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Taxation and Innovation

An empirical study of the impact of corporate taxation on innovation in Europe

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Abstract

This master's thesis aims to study the empirical relationship between taxation and innovation in Europe. To analyse this relationship, we propose the following research question: How do corporate income tax rates impact the number of patent applications in Europe?

In order to investigate this research question, we construct a unique panel dataset from OECD patent and taxation data. The panel includes observations from 26 European OECD countries in the time period 1981 to 2017. The study is based on a quantitative analysis with a deductive and explanatory research approach. We develop an econometric model using fixed effects estimation which we use to analyse a two-sided hypothesis.

The analyses suggest that an increase in corporate taxation has historically led to decreased innovation. We do not find statistically sufficient evidence to conclude this effect for the two time periods 1981 to 1989 and 1990 to 1999, but we find a significant effect in the time period of 2000 to 2010.

Contradictorily to the existing literature, we also find evidence that suggests that the historical effect that is observed until 2010 flips in the time period from 2010 to 2017. We discuss whether this change might be a sign of a turning trend in the impact of corporate taxation on innovation in Europe. Because multiple European countries recently have introduced special tax policies, we argue that the introduction of patent boxes might be an explanation.

These findings are an exciting turn of events. However, further research is necessary to fully conclude or disprove the latter finding of a regime change in corporate taxation of innovation.

Our results contribute to the existing literature by studying the impact of corporate taxation on innovation in a larger sample of European OECD countries and over a longer time frame than previous research. We also contribute with new insight related to a potential regime change.

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After five incredible years together at Norwegian School of Economics, we are pleased to mark the finale of our master's degree. Together we have learned from each other, challenged each other, and motivated each other. The development of this master thesis has been inspiring yet challenging. In particular, collecting, structuring, and analysing large amounts of data material has been demanding. Moreover, this work has given us the opportunity to study an important topic which we did not have much knowledge of beforehand. As a result, we have acquired valuable insights which we hope to pass on to others through this master thesis.

We would like to thank our supervisor, Floris T. Zoutman, for his encouragement, advice, and constructive discussions. We would also like to thank Steffen Juranek. Without the advice and support from Zoutman and Juranek, this master thesis would not have come together. We would also like to thank our family and friends for their inspiration and motivation throughout this semester.

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1. Introduction

"On the one hand, taxation is an essential attribute of commercial society [...] on the other hand, it is almost inevitably [...] an injury to the productive process" (Schumpeter, 1942, p. 198).

1.1 Background

Economies are complex systems developed from the actions and activities of many participants. This complexity makes it difficult, but also fascinating to understand the determinants of economic growth. While there are many determinants of economic growth, innovation is amongst the most prominent.

Innovation contributes to increased productivity that triggers positive effects on economic growth (European Central Bank, 2017). Taxes are typically designed for redistribution of wealth and gathering of public revenues, but not necessary with innovation in mind. Yet taxes reduce the expected net returns to innovation inputs and can lead to less innovation as an unwanted by-product (Akcigit & Stantcheva, 2020). It is apparent why policymakers must understand how taxation policies impact innovation.

While taxation is essential for the modern welfare state, economists debate whether taxation impacts innovation and whether lower taxation can stimulate innovation and hence economic growth. If lower taxes do not stimulate innovation, reduced taxation can distort government budget balances and increase inequality across Europe.

Furthermore, many European countries have made changes to their corporate taxation policies throughout the last decades. Countries such as Denmark, Great Britain, and France have all adjusted their corporate taxation rates, but we currently know little about how the tax changes have impacted innovation. In this study, we contribute to this debate by analysing how corporate taxation impact innovation in Europe.

1.2 Purpose

In a recent research article, Akcigit, Grigsby, Nicholas and Stantcheva (2018) study innovation in the U.S. by exploiting patent data to show that increased corporate income tax rates reduce the number of patent applications. The purpose of this master thesis is to study whether a similar relationship between innovation and corporate taxation exists in Europe. In other words, we analyse whether corporate taxation impacts the number of patent applications in Europe.

In order to achieve this purpose, this thesis specifically aims to answer the following research question:

How do corporate income tax rates impact the number of patent applications in Europe?

The study is based on a quantitative analysis with a deductive research approach. This means that we develop an econometric model based on fixed effects and draw up a two-sided hypothesis. The objective is to analyse whether we can reject the null hypothesis.

We exploit the universe of patent applications to the European Patent Office (EPO) and country-specific corporate tax rates in Europe. Patent data is retrieved from the OECD REGPAT database while taxation data is retrieved from the OECD tax database. We create a unique panel dataset of number of patent applications and corporate income tax rates across 26 European OECD countries in the time period between 1981 to 2017.

This study builds upon the existing literature on the empirical relationship between innovation and corporate taxation. Amongst European studies, Ernst and Spengel (2011) and Karkinsky and Riedel (2009) find negative impacts of corporate taxation on the number of patent applications in Europe. We contribute to this literature by studying this impact in a larger sample of European OECD countries over a longer time frame.

The outcome is particularly relevant for policy makers since we argue that innovation is an important driver of economic growth. If higher corporate tax rates indeed reduce innovation, this provides an incentive for countries not to increase their corporate tax rates.

1.3 Structure

This study is divided into eight chapters. Chapter 2 provides an overview of existing literature on the empirical relationship between innovation and taxation. Here, we highlight several research papers that have studied similar topics. Chapter 3 describes the methodology. Here, we develop the econometric model and hypothesis. Chapter 4 provides descriptive statistics which are helpful in understanding the structure of the underlying data. This chapter also presents and discusses the regression analyses. Chapter 5 discusses the results, limitations of the study and topics for further research. Chapter 6 presents a conclusion in the form of an answer to the research question. Chapter 7 and 8 respectively present bibliography and appendix.

2. Theory

This chapter provides overview of literature on the relationship between innovation and taxation. First, we discuss innovation and the role of patents. Next, we discuss corporate taxation. Last, we review existing literature on the empirical relationship between innovation and taxation.

2.1 Innovation

The European Central Bank (2017) describes why innovation is essential to the economy: “Simply put, innovation can lead to higher productivity, meaning that the same input generates a greater output. As productivity rises, more goods and services are produced – in other words, the economy grows”.

The impact of innovation on economic growth has been discussed by many great economists. In the paper *Endogenous Technological Change*, Romer (1990) states that technological change lies at the heart of economic growth. Romer builds on the neoclassical model introduced by Solow (1956), adding technological change to create an endogenous explanation of economic growth.

The impact of innovation on economic growth has also been empirically documented, for example in *The Rise of American Ingenuity: Innovation and Inventors of the Golden Age* by Akcigit, Grigsby and Nicholas (2017). In this paper, the researchers conclude that states in the U.S. with the most innovations witnessed the fastest growth between 1900 and 2000.

Given that the relationship between innovation and economic growth is well-established, we move on to study the concept of innovation.

A fascinating perspective on innovation originates from the economist Joseph Schumpeter. In his book Capitalism, Socialism, and Democracy (1942), Schumpeter introduces the expression *Creative Destruction*. He explains:

> “The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, ... [This process] incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism.” (p. 83).

Schumpeter (1942) describes how innovation can be a developing and revolutionising process which drives the economy forward. Creative destruction establishes the foundation for how we understand innovation today. However, there are numerous definitions of innovation.

In a research paper, Baregheh, Rowley and Sambrook (2009) find approximately 60 various definitions of innovation. As a result of their findings, the authors recommended the following definition: “Innovation is the multi-stage process whereby organizations transform ideas into new or improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace”.

Furthermore, we highlight two definitions from the European Central Bank, and OECD and Eurostat. The European Central Bank (2017) states: “Innovation describes the development and application of ideas and technologies that improve goods and services or make their production more efficient”. Likewise, OECD and Eurostat (2018) states: “An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit’s previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)” (p. 32).

In addition, OECD and Eurostat (2018, p. 34) defines two types of innovation: Product innovation and process innovation. A product innovation is a new or improved good or service that differs significantly from the firm’s previous goods or services and that has been introduced in the market. A business process innovation is a new or improved business process for one or more business functions that differs significantly from the firm’s previous business processes and that has been brought into use by the firm.

Building on how innovation is defined in the literature, it is necessary to explain how to measure it. Next, we discuss the role of patents and why patents are suitable for measuring innovation.

2.1.1 Patents

“A patent is an exclusive right granted for an invention, which is a product or a process that provides, in general, a new way of doing something, or offers a new technical solution to a problem” (World Intellectual Property Organisation (WIPO), n.d.A). As we can observe from this definition, there are many similarities to how we understand innovation. WIPO (n.d.a) describes that patents provides the right to prevent others from commercially exploiting the patented invention which implies that the invention cannot be commercially made, used, distributed, imported, or sold by others without consent.

Haus and Juranek (2014) describe that the purpose of the patent system is to encourage innovation. By allowing for time-restricted monopoly, inventors are able to generate profits. The underlying assumption is that innovation generates long-term social welfare which compensates for the short-term welfare loss of monopoly. The time-restricted monopoly refers to that granted patents are protected for 20 years from the filing date of the application (World Intellectual Property Organisation, n.d.a).

In order to receive patent protection, the inventor must file a public patent application. Each patent application includes information about the patent inventor and patent applicant, including their respective host country. The host country of the patent inventor shows the location where the patented innovation was created, while the patent applicant shows the location of the legal owner subject to taxation (Böhm, Karkinsky, Knoll and Riedel, 2015).

A patent is a territorial right, and the exclusive rights are only applicable in the country or region in which a patent has been filed and granted (World Intellectual Property Organisation, n.d.a). However, the Patent Cooperation Treaty (PCT) enables inventors to seek patent protection for an invention simultaneously in multiple countries by filing an international patent application (World Intellectual Property Organisation, n.d.b). An example is the European Patent Office (EPO), which provides inventors patent protection in up to 44 European countries (European Patent Office, n.d.) and the opportunity to file for protection in several other countries through the PCT.

In the literature, we find that patent data is the dominating measure of innovation. Several research papers use patent data for measuring innovation, including Akcigit et al. (2018), Mukherjeea, Singhb, and Žaldokas (2017), Böhm, Karkinsky, Knoll, and Riedel (2015), Atanassov and Liu (2015), Ernst, Richter, and Riedel (2014), Ernst and Spengel (2011) and Karkinsky and Riedel (2009).

In a research review paper, Akcigit and Stantcheva (2020) argue that patents are by nature highly correlated to the quantity of innovation. Ernst and Spengel (2011) also that patents often are used as indicator for innovative activity and that patents and research & development (R&D) are closely related. Additionally, several empirical studies have found strong relationships between patents and R&D, including Griliches (1990), Hall, Griliches and Hausman (1986) and Bosch, Lederman, and Maloney (2005).

Although patents appear to be the dominating measure of innovation, we also find researchers who use other output measures, such as new products introduced in markets. We also find researchers who use other output measures, such as new products introduced in markets. We also find some researchers who use various input measures, such as R&D spending, discussed in Dechezleprêtre, Martin & Bassi (2016).

However, the use of such measures does not appear to be widespread. The use of patents as a measure of innovation appears to be the established practice. Going forward, we therefore use patent applications as our measure of innovation in Europe.

2.2 Taxation

Taxation is essential to the redistribution of wealth and gathering of public revenues in the modern welfare state. Tax revenues pay for public services such as infrastructure, courts of justice, national defence, health care and education (Smith, 2015).

In recent decades, tax policies related to innovation have gained interest from governments in many European countries (Ernst, et al., 2014, p. 694). Accordingly, numerous European countries have made changes to their general tax policies. General tax policies refer to standard personal and corporate income taxation (Akcigit and Stantcheva, 2020, p. 3).

We also observe increase in the use of specific tax policies. Specific tax policies refer to tax policies targeted at innovation (Akcigit & Stantcheva, 2020, p. 3). An example of this is patent boxes. A patent box is a tax regime that applies a lower corporate tax rate on income from patent ownership (Gaessler, Hall and Harhoff, 2018).

According to Ernst et al. (2014), most countries tax patent income at the same tax rate as the corporate income tax rate (p. 700). In this study, we mainly focus on general tax policies in the form of corporate income tax rates.

2.2.1 Corporate income tax

A statutory corporate income tax (CIT) rate represents the tax rate faced by a firm in a jurisdiction (OECD, 2020, p. 9). The statutory CIT rate measures the marginal tax that must be paid on an additional unit of income (OECD, 2020, p. 9). Because CIT rates are present in every European OECD country, CIT rates can be applied to compare corporate taxation both across jurisdictions and over time. In the report *Corporate Tax Statistics*, OECD (2020, p. 9) describe how the statutory CIT rates have declined worldwide the past decades.

OECD (2021b) describes four ways to calculate the CIT rate: Central government CIT rate, adjusted central government CIT rate, sub-central government CIT rate and combined CIT rate. Though this is somewhat technical, it is important for the forthcoming analysis and discussion.

The central government CIT rate shows the basic central government statutory (flat or top marginal) CIT rate, measured gross of a deduction (if any) for sub-central tax (OECD, 2021b).

The adjusted central government CIT rate shows the basic central government statutory CIT rate (inclusive of surtax (if any)), adjusted (if applicable) to show the net rate where the central government provides a deduction in respect of sub-central income tax (OECD, 2021b).

The sub-central government CIT rate shows the basic sub-central (combined state/regional and local) statutory CIT rate, inclusive of sub-central surtax (if any) (OECD, 2021b).

The combined CIT rate shows the basic combined central and sub-central (statutory) CIT rate given by the adjusted central government rate plus the sub-central rate (OECD, 2021b).

2.3 Empirical relationship between innovation and taxation

Finally, we review literature on the empirical relationship between innovation and taxation and present the most interesting findings. In the review, we concentrate on research papers which study the impact of corporate taxation on patent application in the U.S. and Europe. The chapter are grouped by research paper.

2.3.1 Taxation and Innovation in the 20th Century

In the working paper *Taxation and Innovation in the 20th Century*, Akcigit et al. (2018) study the impact of personal and corporate taxation on innovation in the U.S. over the twentieth century.

By utilising four comprehensive datasets, the researchers are able to study inventors and firms engaged in inventive activity between 1940 to 2000. The researchers are also adjusting for numerous changes in the U.S. tax code over the 20th century. The datasets include panel data of inventors who have patented since 1920, a dataset of employment, location, and patents of firms active in R&D since 1921, a state-level corporate tax database since 1900, and a database of state-level personal income taxes.

Akcigit et al. (2018, p. 34) find that both personal and corporate taxes matter for innovation, and that the quantity, quality, and location of innovation are all affected by the U.S. tax system.

Specifically, they find that higher corporate income taxes negatively affect the quantity and quality of innovative activity in U.S. They also find that corporate inventors respond more strongly to taxes compared to non-corporate inventors.

2.3.2 Do corporate taxes hinder innovation?

In the research paper *Do Corporate Taxes Hinder Innovation?*, Mukherjee, et al. (2017) study how changes in state-level corporate tax rates impact innovation in the U.S. from 1990 to 2006.

The researchers find that an increase in taxes reduced future innovation. Their estimates imply that when firms are affected by a tax increase, 67 percent of the firms file for approximately one less patent following the increase, compared to firms which are not exposed to a tax increase, while subject to similar economic conditions.

Interestingly, the researchers find that declines in innovation is not limited to patenting activity. Declines in patenting are also accompanied by declines in R&D expenditures and new product introductions (Mukherjee et al., 2017, p. 196). Thus, the researchers conclude that the effect of corporate taxation impacts all stages of innovation.

2.3.3 Corporate Income Taxes, Financial Constraints and Innovation

Similarly, in the working paper *Corporate Income Taxes, Financial Constraints and Innovation*, Atanassov and Liu (2015) study how changes in state-level corporate income taxes impact innovation in the U.S. from 1988 to 2006. They find that tax decreases significantly increase both quality and quantity of innovative output. Quantity is measured by number of patents while quality is measured by citations per patent.

Atanassov and Liu (2015, p. 8) explain the reasoning behind this. After a tax decrease, firms are able to allocate resources from tax avoidance to innovative activity. This shift towards innovating activity typically appears two or more years after a tax decrease. Hence, where Mukherjee, et al. (2017) observe a stronger effect from tax increases, Atanassov and Liu (2015) observe a stronger effect from tax decreases. In fact, Atanassov and Liu (2015, p. 3) find that tax increases have little impact on innovation in the U.S. They explain that their results are especially relevant for more financially constrained firms, firms with weaker governance and firms that to a greater extent engage in tax avoidance (Atanassov & Liu, 2015, p. 7). The conflicting results appear to be caused by different estimation methodologies.

Though these observations and results are noteworthy, we point out that all three papers are based on patent data from the U.S. patent office (USPTO). Next, we discuss two studies based on European patent data.

2.3.4 Taxation, R&D Tax Incentives and Patent Application in Europe

In the discussion paper *Taxation, R&D Tax Incentives and Patent Application in Europe*, Ernst and Spengel (2011) study how corporate income taxes affect R&D and patenting activity in 20 European countries between 1998 to 2007.

Ernst and Spengel (2011, p.26) find a negative effect of the combined statutory corporate income tax rate on the IP phase and the number of patent applications. The marginal effect is estimated as an increase of the average number of applications by 0.09 following a decrease of the corporate income tax rate of ten percentage points.

The researchers also find that larger firms are more sensitive to corporate income tax rates than smaller firms. In addition to increasing the number of patent applications, lower corporate income tax stimulates earlier R&D investments and attract patents developed in cooperation with foreign inventors, which increase the fiscal tax base and revenue in the host country (p. 26).

2.3.5 Corporate Taxation and the Choice of Patent Location within Multinational Firms

Likewise, in the research paper *Corporate Taxation and the Choice of Patent Location within Multinational Firms*, Karkinsky and Riedel (2009) study how corporate income tax affect patenting activity in multinational firms between in 18 European countries 1995 to 2003.

Furthermore, Karkinsky and Riedel (2009) study how multinational firms use patents to shift taxes to low-tax countries, minimising their corporate tax burden. They explain that profit shifting activities are larger in multinational firms with high IP holdings and high R&D incentives (p. 177) while using Microsoft and Pfizer as examples (p. 185).

Karkinsky and Riedel (2009, p. 185) conclude that corporate tax rates exert a strong negative impact on the number of patent applications. An increase of one percentage point in the statutory corporate income tax rate reduces the number of patent applications to the European Patent Office by 3.5 percent. Moreover, the effect appears robust even when controlling for firm size and time-varying country characteristics.

Noteworthily, all five papers find negative effects of corporate taxation on innovation in U.S. and Europe. Moreover, we observe that these papers study relatively short time periods compared to Akcigit et al. (2018). In addition, the most recent study in Europe, exploits data that dates back to 2007. Since we also know that many countries have reduced their statutory CIT rates the last 15 years, this illustrates the need for updated studies.

3. Methodology

This chapter aims to describe the methodological framework used in this study. First, we describe the research design and the data collection process. Next, we develop the econometric model in order to explain the empirical relationship between innovation and corporate taxation across European OECD countries and over time. Last, we present our hypothesis.

3.1 Research design

To analyse the empirical relationship between innovation and corporate taxation, this study is based on a quantitative analysis with a deductive research approach. Because we combine cross-sectional and time series patent and taxation data, which requires advanced statistical analysis, the quantitative method become the natural choice. Given the nature of the thesis' research question, the study follows a deductive approach. Saunders, Lewis & Thornhill (2009, p. 124) explain that the deductive approach involves developing a hypothesis which subsequently is tested using empirical data. The deductive approach also allows an explanatory design since we aim to explain the relationship between two variables. In order to explain such relationship, we develop an econometric model which we use to determine whether to reject the null hypothesis.

3.2 Data collection

The study collects secondary data from several databases. These are combined to create a unique panel dataset of patent applications and corporate income tax rates across 26 European OECD countries between 1981 to 2017. This chapter explains the process behind the collection, merging, and modification of these datasets. To perform these computations, we use the programming language R.

3.2.1 Patent data

The data on patents are retrieved from the "*OECD, REGPAT database, January 2021*" (OECD, 2021a). This database provides datasets that fully originate from the EPO's Worldwide Statistical Patent Database (PATSTAT Global, Autumn 2020). The database covers patent applications by priority date (first filing) filed to the EPO from 1977, and patent applications filed under the Patent Co-operation Treaty (PCT) at international phase from

1977. The REGPAT database provides patent applications to the EPO on 5,500 regions across 205 countries, including all European countries. This amounts to 3,990,540 observations in total, of which 1,893,944 observations are obtained from European countries.

3.2.2 Taxation data

The taxation data originate from the OECD Tax Database. The database provides statutory corporate and capital income taxes for OECD countries from primarily year 2000 to 2020 (OECD, 2021b). The database also consists of a dataset of historical statutory corporate and capital income taxes from 1981 to 1999 (OECD, 2008). Merging these two datasets provides inter alia corporate income tax covering all 26 European OECD countries[1] over a period of 39 years, amounting to 983 observations. However, in the dataset from 1981-1999, there are some missing values for countries that either became members of the OECD during the time period, or more recently.

3.2.3 Panel data

Using the patent data from the REGPAT database with patent applications to the EPO, we are able to count the number of patents per country per year. Simultaneously, we remove duplicates due to multiple applicants sharing application rights. Last, we merge the count of patent application data with the taxation data and create the panel dataset.

A panel dataset is a dataset that combines cross-sectional and time series data. We denote the number of cross-sectional European OECD countries by $I = 26$ and the number of time periods by $T = 36$. Without any missing values, this would amount to a balanced panel of 936 observations. However, there are missing values, and we modify the panel for certain observations.

Although we have data from 1981 to 2020, we must shorten the time period from 2020 to 2017. This is because there is approximately 31-month lag from the patent's priority date until the patent is included in the OECD REGPAT database (OECD, 2004). Because this process takes about two to three years, the observations from 2018 to 2020 are considered unreliable and removed from the panel.

[1] European OECD countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom.

We also have to control for countries that have experienced political changes during the time period. Specifically, Czech Republic, Germany, Latvia, Slovakia, and Slovenia have experienced unique alterations to their political systems during the time period. For this reason, we have removed observations of these countries for specific periods[2].

Furthermore, it is necessary to add control variables into the panel. For this reason, we gather data about EPO membership and GDP. EPO memberships are retrieved from the EPO website which shows each country's entry data in the EPO (EPO, 2019). We also gather data on gross domestic product (GDP) per capita annual percentage growth in local currency per country per year, and GDP per capita in current U.S. dollars for each country per year. Both datasets are sourced from the World Development Indicators provided by the World Bank's DataBank (World Bank, 2021a; World Bank, 2021b).

The final variable added to the panel is population per country and year. Population data is sourced from Eurostat Database "*Population on 1 January by age and sex"* (Eurostat, 2021). This variable is not an independent variable in the analysis, but it is included to compute the number of patent applications per 100,000 capita per year. By adjusting for population, we create a more comparable measure of patent applications when comparing countries. This variable represents our dependent variable in the analyses.

We also remove the observations with missing values, so that the number of observations for all variables are equal. After the modifications, we are left with 796 observations in the panel.

[2] Observations are removed for Czech Republic (1981-1992), Germany (1981-1990), Latvia (1981-1990), Slovakia (1981-1992) and Slovenia (1981-1991).

3.3 Data analysis

An econometric analysis generally begins with the premise that y and x are two variables, representing some population, while we are interested in study how y is impacted by changes in x (Wooldridge, 2016, p. 22). This premise is applicable in this study, where we analyse how changes in corporate taxation impact innovation.

In this chapter, we introduce the econometric model based on fixed effects. Here, we also introduce the different variables, confounders, and potential omitted variables. Last, we introduce our hypothesis.

3.3.1 Fixed effects estimation

The general two-way fixed effects model is given by:

$$y_{it} = \beta_1 x_{it} + \delta_t + \alpha_i + \epsilon_{it}$$

where individual i = 1, 2, ..., I and time t = 1, 2, ..., T.

In the general model we have an independent variable x_{it} that differs between both cross-sectional individuals and over time. We also have a decomposed error term $\delta_t + \alpha_i + \varepsilon_{it}$. The components are separated to only be dependent on time (δ_t), differ only between cross-sectional individuals (α_i) and vary across time and cross-sections (ε_{it}). These three error components together form the stochastic error term (u_{it}). The point is that we need to control adequately for all three variations. By adding control variables and using a within group transformation, we are able to take into account the cross-sectional and time fixed effects (Wooldridge, 2016).

The specific two-way fixed effects model is given by:

$$\log(pats\_pht_{it}) = \beta_1\, CCITR_{it} + \beta_c\, Controls + CountryFixedEffects + YearFixedEffects + \epsilon_{it}$$

Where country i = 1, 2, …, 36 and years t = 1, 2, …, 26.

The country- and year-fixed effects are included in order to account for the average impact of unobservable time-invariant differences between countries and unobservable variables that differ over time but are constant over countries.

With year fixed effects we are controlling for factors that impact all countries equally in different years. This means that we control for occurrences that are year specific and that could affect innovation. By running an OLS regression on the two-way fixed effects model with control variables, we can estimate the robust effect that CIT rates have on the number of patents per 100,000 capita while accounting for country-level heterogeneity and time shocks.

In addition to fixed effects, clustered standard errors are used in the model. As explained by Abadie, Athey, Imbens and Wooldridge (2017), including clustered standard errors is applicable in an experimental design situation when clusters are not randomly sampled and there is heterogeneity in the treatment effects. These recommendations indicate that clustered standard errors are relevant for our model, as the countries and differences between them are systematic and not random.

The reason we include clustered standard errors is to reduce the risk of biased standard errors which otherwise could lead to incorrect inference about the estimators' statistical significance (Hansen, 2007). This bias can occur in the presence of heteroskedasticity and serial correlation in the standard errors within a country (Hanck, Arbold, Gerber & Schmelzer, 2020).

We confirm the need to cluster standard errors by running a Breusch-Godfrey test for serial correlation, and a Breusch-Pagan test for heteroskedasticity in the idiosyncratic error. The tests are shown in appendix figure A.1 and figure A.2.

3.3.2 The dependent variable

For the dependent variable in the model, we apply the natural logarithm to the number of patent applications per 100,000 capita per country per year ($pats\_pht_{it}$). By using the natural logarithm, the output of the regression is easier to interpret.

The dependent variable in the model derives from the count of number of patent applications per country per year. By using the population for the associated country in the patent application, we are able to compute the number of patent applications per 100,000 capita per country per year. To apply the natural logarithm to the dependant variable, patents applications per 100,000 is calculated with the formula:

$$patent\ applications\ per\ 100\ 000_{it} = \frac{1 +\ patent\ applications_{it}}{population_{it}} * 100\ 000$$

The reason why 1 is added to the number of patent applications is that there are observations of zero patent applications. When applying the natural logarithm, we cannot have zero values since the log of zero is undefined. Adding 1 to the observations handles this problem. This means that there is a slight inaccuracy in the regression's dependent variable. However, since all observations of patent applications are added 1, the ratio does not change in size and the overall effect that is measured in the analysis remains unchanged.

Adjusting the dependent variable for population is necessary because the countries in the panel vary considerably in population. Accordingly, adjusting for population creates a variable that is comparable across all countries.

3.3.3 The independent variables

The model applies the combined corporate income tax rate ($CCITR_{it}$) as the independent variable. We have earlier described that the combined CIT rate shows the basic combined central and sub-central CIT rate (OECD, 2021b). β_1 is the coefficient of the independent variable.

In the model, we apply the natural logarithm to the dependent variable. The interpretation of the β_1-coefficient is therefore that 1 unit increase in the independent variable $CCITR_{it}$ implies $100 * \beta_1$ percent change in the dependent variable $pats\_pht_{it}$. As the $CCITR_{it}$ observations in the panel are in the interval [0, 100], the 1-unit increase is equal to 1 percentage point increase in the interpretation of the β_1-coefficient.

In chapter 2.2, we introduced four different tax variables which all have been considered as potential independent variables. Here, we described the differences between central government CIT rate, adjusted central government CIT rate, sub-central government CIT rate and combined CIT rate. Due to a considerable number of missing values (NAs) of adjusted central government CIT rate and sub-central CIT rate, these two variables are not considered reasonable alternatives. However, both central government ($CITR$) and combined CIT rate ($CCITR_{it}$) have reasonable numbers of observations. Thus, both appear to be reasonable choices of independent variables.

There are a few reasons why we use the combined CIT rate ($CCITR_{it}$) as the independent variable. First, Ernst and Spengel (2011) argue that the use of the combined CIT rate includes the taxation of profits from intellectual property (IP) by focusing only on the taxation of returns. Because the combined CIT rate is not affected by the tax shields from financing, this is therefore an appropriate measure of the tax burden.

Second, the correlation between the central government CIT rate ($CITR$) and combined CIT rate ($CCITR_{it}$) is high. This correlation is estimated to 87.8 %. Furthermore, in the panel, we only find a few observations within nine countries where the two variables differ. This may indicate that both variables will absorb the same effects in the regression. In appendix 8.2, we show that the implications of using this independent variable ($CCITR_{it}$) is minimal compared to using the central government CIT rate.

Third, the applicant is eligible to pay tax within the country to which a patent is applied for. For example, we assume that all German patent applications are filed by German firms. Because German firms are eligible to pay both sub-central CIT and central government CIT, this will be absorbed by the combined CIT. We find support for this argument in the literature. In a research paper, Böhm et al. (2015) find that the patent inventor and patent applicant were located in different countries in only 8 % of patent applications in Europe from 1990 to 2007.

3.3.4 Control variables

The control variables used in the model are EPO membership, GDP per capita and GDP growth per capita. These are all variables that we need to include in order to enhance the internal validity of the regression, as they explain variation in the dependent variable.

We control for countries' EPO memberships (EPOm) because being a member of the EPO makes it easier to file for international patents. Consequently, when a country becomes a member of the EPO, there is an observable increase in patent applications. EPOm is a dummy variable of 0 as long as the country is not a member of EPO and becomes 1 when the country becomes a member of EPO.

In the literature, GDP is also a common control variable used in several similar studies (Akcigit et al., 2018; Atanassov & Liu, 2015; Ernst & Spengel, 2011; Karkinsky & Riedel, 2009). Hence, GDP per capita in current U.S. dollars is added to control for economy size, economic activity and living standards. We use the natural logarithm of GDP to adjust for the differences in scale compared to the other variables. GDP growth (GDPG) is also added as a control variable, in order to control for economic growth.

3.3.5 Confounders and potential omitted variables

In addition to control variables, we have to discuss the confounders in our model and how we adjust for them. In our analyses, we use two-way fixed effects to adjust for unobserved time-invariant confounders, such as omitted variables. As Hill, Griffiths and Lim (2017) put it, this is one of the advantages of using fixed effects on panel data, as when the data is transformed all unmeasured characteristics of the country and year are subtracted out.

Generally, the country-specific fixed effects are unobservable, time-constant factors that affect the dependent variable and are often referred to as the unobserved heterogeneity. This can for example be public infrastructure. The reason for this is that i.e., the level of public services is usually correlated with taxation, but to measure quality and quantity of public infrastructure is difficult (Bartik (1991); Phillips & Goss (1995)). Another example of a country-specific unobservable effect could be that some countries have a culture that is more positive to innovation and change than other countries, and therefore apply for more patents.

The other fixed effect included in the analyses is year-specific fixed effects. By including these, we are able to control for unobservable variables that vary over time but are constant across countries. Examples of this type of effects could be the introduction of computers and internet making it easier to apply for patents, economic crises or large changes in supply or demand in certain industries.

3.3.6 Hypothesis

The regression model estimates the average effect of corporate income tax rates on the number of patent applications per hundred thousand capita in European OECD countries from the years 1981 to 2017. The β-coefficient of $CCITR_{it}$ represents this effect. The effect is analysed to answer the research question: *How do corporate tax rates impact the number of patent applications in Europe?*

In order to study this research question, we draw up a two-sided hypothesis which we analyse through our fixed effects model:

H_o: β-coefficient of $CCITR_{it}$variable = 0

H_1: β-coefficient of $CCITR_{it}$variable ≠ 0

If the β-coefficient is statistically significant, we can reject the null hypothesis that corporate tax rates do not impact the number of patent applications in European countries. In that case, the β-coefficient is such that an increase in the corporate tax rate of 1 percentage point in a country increases (decreases) the number of patents per hundred thousand by $\beta * 100\ \%$ in a certain country.

4. Analysis

This chapter provides an overview of the analysis in this study. First, we present descriptive statistics of the panel. Next, we present several regression analyses and explain how we interpret the results. Last, we discuss the robustness of the analysis.

4.1 Descriptive statistics

This chapter aims to show the underlying structure of our data. This will be useful when explaining and discussing the results. We begin by presenting descriptive statistics of the patent and taxation data individually. Then, we present descriptive statistics of the constructed data panel.

4.1.1 Descriptive statistics for patent data

Figure 1 shows the development of number of patent applications for the 26 countries in the panel each year from 1981 to 2020. Overall, the graph shows a steady increase in patent applications. However, the steep decrease from 2017 to 2020 is noteworthy. We have included this graph to visualise the average 31-month lag effect on EPO filing date to publication date in the dataset, as presented in chapter 3.2. Accordingly, we limit the time-period to 1981 to 2017 in order to exclude unwanted effects in the analysis. The number of patent applications in 1981 and 2017 also turn out to be the minimum and maximum observations. In this period, the number of patent applications has increased by 684 %.

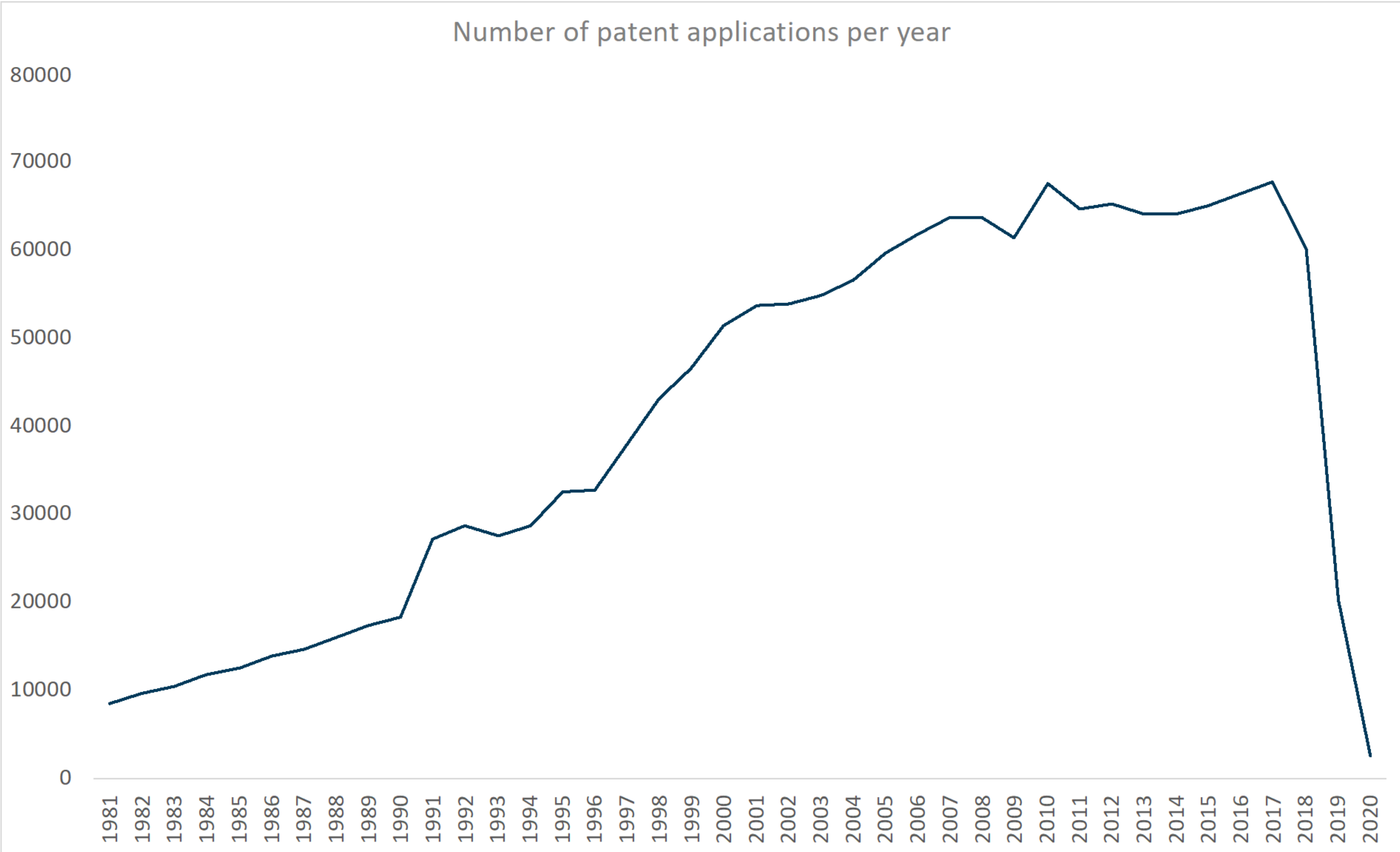

Figure 1: Development of number of patent applications for the complete panel (1981-2020)

Figure 2 shows the development of patent applications per 100,000 capita ($pats\_pht$) from 1981 to 2017. The bold black line shows the mean development for all countries in the panel. Additionally, we add a sample of countries to the graph, in order to give a broader picture of how innovation have developed in the various countries. From this graph, we observe that the mean of patent applications per 100,000 capita steadily increases during the time period.

There are a few countries, namely Sweden, Finland, Netherlands, and Germany, which appear to have experienced a substantial increase in approximately the time period from 1993 to 2002. Countries such as France, Ireland and Norway also have a steady increase in the time period. While the observations from France coincide pretty well with the mean, the two latter countries appear to be just below the mean for all years. Other countries on the other hand, such as Great Britain, Italy, and Spain, have seen a much smaller increase over the period.

This graph reflects how innovative each country is. We observe that there are pretty substantial differences between countries, and that there also are large differences in change within each country. While the variance in innovativeness in 1981 is pretty low, this has changed over the years, and in 2017 the variance in innovativeness between the countries is larger.

During the 1980's, there are about the same number of countries above the mean as below the mean, and the average trend is a relatively subtle but steady increase in patent applications. During the early 1990's we observe that the mean declines, while at the same time a number of countries keep increasing. For example, Finland and Denmark move above the mean in these years. Great Britain and France also have a slight decrease in the early 1990's. From mid-90's to 2000 however, several countries experience a steep increase, pulling the mean upwards. We also observe that the majority of the countries (six of eleven) move above mean in the 1990's.

From year 2000 to 2010, the mean indicates that the increase rate is about the same as in the 1990's. However, several countries experience sizeable year-to-year differences. France also moves below the mean in 2005. From 2010 to 2017, several of the highly innovative countries experience substantial decreases, namely Sweden, Finland, and Germany. A few countries have almost a convex development in these ten years, namely Netherlands, Denmark, Ireland, and Norway. Finally, France experiences a decrease from 2015 to 2017.

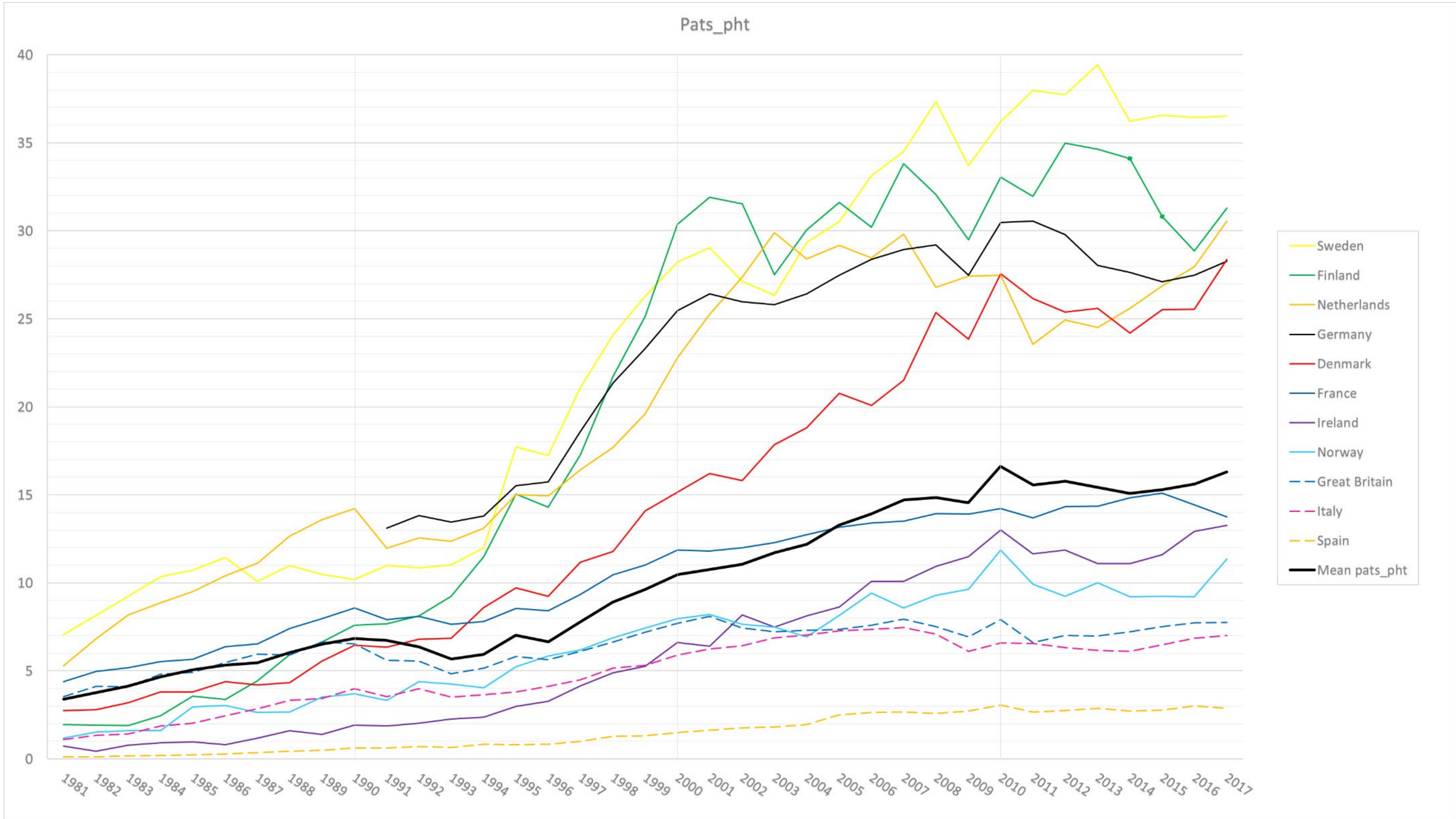

Figure 2: Development of Patent applications per 100 000 capita (pats_pht), mean and for a sample of countries (1981–2017)

4.1.2 Descriptive statistics for taxation data

Figure 3 shows the development of the combined corporate income tax rate ($CCITR$) from 1981 to 2017 for the same sample of countries as in figure 2. Again, the bold black line shows the mean development of all countries in the panel. This shows how the mean combined CIT rate has progressed over time. The $CCITR$ appears to have been steadily decreasing from 1985. The maximum mean of 40.96 % is observed in 1985 while the minimum mean of 20.22 % is observed in 2017.

As the mean illustrate, we observe that for the most countries, the $CCITR$ has steadily declined. There are however a few countries that have a steep decline in certain periods. For example, Finland has a steep decline of 36.75 percentage points from 1985 to 1993 and Sweden has a steep decline of 30.1 percentage points from 1989 to 1991. Ireland has a steep decline of 23.5 percentage points from 1997 to 2003 and Germany a steep decline from 1997 to 2001 of 18.54 percentage points.

France on the other hand stands out with its many fluctuations from the mean. Their $CCITR$ was at 50 % from 1981-1985, while steadily decreasing to 33.33% in 1993, following an increase to 41.66 % in 1997, followed by a decrease to 34.43 % in 2010, followed by a steady increase to 44.43 % in 2017. Of all the countries in the panel, France is furthest away from the mean. Other countries also experience slight increases in the period, but the general trend is negative.

We observe that most countries' $CCITR$ are above the mean in 1981 and for the most part of the 1980's. During the late 1980's and early 1990's there seems to have been a change, as most countries either decline or below the mean in this period and through the 1990's. From approximately year 2000 however, an increasing number of countries' $CCITR$ increases above the mean, while countries such as Ireland seem to be pulling the mean down.

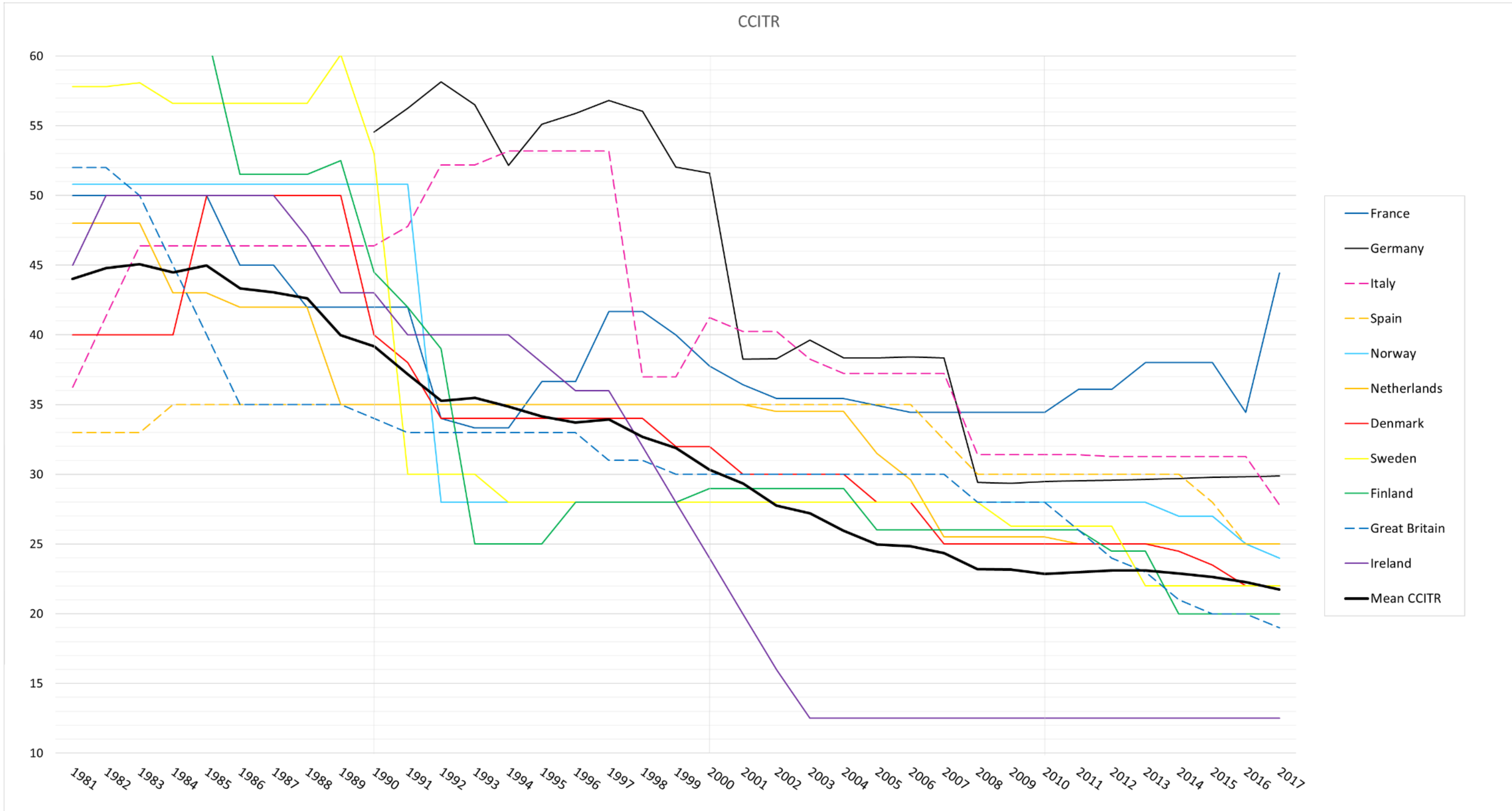

Figure 3: Development of Combined corporate income tax rates ($CCITR$), mean and for a sample of countries (1981– 2017)

4.1.3 Descriptive statistics for panel data

Table 1 displays descriptive statistics of all variables in the panel. Here, there are a couple of things that can be addressed. Because the panel is unbalanced, we have 796 observations in total.

We observe considerable variation in the number of patent application. Here, the standard deviation is greater than the mean indicating large variations between countries. We also observe similar tendencies in patent applications per 100,000 inhabitants. For example, this might hint to large differences in the countries' abilities to innovate. Additionally, we note that the mean and median of patent applications differ, meaning that the variable is asymmetrical. For instance, a few observations might pull the mean up.

However, it may not be intuitive that the minimum of patent applications per 100,000 inhabitants are equal to 0.02 when the minimum of patent application is equal to zero. Again, we point out that this is because the variable patent applications per 100,000 inhabitants is computed to be applicable with the natural logarithm.

The last four variables are used as control variables. The dummy variable EPOm's mean tells us that in 80 % of the observations a country is a member of EPO. We observe high standard deviations in GDPG, GDP and population due to considerable variation in country economic size and situation. For example, minimum and maximum population is respectively 279,049 (Iceland, 2000) and 82,536,680 (Germany, 2003). Given this, variation in other variables is expected between the countries.

Table 1: Descriptive statistics of panel data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Patent applications	796	1,958.41	3,925.98	0	65	462.5	2,014.8	24,933
Patents per 100 000 capita	796	11.32	15.59	0.02	0.91	6.08	13.95	94.21
Combined corporate income tax rate ($CCITR$)	796	31.76	10.93	9	25	30	38.3	62
EPO membership	796	0.80	0.40	0	1	1	1	1
Gross domestic product per capita growth	796	2.10	3.10	-14.27	0.69	2.03	3.55	23.99
Gross domestic product per capita	796	28,008.80	20,794.53	2,429.21	13,098.58	23,050.67	38,869.19	118,823.60
Population	796	19,518,653	22,776,724	279,049	5,111,874	9,820,103	37,968,648	82,536,680

4.1.4 Histograms

To provide additional understanding of the dependent variable and the main independent variable, we visualise the data with histograms combined with the kernel density estimate curve with a Gaussian distribution. This means that the y-axis is not modelled with frequencies but reflect the probability density.

Figure 4 shows the histogram of patent applications per 100 000 inhabitants and the density estimate curve. What we grasp from this visualisation of the data is that it is right-skewed. There appears to be a lot of observations between 0 to 5 patent applications per 100 000, while we have a decreasing number of observations as the variable increases in size.

There also seems to be some applications per 100 000 at around 70 to 80. This could for example be explained by a country that is highly innovative but still has a relatively small population, such as Switzerland or Luxembourg. This corresponds to the descriptive statistics of the variable, where the mean was 12.02 with a standard deviation of 16.17 while the median was at 6.63.

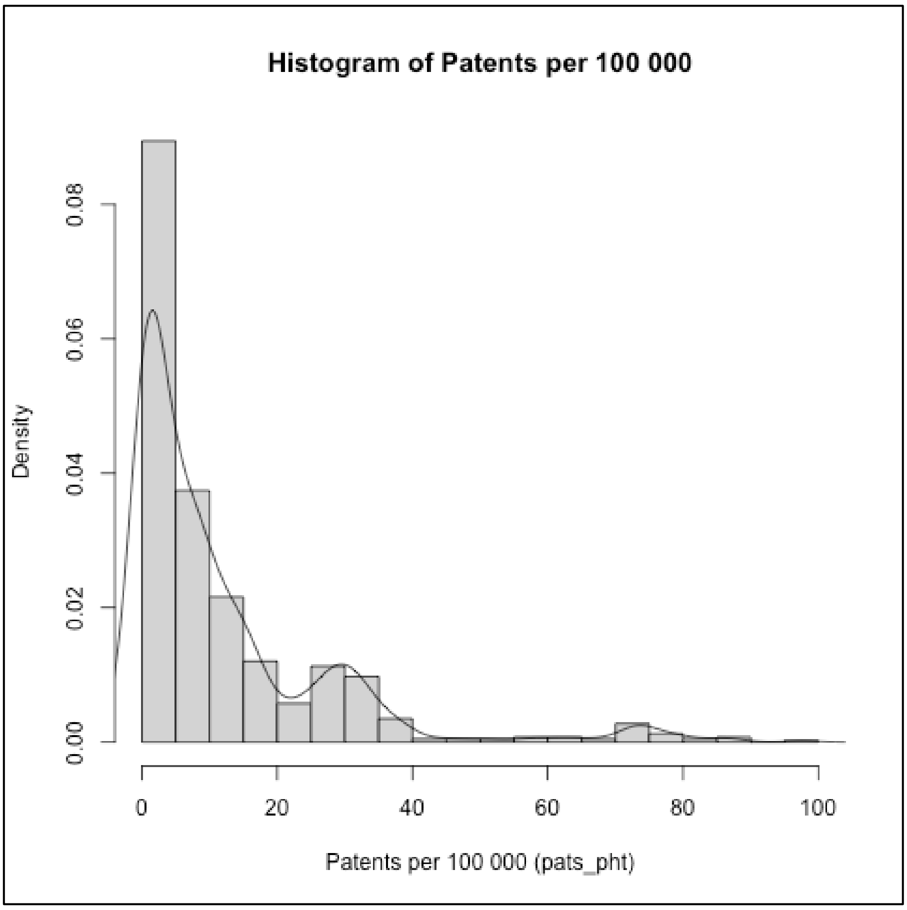

Figure 4: Histogram of Patent applications per 100 000 capita

Figure 5 on the other hand displays a histogram of the combined corporate income tax rates ($CCITR$) in the panel, along with the density estimate curve. This histogram might seem bell shaped at first sight, but as the tails are cut off, it does seem to be more of a truncated distribution. This can be explained by the nature of the variable. It is extremely rare to observe tax rates at 0 % or 100 %, and as we see from the histogram of our sample, the cut off-points are approximately at 5 % and 55 %. As the descriptive statistics also indicate, most observations are in the interval of 25 % to 30 %.

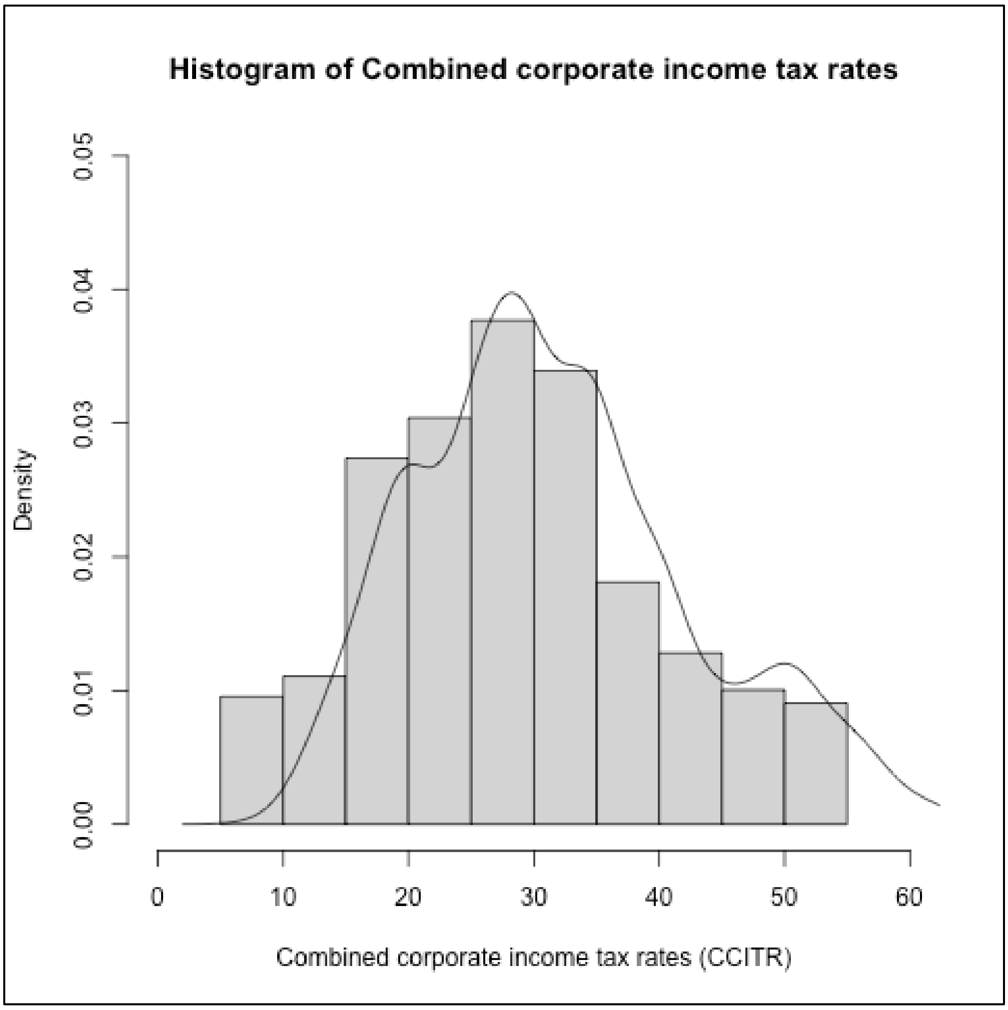

Figure 5: Histogram of Combined corporate income tax rates (CCITR)

4.2 Regression analyses

In this chapter we present, discuss, and interpret the regression analyses. The analysis is divided in two parts. First, we run a regression of the entire panel from 1981 and 2017. Second, we split the panel in four time periods, and run regressions of each time period: 1981-1989; 1990-1999; 2000-2009; 2010-2017. Analysing each time period separately makes it possible to capture potential variation between different periods.

4.2.1 Regression of entire period

Table 2 present the regression of the entire panel from 1981 to 2017 using the FE-model. Here, the dependent variable is the natural logarithm of patent applications per 100,000 capita denoted as $\log(pats\_pht)$ in the table.

Column (1) shows the regression with only the isolated independent tax variable. Column (2) includes both independent tax variable and control variables. This column represents the econometric model introduced in chapter 3.3.

From the regressions in Table 2, we perceive that an increased tax rate seems to have a negative effect on patent applications. When we run the regression with fixed effects but without controls, the effect is significant. However, with the robust model including both fixed effects and controls, the effect decreases and is no longer significant. The difference in size and significance between these two β-estimates is therefore due to that some of the effects on patent applications are explained by the controls. We will not discuss these controls in depth, but as they are all significant, we seem to have included necessary and important control variables in our model.

Although the β-coefficient for $CCITR$ in column (2) is not significant, the effect is as the literature suggest, and as we expect, negative. This means that we cannot conclude that an increase in combined corporate income tax rates of 1 percentage point decreases the number of patent applications per 100 000 inhabitants by 0.7%, but it gives us an indication that the effect is negative.

As we discussed in the descriptive statistics chapter, we observe in Figure 2 that the growth rate of the number of patent applications during the 36 years of observations has on average varied greatly. The same can be said for the combined CIT rate. Additionally, as mentioned the are a few observations missing from some countries in the first 10 to 15 years in our panel, which might affect the estimation of the β-coefficient. We therefore find it necessary to divide the analysis in four periods to study $CCITR$'s effect on $pats\_pht$ in different decades.

Table 2: Linear Panel Regression Model of Tax Effects on Patent Applications

	Dependent variable:	
	log(pats_pht)	
	(1)	(2)
CCITR	-0.016^{*}	-0.007
	(0.009)	(0.006)
EPOm		0.512^{***}
		(0.131)
GDPG		-0.009^{*}
		(0.005)
log(GDP)		1.062^{***}
		(0.214)
Observations	796	796
R^2	0.036	0.472
Adjusted R^2	-0.046	0.425
F Statistic	27.095^{***} (df = 1; 733)	163.405^{***} (df = 4; 730)

*Notes: Both regressions estimated using OLS on the two-way FE-model, estimating the independent variable CCITR's effect in the dependent variable patents per 100 thousand capita (pats_pht). All regressions are included country and year fixed effects. (1) is based on the two-way FE-model without controls. (2) is the full two-way FE-model with controls as presented in methodology. All controls' coefficients included. Standard errors clustered at country-level reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.*

4.2.2 Regression of time periods

Table 3 presents the regression divided in four time-periods using the FE-model. The reason why we divide the panel in four periods is that we wish to see if the combined CIT rate affects the number of patent applications differently during different decades.

The panel has its first observation in 1981 and last in 2017. This implies that we cannot divide in perfect decades, and that the first period is nine years, second and third periods are ten years, and the fourth periods is eight years. Ideally, the analysis would be divided in four decades, but we do not consider this to be problematic for the interpretation of the regression.

In the first time period (1981 – 1989), the β-coefficient of $CCITR$ (-0.4 %) is slightly negative. This means that an increase in the combined CIT rate reduces the number of patent applications in the period.

This period has the least observations of 135. This is nearly half as many as in the third time-period where we find a similar but significant effect. In chapter 3.2, we describe why we remove certain countries due to unique political alterations. Furthermore, we are missing tax data on Estonia, Hungary, Iceland, Lithuania, Luxembourg, and Poland in this time period. Due to these circumstances in the data, this estimate can be seen as less statistically reliable when comparing time periods.

Another element that may affect the estimation of the coefficient can be seen in of the descriptive statistics. Here we see that that the mean combined CIT rate increases from 1981 to 1983 and moves almost horizontally from 1983 to 1985, before declining from 1985. At the same time, the mean number of patent applications increase rapidly from 1981 to 1985. The increase and horizontal development in the combined CIT rate are contrary to the trend from 1985 to 2017, at which it declines.

Compared to the first period, the regression results of the second period (1990-99) are very similar. Both the estimated β-coefficients and standard error of the independent variable $CCITR$ are identical. However, this is not due to identical movements in the underlying data, which we observe in figure 2 and figure 3.

In the second period, the mean combined CIT rate declines by nearly 10 percentage points. This is a dramatic decline implying that the mean combined CIT rate declined by approximately 1 percentage point each year. The Nordic countries, especially Norway, Sweden, and Finland, are strong contributors to this decline.

Furthermore, the movement in the mean number of patent applications experiences a drawback in the first half of the period. In fact, after a nine-year period of growth, the mean number of patent applications decline from 1990 to 1993. Combined with the decline in combined CIT rate, there does not seem to be a negative effect within these years, which might affect the β-estimate for the 1990's. From 1993 to 1999 however, patent applications continue to increase. A contributing factor to why we do not find a significant negative effect in this period may be that the number of patent applications declines before it increases, while at the same time $CCITR$ declines.

On another note, we observe that the number of observations has risen to 195. This is because, as explained earlier, observations from additional countries are included in the panel at this point.

In the third time period (2000 – 2009), we observe that the estimated β-coefficient of $CCITR$ increases in strength and becomes significant at the 10 %-level.

As pointed out in the descriptive statistics, the mean number of patent applications grows considerably in this period. At the same time, the mean $CCITR$ decreases steadily. Although some of a special case, Ireland increases their patent applications rapidly, while at the same time drastically decreasing their $CCITR$ in this period. We observe few countries in the 2000's that have an opposite development in the innovation and tax measures to the mean, which may explain why the estimate in this time period is significant.

Interestingly, we note that our results in this period are similar compared to the findings of Ernst and Spengel (2011). In their study, Ernst and Spengel (2011) find a negative effect of the combined CIT rate on the number of patent applications in Europe between 1998 to 2007. The similar findings and the significance of our β-coefficient is not surprising as we analyse a similar time period as applied by Ernst and Spengel (2011). However, we only find significance at 10 %-level. This may imply that the empirical relationship is not as strong as expected.

An interesting question is whether the financial crisis in 2007/08 impacts our results. In contrast, Ernst and Spengel (2011) do not include the financial crisis in their data. However, we observe that the increase in patent applications slows down from 2007 to 2008 and decline from 2008 to 2009. This is likely an effect of the crisis.

Considering taxation, we also know that the crisis led to two conflicting measures. On the one hand, several countries required public revenues to help recovering the economy. In these countries, the solution became to increase the taxes (Hallerberg, 2012). In our panel, this includes namely Portugal, Greece, and Iceland. On the other hand, some countries decreased taxes to stimulate the economy. As shown in figure 3, the overall trend in $CCITR$ in our panel was negative in this period.

In the fourth time period (2010 – 2017), there are several interesting incidents that must be discussed. Here, the β-coefficient of $CCITR$ switches sign from negative to positive and is significant at the 10%-level. Intuitively, the interpretation is that an increase of 1 percentage point in the combined CIT rate increases the number of patent applications by 1.3 %. This is contrary to the β-coefficient in the three previous time periods where an increase in tax implicates a reduction in the number of patent applications.

This appears to have a reasonable explanation. From 1983 to 2009, the mean development in both the number of patent applications and combined CIT rate are moving in opposite directions. Until 2010, the trend in the number of patent applications is positive while the trend in the combined CIT rate is negative. However, from 2010 to 2017, the trend of increasing patent applications stops. We observe from figure 2 that the mean number of patents decreases and then the trend flattens. At the same time, we observe from figure 3 that the mean $CCITR$ appears to flatten before it declines slightly from 2013.

From 2009 to 2010, the number of patent applications experience a large increase. Although we observe similar movements in previous years, this increase appears to be more systematic than previous movements. For example, in the time around the financial crisis in 2007/08, we observe several declines, namely in Finland, Netherlands, Great Britain, and Italy. Although the mean also declines between 2007 to 2009, this effect has a more natural-looking shape.

In contrast, the spike in patent applications in 2010 appears to be considerably more systematic. Here, the mean clearly increases from 14.55 in 2009 to 16.63 in 2010 before it declines back to 15.57 in 2011. In 2010, the EPO introduced a new rule (Rule 36 EPC) concerning divisional patents (EPO, n.d.). Sometimes the parent application needs to be split into multiple distinct inventions in order to be granted as multiple divisional applications. In short, this rule shortened the time frame in which applicants had to divide parent applications in divisional applications. This contributes to explains the systematic spike.

Despite the effect of the new rule, the mean number of patent application continues to decline from 2012 to 2014. While the effect from 2009 to 2011 appears to be explained by the new rule, the decline from 2012 to 2014 must have another explanation. For example, it may be after-effects of the financial crisis. From 2014 the trend seems to again turn, and we observe an increase from here on out. This may be a sign that the economic activity moves back to a more normal pace.

The increase in mean $CCITR$ from 2010 to 2013 may also be explained by the effects of the financial crisis. A couple of countries with weak corporate sectors and small open economies, i.e. Hungary, Latvia and Portugal, increased their corporate taxes temporarily from 2010 to handle sovereign debt following the financial crisis (Hallerberg, 2012). We observe that an increase in tax, temporary or not, applies to seven countries in our panel, while the rest either kept their corporate tax rate flat or decreased slightly. This increase and lack of big variations of $CCITR$s within countries, while at the same time we see large variations in slope of within-country patent applications may explain why we get a positive and significant result.

Table 3: Linear Panel Regression Model of Tax Effects on Patent Applications divided in four time periods

	Dependent variable:			
	log(pats_pht)			
	(1981-89)	(1990-99)	(2000-10)	(2010-17)
CCITR	-0.004	-0.004	-0.017*	0.013*
	(0.006)	(0.006)	(0.009)	(0.007)
EPOm	0.313***	0.512***	0.163	
	(0.097)	(0.176)	(0.102)	
GDPG	0.027	-0.016	-0.008	0.001
	(0.019)	(0.014)	(0.009)	(0.005)
log(GDP)	0.996**	0.063	1.349***	0.122
	(0.413)	(0.239)	(0.275)	(0.272)
Observations	135	193	260	208
R^2	0.248	0.242	0.432	0.015
Adjusted R^2	0.067	0.084	0.334	-0.185
F Statistic	8.904*** (df = 4; 108)	12.678*** (df = 4; 159)	41.960*** (df = 4; 221)	0.895 (df = 3; 172)

*Notes: All regressions estimated using OLS on the two-way FE-model presented in methodology. All regressions include country and year fixed effects. Column 1 includes all observations in the 1980's, column 2 includes all observations in the 1990's, column 3 includes all observations in the 2000's, column 4 includes all observations in the 2010's. All controls' coefficients included. Standard errors clustered at country-level reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.*

4.3 Robustness analysis

To test if the results of the main regression in Table 2 are correct, we run a series of robustness checks to see if $CCITR$'s coefficient changes in size or significance. We have done five alterations to the panel and run the regression model on these data. Table 5 shows the results of these checks. By running these checks, we are able to see if some countries affect the results in such a way that they should be excluded from the analysis.

In the first test we check to see if highly innovative countries have a significant tax effect. We suspect that since the mean number of patents have increased in the time period, while $CCITR$ has decreased, we might be able to produce results similar to the analyses in the literature review if we only analyse the 6 countries with the highest $pats\_pht$ means. These six countries are Luxembourg, Switzerland, Germany, Sweden, Finland, and Netherlands. From column (1) in Table 5, we observe that $CCITR$'s coefficient indeed is negative and significant at the 10 %-level.

Because this result is significant, it is interesting to see if we get a similar effect if we remove the 6 least innovative countries from the panel. Removing the least innovative countries will check if we have countries in our panel that are so little innovative that they prevent us from finding a significant effect of taxes on innovation.

In the second test, we therefore exclude the six least innovative countries measured by the lowest mean $pats\_pht$. These countries are Slovakia, Poland, Greece, Portugal, Lithuania, and Latvia. As we see from $CCITR$'s β-coefficient in column (2), the result of excluding the least innovative countries from the panel does not yield any huge difference from the results in the main regression. The effect of taxes on patent applications increases slightly, but we do not observe any change in significance. We do however observe that most of the least innovative countries, measured in mean $pats\_pht$, also have missing observations in the panel.

To check if missing values in general is a problem in our analysis, we run a regression in column (3) where countries with any missing data are excluded. In the third test, we exclude countries Czech Republic, Germany, Estonia, Hungary, Iceland, Lithuania, Luxembourg, Latvia, Poland, Slovenia, Slovakia. The result suggests that missing values does not affect the results and that this is properly handled by the statistics software. In addition, we have missing values in fairly random countries, as these countries are spread across high/medium/low innovative and $CCITR$.

The checks in column (1) and (2) test based on innovativeness. The test in column (4) tests to see if we get a different result if we exclude the six countries with the lowest mean $CCITR$s. These countries are Lithuania, Latvia, Iceland, Hungary, Slovenia, and Estonia. The test in column (5) tests the opposite, removing the 6 countries that have the highest mean $CCITR$s. These countries are Germany, Italy, France, Belgium, Portugal, Greece.

As we see in column (4), excluding the countries with low taxes does not influence the estimated effect in terms of significance, but the effect increases to -1.0%. Excluding high-tax countries (5) yields a similar result, as the effect increases to -1.2%, but not significant either. The reason we test for this is to see if countries with a low or high mean tax rate influence the tax effect for the remaining countries. The difference in results between these two tests can be explained, as a large part of the low-tax countries have little within-country variation in tax over time, while the high-tax countries vary more.

All robustness checks provide a coefficient for $CCITR$ that is equal to (column 3) or similar to (column 2 & 4) the same coefficient in the main regression. The results of the test in column 1 is not very surprising as these countries have all experienced great within-country variation in addition to having a high mean $pats\_pht$. This is picked up by our fixed-effects model, and therefore creates a significant β-coefficient. Although the effect in test (1) is similar to what we find in the related literature, the sample is rather small and not representative for all European countries.

These tests further strengthen our results, as the effect that we find in the main regression do not seem to deviate with any alteration that seems relevant to the results. Therefore, we argue that the results of our main regression appear to be robust after various robustness checks.

Table 4: Robustness checks

	Dependent variable:				
	log(pats_pht)				
	(1)	(2)	(3)	(4)	(5)
CCITR	-0.016*	-0.008	-0.007	-0.010	-0.012
	(0.009)	(0.007)	(0.006)	(0.006)	(0.009)
EPOm	0.719***	0.455***	0.667***	0.623***	0.458***
	(0.066)	(0.141)	(0.177)	(0.154)	(0.148)
GDPG	-0.006	-0.010	0.004	-0.007	-0.013**
	(0.012)	(0.008)	(0.005)	(0.007)	(0.006)
log(GDP)	0.453	0.658**	0.597**	0.906***	1.014***
	(0.300)	(0.270)	(0.269)	(0.257)	(0.253)
Observations	193	631	555	657	584
R^2	0.551	0.394	0.412	0.515	0.442
Adjusted R^2	0.413	0.332	0.349	0.468	0.380
F Statistic	45.034*** (df = 4; 147)	92.999*** (df = 4; 571)	87.730*** (df = 4; 500)	158.798*** (df = 4; 597)	103.960*** (df = 4; 524)

*Notes: All regressions estimated using OLS on the two-way FE-model, estimating the independent variable CCITR's effect in the dependent variable patents per 100 thousand capita (pats_pht). All regressions are included country and year fixed effects. All controls' coefficients included. Standard errors clustered at country-level reported in parentheses. See text for column explanations. *p<0.1; **p<0.05; ***p<0.01.*

In addition to the robustness checks, there are a few aspects that also may influence our results. First, we omit observations where any of the variables are missing. This is done due to the sourced data on different variables not being complete. Although some observations from different countries have been intentionally omitted due to political issues, having complete data without missing values for all other observations would strengthen the robustness of the analysis. Whether it would strengthen the robustness of our results or change the results is impossible to conclude.

In the analysis of time periods, the periods differ in years. In addition, we do not observe all the same countries, as i.e., Germany, Latvia, Czechia, Slovakia and Slovenia are not present in any of the 80's data. This might be a problem in regard to comparing the four periods as the number of observations is not the same in each period. This is also a problem generated from there being NAs in the data. Although this is not necessarily critical, one can argue that it weakens the robustness of the results.

5. Discussion

In this chapter we discuss the results of the analysis. First, we discuss how our results compare to similar research on the empirical relationship between innovation and corporate taxation. Next, we discuss some limitations of our study. Last, we point to topics for future research.

In the analysis in chapter 4, we find an overall negative effect of corporate taxation on the number of patent applications between 1981 to 2017. However, the β-coefficient is not statistically significant on any level. Therefore, we cannot reject the null hypothesis based on the main regression.

When analysing the panel in four time periods, we see a similar negative effect in the first three periods. The negative effect is not significant in the 1980's or the 1990's, but becomes significant at the 10 %-level in the 2000's. This implies that we cannot fully trust the estimates from 1981 to 1999, but we can with reasonable certainty say that we find evidence of the effect being negative from 2000 to 2009. Additionally, we also find a significant coefficient at a 10 %-level from 2010 to 2017, but here the effect is positive. The two significant β-coefficients demonstrates that there appears to be an empirical relationship between taxation and innovation.

In the introduction we present *Innovation and Taxation in 20th Century* by Akcigit et al. (2018), which serves as the starting point for our study. In absence of comparable research in Europe, specifically over a longer time frame, our main regression replicates the study in this paper to the best of our ability. Likewise, we also introduce papers by Mukherjee et al. (2017) and Atanassov and Liu (2015). Furthermore, we introduce papers by Ernst and Spengel (2011) and Karkinsky and Riedel (2009), which similar to our study exploits European patent data. Interestingly, all five papers find various significantly negative effects of corporate taxation on innovation in U.S. and Europe.

For example, Ernst and Spengel (2011) find that an increase in the combined CIT rate reduces the number of patent applications in Europe. Notably, Ernst and Spengel (2011) study a nearly identical sample (20 of our 26 countries) and time period (1998-2007) as our third interval (2000-2009). Given this, it may not be that remarkable that we also find a significant negative coefficient in this period.

Furthermore, the samples of countries also differ from each study. For natural reasons, the samples of the research papers based on U.S. patent data are not comparable. One can also argue that neither Ernst and Spengel (2011) or Karkinsky and Riedel (2009) are directly comparable. These two studies are limited to 18 and 20 European countries years, while we include 26 European countries. This may also explain why we find differences in significance for certain periods.

A potential explanation to differences in results may also be the models' purposes and assumptions. For example, similar research mainly measures patent application per firm in certain countries, while we associate the patent application directly to the country and study patent applications per 100,000 capita. For instance, Atanassov and Lui (2015) and Mukherjee et al. (2017) separate the independent variable by increase and decrease.

Another distinction between our study and other comparable research, is the time period. While Ernst and Spengel (2011) and Karkinsky and Riedel (2009) are limited to ten and nine years, we study the effect of corporate taxation on innovation over 36 years. Hence, we cannot compare our results directly with others, but we note that we find negative coefficients in the years building up to Ernst and Spengel (2011) and Karkinsky and Riedel (2009). Furthermore, our study is the only one that includes the years from 2010 to 2017. In contrast, we find a positive significant effect in the fourth interval (2010-17). The coefficient is also significant on the 10 %-level. This is contradictory to previous research which has only found negative coefficients of corporate taxation. For this reason, it may be valuable to reflect on the reasons behind the positive coefficient.

As we recognise from the literature, there has happened a lot in recent years with regard to the taxation of patents. In 2013, the OECD adopted an action plan to address base erosion and profit shifting (BEPS) (OECD, 2021c). This was partly due to an increasing number of countries offering patent boxes or other ways of deducting tax on patents, R&D or IP. A simple literature search reveals that a substantial number of countries have introduced such tax regimes during the last two decades, and that most are introduced from 2007. Thus, these effects cannot have been observed by Ernst and Spengel (2011) or Karkinsky and Riedel (2009).

France and Ireland are notably the countries that have had such regimes in Europe for the longest periods of time. Ireland had a patent box since 1973 that was abolished in 2010 due to budgetary reasons (Ciaramella, 2017). However, a new patent box was reintroduced in 2016. France introduced its first patent box in 2000, but has since been amended in 2005, 2010 and in 2019 (PwC, 2019). Of the remaining European countries in our panel, 14 countries have a patent box today, of which 10 were introduced in the years we observe in our panel. Specifically, patent boxes have been introduced in the following countries during the time period we analyse: Ireland (1973/2016), France (2000/2005/2010), Hungary (2003), Netherlands and Belgium (2007), Luxembourg and Spain (2008), Great Britain (2013), Portugal (2014) and Italy (2015) (Ciaramella, 2017; OECD, n.d.; Martins, 2018; PwC, 2015).

As explained in chapter 2.2, a patent box is a tax regime that applies a lower corporate tax rate on the income from patent ownership (Gaessler et al., 2018). This implies that if a country has a patent box, the statutory corporate income tax rate is unaffected as the patent box is a tax subsidy on the CIT rate.

Because these tax regimes were mainly introduced around 2010, this may explain why we find a significantly positive effect of combined CIT rates on patent applications from 2010 to 2017. The regime change may be a sign that combined CIT rates have lost explanatory power during the last ten to fifteen years, due to the growing use of patent boxes. The reason for this might be that the general tax policies are unaffected by changes in the specific tax policies.

Related to patent boxes much discussed topic, and the reason the OECD adopted an action plan to address BEPS, is the fact that patent boxes increase incentives to transfer patents across borders. Although we assume that patent transfers are not a problem in our data, this might be an assumption that does not hold. This is especially a relevant discussion for the data of years from approximately 2007. Gaessler et al. (2018) find that there is a small but existent relationship between the introduction of a patent box and patent transfers across borders. The researchers further state that the more valuable a patent is, the more likely it is to be relocated to a country with low tax. This implicates that patents that generate large incomes may have been transferred and therefore imperfects the data we study. Ultimately, this could impact the inference of our analysis.

Furthermore, there is a growing literature on the transfer of patents across borders, i.e., Gaessler et al (2018). The reason why this is especially important to understand in Europe is the fact that there are large differences in tax rates between countries. In addition to this, as we also observe, European countries have reduced their taxes significantly during the last decades and a country's taxes are affected by its neighbouring countries' taxes. The practice of tax avoidance and patent transfers is therefore a considerable factor when understanding how firms react to patenting and R&D following such changes in taxes that we have not accounted for. However, this has not been part of our study.

5.1 Limitations

In this chapter, we point to some limitations of this study. Limitations are characteristics of design and assumptions that impact the interpretation of the results. Like we have described, econometric models are developed with different purposes and assumptions in mind. Accordingly, we cannot take into account every aspect of innovation and taxation.

First, an essential limitation is that innovation will respond to taxation through different channels besides the statutory combined CIT rate in a country. In other words, corporate taxation is not the only way innovations are taxed. Although specific tax policies have been outside the scope of this study, we understand the drawback of not including specific policies.

In the last decade, various European OECD countries have introduced special tax policies. For example, Great Britain introduced tax box in 2013 (Ciaramella, 2017). A patent box aims to stimulate innovation, and thereby patenting activity. If countries rather introduce patent boxes to stimulate innovation instead of reducing corporate tax rates, and this is the reason for the increase in number of patent applications in the last decade, this is a limitation in our study. This is also a potential explanation to why we find a positive relationship between patent applications and combined CIT rate in the fourth time period. Given that a growing number of countries introduce such policies, this may reduce the accuracy of similar research in the future.

However, there are also reasons to why we do not control for this. First, specific tax policies vary considerably between countries. Second, data related to specific tax policies are difficult to obtain. The combination of these two issues makes it challenging to control for patent boxes in different European OECD countries.

Although not the direct goal of this study, we could have applied data on tax reforms on patents if we had found adequate data. This is however a laborious exercise that is complicated to perform correctly and has not been a priority in this thesis.

Another potential limitation is the absence of several other independent variables. Certain research papers choose to split the independent tax variable in two variables in order to separate the effect of tax increases and decreases. For example, Mukherjee et al. (2017) and Atanassov and Liu (2015) both separate their independent variable. Accordingly, such studies are able to capture these effects both ways. For instance, we may have found that tax decreases are not particular stimulating for the number of patent applications per 100,000 capita, but that tax increases are specifically damaging. This may have helped to strengthen our results.

A third consideration, debated by Akcigit et al. (2018), suggest that innovation may respond to corporate taxation with a lag. This means that changes in corporate taxation do not affect innovation immediately, but rather reduce future innovation. Akcigit et al. (2018) suggest that this lag starts one year after the tax change and may increase to three years depending on how long the innovation process is.

Given that this lag also applies for European OECD countries, this is a limitation of our study. Despite this, there may also be forward-looking effects amongst inventors, because innovation demands investments which are paid off many years into the future. Accordingly, Akcigit et al. (2018) describe that current tax rates may be the best predictor of future tax rates. Given that this is also true, this will counteract the limitation of lag.

5.2 Future research

This study has given an opportunity to study the combined universe of patents and corporate taxation. Although we have gained valuable insights, there have also surfaced unanswered questions which would be interesting topics for future research.

First, we have spoken about the fact that innovation will respond to taxation through several channels beside the statutory combined CIT rate. For this reason, there may be interesting to study the impacts of specific tax policies on innovation. In particular, patent boxes are relevant. Like we also have described, more and more countries introduce specific tax policies, which may help to increase access to data for future research. An attempt to calculate the B-index is a potential start to this research.

Second, the scope of this study has been limited to study the quantity of innovation. However, we also observe a considerable academic interest in quality of patents. Given that taxation (no longer) impacts the quantity of innovation, how do this correspond to the impact on the quality of innovation? For example, citations per patent may be a reasonable starting point.

Third, when diving into the universe of innovation, the mobility of patents is a recurrent topic in many papers. Specifically, the transferring of patents across borders appears to be increasing in volume. This may also be connected to a study of the quality of innovation, since Bösenberg and Egger (2017) argue that "more valuable patents are more likely to be transferred". An interesting debate is whether corporate inventors move to countries with lower taxation.

Fourth, we build on the existing literature by adding more countries to our panel than Ernst and Spengel (2011) and Karkinsky and Riedel (2009). Although the scope of this study is to study European OECD countries, there may also be appropriate to study as larger sample of European countries. However, this is reliant of better access to data.

6. Conclusion

The purpose of this master's thesis has been to analyse the impact of corporate taxation on innovation in Europe. This has been analysed through the following research question:

How do corporate income tax rates impact the number of patent applications in Europe?

Using a panel dataset constructed from OECD patent and taxation data and developing a fixed-effects model, we investigate whether there is a relationship between corporate tax rates and patent applications in European OECD countries.

The original inspiration for this master's thesis was a working paper by Akcigit et al. (2018), studying this very relationship in the United States. One of the reasons why the research by Akcigit et al. (2018) stands out, is that it detects an empirical relationship over a very long timeframe. In absence of comparable long timeframe studies in Europe, we replicate a simpler yet similar study to Akcigit et al. (2018) by studying 26 European OECD countries from 1981 to 2017.

Our analyses have present multiple exciting findings. The regression analyses suggest that historically, an increase in corporate taxation have led to decreased innovation. Although our main regression of the entire time frame does not prove this impact significantly, we find a significant effect in the data from the first decade of the twenty-first century. In the two previous decades, 1980's and 1990's, we find a negative yet not significant effect. The negative effect is in accordance with the existing literature, which find significantly negative effects in similar time periods.

However, we find evidence suggesting that from 2010 to 2017 the historical relationship between taxation and innovation flips. In this period, we find that an increase in corporate income taxes lead to increased innovation. In addition to being contradictory to findings in similar studies, this might seem counter-intuitive at first sight. Nonetheless, we argue that there might be adequate evidence to explain this as being a regime change in corporate taxation of patents.

We observe that there are a growing number of countries that have introduced patent boxes in recent years. Such tax deductions are not accounted for in our analyses, and therefore we cannot conclude that this in fact is the main explanatory factor, but it provides a possible explanation. Further research is needed on this topic to conclude whether patent boxes in fact have taken over the explanatory power that corporate tax rates have previously had on the development of patent applications in Europe.

Our results contribute to the existing literature in multiple aspects. Before we began the process of writing this master’s thesis, the object was to contribute to the literature by studying the impact of corporate taxation on innovation in a larger sample of European OECD countries and over a longer time frame than previous research. As the study and results have progressed, we also argue that we contribute with new insight related to the regime change.

To answer our research question, we argue that the trend has historically been that higher corporate tax rates result in less patent applications in Europe. However, during the 2010’s, this trend seems to have turned due to an increasing number of countries introducing patent boxes.

In the introduction of this master’s thesis, we argue that the outcome of our study is relevant for policy makers. Though this argument is somewhat bold, we believe that policy makers, in particular national tax authorities, must pay attention to the possibility of a turning trend in the taxation of innovation.

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8. Appendix

8.1 Supplementary tests

Figure A.1: Breusch-Godfrey test for serial correlation

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        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  log(pats_pht) ~ CCITR + EPOm + GDPG + log(GDP)
chisq = 383.89, df = 18, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Figure A.2: Breusch-Pagan test for heteroskedasticity

```
        studentized Breusch-Pagan test

data:  reg2
BP = 40.901, df = 4, p-value = 2.818e-08
```

8.2 Choice of independent variable

Like we discussed in chapter 3, we recognise that the standard central government CIT rate ($CITR$) may be a reasonable independent variable. Therefore, we include $CITR$ as an alternative independent variable in column 2. This illustrates that the difference between using these two variables is minimal.

While both β-coefficients of $CCITR$ and $CITR$ are negative, none of these are significant on any level. Likewise, the coefficients and standard error of each control variable remain nearly identical.

When including both $CCITR$ and $CITR$ as independent variables in column 3, we observe that the signs of the coefficients become contrary, where $CCITR$ is negative and $CITR$ is positive. Likewise, we observe the similar results when using only $CITR$ or both variables in the divided four time period regression. Although we observe that the $CCITR$ become significant, we cannot fully trust this result.

This appears to be a problem of collinearity caused by the high correlation (87.8 %) between these two variables. Although Wooldridge (2016) explains that correlation between variables is allowed, he also explains that high correlation can reduce the accuracy of the model. In our model, we experience switching signs between two correlated variables which is common with collinearity. Intuitively, two correlated variables should not work in the opposite direction. Thus, we cannot fully trust the p-values of $CCITR$ when combining both variables. In addition to the concluding discussion in chapter 3, we therefore conclude that the use of the most holistic measure of corporate income tax rates, $CCITR$, is the best measure to use.

Table A.1: Linear Panel Regression Models of Tax Effects on Patent Applications using different independent variables

	Dependent variable:		
	log(pats_pht)		
	(CCITR)	(CITR)	(BOTH)
CCITR	-0.007		-0.011
	(0.006)		(0.011)
CITR		-0.004	0.005
		(0.005)	(0.011)
EPOm	0.511***	0.525***	0.501***
	(0.131)	(0.137)	(0.118)
GDPG	-0.009*	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)
log(GDP)	1.061***	1.056***	1.079***
	(0.214)	(0.215)	(0.197)
Observations	796	796	796
R^2	0.472	0.468	0.473
Adjusted R^2	0.425	0.420	0.426
F Statistic	163.450*** (df = 4; 730)	160.399*** (df = 4; 730)	131.091*** (df = 5; 729)

*Note: All regressions estimated using OLS on the two-way FE-model. Column (1) estimates the independent variable CCITR's effect on the dependent variable patents per 100 thousand capita (pats_pht). Column (2) estimates the independent variable CITR's effect on the dependent variable patents per 100 thousand capita (pats_pht). In column (3) both CCITR and CITR are included as independent variables estimating the effect on the dependent variable. All regressions are included country and year fixed effects. All controls' coefficients included. Standard errors clustered at country-level reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.*