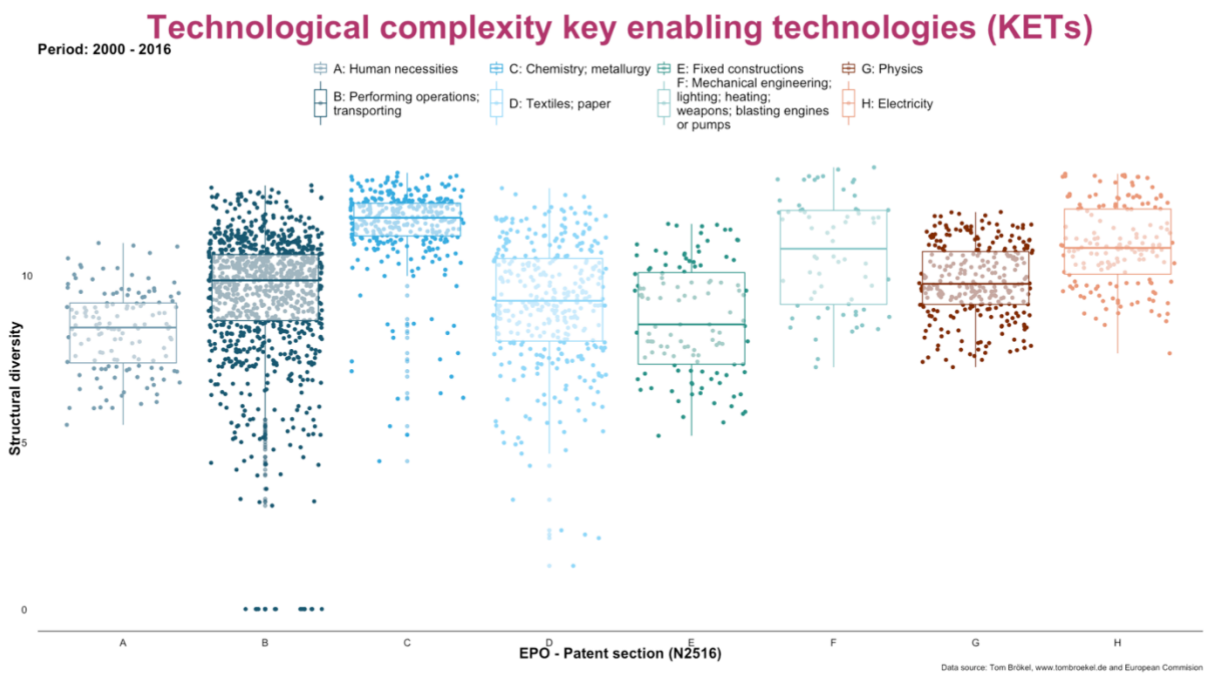

Figure 2 – Technological complexity key enabling technologies (KETs) 2000 – 2016.

There is as difference in observations, where green tech has N1190 and KETs N2516, and this also shows in the box plot concentrations. The two plots seem to follow each other in the different CPC sections, e.g. section *C: Chemistry is receiving high scores in both plots* as well as *H: Electricity*. This is on point with relatedness theory and recent developments in green technology, where breakthroughs have been seen, for example, in fuel-cell technology (Tanner, 2016).

4.2 Concentration of green technologies in space

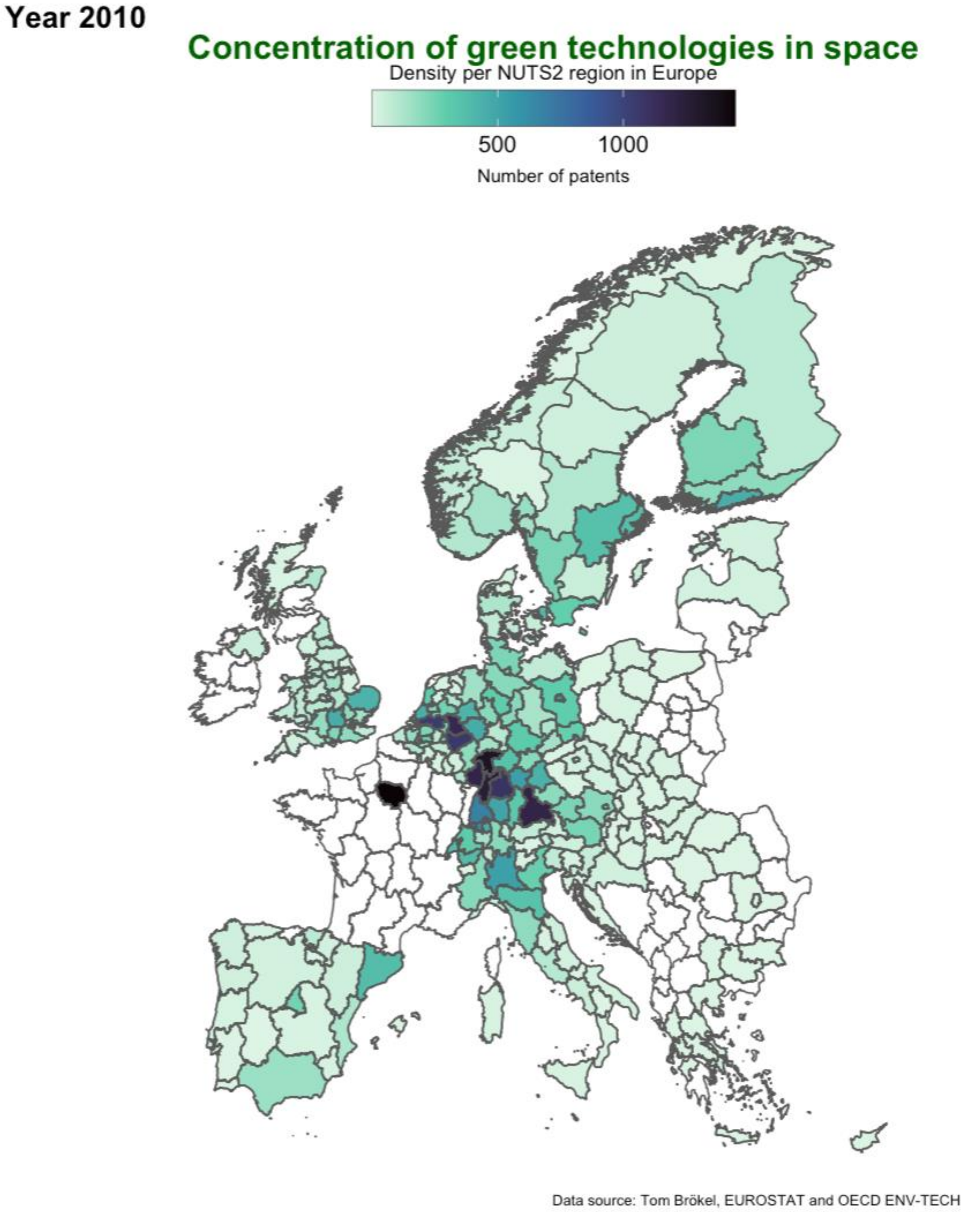

Figure 3 – Green technologies concentration in space, European NUTS2 regions year 2010.

NUTS2	Region	Year	Number of patents
FR10	Ile-de-France	2010	1445
DE71	Darmstadt	2010	1331
DE12	Karlsruhe	2010	1250
DE21	Oberbayern	2010	1201
DEB3	Rheinhessen-Pfalz	2010	1196
DEA1	Düsseldorf	2010	1165
DE11	Stuttgart	2010	1096
DEA2	Köln	2010	1065
NL41	Noord-Brabant	2010	1048
DE13	Freiburg	2010	683

Table 1 – Top 10 European regions 2010 – green patents.

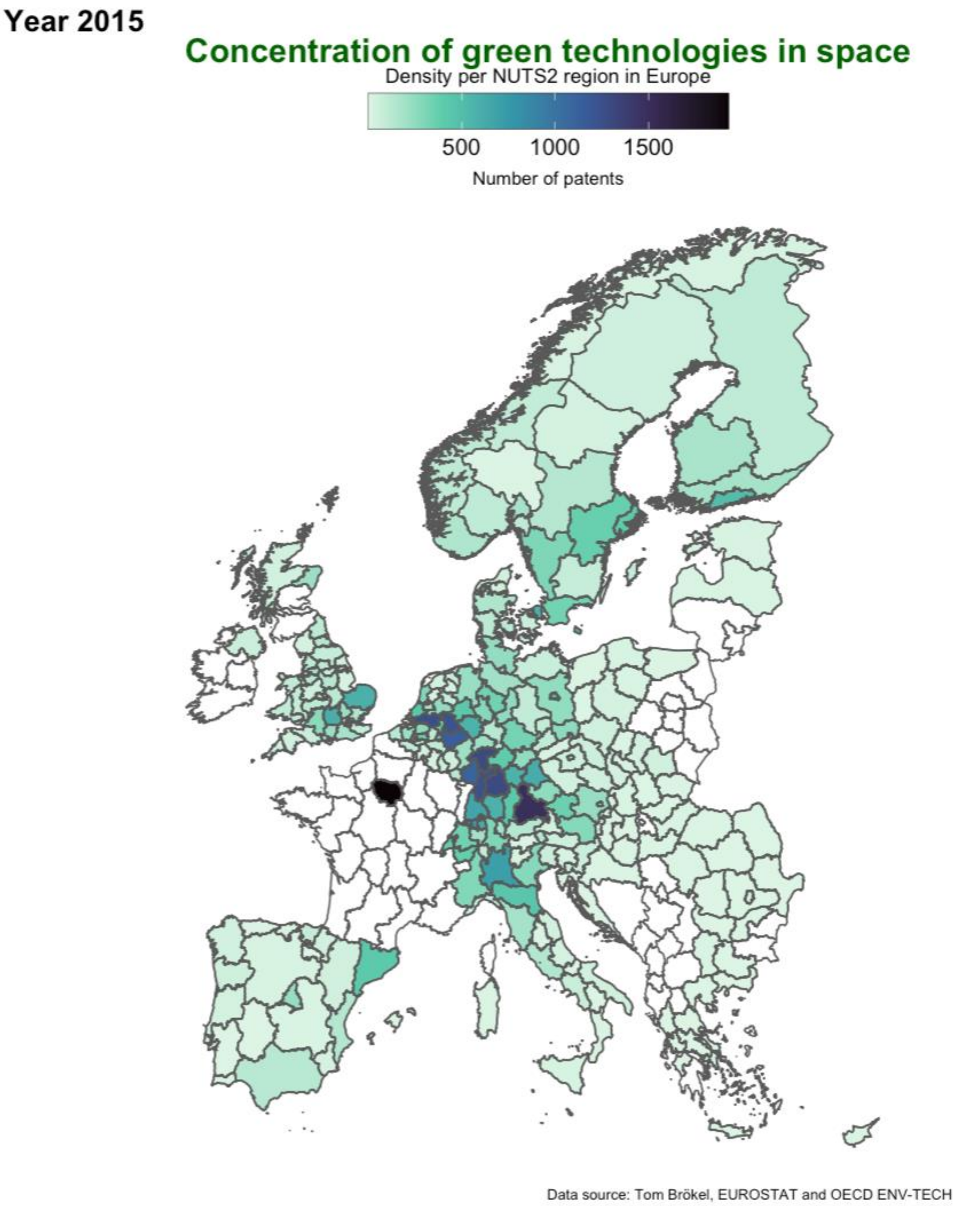

Figure 4 – Green technologies concentration in space, European NUTS2 regions year 2015.

NUTS2	Region	Year	Number of patents
FR10	Ile-de-France	2015	1927
DE21	Oberbayern	2015	1494
DE71	Darmstadt	2015	1291
DE11	Stuttgart	2015	1284
NL41	Noord-Brabant	2015	1248
DE12	Karlsruhe	2015	1235
DEA1	Düsseldorf	2015	1221
DEA2	Köln	2015	1141
DEB3	Rheinhessen-Pfalz	2015	1111
CH03	Nordwestschweiz	2015	741

Table 2 – Top 10 European regions 2015 – green patents.

Year 2019

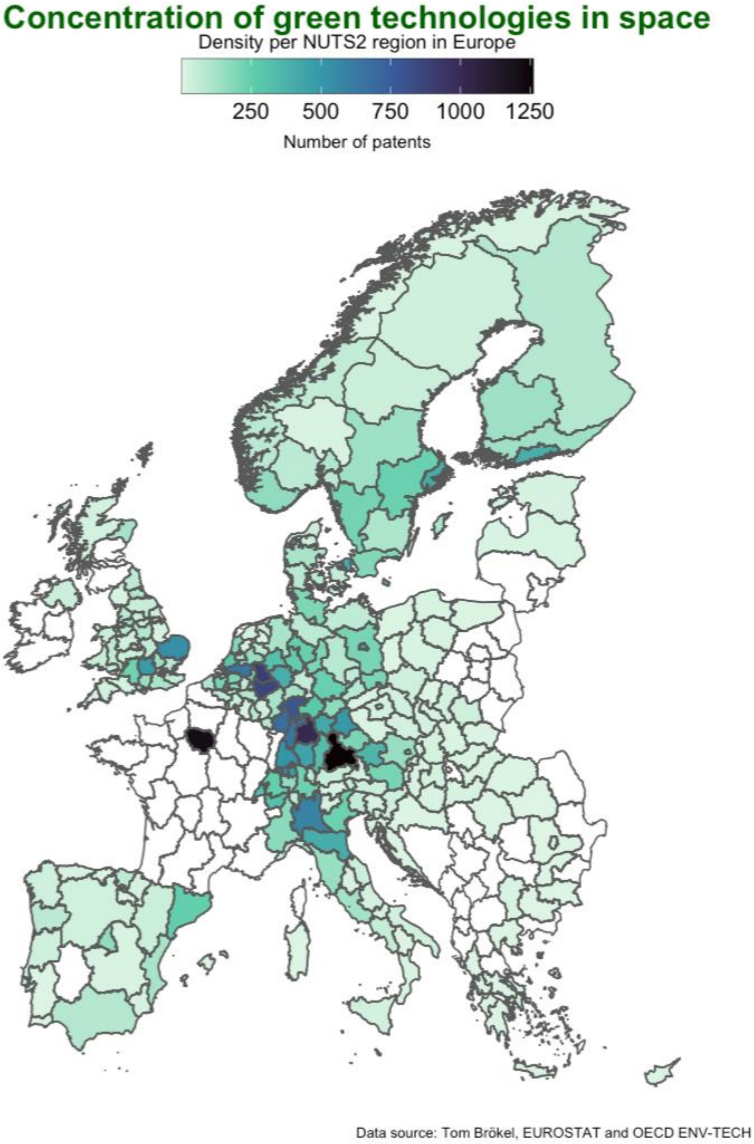

Figure 5 – Green technologies concentration in space, European NUTS2 regions year 2019.

NUTS2	Region	Year	Number of patents
DE21	Oberbayern	2019	1260
FR10	Ile-de-France	2019	1219
DE11	Stuttgart	2019	1015
DEA1	Düsseldorf	2019	907
DEA2	Köln	2019	864
DE71	Darmstadt	2019	784
DEB3	Rheinhessen-Pfalz	2019	683
DE12	Karlsruhe	2019	649
NL41	Noord-Brabant	2019	644
ITC4	Lombardia	2019	588

Table 3 – Top 10 European regions 2019 – green patents.

To help answer hypothesis 1, the density of ENV-TECH patents for European NUTS2 regions are calculated for the years 2010, 2015 and 2019. Figures 3-5 clearly indicate that green technologies concentrate in space with different density in European regions. The concentration is highest in developed regions with complex capabilities, which is in line with the findings of Montresor and Quatraro (2020). Figures 3-5 also indicate that peripheral regions generate new green technologies, but this is just a few compared to the top ten in Tables 1-3. However, this does suggest that it is also possible for peripheral European regions to diversify into green technologies.

The Italian region of Lombardia is presented in Table 3 which may be in line with Colombelli, Krafft and Quatraro (2014) and their analysis on new nanotechnology that showed regions in Germany, France and Italy ahead of the curve in the emergence of new technology in general. There are almost no noticeable changes between the different years 2010, 2015 and 2019. However, some changes in the top ten placements, Tables 1-3, have been taking place, and the number of patents has decreased from 2015 to 2019. The overall patenting for green technologies having a downward trend is also supported by our findings in the next section 4.3.

4.3 The greening process in regions after the Paris Agreement.

The data used in the empirical study of the greening process is two NUTS2 regional datasets containing patent output on a total, green, full green, and KET level, where one is a complete list of patent output at NUTS2 level split between total, green and full green patents and listed by the years 2000 to 2019, and the other dataset used is a dataset containing KET codes and sorted by their CPC code also at a NUTS2 level. The two datasets were merged by sorting the total KET patents by year and region, to match the other dataset. The sample size of the data includes all European regions at a NUTS2 level, in addition to EFTA countries, candidates to the EU, and other countries such as Australia, Israel and Russia. Since our research is concentrated on the EU and its regions, we sorted the data thereafter to only include EU regions. To decide which regions to analyze we use the regions that have a high concentration of complex green technology, as well as a high number of KET patents. The regions we chose are Oberbayern, Ile-de-France and Stuttgart, with a common denominator for these three regions being that they are all urban regions having many company headquarters. Both of the German regions have headquarters of car manufacturers like Mercedes Benz, BMW and Porsche, in addition to tech companies such as Siemens (Siemens AG, 2020). This can give us a good indication on how green patent output has developed, since these two regions have companies that are involved in technological development into greener solutions, such as electric vehicles and other sustainable solutions, and Stuttgart and Oberbayern also have companies that are involved in key enabling technologies. There is a great overlap between green technologies and KET technologies which was confirmed by testing the correlation between the patent technologies. The correlation test of different patent technologies in Figure 6 shows that green and KET patents have a 96% correlation, and in addition there is a large overlap in full green patents and KETS with a 63 % correlation. Our use of green patents as the measure for green innovation is based on the hypothesis, where we check how green patents have developed since 2015. By using green patents we get a larger data sample to determine whether our hypothesis is true.

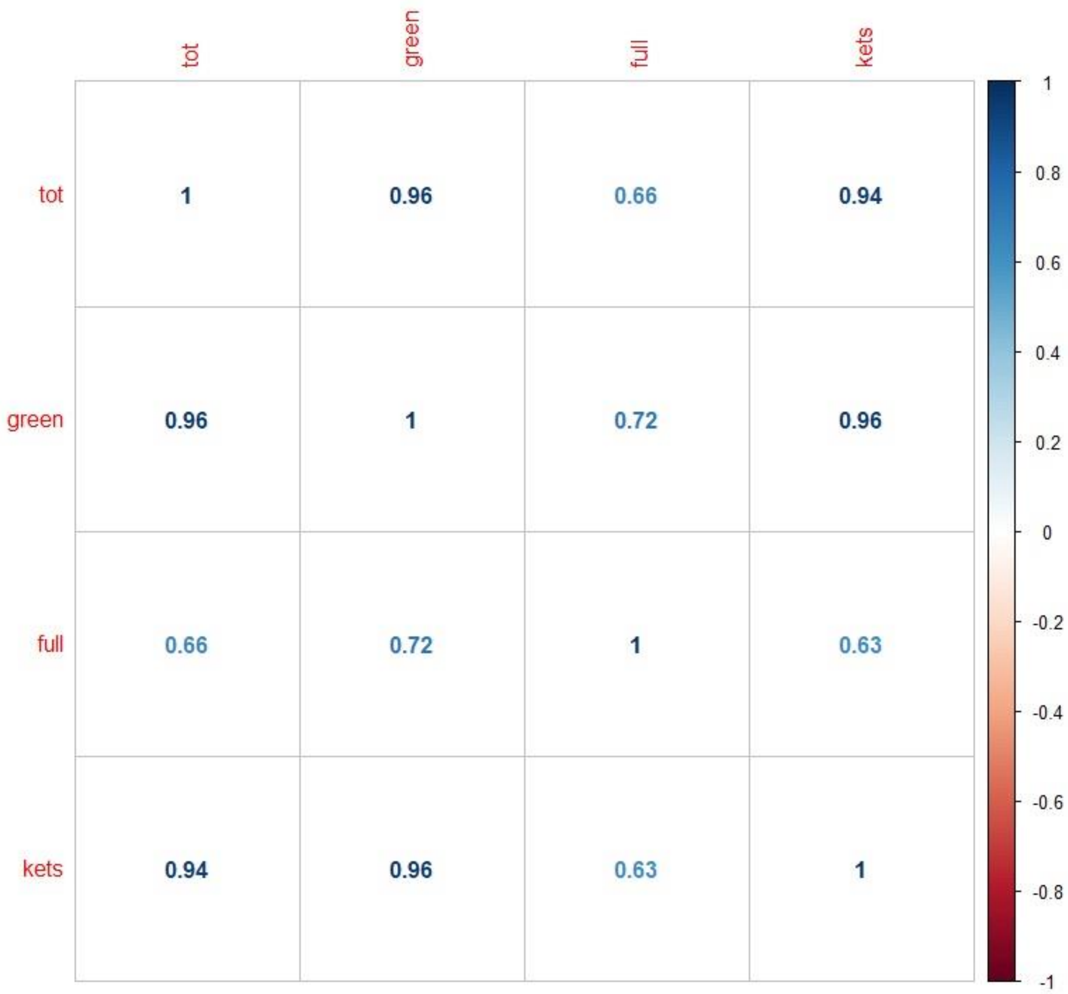

Figure 6 – Correlation Matrix of Patent Technologies.

Our main point of interest is how the effect on green innovation has been after 2015 with the signing of the Paris Agreement and more green-related policy in the EU. Therefore, we constructed a variable as an intercept point in our analysis to separate the years 2015-2019, so we can see the isolated development from the other years. The parameter in *lm* is by default *contr.treatment* which in our case means that the values output for *over15*=false, *over15true*, and *year:over15TRUE* give how much we shall add when o*ver15*TRUE. That is, *year: over15* gives the change in the regression line at the year 2015. We created variables for each of the individual regions.

The dependent variable in our analysis is green patents divided by total patents, where we have both green and full green as variables in our dataset. However, full green, which gives a more precise number on complete green patents, has a much smaller sample size and in many cases is too small to conduct analysis from. To avoid discrimination in the form of the difference in size of regions, we divide green with the total patents, so it becomes a percentage of the total patent output in the regions. The reason for only using these variables for our test is because of the generalization of analyzation and hypothesis on how green innovation has been since 2015.

$$Indicator\ Variable: over15 < -(year > 2015)$$

$$\frac{green}{total} = a1 + b1,\ \ When\ year \leq 15 \qquad (1)$$

$$\frac{green}{total} = a1 + a2 + (b1 + b2)year, when\ year > over15 \qquad (2)$$

$$\frac{green}{tot} = a1 + a2 + \big(b1 + b2I(year > 2015)\big)year \qquad (3)$$

We wish to see how *green* divided by *tot* variates with year by drawing a straight line. We can do this in R with the function "*lm*". This assumes that the residuals are normal distributed; in our case they are not, though due to the size of the dataset we still get a good line. Therefore, we use glm (Generalized Linear Models) function in R. When investigating the regression, we would like to see if there is a break at year 2015. For that purpose, we introduce the indicator variable *over15* which is 0 when *year <= 2015* and 1 when *year > 2015*. In glm we need to introduce the interaction term *year:over15* to the model break year + over15. Eq. (1) is when *year <= 15* and Eq. (2) when *year >2015*. Or written in one formula we get Eq. (3), where *b2* is the coefficient for *year:over15*. This means that in the file output we find the value of *b2* as *year:over15*. This indicates the change in slope as we pass 2015. The p-values show greater significance when we do the binomial test (Uboe, 2012). This is presumably because the binomial distribution fits the data better than normal distribution. The variable *aar:over15* is *year-2000*, which gives a lower number back in the test and is more understandable to read.

When starting to perform our test, we wanted to check how the trend of green patent output is at a national level, where we did a general plot to examine the trend of green patent as a percentage of total patents at a national level. We found that the trend has declined since 2014, reaching its lowest point in 2019 in Germany as seen in Figure 6. However, this does not give a completely clear picture because we have not considered whether there has been an increase in the pool of total patent output during these years. This can give a misinterpretation of the findings, by showcasing a downward trend of green patents, while there is actually an increase, but due to the total output increasing, the share becomes lower. Therefore, we checked the trend of total patents to examine if there has been a significant increase in total patent output after 2015. However, viewing the data shows that there has been no significant growth of total patent output in these countries, compared to green. This gives us the possibility to further test at a regional level.

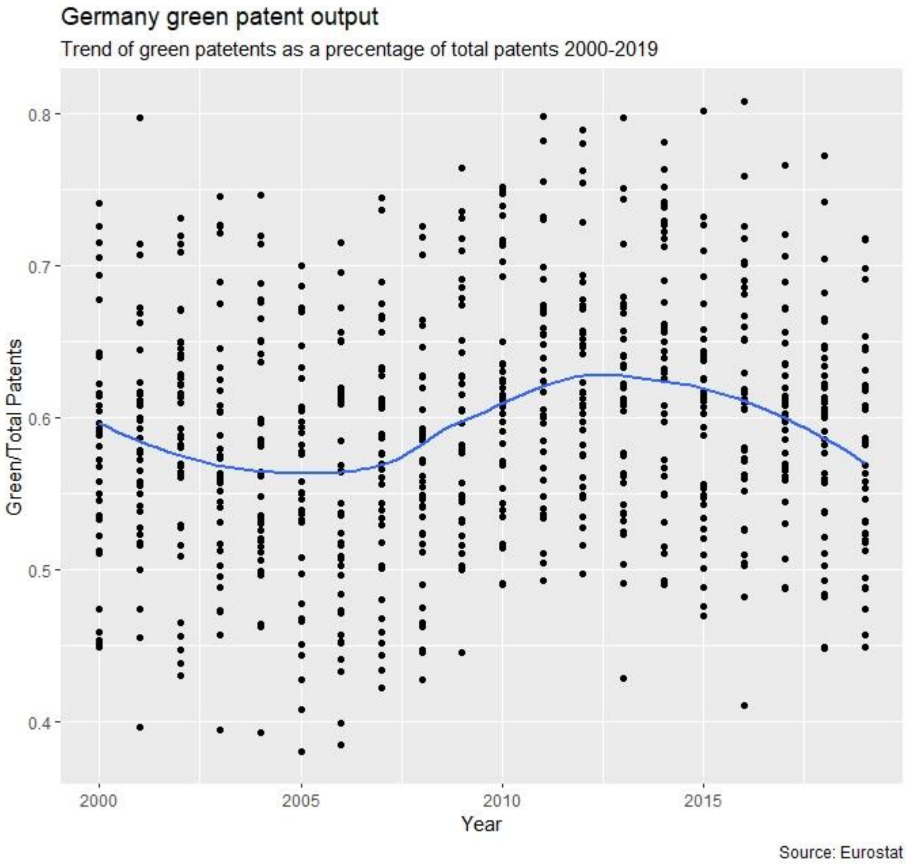

Figure 7 – German trend of green patent output.

In our test of how green innovation has been after 2015, we have made an interesting discovery, where the years 2015 to 2019 are significant for countries such as Germany and France in terms of development of the share of green patent output. This gives us the precedent to check whether this is only at a national level, or if the regions in these countries with a high concentration of green technology and KET are facing the same trend.

This raises the question on why the innovation output decreases after 2015, and why these years are only significant for those countries. We found that the regions Ile-de-France, Oberbayern and Stuttgart have a high concentration of green complex technology, and we want to investigate these regions more to see how the development has been in these regions, both from 2000 and 2015.

We start by checking Ile-de-France and do a general check to see if there has been a change in the total output that can give a misleading answer, when checking green patent as a share of total. From Figure 7 we see that there is no significant change in the slope of total patents independently from green, where both develop at a similar rate. This is also the same for Oberbayern and Stuttgart, where there is no significant change in the total patent output compared to green.

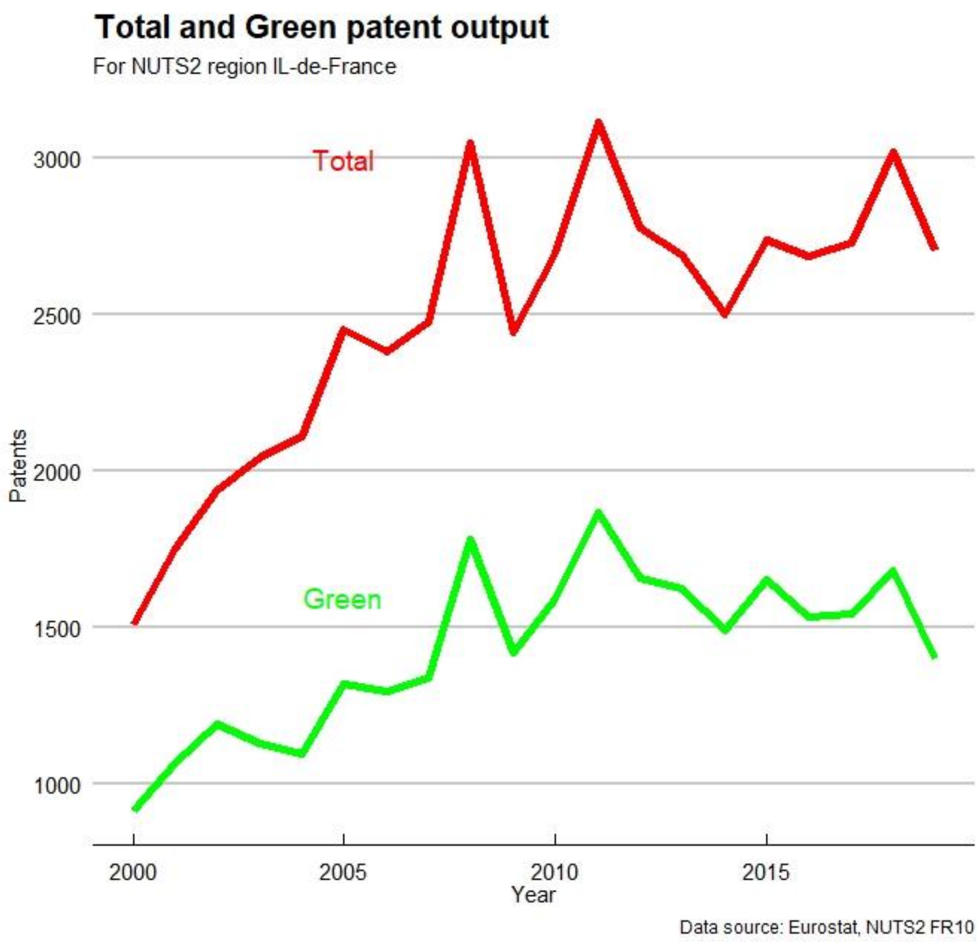

Figure 8 – Comparison of total and green patent output.

We continue our test of Ile-de-France with a graph showing the linear evolvement, in addition with a line that tracks the year-to-year development of green patent output. This is combined with a correlation test where we can examine the significance of the different technologies as well as the indicator variable and how the development from 2015 has been. From the general linear model test, we see that the coefficient for *over15* (b2) in Eq. (3) is negative. The negative coefficient shows us that there is a decline after 2015.

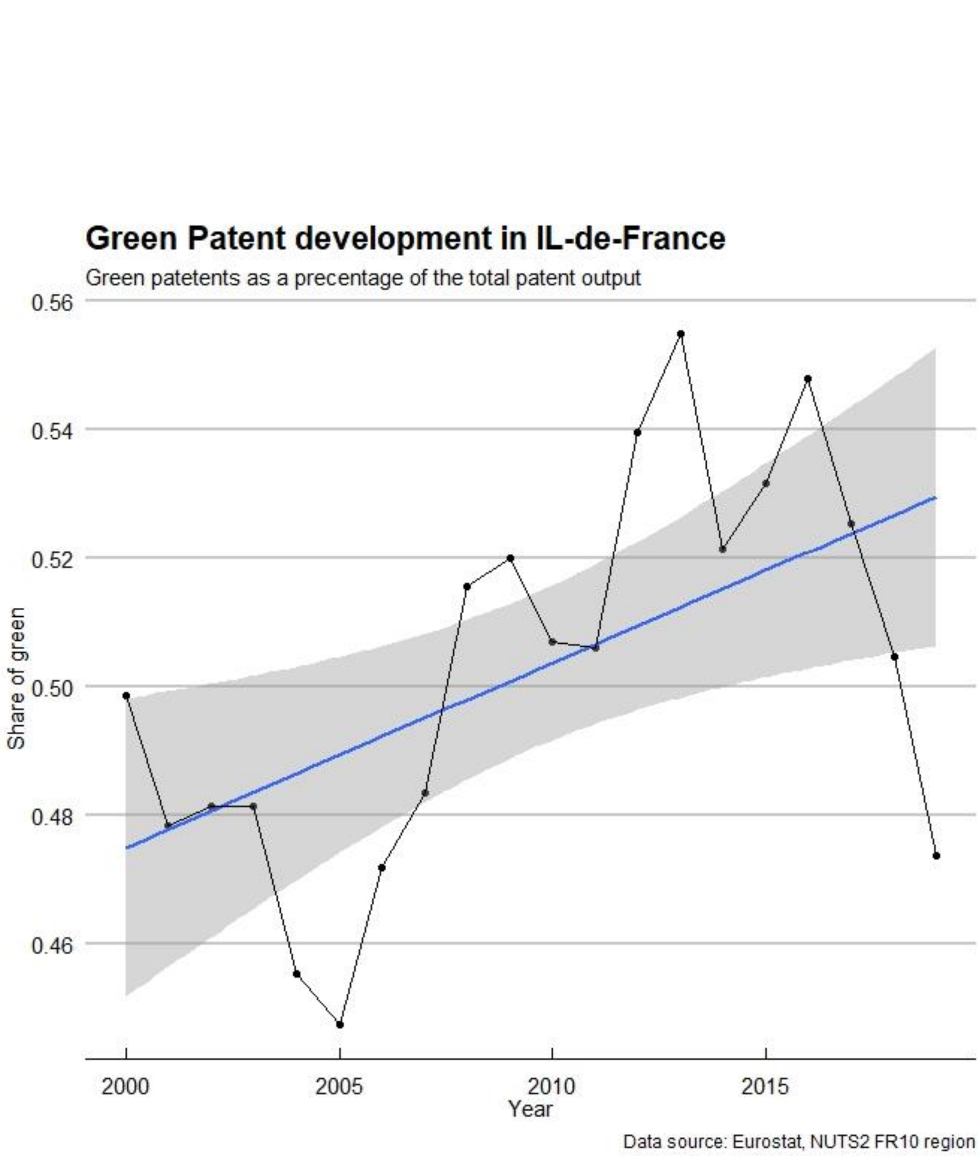

Figure 9 – Green Patent development for Ile-de-France

	Dependent variable:	
	over15	green/tot
	logistic	*OLS*
	(1)	(2)
green	0.020^{***}	
	(0.002)	
total		0.005^{***}
		(0.001)
over15	1.911^{***}	58.490^{***}
	(0.262)	(17.813)
aar:over15	-0.118^{***}	
	(0.015)	
year:over15		-0.029^{***}
		(0.009)
Constant	-0.156^{***}	-8.970^{***}
	(0.019)	(2.134)
Observations	20	20
R^2		0.643
Adjusted R^2		0.576
Log Likelihood	-118.490	
Akaike Inf. Crit.	244.979	
Residual Std. Error		0.020 (df = 16)
F Statistic		9.613^{***} (df = 3; 16)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4 – General linear model test of Ile-de-France.

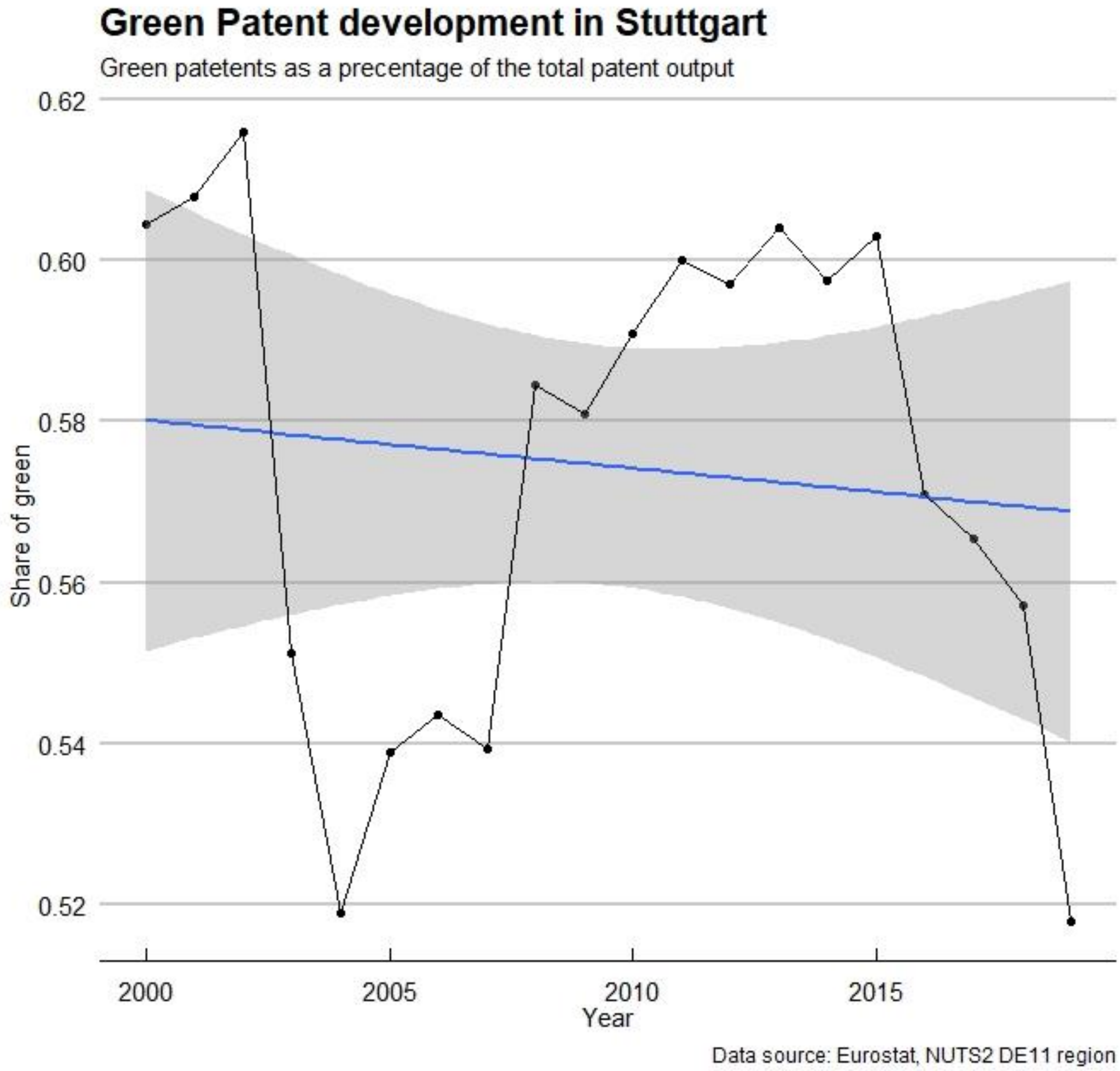

Figure 10 – Green patent development in Stuttgart.

	Dependent variable:	
	over15	green/tot
	logistic	*OLS*
	(1)	(2)
green	0.010***	
	(0.002)	
total		0.002
		(0.002)
over15	1.151***	37.095
	(0.304)	(26.437)
aar:over15	-0.077***	
	(0.017)	
year:over15		-0.018
		(0.013)
Constant	0.243***	-2.688
	(0.022)	(3.167)
Observations	20	20
R^2		0.255
Adjusted R^2		0.116
Log Likelihood	-140.574	
Akaike Inf. Crit.	289.148	
Residual Std. Error		0.029 (df = 16)
F Statistic		1.828 (df = 3; 16)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5 – General linear model test of Stuttgart.

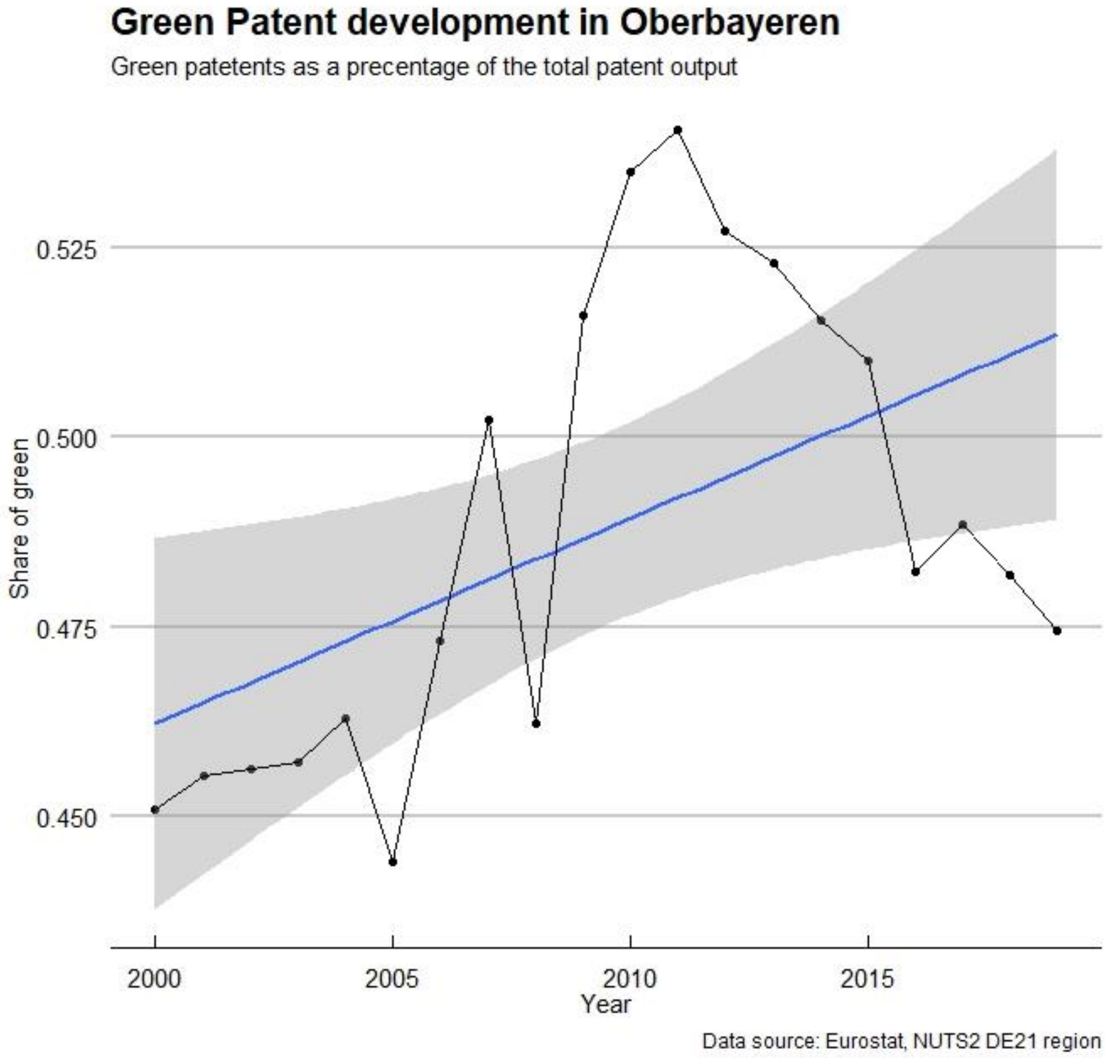

Figure 11 – Green patent development in Oberbayern.

	Dependent variable:	
	over15	green/tot
	logistic	*OLS*
	(1)	(2)
green	0.024^{***}	
	(0.002)	
total		0.006^{***}
		(0.001)
over15	0.361	18.213
	(0.275)	(16.621)
aar:over15	-0.036^{**}	
	(0.016)	
year:over15		-0.009
		(0.008)
Constant	-0.223^{***}	-11.680^{***}
	(0.020)	(1.991)
Observations	20	20
R^2		0.704
Adjusted R^2		0.649
Log Likelihood	-111.585	
Akaike Inf. Crit.	231.170	
Residual Std. Error		0.018 (df = 16)
F Statistic		12.686^{***} (df = 3; 16)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6 – General linear model test of Oberbayern.

The results of the tests done on the different regions show that the variable *over15* is significant for the three regions. One can first notice that for all three regions, the point line between the years for the share of green patents is falling, and for Stuttgart the linear line is declining, see Figure 9. In the first test of Ile-de-France, we find that *year:over15* is statistically significant and negative, which gives us the breaking point of the slope. The p-values for the test are all significant for *aar:over15* and *year:over15* in the binomial test of the different regions, where the variable *aar:over15* gives a lower p-value due to it only taking into account the 20 years.

Ile-de-France has a sharp decline from 2016. This is backed up by the test of the generalized linear model, where the *over15* intercept point is negative and statistically significant for the test.

For Stuttgart and Oberbayern, the findings are similar as seen in the graphs and model tests. There is a downward trend from year 2015, which is significant for the models.

From all three regions the trends are similar: the share of green patents is declining in the year 2015 and onwards. However, Stuttgart has a trendline that decreases for the whole interval of 2000 to 2019.

The finding of Montressor & Quatraro (2020), namely that regions with KET capabilities are more prone to develop green capabilities, is taken into account. The regions have a high share of green patent output, where the green patents vary from 45% to 55% of all patent output in their independent region. In addition, there is an overlap between the green and KET capabilities, as seen in the correlation matrix of the different technologies (see Figure 6), where there is 0.97 correlation between the two technologies. This supports the finding of our test, where green and KET follow each other, and where there is a fall in green patent output there is also a fall in KET output. The results raise the question of why there is a downward development of the green technologies.

The regions tested all have large populations, a large concentration of companies and institutions. This can explain why they are high on the concentration of green technologies. To check whether the trend of decline in green patent output was only exclusive to these regions, or if this is the case for other regions across the EU, we also checked different regions in addition to these three. We checked at national levels in Eastern European nations such as Poland, Lithuania, and the Czech Republic, where the intercept point of *over15* also gives a negative coefficient (see Appendix-G for tests). However, the test done shows that the decrease from 2015 is not statistically significant. The decrease in the three technological regions is more significant and the p-value is smaller compared to less technological regions.

The answer to hypothesis two, where we wanted to test if regions with KET capabilities increased the greening process after 2015, is no, as there has been a decline of the share for all the regions tested. There needs to be change in the stimulation of growth for green technologies as stated in the findings of the Roadmap to 2050 ((EU), 2012). This, in combination with the concentration in space of green technologies, gives precedent that there are policy implications based on our findings.

5 Discussion and Conclusion

Using *"structural diversity"* to investigate and compare the complexity of ENV-TECH and KETs, the results indicate that green technologies are more complex than KETs. This is in line with recent research that new green technologies are more complex and more novel than their non-green counterparts (Barbieri, Marzucchi, & Rizzo, 2020; Montresor & Quatraro, 2020). The results from the concentration analysis of green technologies in space clearly indicate that some specific regions are ahead of the curve in creating new green technologies and the results support hypothesis 1: *Complex green technologies concentrate in space.* Green technologies concentrate with predominance in certain European regions that are highly populated and have dense industrial clusters. This is comparable to Balland et al. (2020) who found that patenting of complex technologies concentrates in US cities. Furthermore, the results indicate that a presence of complex technology makes it easier for regions to diversify into new green technology and this can be one explanation for why novel green technology concentrates in space. This may have policy implications, as the idea behind the EU's smart specialization initiative is that countries should identify their existing or potential competitive advantages, where they can specialize and create capabilities in a different way than other countries or regions (B. T. Asheim, 2019). The results support that new green technologies are mostly created in the same regions, and that other regions may have challenges venturing into the green technology field. This is one reason for why it is important to create knowledge networks between economic actors and obtain the degree of relatedness so sustainable opportunities can be identified (Balland, 2016). Keeping in mind the ambitious targets for the climate, regions and economic actors may have to be incentivized with policy measures.

That all three regions show a significant downward trend after 2015 in the share of green patents raises questions regarding what is fueling this downward trend. The EU has made discoveries that green innovation might stagnate from 2020 (European Comission, 2013) if there is no policy change towards the greening process. However, with treaties such as the Paris Agreement and large policy changes with increased focus on stimulating green growth, one could have made the opposite assumption: namely, that there should have been an increase in green innovation. This paper has examined how green technologies concentrate in space and has tested how the development in certain regions with an extra focus on the years after 2015 has been for green patents. The results indicate that green technology concentrates in space; however, there is no significant evidence that supports hypothesis 2: *The greening process in* *regions with KET capabilities increased after the Paris Agreement*. The findings do more to support the critical finding by the EU, which is that green innovation can stagnate in 2020. Furthermore, one can even draw the conclusion that the stagnation is already happening. The findings emphasize the need for policy implementation, as ongoing in the EU, and raise questions regarding what is fueling this decrease.

Further research

We found in our literature review that change of both actions and focus in industries such as the oil and gas sector have become more visible in terms of transforming into greener activities. Statements such as that of the CEO of Shell, that it is no longer an oil and gas company but an energy transition company (Pickl, 2019), enhance this sentiment. The growth of KETs in the EU has had ramifications for the dirty energy industry, which supports the findings that KETs may have an impact on regions' ability to develop 'pure' green and green 'hybrid' technology (Montresor & Quatraro, 2020). This has been the case for the major European oil companies such as Equinor, BP and Total, who are positioning themselves to be full range energy companies (Pickl, 2019). As a result, it would be interesting to further research the perceived change of the energy sector to see how it can and does affect green innovation. However, this is beyond the scope of this paper.

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Appendices

Appendix A – R-code: ENV-TECH complexity plot

```
library(readxl)
library(readr)
library(dplyr)
library(ggplot2)
library(ggthemes)

#Read in technological complexity 1970 - 2016 XLSX from
www.tombroekel.de
comx <- read_excel("~/Projects/master/complexity.xlsx")

#Read in green cpc codes from OECD ENVTECH
green_codes <- read_excel("~/Projects/master/Green codes.xlsx")

#Tidy ENV-TECH dataset
greencd <- substr(green_codes$`IPC OR CPC CLASS`,1,4)
greencd <- unique(greencd)
greencd <- as_tibble(greencd)
greencd <- greencd %>% rename(CPC = value)

#Create dataframe with only complexity of green patents 4CPC and
remove NAs
gcomx <- greencd %>% left_join(comx, by="CPC")
gcomx <- gcomx %>% na.omit

#Create column with CPC1 codes for better visualization and set year
from 2000
gcomx$CPC1 = substr(gcomx$CPC,1,1)
gcomx <- gcomx %>% filter(year >= 2000)

#Create plot showing the complexity of ENVTECH
p <- ggplot(data = gcomx, aes(x=CPC1, y=structural,
                         colour = CPC1)) +
  geom_jitter() + geom_boxplot(alpha=0.5)

p + theme_economist_white(gray_bg = FALSE) +
  scale_colour_economist(labels = cpcsec) +
  labs(title = "Technological complexity green patents (ENVTECH)",
       subtitle = "Period: 2000 - 2016",
       colour = "",
       x= "EPO - Patent section (N1190)",
       y= "Structural diversity",
       caption = "Data source: Tom Brökel, www.tombroekel.de and
European Commision") +
  theme(legend.text = element_text(size = 14),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.ticks = element_blank(),
        plot.subtitle = element_text(hjust = 0, size = 16, face =
"bold"),
        plot.title = element_text(hjust = 0.5, color = "darkgreen",
size = 36),
        axis.title.x = element_text(face = "bold", size = 16),
        axis.title.y = element_text(face = "bold", size = 16))
```

```
#Bibliography
citation("readxl")
#Hadley Wickham and Jennifer Bryan (2019). readxl: Read Excel Files.
R package version
#1.3.1. https://CRAN.R-project.org/package=readxl
citation("readr")
#Hadley Wickham and Jim Hester (2020). readr: Read Rectangular Text
Data. R package version
#1.4.0. https://CRAN.R-project.org/package=readr
citation("dplyr")
#Hadley Wickham, Romain François, Lionel Henry and Kirill Müller
(2021). dplyr: A Grammar
#of Data Manipulation. R package version 1.0.6. https://CRAN.R-
project.org/package=dplyr
citation("ggplot2")
#H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-
Verlag New York, 2016.
citation("ggthemes")
#Jeffrey B. Arnold (2021). ggthemes: Extra Themes, Scales and Geoms
for 'ggplot2'. R
#package version 4.2.4. https://CRAN.R-project.org/package=ggthemes
```

Appendix B – R-code: KETs complexity plot

```
library(readxl)
library(readr)
library(dplyr)
library(ggplot2)
library(ggthemes)

#Read in technological complexity 1970 - 2016 XLSX from
www.tombroekel.de
comx <- read_excel("~/Projects/master/complexity.xlsx")

#Read in KETs cpc coded from European Commision
KETs <- read_excel("~/Projects/master/KETs.xlsx")

#Tidy KET CPC dataset
KETcd <- substr(KETs$KETs,1,4)
KETcd <- unique(KETcd)
KETcd <- as_tibble(KETcd)
KETcd <- KETcd %>% rename(CPC = value)

#Create dataframe with only complexity of KET patents 4CPC and
remove NAs
kcomx <- KETcd %>% left_join(comx, by="CPC")
kcomx <- kcomx %>% na.omit

#Create column with CPC1 codes for better visualization and set year
from 2000
kcomx$CPC1 = substr(kcomx$CPC,1,1)
kcomx <- kcomx %>% filter(year >= 2000)

#Create plot showing the complexity of KETs
k <- ggplot(data = kcomx, aes(x=CPC1, y=structural,
                              colour = CPC1)) +
  geom_jitter() + geom_boxplot(alpha=0.5)

k + theme_economist_white(gray_bg = FALSE) +
  scale_colour_economist(labels = kpcsec) +
  labs(title = "Technological complexity key enabling technologies
(KETs)",
       subtitle = "Period: 2000 - 2016",
       colour = "",
       x= "EPO - Patent section (N2516)",
       y= "Structural diversity",
       caption = "Data source: Tom Brökel, www.tombroekel.de and
European Commision") +
  theme(legend.text = element_text(size = 14),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.ticks = element_blank(),
        plot.subtitle = element_text(hjust = 0, size = 16, face =
"bold"),
        plot.title = element_text(hjust = 0.5, color = "maroon",
size = 36),
        axis.title.x = element_text(face = "bold", size = 16),
        axis.title.y = element_text(face = "bold", size = 16))
```

```
#Bibliography
citation("readxl")
#Hadley Wickham and Jennifer Bryan (2019). readxl: Read Excel Files.
R package version
#1.3.1. https://CRAN.R-project.org/package=readxl
citation("readr")
#Hadley Wickham and Jim Hester (2020). readr: Read Rectangular Text
Data. R package version
#1.4.0. https://CRAN.R-project.org/package=readr
citation("dplyr")
#Hadley Wickham, Romain François, Lionel Henry and Kirill Müller
(2021). dplyr: A Grammar
#of Data Manipulation. R package version 1.0.6. https://CRAN.R-
project.org/package=dplyr
citation("ggplot2")
#H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-
Verlag New York, 2016.
citation("ggthemes")
#Jeffrey B. Arnold (2021). ggthemes: Extra Themes, Scales and Geoms
for 'ggplot2'. R
#package version 4.2.4. https://CRAN.R-project.org/package=ggthemes
```

Appendix C – R-code: Character vectors for complexity plots

```
cpcsec <- c("A: Human necessities",
                                 "B: Performing operations;
transporting",
                                 "C: Chemistry; metallurgy",
                                 "D: Textiles; paper",
                                 "E: Fixed constructions",
                                 "F: Mechanical engineering;
lighting; heating;
weapons; blasting engines
or pumps",
                                 "G: Physics",
                                 "H: Electricity",
                                 "Y: General tagging of
new technological developments")

kpcsec <- c("A: Human necessities",
            "B: Performing operations;
transporting",
            "C: Chemistry; metallurgy",
            "D: Textiles; paper",
            "E: Fixed constructions",
            "F: Mechanical engineering;
lighting; heating;
weapons; blasting engines
or pumps",
            "G: Physics",
            "H: Electricity")
```

Appendix D – R-code: Maps Europa NUTS2 density green technologies

```
library(readr)
library(eurostat)
library(dplyr)
library(ggplot2)
library(ggthemes)

#Import dataset with patentdata and all NUTS2 codes
allpatN2 <- read_csv("~/Projects/master/
Green_KTs_patents_NUTS2_2000_2019.csv")

#Get NUTS2 geospatial year 2016
geonut2 <- get_eurostat_geospatial(output_class = "sf",
                                   resolution = "01",
                                   nuts_level = 2,
                                   year = 2016)

#Remove Turkey and Iceland from NUTS2 geospatial
geonut2 <- geonut2 %>% filter(geonut2$CNTR_CODE != "TR")
geonut2 <- geonut2 %>% filter(geonut2$CNTR_CODE != "IS")

#Tidy NUTS2 geospatial
nut2016 <- subset(geonut2, select = -c(CNTR_CODE, NUTS_NAME,
LEVL_CODE,
                                       FID, NUTS_ID, geo, NAME_LATN,
MOUNT_TYPE,
                                       URBN_TYPE, COAST_TYPE))
nut2016 <- nut2016 %>% rename(NUTS2 = id)

#Tidy dataset with patentdata and all NUTS2 codes
filterg <- allpatN2$num.pats.kts.cpc4 >= 1
patg <- allpatN2[filterg,]
rm(filterg)
totg2016 <- merge(patg, nut2016, by = "NUTS2")
eug2016 <- subset(totg2016, select = -c(X1,
num.pats.green.cpc4,CPC_Class_4,num.pats.green.cpc.full,
                                        num.pats.kts.cpc.full,
                                        total.pats.CPC4))
#Tidy data for 2010
year <- eug2016$app_year == 2010
eug2010 <- eug2016[year,]
rm(year)

eug2010 <- eug2010 %>% group_by(NUTS2, app_year) %>%
  summarise(sum(num.pats.kts.cpc4))

eug2010 <- merge(eug2010, nut2016, by = "NUTS2")

eug2010 <- eug2010 %>% rename(sum2010 = `sum(num.pats.kts.cpc4)`)

#Tidy data for 2015
year <- eug2016$app_year == 2015
eug2015 <- eug2016[year,]
rm(year)
```

```
eug2015 <- eug2015 %>% group_by(NUTS2, app_year) %>%
  summarise(sum(num.pats.kts.cpc4))

eug2015 <- merge(eug2015, nut2016, by = "NUTS2")

eug2015 <- eug2015 %>% rename(sum2015 = `sum(num.pats.kts.cpc4)`)

#Tidy data for 2019
year <- eug2016$app_year == 2019
eug2019 <- eug2016[year,]
rm(year)

eug2019 <- eug2019 %>% group_by(NUTS2, app_year) %>%
  summarise(sum(num.pats.kts.cpc4))

eug2019 <- merge(eug2019, nut2016, by = "NUTS2")

eug2019 <- eug2019 %>% rename(sum2019 = `sum(num.pats.kts.cpc4)`)

#Create plot 2010
p2010 <- ggplot() +
  geom_sf(data = eug2010, aes(geometry=geometry, fill=sum2010)) +
  geom_sf(data = geonut2, alpha = 0) +
  coord_sf(xlim = c(-11,37), ylim=c(35,70), datum = NA) +
  theme_economist_white(gray_bg = FALSE) +
  scale_fill_viridis_c(option = "mako", direction = -1) +
  labs(title = "Concentration of green technologies in space", tag =
"Year 2010",
       subtitle = "Density per NUTS2 region in Europe",
       colour = "",
       caption = "Data source: Tom Brökel, EUROSTAT and OECD ENV-
TECH") +
  theme(plot.subtitle = element_text(hjust = 0.5, size = 12,
lineheight = 1.5),
        plot.title = element_text(hjust = 0.5, color = "darkgreen",
size = 20),
        plot.tag = element_text(face = "bold", size = 18)) +
  guides(fill = guide_colorbar(title = "Number of patents",
                               title.position = "bottom",
                               title.hjust = 0.5,
                               label.hjust = 0.5,
                               frame.colour = "black",
                               barwidth = 15,
                               barheight = 1.5))

#Create plot 2015
p2015 <- ggplot() +
  geom_sf(data = eug2015, aes(geometry=geometry, fill=sum2015)) +
  geom_sf(data = geonut2, alpha = 0) +
  coord_sf(xlim = c(-11,37), ylim=c(35,70), datum = NA) +
  theme_economist_white(gray_bg = FALSE) +
  scale_fill_viridis_c(option = "mako", direction = -1) +
  labs(title = "Concentration of green technologies in space", tag =
"Year 2015",
```

```
       subtitle = "Density per NUTS2 region in Europe",
       colour = "",
       caption = "Data source: Tom Brökel, EUROSTAT and OECD ENV-
TECH") +
  theme(plot.subtitle = element_text(hjust = 0.5, size = 12,
lineheight = 1.5),
        plot.title = element_text(hjust = 0.5, color = "darkgreen",
size = 20),
        plot.tag = element_text(face = "bold", size = 18)) +
  guides(fill = guide_colorbar(title = "Number of patents",
                               title.position = "bottom",
                               title.hjust = 0.5,
                               label.hjust = 0.5,
                               frame.colour = "black",
                               barwidth = 15,
                               barheight = 1.5))

#Create plot 2019
p2019 <- ggplot() +
  geom_sf(data = eug2019, aes(geometry=geometry, fill=sum2019)) +
  geom_sf(data = geonut2, alpha = 0) +
  coord_sf(xlim = c(-11,37), ylim=c(35,70), datum = NA) +
  theme_economist_white(gray_bg = FALSE) +
  scale_fill_viridis_c(option = "mako", direction = -1, guide =
FALSE) +
  labs(title = "Concentration of green technologies in space", tag =
"Year 2019",
       subtitle = "Density per NUTS2 region in Europe",
       colour = "",
       caption = "Data source: Tom Brökel, EUROSTAT and OECD ENV-
TECH") +
  theme(plot.subtitle = element_text(hjust = 0.5, size = 12,
lineheight = 1.5),
        plot.title = element_text(hjust = 0.5, color = "darkgreen",
size = 20),
        plot.tag = element_text(face = "bold", size = 18)) +
  guides(fill = guide_colorbar(title = "Number of patents",
                               title.position = "bottom",
                               title.hjust = 0.5,
                               label.hjust = 0.5,
                               frame.colour = "black",
                               barwidth = 15,
                               barheight = 1.5))

#Bibliography
citation("eurostat")
#(C) Leo Lahti, Janne Huovari, Markus Kainu, Przemyslaw Biecek.
Retrieval and analysis of
#Eurostat open data with the eurostat package. R Journal
9(1):385-392, 2017. Version 3.7.5
#Package URL: http://ropengov.github.io/eurostat Manuscript URL:
#https://journal.r-project.org/archive/2017/RJ-2017-019/index.html
```

Appendix E – R-code: Top 10 Regions Europa NUTS2 green technologies

```
library(formattable)
library(dplyr)
library(readr)
library(eurostat)

#Import dataset with patentdata and all NUTS2 codes
allpatN2 <- read_csv("~/Projects/master/
Green_KTs_patents_NUTS2_2000_2019.csv")

#Get NUTS2 geospatial year 2016
geonut2 <- get_eurostat_geospatial(output_class = "sf",
                                   resolution = "01",
                                   nuts_level = 2,
                                   year = 2016)

#Tidy NUTS2 geospatial
nut10 <- subset(geonut2, select = -c(CNTR_CODE, LEVL_CODE,
                                       FID, NUTS_ID, geo, NAME_LATN,
MOUNT_TYPE,
                                       URBN_TYPE, COAST_TYPE))
nut10 <- nut10 %>% rename(NUTS2 = id)

#Tidy dataset with patentdata and all NUTS2 codes
filterg <- allpatN2$num.pats.kts.cpc4 >= 1
patg <- allpatN2[filterg,]
rm(filterg)
totg10 <- merge(patg, nut10, by = "NUTS2")
eug10 <- subset(totg10, select = -c(X1,
num.pats.green.cpc4,CPC_Class_4,num.pats.green.cpc.full,
                                        num.pats.kts.cpc.full,
                                        total.pats.CPC4))

#Tidy data for 2010
year <- eug10$app_year == 2010
eu10 <- eug10[year,]
rm(year)

eu10 <- eu10 %>% group_by(NUTS2, app_year, NUTS_NAME) %>%
  summarise(sum(num.pats.kts.cpc4))

eu10 <- merge(eu10, nut10, by = "NUTS2")

eu10 <- eu10 %>% rename(sum2010 = `sum(num.pats.kts.cpc4)`)

topeu10 <- subset(eu10, select = -c(geometry))

topeu10 <- topeu10 %>% arrange(desc(sum2010)) %>% slice(1:10)
topeu10 <- topeu10 %>% relocate(NUTS_NAME, .after = NUTS2)
topeu10 <- topeu10 %>% rename(Year = app_year)
topeu10 <- topeu10 %>% rename("Number of patents" = sum2010)
topeu10 <- topeu10 %>% rename("Region" = NUTS_NAME)

#Create top 10 table for 2010
formattable(topeu10,
```

```
            align =c("l","l","c","r"),
            list(`Indicator Name` = formatter(
              "span", style = ~ style(color = "grey",font.weight =
"bold"))
            ))

#Tidy data for 2015
year <- eug10$app_year == 2015
eu15 <- eug10[year,]
rm(year)

eu15 <- eu15 %>% group_by(NUTS2, app_year, NUTS_NAME) %>%
  summarise(sum(num.pats.kts.cpc4))

eu15 <- merge(eu15, nut10, by = "NUTS2")

eu15 <- eu15 %>% rename(sum2015 = `sum(num.pats.kts.cpc4)`)

topeu15 <- subset(eu15, select = -c(geometry))

topeu15 <- topeu15 %>% arrange(desc(sum2015)) %>% slice(1:10)
topeu15 <- topeu15 %>% relocate(NUTS_NAME, .after = NUTS2)
topeu15 <- topeu15 %>% rename(Year = app_year)
topeu15 <- topeu15 %>% rename("Number of patents" = sum2015)
topeu15 <- topeu15 %>% rename("Region" = NUTS_NAME)

#Create top 10 table for 2015
formattable(topeu15,
            align =c("l","l","c","r"),
            list(`Indicator Name` = formatter(
              "span", style = ~ style(color = "grey",font.weight =
"bold"))
            ))

#Tidy data for 2019
year <- eug10$app_year == 2019
eu19 <- eug10[year,]
rm(year)

eu19 <- eu19 %>% group_by(NUTS2, app_year, NUTS_NAME) %>%
  summarise(sum(num.pats.kts.cpc4))

eu19 <- merge(eu19, nut10, by = "NUTS2")

eu19 <- eu19 %>% rename(sum2019 = `sum(num.pats.kts.cpc4)`)

topeu19 <- subset(eu19, select = -c(geometry))

topeu19 <- topeu19 %>% arrange(desc(sum2019)) %>% slice(1:10)
topeu19 <- topeu19 %>% relocate(NUTS_NAME, .after = NUTS2)
topeu19 <- topeu19 %>% rename(Year = app_year)
topeu19 <- topeu19 %>% rename("Number of patents" = sum2019)
topeu19 <- topeu19 %>% rename("Region" = NUTS_NAME)
```

```
#Create top 10 table for 2019
formattable(topeu19,
            align =c("l","l","c","r"),
            list(`Indicator Name` = formatter(
              "span", style = ~ style(color = "grey",font.weight =
"bold"))
            ))

#Bibliography
citation("formattable")
# Kun Ren and Kenton Russell (2021). formattable: Create
'Formattable' Data Structures. R
# package version 0.2.1. https://CRAN.R-project.org/
package=formattable
```

Appendix F – R-code: Region variables and correlation matrix

```
library(openxlsx)
library(tidyverse)
library(dplyr)
library(glm)
library(stargazer)
library(corrplot)
library(Hmisc)

totalgreen <- read.xlsx("total_pats_NUTS2_2000_2019.xlsx")
colnames(totalgreen) <- c("stat","year","tot","green","full")
ketpat<- read.csv("Kets_per_year.csv",sep = ",")

#Creating the variables for regions
#Paris
par<-totalgreen[totalgreen$stat=="FR10",]
pakt<-patket[patket$stat=="FR10",]
par<-cbind(par,paket[1:20, 4])
par
# Stutgart
stutgreen<-totalgreen[totalgreen$stat=="DE11",]
stutkt<-patket[patket$stat=="DE11",]
stutkt
stut<-cbind(stutgreen,stutkt[1:20, 4])

#Oberbayeren
baygreen<-totalgreen[totalgreen$stat=="DE21",]
baykt<-patket[patket$stat=="DE21",]
bay <- cbind(baygreen,baykt[1:20,4])

#Correlation matrix
par <- cbind(pargreen,pariskts[1:20,4])
par<-subset(par,select =  c("tot", "green", "full", "Kets"))
par<-subset(par, select = -c(full))
paround<-round(cor(par),2)
pacor<-cor(par, method ="spearman", use = "complete.obs")
corrplot(pacor)
ggcorrplot(pacor)
pacor2<-rcorr(as.matrix(par))
```

Appendix G – R-code: Plot and test code

```
#Test results of east European countrieswith this formula: grtot.lm <-
lm(green/tot ~ year * over15)
Chech Republic
year:over15TRUE -0.044556   0.022234  -2.004   0.0468 *


Poland:
  year:over15TRUE  -0.020330   0.024325  -0.836  0.40393

Lituhania:

  year:over15TRUE  -0.086241   0.075053  -1.149   0.2674

Latvia:
  year:over15TRUE  7.815e-02  4.167e-02   1.875  0.07912 .

# Plot for Germany
de <- totalgreen[3142:3901,]
g<-ggplot(de, aes(x=year,
y=green/tot))+geom_point(size=tot)+geom_smooth(method = "loess",
se=FALSE)
+labs(title = "Germany green patent output",subtitle = "Trend of green
patetents as a precentage of total patents 2000-2019", y="Green/Total
Patents", x="Year", caption = "Source: Eurostat")


#Plot code
t<-ggplot(data=par, aes(x=year, y=tot)) +
geom_line(aes(x=year,y=tot),color='red', size= 2) +
  geom_line(aes(x=year,y=green),color='green', size=2)
+ylab('Patents')+xlab('Year')
+annotate("text", x=2005, y= 3000, label="Total", color='red',
size=5)+annotate("text", x=2005, y=1600, label="Green", color='green',
size=5)
t
t+labs(title = "Total and Green patent output", subtitle = "For NUTS2
region IL-de-France", caption = "Data source: Eurostat, NUTS2 FR10" )+
  theme_economist_white(gray_bg = FALSE)



over15 <- (year > 2015)
grtot.lm <- lm(green/tot ~ year * over15)
summary(grtot.lm)
grtot.glm <- glm(cbind(green,tot-green) ~ aar * over15,family = binomial)
summary(grtot.glm)
m2<-(lm(green/tot ~year * over15))
m3<-(lm(green/tot ~kets +year * over15), data=stut)
totalgreen$aar <- totalgreen$year - 2000
grtot.glm <- glm(cbind(green,tot-green) ~ aar * over15,family = binomial)
summary(grtot.glm)
stargazer(grtot.glm,
m2,type="html",dep.var.labels=c("over15"),covariate.labels=c("green","tot
al"), out="bmodels.htm")
```