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Impact of universities' R&D on regional technological complexity

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I would like to express my deep gratitude to my supervisor Professor Tom Broekel for assisting me in the best possible way and always pushing me against my limits. A special thanks to my parents, Tauqeer Ahmad Malik and Farnaz Tabassum and, my sister doctoral candidate, Fatima Tauqeer for believing in me and fully supporting me during my study period. I would also like to thank my program coordinator Anne Lin Brobakke for helping and guiding me throughout my study program.

This study is very close to my heart because I created it from the scratch, studied a lot around the research topic, and improved it until it became seamless to the best of my abilities. Over the last three months, this study has occupied me and while I was finalizing it to submit, I must admit that it has been an overwhelming experience for me. I thoroughly enjoyed the process of data wrangling, reviewing the literature, and writing the thesis. I hope that it may inspire someone.

Finally, I would like to thank my department UiS business school for delivering a quality master's program and enabling me to hone my research skills and to conduct a study like this.

Abstract

There is growing evidence in the literature that knowledge generated and diffused by academic institutions plays an important role in innovation and economic growth. There is a need to empirically test the relationship between regional technological complexity and academic research, i.e., evaluating the effect of higher education institutions (HEIs) R&D on regional technological complexity. Hence, this thesis focuses on studying the association between capital expended for research and development (R&D) activities by academic institutions and regional technological complexity.

In this study, I have used Broekel's structural diversity method to measure the regional technological complexity of NUTS 3 regions in Norway, using panel data of 17 Norwegian regions from 1999-2015 in addition to patent and population data. The study aims to evaluate the impact of universities' R&D efforts on regional technological complexity. I have employed regression and statistical modeling to test the hypothesis,

"Technological complexity of a region depends on the R&D expenditure input of that region."

The findings of this study reveal that private R&D expenditures have a significant positive relation with regional technological complexity whereas universities' R&D is not statistically different from zero. This can be explained by the basic nature of research conducted by universities that work as a building block for private research and development. These findings can act as basic knowledge for policymakers, enabling them to recognize the best R&D practitioners for benchmarking.

Finally, the method employed in this study and the results can also help the research and development departments of governments to develop approaches for strengthening regional and national innovation performance by highlighting the lesser-studied and value-creating role of academic institutions. Moreover, the findings add to the knowledge on facilitators in public-private innovation.

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Figures and Tables

Abbreviations

HEI	Higher Education Institutions
TC	Technological Complexity
R&D	Research and Development
SME	Small and Medium Enterprises
OECD	Organization for Economic Co-Operation and Development
NIFU	Nordic Institute for Studies in Innovation, Research and Education
CPC	Cooperative Patent Classes
KCI	Knowledge Complexity Index
NDS	Network Diversity Score
NUTS	Nomenclature of Territorial Units for Statistics

"Are those who know equal to those who do not know?"

~Al-Quran~

1 Introduction

Innovation has become an integral part of regional, national, and international development and sustained economic growth in all advanced economies. For the last couple of decades, an increasing trend among many countries including Norway is the investigation of key facilitating factors associated with regional economic development and successful innovation. Accompanying this trend is the rise in research on synthesizing knowledge of innovation and technological complexity. The increasing number of innovation studies calls for a better and harmonized understanding of this research topic. Moreover, the literature pertaining to technological complexity suggests that proficiencies in complex technologies matter for regional growth. The current body of studies on innovation and technological complexity reveals several factors that show an association with economic development and growth (Barrio-Castro & García-Quevedo, 2005; Fritsch & Slavtchev, 2007; Mewes & Broekel, 2020; Romer, 1990). One such key factor is knowledge production and diffusion from higher education institutions[1] (HEIs) or universities (Fritsch & Slavtchev, 2007). HEIs have growingly been examined by their capacity to actuate innovation dynamics in a region. However, there is limited available knowledge that fully captures the direct and indirect role of HEIs on economic growth and no previous study has looked at the effect of knowledge generated by HEIs on regional technological complexity.

Until now, to measure the universities' effort in regional economic development and innovation, researchers have used different measures. Most of this research is fragmentary and several of these measures are unable to fully characterize the total effect of academic research on innovation as the knowledge generated by the universities also greatly influences private research and innovation (Barrio-Castro & García-Quevedo, 2005). There is a need to empirically test the relationship between regional technological complexity and academic research, i.e., evaluating the effect of HEIs' R&D on regional technological complexity. Hence, this thesis focuses on studying the association between capital expended for research and development (R&D) activities by academic institutions and regional technological complexity.

To dig deep into the relationship between HEIs and regional technological complexity, this thesis looks at a testable hypothesis that states:

> "Technological complexity of a region depends on the R&D expenditure input of that region."

[1] HEIs and universities will be used interchangeably in this study.

The findings from the analyses will give a more accurate picture of how R&D is helping in developing regional technological complexity which ensures long-term sustainable economic growth (Mewes & Broekel, 2020).

1.1 Background

A large group of economists has identified several paradigms of innovative specialization, which shape the technological and economic future of a region. These paradigms include specific production techniques (Rigby & Essletzbichler, 1997), industrial distribution (Scott, 1996), institutional and organizational structures (Saxenian, 1994; Storper, 1993), and research and development culture (D. B. Audretsch & Feldman, 1996). Other paradigms such as Romer's endogenous growth theory formed the basis for the modern understanding of economic growth. According to Romer's theory, knowledge is the backbone of sustainable economic growth (Romer, 1990). His model connects innovation and economic growth to the number of people employed in the knowledge sector and underpins the concept of a knowledge-based economy and knowledge being the new form of capital. Although the focus on empirical measurement of knowledge and its production has drawn attention to several aspects of a knowledge-based economy, it is not clear how knowledge transforms into economic growth.

In addition to knowledge production alone being a facilitating factor for economic growth, concomitant factors such as spatial concentration of knowledge and knowledge spillover have also surfaced as important research topics associated with regional economic development. Different economically developed regions mastering specialization in different fields is proof that there exists a localized technological competence, confined skill, and unique industrial ecosystem (Gertler, 1995; Storper, 1993). These local capabilities develop over a period of time and shape the future choices of the region (Essletzbichler & Rigby, 2007). Due to this long-term accumulation of knowledge, it becomes spatially concentrated in certain regions (Feldman, 1994). That is why regions differ in terms of economic output because of the difference in the kind and quality of knowledge generation. There is a need for an accurate measure to identify regional economic growth via the complex ecosystem of knowledge production. Since knowledge complexity and technological complexity have mutual causality with each other, they can be interchangeably used (Broekel, 2019).

Sustainable regional innovation is a result of institutional practices, which encourage open innovation, higher absorptive capacity, and connection with knowledge-producing institutions both regional and exterritorial (Asheim & Coenen, 2005; Bathelt, Malmberg, & Maskell, 2004; Cohen & Levinthal, 1990).

Significant research has been conducted to identify the knowledge production of a region and its effects on the economic performance of that region. Relatively less attention has been given to the quality or significance of the knowledge produced among regions. To understand the spatial knowledge composition of a region we need a precise measure of knowledge and technology (Pavitt, 1982). Despite intense discussion on the topic of knowledge complexity and its implications on economic growth, currently, there is no standard definition or way to calculate knowledge complexity or technological complexity (Mewes & Broekel, 2020).

Many researchers have tried to identify the differences between regional knowledge and its value. Rigby measured the differences between technologies using patent data (Rigby, 2015). Fleming and Sorenson approximated the knowledge complexity by enumerating the degree of interdependence related to subcomponents of knowledge (Fleming & Sorenson, 2001). In a recent study by Broekel, structural diversity has been used to measure the complexity of technologies (Broekel, 2019). This method is effective and empirically precise. A more detailed description of the method has been explained in chapter 3 (methods and materials).

In this study, I have used Broekel's structural diversity method to measure the regional technological complexity of NUTS 3 regions in Norway, using panel data of 17 Norwegian regions from 1999-2015 to investigate the impact of universities' R&D efforts on regional technological complexity.

1.2 Motivation

There are a couple of reasons why I was motivated to study this subject. First, my master's specialization is in innovation studies, as I have a huge interest in innovation and factors that lead to innovation. Secondly, Norway has become the hub of innovation enterprises and start-ups as R&D expenditures in Norway have soared in the last few decades. Not only that, the culture of scientific parks and closely knitted collaboration of Norwegian universities with start-ups and firms enthralled me. It motivated me to think about the economic benefits of such an integrated system. These questions pushed me to study more about the topic. Ever since then, I have been religiously following the influence of Norwegian universities on private innovation.

From an academic point of view, the motivation for doing this research is to add to the existing body of research on innovation and technological complexity as there has been no study conducted in Norway that looks at the association of HEIs and technological complexity.

Lastly, I wanted to master my data management and analysis skills and this thesis was a great opportunity to do so.

1.3 Problem statement and research question

From the available literature, it is known that technological complexity is significantly associated with economic growth (Mewes & Broekel, 2020). We also know that academic institutions serve as enablers of innovation (Fritsch & Slavtchev, 2007). However, the scarcely available literature has solely focused on the number of patents as a measure for regional development and innovation. The increasing and somewhat disharmonized research around innovation calls for a better understanding of the relationship between technological complexity and factors that either promote or hinder technological complexity. The core question this study aims to answer is:

> What is the relationship between the knowledge produced by higher education institutions and technological complexity?

The answer to this broad question would help us comprehend how universities' R&D expenditure develops regional technological complexity leading to the economic development of a region. Hence, in this study, I have looked at the effect of universities' R&D on the regional technological complexity.

1.4 Layout

The following table presents the title and description of the five chapters constituting the body of the thesis.

Chapter	Title & Description
1	Introduction: introduces the topic and provides a brief background.
2	Literature review and conceptual framework: presents a detailed review of the literature starting from the description of technological complexity, followed by its connection with the academic research.
3	Materials and methods: gives an overview of research methods that were followed in the study. It provides information on the conceptual framework, the hypothesis, the study design, and how the data management and analysis was done.
4	Results and Discussion: presents the main results and discussion of the results
5	Conclusion and future implications: presents the conclusion of the study and some suggestions for future research

2 Literature review and conceptual framework

There has been abundant research on the innovation and complexity of technology. There is a plethora of literature available on the role of academic institutions in promoting economic growth. However, this subject is very broad, and many aspects have been insufficiently researched, for instance, the capacity of HEIs through their engagement with the local and regional government in policy-making and regional strategies, or the potential of HEIs in boosting regional innovation, etc. This chapter presents the pre-identified themes and factors taken out from the literature that formed the framework on which the main hypothesis of this thesis was identified.

2.1 Effect of technological complexity on economic growth

To understand the association between HEIs and technological complexity, it is important to comprehend the concept of complexity of technologies first. The complexity of technologies or technological complexity is a relatively new research topic. There is no harmonized approach to defining technological complexity in the literature and has been used subjectively. Rogers and Shoemaker have defined technological complexity as the "degree to which an innovation is perceived as labored to understand and use" (Rogers & Shoemaker, 1971). When it comes to defining technological complexity, the dominant focus in the literature has been in terms of the ‘level of interdependence’ among the components of a technology (Fleming & Sorenson, 2001).

Furthermore, some studies have shown an association between technological complexity and regional growth by using patent data and structural complexity measures, for instance, the study by Broekel shows a promising association and concludes that technological complexity is imperative for regional economic growth (Mewes & Broekel, 2020). A detailed description of Broekel’s measure follows in chapter 3 (methods and materials).

Each technology differs in its value and penetration in space (Dosi, 1982). There has been a considerable theoretical effort to measure the quality and value of individual patents. Trajtenberg used the number of forward citations as a measure to assess patent quality (Trajtenberg, 1990). Others have tried different measures like family size, litigation, and renewal (Harhoff, Scherer, & Vopel, 2003; Lanjouw & Schankerman, 2004). These measures provide one indicator for the value of knowledge held by a firm or region. The other important factor which affects the value of knowledge is the degree of replicability

(Balland & Rigby, 2017). The factors which affect the replicability of certain knowledge include the cost of replication (Howells, 2002), complexity (Cavusgil, Calantone, & Zhao, 2003), cost of absorption (Cohen & Levinthal, 1990), and complexity of knowledge architecture (Simon, 1962).

Despite this broad realization, there is also no harmonized approach to calculating technological complexity. Several researchers have implicitly tried to find the most accurate method to capture technological complexity. In their paper, Fleming and Sorenson used the N/K model to calculate the approximation of knowledge complexity (Fleming & Sorenson, 2001) defined it as the interaction of the number of subparts (N) and their interdependence (K). This model has been used in many studies to measure knowledge complexity. However, according to Broekel, this model has not been used efficiently to measure complexity according to different technology levels (Broekel, 2019). Hidalgo and Hausmann introduced the economic complexity index (ECI) which is one of the most prominent methods (Hidalgo & Hausmann, 2009). The ECI approach was developed to evaluate the economic complexity of countries according to their export portfolio but Balland and Rigby have used ECI to calculate technological complexity based on the patent data of regions (Balland & Rigby, 2017). However, the knowledge complexity index (KCI) is a spatially distributed measure so the chances of endogeneity cannot be overlooked (Mewes & Broekel, 2020). Moreover, the empirical characteristics of KCI are not interchangeable with technological complexity (Broekel, 2019).

The knowledge production function formulated by Griliches forms the conceptual underpinnings of this study to investigate and analyze the effect of universities on the technological complexity of regions (Griliches 1979, Broekel 2019). There is plenty of empirical evidence which supports Griliches's knowledge function and it has been used in many applied studies conducted at the regional level (Audretsch 1998). According to Griliches's knowledge function, the regional innovation output is a function of regional innovation input (Griliches, 1979). In a nutshell, different researchers have used different units of measure to capture innovation input, and most of these measures are related to regional R&D expenditure e.g., R&D personal, R&D man-years, salaries for R&D personnel, etc.

In conclusion, although the association between technological complexity has been studied implicitly and technological complexity is a major driver for economic growth, there is the limited latest evidence on how this complexity arises in certain regions.

2.2 Academic research as an enabling factor for technological complexity

Many scholars believe that innovation is a result of the combination and modification of existing knowledge (Basalla, 1988; Gilfillan, 1935; Henderson & Clark, 1990; Schumpeter, 1939; Usher, 2013; Weitzman, 1996)**.** Most of the new inventions are derived from existing technological components that are combined in a specific network to produce a novel technology e.g., a smartphone is a recombination of existing technologies (Fig 1). There are two main sources of knowledge. Firstly, the research and development (R&D) departments of academic institutions play an important role in generating knowledge that is translated and applied in the innovation field. This knowledge forms the basis for knowledge generated by the second source, which is the private R&D sector (Edquist, 1997). A number of studies have looked at the effect of academic R&D on innovation. According to one study that explored the effect of academic institutions on regional innovative output in West Germany, the authors concluded that the intensity and quality of the research conducted by the academic institutions have a significant effect on regional innovative output, i.e., the number of regional patent applications (Fritsch & Slavtchev, 2007). However, it is important to note that the effect of academic R&D is not straight as it finds its utility in private R&D activities and thus is difficult to capture its complete effect on economic growth.

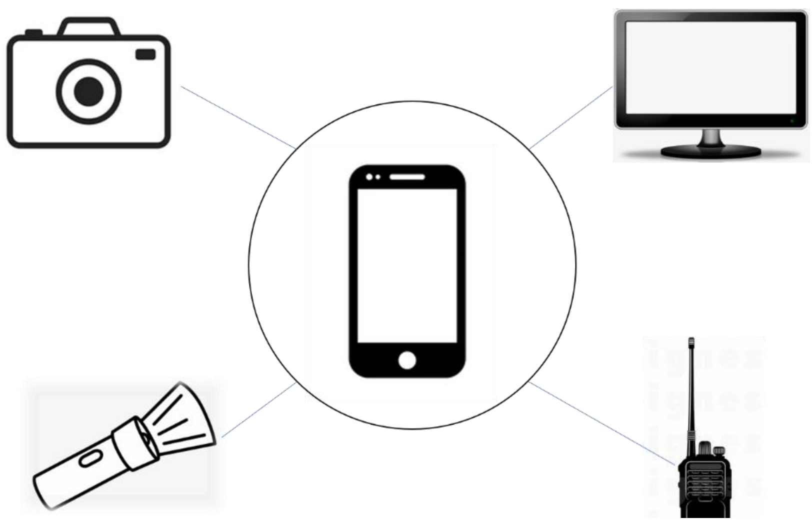

Figure 1: Smartphone as a combination of existing technologies.

According to numerous innovation studies, although knowledge is cumulative in nature as it amasses from the combination of existing knowledge but it is difficult to replicate knowledge subsets that are developed at a different location (Balland & Rigby, 2017). Many researchers have worked to identify these hidden barriers, which make it difficult to diffuse certain types of knowledge. An institute has systematic organizing principles (Kogut & Zander, 1992) or routines (Nelson & Winter, 1982) that combine tacit and complex knowledge held by expert resources to perform specialized procedures, which produces a complex technology. This whole process itself possesses a tacit dimension (Nelson & Winter, 1982). When these organizing principles or routines are shared over the economic agents to develop an interconnected network, a portrait of a knowledge-based technological complex region is generated (Asheim & Gertler, 2005; Lundvall & Johnson, 1994; Tallman, Jenkins, Henry, & Pinch, 2004). Knowledge-based institutions cannot merely be judged by the sum of their knowledge (Balland & Rigby, 2017) rather it is conformed of the complexity that arises due to the interaction of this knowledge (Hidalgo & Hausmann, 2009).

Extensive research has been conducted to identify the knowledge production of a region and its effect on the economic performance of that region. Relatively less attention has been given to the quality or significance of the knowledge produced in regions and how different regions differ in terms of the knowledge they yield. To understand the spatial knowledge composition of a region we need a precise measure of knowledge and Technology (Pavitt, 1982). Despite intense discussion on the topic of knowledge complexity and its implications on economic growth, currently, there is no standard definition of knowledge complexity (Mewes & Broekel, 2020). In recent years, researchers have tried to identify the differences between regional knowledge and its significance. Rigby measured the differences between regional technologies using patent data (Rigby, 2015). Fleming and Sorenson approximated the knowledge complexity by enumerating the degree of interdependence related to subcomponents of knowledge complexity (Fleming & Sorenson, 2001).

In conclusion, academic knowledge generated by HEIs is associated with technological complexity. However, data on quality measures of academic R&D that have an impact on technological complexity is limited and is challenging to capture due to its dissemination into different private actors. This knowledge is crucial to justify the role of academic knowledge in economic development and to guide evidence-based policy.

2.3 Conclusion

Generally, the extent to which academic R&D may affect technological complexity has never been explored before. Addressing this research question is crucial to better understand the significance of the output of academic institutions and to shed some new light on the technology policy framework.

3 Materials and methods

This chapter gives an overview of the research methods that were followed in the study. It provides information on the conceptual framework, the hypothesis, the study design, and how the data management and analysis was done.

3.1 Conceptual framework

The conceptual framework of this study was acquired from reviewing the available literature to investigate and analyze the effect of universities on the regional technological complexity of regions. The knowledge production function formulated by Griliches supports the conceptual underpinnings needed to create the hypothetical mode for this study (Broekel, 2019; Griliches, 1979). There is sufficient literature that supports Griliches's knowledge function and it has been used in many applied studies conducted at the regional level (B. Audretsch, 1998). According to Griliches's knowledge function, the regional innovation output is a function of regional innovation input (REF). Previously, different researchers have used different units of measure to capture innovation input and most of these measures are related to regional R&D expenditure e.g., R&D personal, R&D man-years, salaries for R&D personnel etc.

3.2 Study design

The study aimed to measure the effect of HEIs research on technological complexity. Having this aim in mind, I chose to do an exploratory study using Norway as a spatial region. I applied regression and statistical modeling to construct the regional technological complexity (RTC) model.

Given that, HEIs have been shown to promote regional innovation processes and that technological complexity has an effect on economic growth, I hypothesized that the technological complexity of region *r* depends on the research input of the region *r*.

$$\textbf{Technological complexity}_{\mathbf{r}} \mathbf{= f(R\&D\ input}_{\mathbf{r}}\mathbf{)}$$

After implementing the Cobb-Douglas form of the knowledge production function, the function can be expressed as:

$$\textbf{Technological complexity}_{\mathbf{r}} \mathbf{= a(R\&D\ input}_{\mathbf{r}}\mathbf{)}^{\mathbf{b}}$$

Where,

a = is the constant;

b = the elasticity with which the technological complexity varies corresponding to the R&D input

3.3 Variables and covariates

The exploratory variables are universities' and private R&D expenditures. In addition, a set of explanatory variables or covariates are also included in the model that may affect the regional technological complexity. The covariates consist of R&D efforts of surrounding regions, GDP, and population. These covariates were included after a thorough literature review, document review, and understanding from the discussions with my supervisor and colleagues.

The development of higher or sophisticated technological complexity does not necessarily depend on regional knowledge input but can also be influenced by knowledge spillovers from surrounding regions. In regional innovation studies, there is significant evidence that the knowledge or technology spillovers from surrounding regions influence local regional innovation (Anselin, Varga, & Acs, 1997; Autant-Bernard, 2001; Fischer & Varga, 2003). Two additional explanatory variables, private R&D and universities' R&D expenditures of the bordering regions were added to the model to measure the dimension of knowledge spillover (Autant-Bernard, 2001).

3.4 Final regional technological complexity (RTC) model

After considering all the above dimensions, I constructed the final regional technological complexity (RTC) model as:

$$\mathbf{RTC_i = f(PREX_i, UREX_i, SPREX, SUREX, C_i)}$$

Where,

RTC_i = the technological complexity of region I;

$PREX_i$ = the R&D expenditures conducted by the private sector in region i (NOK, million);

$UREX_i$ = the universities' R&D expenditures in region i (NOK, millions);

SPREX = the R&D expenditures conducted by the private sector in neighboring regions (common border);

SUREX = the universities' R&D expenditures conducted by neighboring regions (common border) and;

C_i = the regional characteristics which may or may not affect the regional technological complexity

3.5 Data management and analysis

For the analyses, panel data of 17 Norwegian regions from 1999-2015 was used. The unit of analysis is the NUTS 3 regions[2]. There is no harmonized approach for selecting a spatial unit (B. Audretsch, 1998). Anselin et al. suggest that the unit should be a city or a metropolitan area because most of the interactions and knowledge transfers take place there (Anselin et al., 1997). NUTS 3 is the smallest spatial unit in the European regions. In most countries, one NUTS 3 unit is either equal to a city or even a part of a city but in the case of Norway, one NUTS 3 unit is almost equal to a county. In Norway, there is a statistical constraint to collect data at the city level. The data about private and universities' R&D expenditures is only available at the county level (NUTS 3). Previous studies carried out in the domain of regional innovation have also used a larger spatial unit than a city (Barrio-Castro & García-Quevedo, 2005; Fritsch & Slavtchev, 2007). Most studies conducted in the USA, have used states as the spatial unit (Acs, Audretsch, & Feldman, 1992; Feldman & Audretsch, 1999; Jaffe, 1989).

3.6 Data sources

For this study, three types of data were used. First, the patent data was obtained from the OECD REGPAT database[3]. This database contains information about patents according to the addresses of the applicants and inventors. It presents the data in a regionalized format so that more than 2 000 regions are covered across Organisation for Economic Co-operation and Development (OECD) countries. This database provides a rich set of datasets as it allows patent data to be merged with other regional data such as GDP or labor force statistics, providing researchers with the opportunity to carry out a wide range of analyses to address topics relating to the regional dimension of innovation.

Second, the panel data of R&D expenditures was taken from NIFU (Nordisk institutt for studier av innovasjon, forskning og utdanning) and Statistics Norway/R&D statistics. Statistics Norway collects data based on regions where R&D expenses are made. This eliminates the overestimation of regions where

[2] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU and the UK. Available from: https://ec.europa.eu/eurostat/web/nuts/background

[3] OECD REGPAT database. Available from: https://www-oecd-org.ezproxy.uio.no/about/members-and-partners/

companies have headquarters. Third, population and GDP data were extracted from Statistics Norway (Statistics Norway, 2021).

3.7 Structural diversity to measure technological complexity

Broekel has developed a new complexity measure based on the structural diversity of technologies to evaluate technological complexity (Broekel, 2019). The measure is not only empirically precise but also reflects the theoretical foundations of technological complexity. It is based on the structural complexity of technology. It assesses the combination of knowledge components of technology. The baseline idea is that the technological innovation or novelty is a result of recombination and modification of existing technologies (Basalla, 1988; Hargadon & Sutton, 1997; Usher, 1954). Therefore, the resulting network is a complex network called a combinatorial network. The network can be described in terms of nodes, representing the knowledge components, and links, representing the combinations (Mewes & Broekel, 2020). The complexity of structure is highly dependent on the number of components and the way they are combined. For example, a table has four legs and one panel, and all four legs are combined to the panel. According to Broekel, the combinatorial network of such an object is star-like where there is one central component - the panel - and one peripheral component – the legs (Mewes & Broekel, 2020). This network has only one topology and hence is a simple network that requires little information to describe (Fig 2).

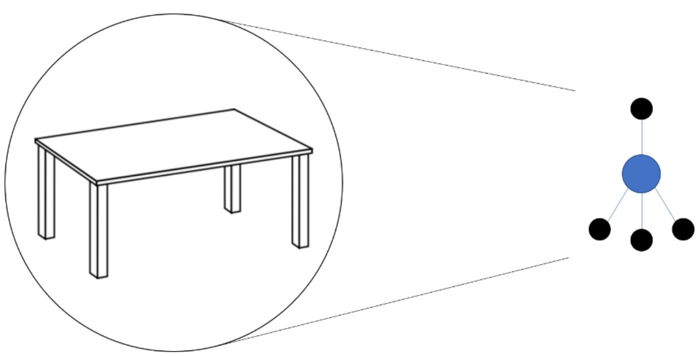

Figure 2: Simple network (star-like)

On the other hand, an airplane has more parts therefore its combinatorial network has more nodes and links which makes it a complex network. The major factor which makes it a complex network is the presence of multiple distinct topologies (Broekel, 2019). There can be a star-like topology (seating connected to the main body), line topology (tail, tube, and cockpit), matrix topology (cockpit control panel), etc. (Fig 3). As the airplane has a greater diversity of topologies than that of a table, it means more information is required to describe it. Therefore, the network of a plane is more complex than a table (Emmert-Streib & Dehmer, 2012). This implies that if a network has higher structural diversity (greater distinct topologies), it requires more information to describe it and more information indicates higher complexity. Broekel uses the same argument to differentiate between simple and complex networks which results in simple and complex technologies (Broekel, 2019).

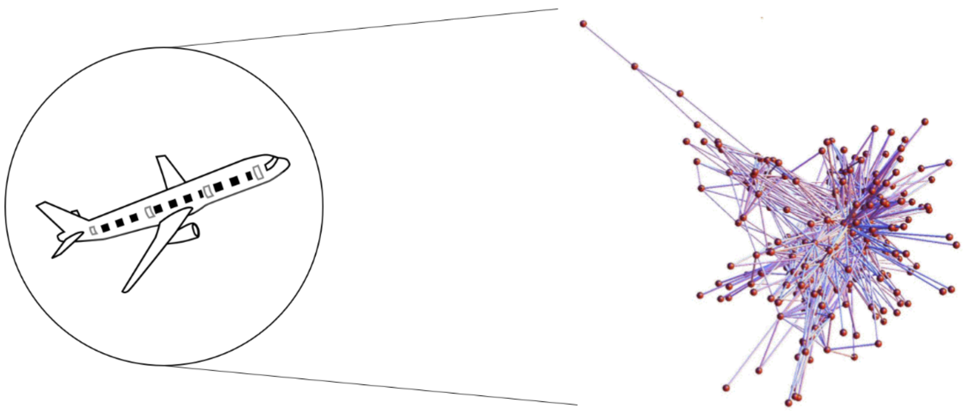

Figure 3: Complex network (the network diagram is hypothetical to demonstrate a complex network).

Emmert-Streib and Dehmer developed the network diversity score (NDS) to empirically measure the network diversity (Emmert-Streib & Dehmer, 2012). Broekel used this feature of NDS to approximate the structural diversity of 655 4-digit technology classes in Cooperative Patent Classes (CPC)[4]. The calculation is done according to the following steps[5]:

1. Define nodes 'V' (all 10-digit technology classes) for technology 'c'.
2. Based on these 10-digit classes, co-occurrence 'E' on patents to generate Network $G_{c,e}$ = (V, E) for technology 'c'.
3. Turn the network into binary:
    a. Positive links = 1
    b. Nonexistent links = 0

[4] The Cooperative Patent Classification (CPC) is an extension of the International Patent Classification and is jointly managed by the European Patent Office 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. Available from: https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/classification/cpc.html

[5] A summarized and modified version of structural diversity method is explained. For detailed method by Broekel kindly refer to (Broekel, 2019)

4. Calculate Individual Network Diversity (iNDS) according to Eq. 1 for a series of subnetworks ($\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}}$). The subnetworks are extracted from the main network ($\mathrm{G}_{\mathrm{c,e}}$) by using the Walktrap algorithm (w = 200, random sample S = 125)

$$iNDS\left(\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}}\right) = \frac{\alpha_{module} \times r_{graphlet}}{v_{module} \times v_{\lambda}} \ldots Eq. 1$$

$$\therefore \alpha_{module} = \frac{M}{V}$$

$$\therefore r_{graphlet} = \frac{N_{graphlet}(3)}{N_{graphlet}(4)}$$

$$\therefore v_{\lambda} = \frac{var(\Lambda(L))}{mean(\Lambda(L))}$$

$$\therefore v_{module} = \frac{var(m)}{mean(m)}$$

Where,

α_{module}	= share of nodules in network
M	= number of modules
V	= number of nodes
$r_{graphlet}$	= ratio of graphlets of sizes 3 and 4
v_{λ}	= variability of the network's Laplacian matrix
v_{module}	= variance of the module sizes

5. NDS is obtained by averaging the iNDS:

$$NDS\left(\left\{\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}} \middle| \mathrm{G}_{\mathrm{c,e}}\right\}\right) = \frac{1}{S} \sum_{\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}} \in \mathrm{G}_{\mathrm{c,e}}} iNDS\left(\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}}\right) \text{ ----}$$

6. NDS is finally transformed according to eq (reference) to get structural diversity, $\mathrm{TC_c}$. A higher value means a higher complexity level and vice versa.

$$TC_c = \log\left(\frac{1}{NDS\left(\left\{\mathrm{G}^{\mathrm{s}}_{\mathrm{c,e}} \middle| \mathrm{G}_{\mathrm{c,e}}\right\}\right)}\right)$$

To get a steady measure (Broekel, 2019), I used a three-year moving window, i.e., to calculate structural diversity TC_c in year 't', combinatorial networks from all patents in year 't' to 't-2' are used.

3.7.1 Calculating Regional Technological complexity in Norway

For the aggregation of regional technological complexity, there is no widely accepted approach in the literature. Generally, calculating the average technological complexity of regional patents will lead to suboptimal results (Broekel, 2019). To obtain the optimal outcome, technological complexity is calculated in percentiles of regional complexity distribution.

To calculate regional complexity in Norway,

1. Each patent CPC class was assigned the complexity score measured by structural diversity.
2. The patents were segregated regionally according to the residential address of the inventor to avoid the "headquarters effect" as most of the patents are filled from there even if it is invented somewhere else (subsidiary) (Broekel, 2019).

One limitation of considering the inventor's address is that if his/her place of residence and place of employment are in different regions, it can distort the spatial distribution of technological complexity by underestimating the technological complexity of high R&D regions and overestimating for surrounding regions (Deyle & Grupp, 2005). According to Statistics Norway, "Most people commute short distances and commuters had their workplace located in a municipality within the same economic region" (Statistisk sentralbyrå[6]). The spatial unit in this research is NUTS 3 regions (counties), therefore this limitation will not have a significant effect on the estimation.

3. An activity vector $A_{r,t}$ was created for region "**r"** at time "**t"** which contains a set of CPC classes that appear on inventor's patents.
4. All CPC classes in the vector set were arranged in descending order based on TC_c.
5. Finally, the regional complexity $RTC_{r,t}$ was calculated by taking an average of the subset of activities that belongs to the 10^{th} percentile[7] of complexity distribution.

The findings related to regional technological complexity calculated by this method are shown in *Table 1*. Almost 60% of the patents filed in Norway are from Oslo, Akershus, Trøndalg, and Rogaland. Finnmark,

[6] According to following article published by SSB: Population and Housing Census, commuting, 2001.

[7] There is no specific percentile to be chosen for calculation but highest 10^{th} percentile produces very robust results (Mewes & Broekel, 2020)

Sogn og Fjordane, Nordland and Hedmark, each account for less than 1% of total patents filled in Norway. Oslo files the highest number of patents and has the highest technological complexity whereas Finnmark files the lowest number of patents and has the lowest technological complexity. It is merely a coincidence that the region with the highest number of patents has the highest technological complexity and vice versa. It does not imply that the number of patents is directly proportional to technological complexity. This will be analyzed in the latter part of the analysis.

Table 1: Regional technological complexity of Norwegian regions, 1999-2015 (average)

Regions	**Technological Complexity (ln)**	**No. of patents**	**No. of patents percentage of total**
Oslo	12.239	127.77	21.41
Akershus	12.176	96	16.08
Trøndelag	11.832	66.77	11.19
Rogaland	11.533	65.22	10.93
Hordaland	12.032	41.66	6.98
Telemark	11.806	34.55	5.79
Buskerud	11.991	33.11	5.55
Agderfylkene	12.172	29.22	4.90
Vestfold	11.827	28.77	4.82
Møre og Romsdal	11.650	24.44	4.10
Østfold	11.886	18.44	3.09
Oppland	11.854	7.66	1.28
Troms	12.041	7.66	1.28
Hedmark	11.704	5.33	0.89
Nordland	11.444	4.77	0.80
Sogn og Fjordane	11.242	4.44	0.74
Finnmark	10.072	0.22	0.17

Source: Author's elaboration of calculation based on structural diversity method by (Broekel, 2019).

3.8 Regional R&D expenditures

To measure the universities' effort in regional development and innovation researchers have used many different indicators. One thing common in these indicators is that all of them are connected to R&D. Andresson and Ejermo (2004) used industry and universities' R&D man-hours as an indicator to measure the effect of universities on regional development, Piergiovanni and Santarelli (2001) preferred the salaries of R&D personnel, Autant-Bernard (2001) used the number of publications by the public sector and Piergiovanni et al. (1997) selected per capita R&D expenditure. The major reason for selecting a specific independent variable is the availability of data. In this research, R&D expenditures incurred by the private and public sector has been used as an indicator for private and universities' R&D effort. R&D expenditures give a holistic view of the effort including R&D personnel salaries, spending on equipment, lab facilities, and experimentation.

Table 2 presents the private and universities' R&D expenses as per different counties of Norway. Oslo and Trøndelag account for 54% of the total R&D expenditures incurred by universities. Less than 1% R&D expenses are conducted in Hedmark, Buskerud Finnmark and Sogn og Fjordane. One of the biggest reasons for this inequality is the demography of these regions.

The number of universities in the region also influences public fund distribution. Private R&D expenditures are concentrated in the same regions as public R&D expenditures with some exceptions. In Troms, private R&D expenses are only 1% whereas universities' R&D expenses are 7 %. Contrarily, in Buskerud, public R&D expenses are 8% whereas universities' R&D expenses are less than 1%. Figure 4 shows the regional complexity, patents, private R&D expenditures, and higher education R&D expenditure in Norway.

Table 2: Private and universities' R&D expenses (Source: NIFU).

Regions	Private R&D Expenditure (in million NOKs)	Private R&D Expenditure percent of total	Universities' R&D Expenditure (in million NOKs)	Universities' R&D Expenditure percent of total
Oslo	4404	25	6739	33
Trøndelag	1910	11	4293	21
Hordaland	1138	7	3097	15
Akershus	3037	17	2130	11
Troms	186	1	1444	7
Rogaland	1356	8	604	3
Agderfylkene	666	4	318	2
Østfold	445	3	316	2
Nordland	225	1	226	1
Møre og Romsdal	595	3	196	1
Oppland	355	2	183	1
Vestfold	808	5	154	1
Telemark	568	3	148	1
Hedmark	84	0	98	0
Buskerud	1370	8	80	0
Finnmark	16	0	79	0
Sogn og Fjordane	211	1	78	0
Total	17373.22	100	20184	100

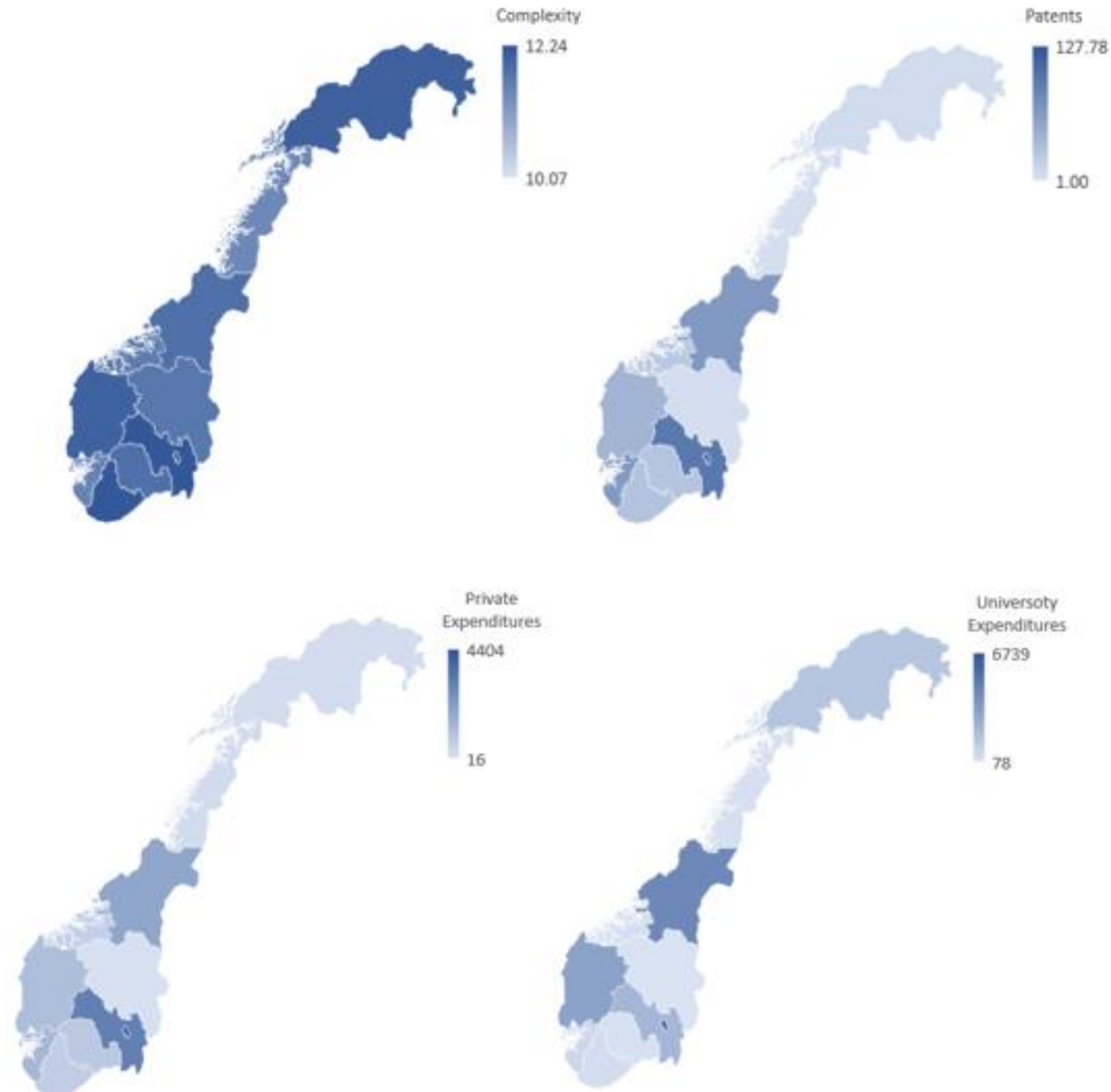

Figure 4: Regional complexity, patents, private R&D expenditures, and higher education R&D expenditure.

The inequality in the total number of regional patents, R&D expenditure, and per capita R&D expenditure is shown in Figure 5. We can see that 20 percent of the regions filed 60 percent of the patents. In the case of universities' R&D expenditure, 80 percent of the budget was used in 20 percent of the regions. However, it is vital to consider the demography, size, and location of the regions otherwise the interpretation can be misleading.

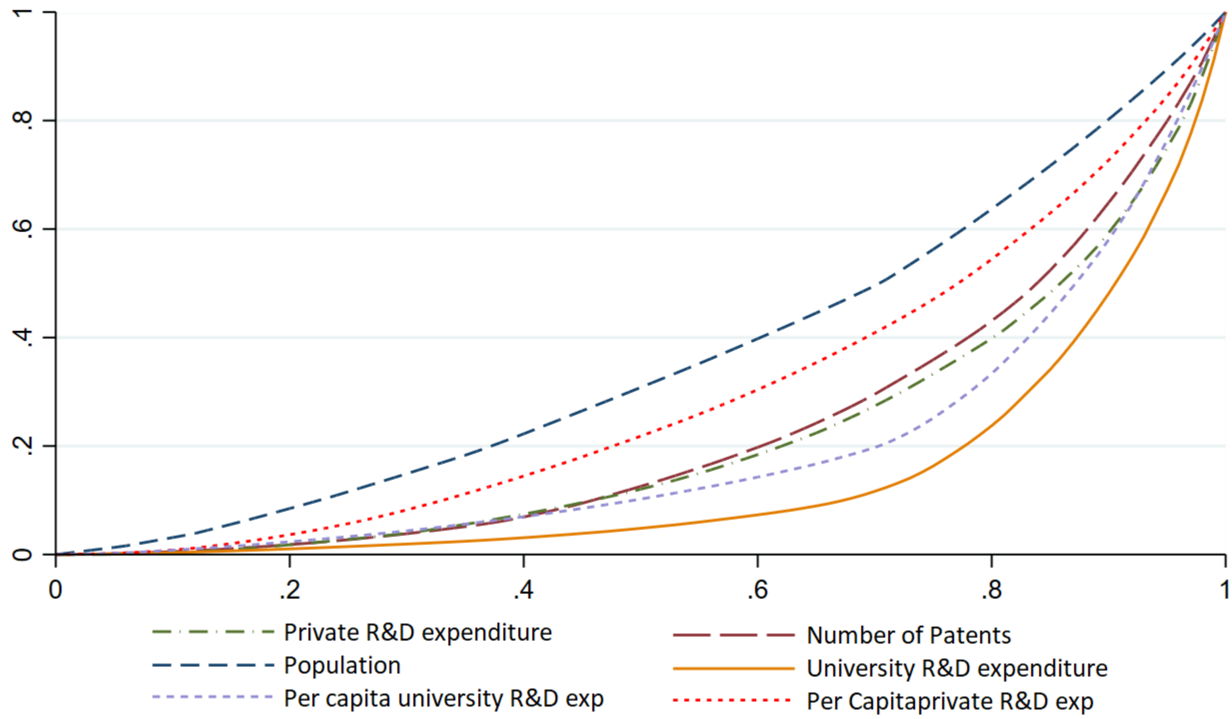

Figure 5: Lorenz curves of spatial inequality.

Norwegian universities research all academic disciplines i.e. engineering and technology, medical and health sciences, social sciences, natural sciences, etc. Research in certain disciplines has more commercial value than the others (Nelson, 1986). However, it is difficult to identify these specific disciplines that produce higher value for the industry, and much comprehensive research is required to precisely establish a connection between them (Fischer & Varga, 2003).

Technology complexity may be affected by the regional characteristics of a region. especially, the regional population and spillovers from surrounding regions. These two determinates were added to the model to control for regional influence. Using panel data of 17 years (1999 - 2015) gave the flexibility to control for the characteristics that do not fluctuate significantly in the specified period. The estimations from panel data created a single value for each region. This enabled to control for invariant variables which are not possible in a cross-study (Baltagi, 1995).

Population (pop) was used to control for the size of the regions. An alternate measure for regional size is the regional GDP. Both the variables show almost similar results therefore it is up to the preference of the researcher/s. I preferred population, as it has been used in many regional studies with panel data (Feldman, 1994; Jaffe, 1989).

Two-years lagged variables for private R&D expenditures ($PREX_{t-2}$) and universities' R&D expenditures ($UREX_{t-2}$) are used for OLS regression. Research shows that patent applications usually use R&D efforts from previous years (Fischer & Varga, 2003). The lag period between R&D activity and patent application is uncertain. Researchers have been using a lag period of 1 year to 4 years depending on the availability of data (Autant-Bernard, 2001; Fischer & Varga, 2003). Many researchers prefer to use the same years' data to see contemporary effects of input variables on output variables (Anselin et al., 1997; Jaffe, 1989) because companies try to file their patents during the early stages of R&D (Grilliches, 1990). In this research, panel data of 17 years has been used. Therefore, I have used a lag period of 2-years[8] in model (1) i.e. technological complexity from 1999-2015 and R&D expenditures from 1997-2013. In model (2), I have used contemporary data.

Model 1 vector:

$$logRTC_{it} = \alpha + \beta_7 logPREX_{it-2} + \beta_8 logUREX_{it-2} + \beta_3 logPOP_{it} + \beta_5 logSPREX_t + \beta_6 logSUREX_t + \beta_9 logNPAT_{it} + u_{it}$$

$i = 1,2,...,N \,;\, t = 1, 2, \ldots, T$

Model 2 vector:

$$logRTC_{it} = \alpha + \beta_1 logPREX_{it} + \beta_2 logUREX_{it} + \beta_3 logPOP_{it} + \beta_5 logSPREX_t + \beta_6 logSUREX_t + \beta_9 logNPAT_{it} + u_{it}$$

$i = 1,2,...,N \,;\, t = 1, 2, \ldots, T$

Where,

logRTC	= Average regional Technological complexity(in ln)
logPREX	= R&D expenditures conducted by private sector(NOK, million) (in ln)
logUREX	= Universities R&D expenditures in region(NOK, millions) (ln)
logPOP	= Regional population (in ln)
logRGDP	= Regional GDP (in ln)
logSPREX	= R&D expenditures conducted by the private sector in neighboring regions (in ln)

[8] Fischer and Verga (2003) used a lag of 2 years in their regional innovation study in Austria. Usually it is between 1 to 4 years, depending on the availability of data.

logSUREX	= Universities R&D expenditures of neighboring regions (common boarder) (in ln)
$logPREX_{it-2}$	= 2-year lagged private RnD expenditures (in ln)
$logUREX_{it-2}$	= 2-years lagged Universities Rend expenditures (in ln)
$logNPAT_{it}$	= number of regional patents (in ln)

In *Table 3*, the descriptive statistics of all the variables in the model are presented.

Table 3: Descriptive statistics

	Variables	Min	Max	Mean	Std. Dev.
1	logRTC	9.45	12.53	11.82	0.50
2	logPREX	1.10	8.73	6.18	1.44
3	logUREX	3.05	9.29	5.87	1.57
4	$logPREX_{it-2}$	1	8.71	6.00	1.53
5	$logUREX_{it-2}$	2.83	9.17	5.71	1.59
6	$logPREX_{s}$	4.06	9.86	7.83	1.17
7	$logUREX_{s}$	4.97	9.96	7.95	1.15
8	logPOP	-2.62	-0.43	-1.41	0.54
9	logNPAT	1	5.19	2.95	1.28
10	logRGDP	9.50	13.24	11.26	0.74

For estimation results were obtained by pooled OLS, fixed effects model, and the random effects model. The poolability test[9] was conducted to choose between pooled model and the fixed effect model. The null hypothesis i.e. intercepts and coefficients are constant across regions and time, was rejected. Therefore, pooled regression is not valid in this case. Breusch-Pagan was conducted to test the difference between pooled model and the random effect model. The null hypothesis i.e. $\sigma_{\mu}^{2} = 0$, was rejected[10]. Hence, we cannot pool the data.

The results of ordinary least square panel regression with fixed effects and random effects are shown in the next chapter (results and discussion). To select an appropriate model between the fixed effects and random effects model, I conducted the Sargan-Hansen test (test of overidentifying restrictions) and the Hausman test.

[9] Poolability test to i.e. intercept and slop coefficients are constant across regions and time.

$$F = \frac{(R_{UR}^2 - R_R^2)/J}{(1-R_{UR}^2)/(n-k)}$$

[10] Breusch-Pagan test checks if the variance of random effect is zero (H_o).

The Hausman statistics as shown in the following chapter (results and discussion) which tests the relation between individual effects and independent variables. After testing, the null hypothesis[11] is rejected it means the estimators from the random effect model are not consistent and a fixed effect model should be preferred. If it is not rejected, it could be interpreted that the estimators are consistent and random effects model is more suitable.

As I have used fixed effect model, therefore, all the variables are in logarithmic form. The results will show the elasticity of the dependent variable with respect to the independent variable.

[11] Hausman Test:

H0= The individual effects are not correlated to explanatory variable.

H1= The individual effects are correlated to explanatory variable.

4 Results and Discussion

In this chapter, the main findings of the estimations are presented in coexistence with the discussion. *Table 4* shows the Pearson's correlation between the variables under examination. There is a strong positive correlation between private and university contemptuous (same year) R&D expenditures and two-years lagged R&D expenditures i.e. 0.96 and 0.99 respectively. This indicates that if both indicators are used in the model there will be multicollinearity. Regional technological complexity has a moderate correlation with private R&D expenditures and a relatively lower correlation with universities' R&D expenditures. Universities mostly conduct basic research which works as a building block for private research therefore, it creates an indirect impact on regional development (Fritsch & Slavtchev, 2007).

Table 4: Correlations

	Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	LOGRTC	1.00									
2	LOGPREX	0.47	1.00								
3	LOGUREX	0.39	0.61	1.00							
4	$LOGPREX_{it-2}$	0.56	0.96	0.61	1.00						
5	$LOGUREX_{it-2}$	0.38	0.60	0.99	0.60	1.00					
6	LOGSPREX	0.25	0.38	-0.14"	0.39	-0.14"	1.00				
7	LOGSUREX	-0.03"	0.08"	-0.41	0.10	-0.41	0.80	1.00			
8	LOGPOP	0.40	0.82	0.73	0.81	0.72	0.18"	-0.10"	1.00		
9	LOGNPAT	0.39	0.74	0.49	0.74	0.47	0.14	-0.01"	0.73	1.00	
10	LOGRGDP	0.36	0.66	0.64	0.67	0.64	0.23	-0.07"	0.73	0.47	1.00

Significance level: " indicates $p > 0.05$ (insignificant). All remaining correlation coefficients are significant at $p < 0.001$.

The correlation between technological complexity and the number of patents is 0.39. In the past, researchers relied on the number of patents to examine regional development (Andersson & Ejermo, 2004; Anselin et al., 1997; Barrio-Castro & García-Quevedo, 2005; Fischer & Varga, 2003; Jaffe, 1989) but the correlation coefficient shows that there is not a strong relationship between regional technological complexity and the regional number of patents. Figure 4 shows that the regions with the lower number of patents can have the same technological complexity as the regions with the higher number of patents. To put that in perspective, we can see that the region with the highest number of patents i.e. 178 has lower technological complexity than some of the regions which have less than 50 patents. The regional population has a significantly strong correlation with private and universities' R&D expenditures.

Table 5 presents two models which I have used to estimate or results. In model (1), a two years-lag was assumed for the R&D expenditures whereas, in the model (2), contemporary data was used. In our estimations, the null hypothesis of the Hausman test was rejected in both models. It means that in both models, the individual effects are correlated to the explanatory variables. Therefore, the estimates of random effect models are not consistent.

Table 5: OLS panel regression with fixed effects and random effects

	1		2	
	Fixed Effects	**Random Effects**	**Fixed Effects**	**Random Effects**
$logPREX_{it-2}$	0.468***	0.43***		
	[0.303; 0.633]	[0.29; 0.57]		
$logUREX_{it-2}$	-0.045	0.038		
	[-0.283; 0.192]	[-0.065; 0.141]		
logPOP	-2.707	-0.888	-3.527	-0.449
	[-4.54; -0.875]	[-1.38; -0.397]	[-5.578; -1.477]	[-0.994; 0.096]
logSPREX	0.367**	0.28***	0.54**	0.408***
	[0.033; 0.703]	[0.063; 0.497]	[0.163; 0.918]	[0.179; 0.636]
logSUREX	-0.039	-0.241	0.275	-0.206
	[-0.485; 0.407]	[-0.426; -0.055]	[-0.215; 0.764]	[-0.396; -0.015]
logPREX			0.024	0.073
			[-0.205; 0.253]	[-0.1; 0.245]
logUREX			-0.042	0.135
			[-0.319; 0.235]	[0.027; 0.243]
$logNPAT_{it}$	0.093**	0.075*	0.089*	0.099*
	[0.005; 0.181]	[-0.005; 0.155]	[-0.011; 0.188]	[0.011; 0.187]
Intercept	2.631	7.191***	0.388	8.041***
	[-1.476; 6.737]	[5.607; 8.775]	[-4.228; 5.005]	[6.238; 9.845]
R_squared	0.405	0.349	0.25	0.31
Observations	146	146	146	146
Regions	14	14	17	17
Hausman	15.26**	15.26**	11.67**	11.67**

Significance level: * = $p < 0.001$, ** = $p < 0.05$ and *** = $p < 0.001$

95% confidence interval in parenthesis

The R-squared for model (1) is 0.405 which is adequately decent if we consider the empirical approach of the model. Coefficients from the Hausman test are statistically significant and are shown at the bottom of the table. The number of observations has dropped by seven due to missing values but it is consistent in all estimations.

4.1 Private and universities' R&D knowledge spillovers

The results of model (1) show that the parameters related to private R&D expenditures are positive and statistically significant whereas the parameters associated with universities' R&D expenditures are not statistically different from zero. The elasticity of private R&D expenditure($logPREX_{it-2}$) is 0.47. Hence, if $logPREX_{it-2}$ increases by one percent, the regional technological complexity will increase by 0.47 percent while keeping the other things constant.

The regressors for R&D expenditures, in the model (2), are using contemporary data to observe its immediate impact on regional technological complexity. Private R&D expenditures and universities' R&D expenditures both are statistically insignificant. The remaining control variables have similar results as in model (1), which is an indication of robustness.

The results show that private R&D expenditures have a significant positive relation with regional technological complexity (Fig 6) whereas universities' R&D is not statistically different from zero. This can be explained by the basic nature of research conducted by universities that work as a building block for private researchers. The results are in line with previous studies finding the impact of R&D on regional development (Andersson & Ejermo, 2004; Autant-Bernard, 2001; Jaffe, 1989; Ronde & Hussler, 2005). Fisher and Varga found a positive significant elasticity between academic research effect and regional innovation but the magnitude of this effect was much smaller than the private R&D. However, in all these studies the estimator for regional innovation was the number of patents.

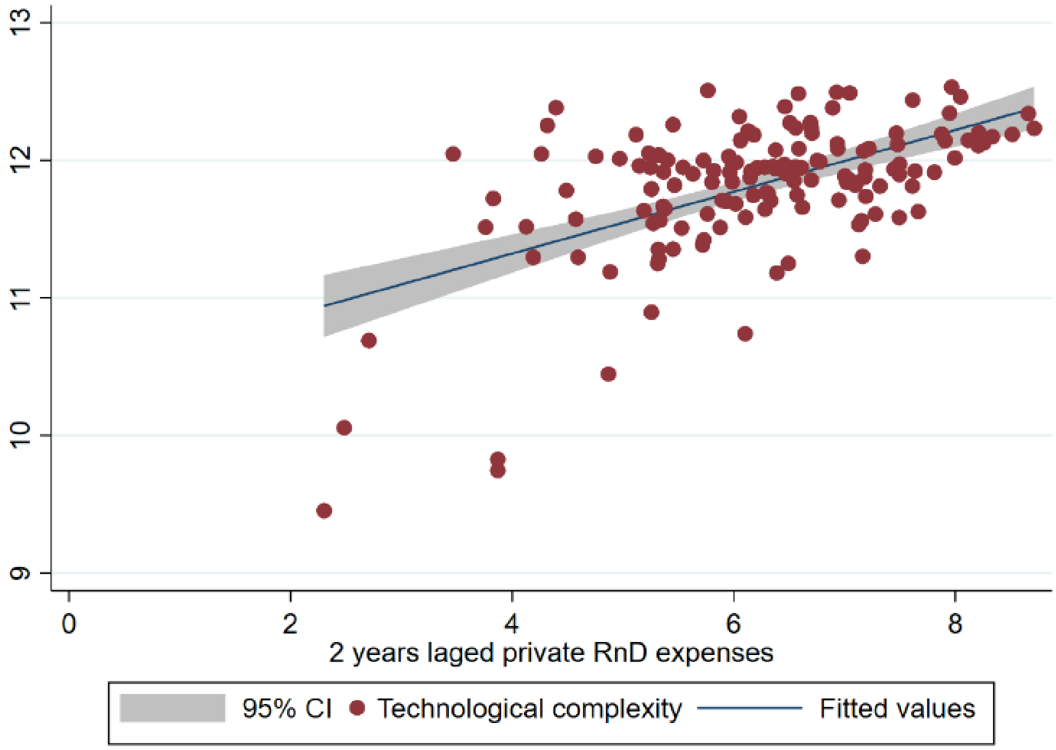

Figure 6: Private R&D scatter plot with regression line.

4.2 Spillovers from surrounding regions

Private R&D expenditure in surrounding regions has a positive impact on the technological complexity whereas universities' R&D expenditures in surrounding regions are statistically insignificant. Academic knowledge is believed to be spatially bound due to its tacit nature (Polanyi, 1967). But if there are proper channels and frequent interactions between different actors, the spillovers become more frequent (B. Audretsch, 1998). Our estimation shows that the elasticity of neighboring regions' private R&D expenditure(logSPREX) is 0.37. Therefore, if logSPREX increases by one percent, the regional technological complexity will increase by 0.37 percent while keeping the other things constant.

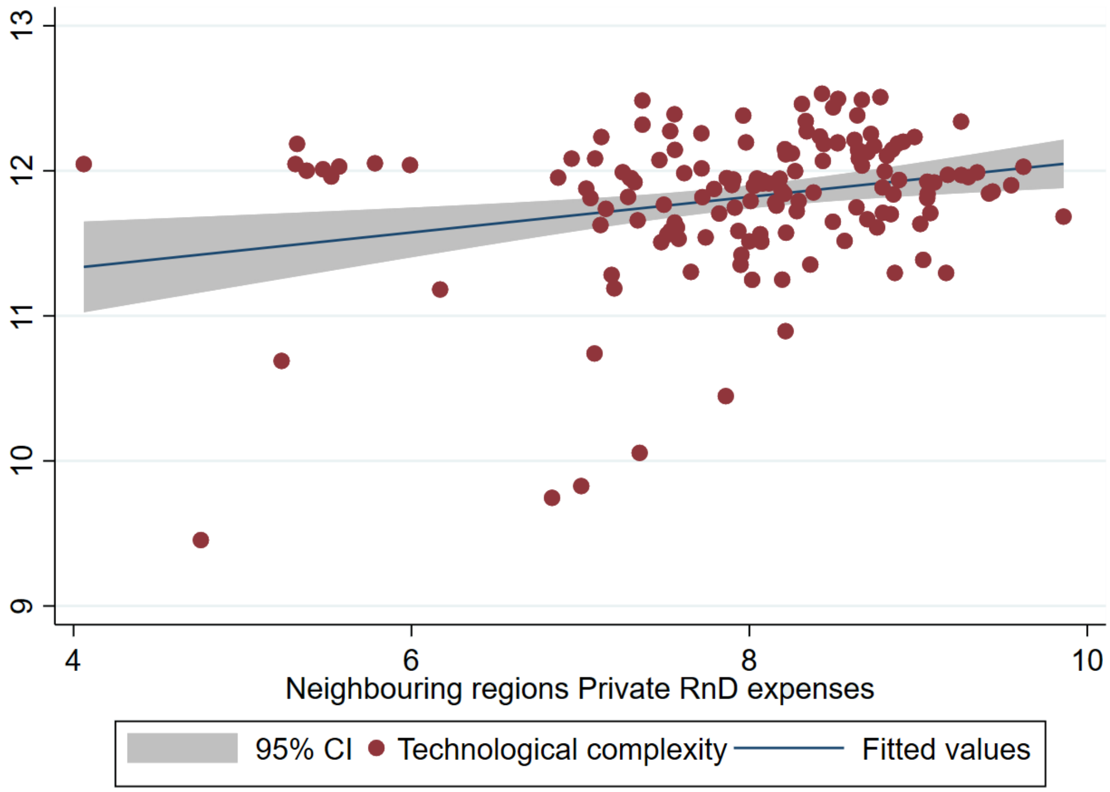

Figure 7: Neighboring regions Private R&D scatter plot with regression line.

In model (2), the results are similar with minor changes in the parameter. The results are in line with previous studies conducted in Germany, Austria, France, and Sweden (Andersson & Ejermo, 2004; Fischer & Varga, 2003; Fritsch & Slavtchev, 2007; Ronde & Hussler, 2005). However, it is important to establish intentional channels to maximize this effect. Otherwise, the positive effect of geographical innovation is minimized (Ronde & Hussler, 2005).

4.3 Regional patent volume and population

According to the estimation, the population does not have a significant impact on regional technological complexity. This effect can also be observed in Figure 5, where we can see that the regions with higher population density have comparable or in some cases lower regional technological complexity than the lesser populated areas. Therefore, we can predict that the regional complexity does not scale with the population as found by Barrio et al. in Spain’s NUTS 2 regions (Barrio-Castro & García-Quevedo, 2005). Whereas, Fritsch et al. concluded a significant scale effect of the regional population in German NUTS 3 regions (Fritsch & Slavtchev, 2007).

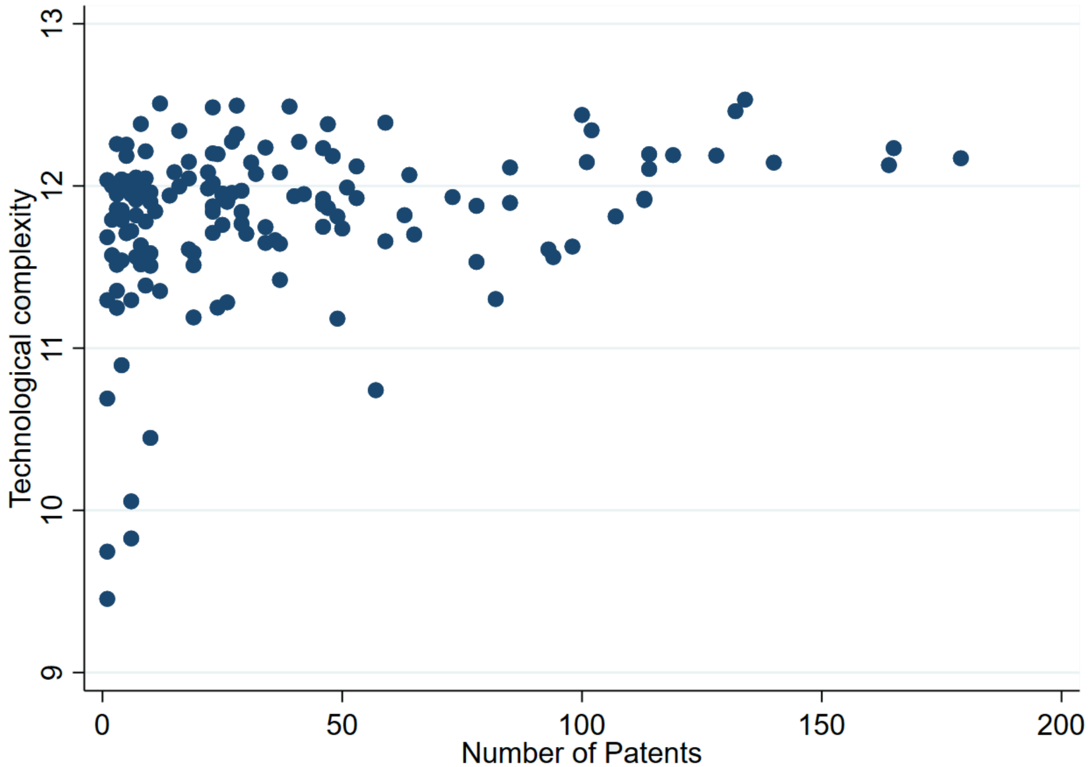

Figure 8: Correlation between technological complexity and number of patents.

The number of regional patents has a positive parameter and is statistically different from zero. This shows that the number of patents has a positive relation with technological complexity. Consequently, regions with a higher number of patents will have higher technological complexity. As Joseph Stalin famously said, "Quantity has a quality all its own". Although the magnitude of this effect is diminutive compare to private R&D. If the number of patents (lognpat) increases by 1 percent, regional technological complexity increases by 0.0963 percent. Broekel had similar results while testing the structural diversity method (Broekel, 2019). However, regional patents and technological complexity are not interchangeable measures. Regions can have a higher number of patents but relatively lower technological complexity and vice versa as seen in Figure 8.

To summarize, the results from our statistical estimation show that the R&D effort made by the firms has a significant impact on regional technological which results in sustainable economic growth (Mewes & Broekel, 2020). The coefficient values are consistent in both the fixed effects model and random effects model. The significance of model (1) suggests that the R&D effort has a lagged effect on technological complexity. As per the definition of complexity, it is a combination or recombination of existing knowledge therefore it takes time to reach a specific level where it full fills all the requirements of a complex technology described in chapter 2 (literature review and conceptual framework). The analysis has not found a direct relation of HEIs[12] with technological complexity. This has been observed in several previous studies (Andersson & Ejermo, 2004; Autant-Bernard, 2001; Jaffe, 1989; Ronde & Hussler, 2005). However, this is the first time I am using technological complexity instead of the number of patents to measure the economic potential of regions. Therefore, while comparison with existing studies the differences in the empirical approach should be noted. Due to the nonprofit orientation of universities, they are seldom interested in commercializing their R&D efforts. Rather they produce basic knowledge which is a necessary input to further the private R&D activities (Jaffe, 1989).

For future analysis in this domain, I recommend additional covariates for regional characteristics that differentiate between regional labor force, education level, type of local industry, service vs manufacturing industry, etc. The main limitation in such empirical analysis is the issue of the availability of data and its credibility. More studies in this domain are recommended to validate the method and to test the replicability of the results.

[12] HEIs and universities have been used interchangeably in this study. (add this to first time we used HIS)

5 Conclusion and future implications

Researchers have been trying to find the indicators of regional innovation and development but there has always been debate regarding the method and unit of measurement. In a recent set of studies, Broekel found that the regions which produce complex technologies observe higher economic growth. This growth is sustainable and long-term(Broekel, 2019; Mewes & Broekel, 2020). Technological complexity measures regional development from a quality point of view instead of quantity.

The purpose of this study was to find direct or indirect relation between universities' R&D output and regional technological complexity. As universities are the basic source of knowledge, their impact on regional technological complexity helps to better understand R&D penetration and its dimension.
For the empirical analysis, NUTS 3 regions of Norway were considered as a spatial unit. Sixteen years of panel data were used to conduct a thorough empirical analysis. Technological complexity was calculated using the structural diversity of technologies according to their network diversity score.

Our findings suggest that private R&D effort has a significant impact on technological complexity whereas universities' R&D expenditures are not statistically associated. These findings can act as basic knowledge for policymakers, enabling them to recognize the best R&D practitioners for benchmarking. The method employed in this study and the results can also help the research and development departments of governments to develop approaches for strengthening regional and national innovation performance by highlighting the lesser-studied and value-creating role of academic institutions. Moreover, the findings add to the knowledge on facilitators in public-private innovation.

The situation in Norway is shared by other countries with growing regional technological complexity. Accordingly, there is a need to enhance commitment to producing high-quality research that will enable the creation of complex regional technology.

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I. Appendix

Stata outputs,

Description:

```
  obs:           153
 vars:            36                          6 Jun 2021 15:59
-------------------------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------
obsn            int     %8.0g                 Observation Number
cty             long    %16.0g     cty        County
cno             str5    %9s                   Registration code
year            int     %8.0g                 Year
cmp             float   %9.0g                 Technological complexity
npat            int     %8.0g                 Number of Patents
prex            int     %8.0g                 Private RnD expences
unex            int     %8.0g                 University RnD expenses
lpex            int     %8.0g                 2 years laged private RnD expenses
luex            int     %8.0g                 2 years laged University RnD expenses
bpex            int     %8.0g                 Neighbouring regions Private RnD expenses
buex            int     %8.0g                 Neighbouring regions University RnD expenses
pop             float   %9.0g                 Population
rgdp            float   %9.0g                 Regional GDP
cgdp            float   %9.0g                 Regional per capita GDP
cpex            float   %9.0g                 Per capita Private RnD expenses
cuex            float   %9.0g                 Per capita University RnD expenses
rpri            int     %8.0g                 Number of researchers in private sector
runi            int     %8.0g                 Number of researchers in Universities
logprex         float   %9.0g
logunex         float   %9.0g
loglpex         float   %9.0g
logluex         float   %9.0g
logbpex         float   %9.0g                 Neighbouring regions Private RnD expenses
logbuex         float   %9.0g
logpop          float   %9.0g                 Population
lognpat         float   %9.0g                 Number of Patents
logrgdp         float   %9.0g
logprex_loglpex float   %9.0g
logunex_logluex float   %9.0g
_est_fe         byte    %8.0g                 esample() from estimates store
_est_re         byte    %8.0g                 esample() from estimates store
e               float   %9.0g                 Residuals
e2              float   %9.0g
yhat            float   %9.0g                 Linear prediction
yhat2           float   %9.0g
-------------------------------------------------------------------------------------------------
Sorted by: cty   year
```

Summary:

Variable	Obs	Mean	Std. Dev.	Min	Max
obsn	153	77	44.3114	1	153
cty	153	9	4.915068	1	17
cno	0				
year	153	2007	5.180937	1999	2015
cmp	146	11.81527	.4995047	9.454325	12.53226
npat	146	36.74658	39.43896	1	179
prex	153	1018.19	1249.862	3	6189
unex	153	1186.569	1990.953	21	10773
lpex	153	888.4183	1104.495	1	6065
luex	153	1038.915	1756.419	17	9585
bpex	153	3997.405	3331.782	58	19130
buex	153	4771.699	4392.654	144	21230
pop	153	.2792493	.1408619	.072492	.647676
rgdp	153	103366.6	91807.37	13328.8	560972
cgdp	153	.3351986	.1205409	.1729284	.8661306
cpex	153	.0028651	.0022141	.000041	.010121
cuex	153	.0030811	.0040157	.000088	.016633
rpri	153	613.0327	766.8452	0	3473
runi	153	813.1634	1323.283	20	6148
logprex	153	6.176951	1.444004	1.098612	8.730529
logunex	153	5.870004	1.568	3.044523	9.284799
loglpex	153	5.996184	1.534183	0	8.71029
logluex	153	5.711359	1.590328	2.833213	9.167954
logbpex	153	7.831572	1.165343	4.060443	9.859013
logbuex	153	7.952706	1.153533	4.969813	9.963171
logpop	153	-1.409008	.5361424	-2.624279	-.4343647
lognpat	146	2.94996	1.281871	0	5.187386
logrgdp	153	11.25807	.7415846	9.497683	13.23743
logprex_lo~x	153	12.17314	2.947116	2.302585	17.3887
logunex_lo~x	153	11.58136	3.154812	5.934895	18.45275
_est_fe	153	.9542484	.2096322	0	1
_est_re	153	.9542484	.2096322	0	1
e	146	2.48e-09	1.09575	-3.127955	1.673563
e2	146	1.192445	1.562417	.000393	9.784102
yhat	146	11.81527	.9329443	10.24098	13.83096
yhat2	146	140.465	22.46946	104.8777	191.2953

Missing data:

Variable	Obs=.	Obs>.	Obs<.	Obs<. Unique values	Min	Max
cmp	7		146	142	9.454325	12.53226
npat	7		146	68	1	179
lognpat	7		146	68	0	5.187386
e	7		146	146	-3.127955	1.673563
e2	7		146	146	.000393	9.784102
yhat	7		146	146	10.24098	13.83096
yhat2	7		146	146	104.8777	191.2953