DISS. ETH NO. 29367

Effective Measures toward Climate Neutrality:

The Role of Taxation, Innovation, and Market Structure

A thesis submitted to attain the degree of
Doctor of Sciences of ETH ZURICH
(Dr. sc. ETH Zurich)

presented by

Vanessa da Cruz
MA UZH in Wirtschaftswissenschaften
born on 01.04.1993
citizen of Switzerland

accepted on the recommendation of
Prof. Dr. Lucas Bretschger
Prof. Dr. Armin Schmutzler

2023

Acknowledgements

As my PhD studies come to an end, I would like to thank the people that supported and accompanied me along the way.

First and foremost, I want to thank my supervisor Prof. Dr. Lucas Bretschger, who gave me the opportunity to pursue my doctorate. Thank you for opening this door to me and your support and guidance throughout my studies. I am grateful to my co-examiner Prof. Dr. Armin Schmutzler for the time he devoted to my thesis. I highly appreciate your comments and feedback to help me improve my work. I also want to thank Prof. Dr. Lint Barrage for chairing my defense.

I want to thank all of RESEC for their kindness and support I have received during these years. A special thanks goes to Dr. Melissa Newham. I am grateful for the excellent collaboration, the time and effort you put toward helping me with my projects and valuable advice throughout this time.

I want to thank Dr. Andreas Steinbauer for always believing in me and mentoring me. Your encouragement and support is what made this all possible.

Thank you to all my dearest friends for being there for me and keeping me sane during the tough times. A special thank you goes to Jochen, Louisa and Rahel. I deeply appreciate your friendship, your unwavering support, and the innumerable moments of laughter we shared. Furthermore, I am profoundly grateful to Flavia Hug. Your constant and tireless helpfulness and the countless discussions we have had over the years have been invaluable.

And finally, I want to thank my family, and a special thank you to my sister who proofread my bachelor thesis, my master thesis and now my doctoral thesis.

I dedicate this thesis to my grandmother, who did not witness this period in my life, but would have been immensely proud.

Contents

List of Tables

List of Figures

Thesis Summary

At present, the global energy system remains heavily dependent on fossil fuels, which are estimated to account for 81% of total energy consumption. To meet the internationally agreed temperature targets, a shift from the current fossil fuel-based economy to a sustainable, decarbonized economy is needed. In this thesis, I analyze several mechanisms that serve to reduce the dependency on fossil fuels. The thesis aims to contribute to the existing literature by advancing empirical knowledge of the forces that accelerate the development of green innovation and promote low-carbon energy use.

The introductory chapter illustrates the importance of climate policy and green innovation in addressing climate change. It argues that effective policies and technological progress offering environmentally-friendly alternatives to fossil fuels are necessary for the global transition to a more sustainable economy. Further, the chapter discusses the mechanisms of climate policy and of mergers and acquisitions. In the subsequent chapters, I empirically address these topics to contribute to the general understanding of mechanisms that induce green innovation and sustainable energy use.

Chapter 2 focuses on the innovation incentive mechanisms of government policies. The chapter empirically analyzes the inducement effect of regional environmental regulation on green innovation activity in the case of California's Cap-and-Trade Program. The goal of the chapter is to gain new insights into the effectiveness of policy-induced incentives in stimulating the development of new and environmentally-friendly technologies. The study finds that the introduction of the emission trading scheme led to an increase in green technological innovation in California.

Chapter 3 focuses on the impact of government regulation on energy use. The chapter provides a micro-level analysis on the effects of the Swiss CO_2 levy on the use of fossil fuels. The study finds that the regulation considerably reduced the use of heating oil by business entities in the industrial and service sector and thereby the CO_2 emissions from the combustion of fossil fuels. The results further show a heterogeneous response to the levy, with entities that regularly use heating oil being more responsive to tax changes

than occasional users.

Finally, Chapter 4 revisits the topic of green innovation by exploring the effects of mergers and acquisitions on green innovation. The chapter addresses the question of how consolidation between companies in the energy industry affects sustainable innovation of the entities by analyzing its impact on the subsequent innovation activities of acquiring firms. The chapter finds that green technological acquisitions – involving target firms that possess intellectual property related to sustainable technologies – significantly increase the green innovation output of acquiring firms post-acquisition.

Zusammenfassung

Nach wie vor ist das globale Energiesystem stark von fossilen Brennstoffen abhängig, deren Anteil am Gesamtenergieverbrauch auf 81 % geschätzt wird. Der Übergang von der derzeitigen auf fossilen Brennstoffen basierenden Wirtschaft zu einer nachhaltigen Wirtschaft erfordert dringende Massnahmen. In dieser Dissertation analysiere ich die Wirkungsmechanismen, die dazu beitragen, die Abhängigkeit von fossilen Brennstoffen zu verringern. Die Dissertation hat zum Ziel, einen Beitrag zur bestehenden Literatur zu leisten, indem die Einflussfaktoren, welche die Entwicklung grüner Technologien und die Förderung eines kohlenstoffarmen Energieverbrauchs begünstigen, empirisch untersucht werden.

Das einleitende Kapitel beleuchtet die Bedeutung von Klimapolitik und grüner Innovation in der Bewältigung des Klimawandels. Darin wird argumentiert, dass wirksame politische Massnahmen und technologischer Fortschritt, der umweltfreundliche Alternativen zu fossilen Brennstoffen bietet, notwendig sind für den weltweiten Übergang hin zu einer nachhaltigen Wirtschaft. Ferner werden in dem Kapitel die Wirkungsmechanismen der Klimapolitik sowie jene von Fusionen und Übernahmen erörtert. In den darauffolgenden Kapiteln erforsche ich diese Thematiken empirisch. Dadurch wird ein Beitrag zum allgemeinen Verständnis der Wirkungsmechanismen geleistet, die grüne Innovation und eine nachhaltige Energienutzung begünstigen.

Kapitel 2 behandelt die Innovationsanreizmechanismen staatlicher Regulierungen. Das Kapitel analysiert empirisch den Anreizeffekt regionaler Umweltregulierung auf grüne Innovationstätigkeit am Beispiel des kalifornischen Cap-and-Trade-Programmes. Ziel ist es, neue Erkenntnisse über die Anreizwirkungen umweltpolitischer Instrumente auf den technischen Fortschritt zu gewinnen. Die vorliegende Studie zeigt, dass die Einführung des Emissionshandelssystems zur Förderung neuer und umweltfreundlicher Technologien in Kalifornien geführt hat.

Kapitel 3 befasst sich mit den Auswirkungen staatlicher Regulierung auf den Energieverbrauch. In dem Kapitel werden die Auswirkungen der Schweizer CO_2-Abgabe auf

den Verbrauch von fossilen Brennstoffen auf Betriebsebene untersucht. Die Studie zeigt, dass die Einführung der CO_2-Abgabe den Verbrauch von Heizöl von Betriebsstätten im Industrie- und Dienstleistungssektor und damit die Emissionen aus der Verbrennung fossiler Brennstoffe erheblich reduziert hat. Die Ergebnisse zeigen darüber hinaus eine heterogene Reaktion auf die Besteuerung, wobei Betriebsstätte, die regelmässig Heizöl verwenden, stärker auf die Steueränderungen reagieren als gelegentliche Nutzer.

In Kapitel 4 wird das Thema der grünen Innovation erneut beleuchtet, indem die Auswirkungen von Fusionen und Übernahmen auf grüne Innovationen untersucht werden. Das Kapitel befasst sich mit der Frage, wie sich die Konsolidierung zwischen Unternehmen in der Energieindustrie auf die Innovation der Unternehmen auswirkt. Hierbei werden die Effekte von Fusionen und Übernahmen auf die Innovationsaktivitäten der übernehmenden Unternehmen nach der Konsolidierung untersucht. Die Analyse zeigt, dass Akquisitionen im Bereich grüner Technologien – bei denen die akquirierten Unternehmen über Patente auf nachhaltige Technologien verfügen – den grünen Innovationsoutput der akquirierenden Unternehmen nach der Akquisition erheblich steigern.

Chapter 1

Introduction

The overwhelming majority of the world's countries ratified the Paris Climate Agreement of 2015. The key objectives of this treaty include country-based mitigation and adaptation measures, in particular reducing emissions to limit global warming well below 2 degrees Celsius above pre-industrial levels. Despite the pledges made by nations, total net anthropogenic greenhouse gas (GHG) emissions have continued to increase, with the majority of emissions coming from the energy supply sector (IPCC, 2022). It is indisputable that emissions of energy-related greenhouse gases from the combustion of non-renewable energy sources present the main cause of global warming and environmental degradation. Mitigating climate change can thus only be attained by decarbonizing the energy system and reducing the demand for fossil fuels. An immediate and radical reduction in GHG emissions is needed to keep global warming within the established limits, yet the world is not on track to achieve the climate goals. How can the economy escape from its dependency on fossil fuels? How can the existing energy system be transformed into one that is more climate-friendly? Great hopes have been pinned on environmental policy, technology and energy substitution.

Achieving the climate targets requires not only short-term emission targets, but a paradigm shift in the energy sector as well as products and processes that will aid the sustainable development such as low-carbon emitting technologies. Technological development of this nature, also referred to as green innovation, can reduce the environmental impact of services and processes and optimize the use of natural resources.[1] This interrelationship between energy use, innovation and environmental policy is at the core of this dissertation.

[1] Throughout this dissertation, the terms green innovation, environmental innovation, and sustainable innovation will be used interchangeably.

1.1 The Importance of Climate Policy & Green Innovation

Rising atmospheric levels of greenhouse gases and the scarcity of non-renewable energy resources call for stricter environmental regulations and the development of sustainable energy sources and technologies. The underlying notion is that polluting economic activities and resource depletion are negative environmental externalities – costs or harmful effects that are not fully reflected in the market price and thus constitute market failures. In contrast to the negative externalities caused by fossil fuel consumption, conduction of research and development (R&D) generates positive externalities through knowledge spillovers. In the presence of spillovers, the development of a new technology or product leads to unintended technological benefits for competitors, reducing the incentives to invest in technological advances. This is especially the case for green innovation as its resulting environmental benefits are largely external (Brown, 2001). Consequently, innovation in low-carbon and resource-efficient technologies tends not to be self-enforcing, causing private actors to under-invest in environmental R&D. In the presence of these positive and negative externalities, the market fails to allocate resources efficiently, and intervention is necessary to correct these market failures.

Externalities are particularly pronounced in the energy sector, as the sector and the environment are inextricably linked (Jamasb & Pollitt, 2008), making this a primary reason why energy consumption and innovation is a public policy concern. This has led to a great deal of research on the optimal policies to correct externalities (see e.g. Pigou, 1920). Through the implementation of environmental policies, governments can take action to reduce carbon emissions and minimize harm to the environment. Technological advances can further accelerate the transition to a decarbonized economy. Progress in renewable energy technologies such as solar and wind power have led to significant cost reductions and increased efficiency in the power generation, and advances in energy storage provide solutions to cope with the variability and uncertainty of renewable energy sources. Technological breakthroughs of this kind are enabling renewables to become increasingly competitive with fossil fuels. However, path dependency may limit the development of low-carbon technologies as investment and innovation have historically focused on fossil fuel-based technologies. This can lead to a lock-in of the economic system due to high switching costs. Climate policies such as carbon pricing instruments can provide impetus to overcome this path dependency by shifting the direction of technological change and encouraging the development and adoption of novel low-carbon technologies (Acemoglu et al., 2012). Such policies, however, have limited public support and are often subject to criticism in public disputes as climate policy measures such as carbon taxes or emissions trading schemes are considered a burden on the economy. Neoclassical economic theory suggests that policies that limit the use of polluting resources lead to a decrease in output and consumption. However, such neoclassical climate change policy models (e.g. the DICE model developed by Nordhaus (1994)) model technological progress as exogenous process. Considering that carbon prices can induce technological change, this represents a limitation and results in an overestimation of the welfare costs of carbon policies. By introducing endogenous and directed technological change (see Gillingham et al. (2008) for an overview of endogenous technological change in climate change models), climate change models take into account that policy decisions and economic activities can encourage innovation and investment in low-carbon technologies. Endogenous technological change in climate change modelling results in lower costs of carbon and greater support of policies aimed at reducing carbon emissions. Thus, the interplay of climate policy and technological progress can facilitate and foster the adoption of renewable energy sources and sustainable development.

The broad concept of sustainable development encompasses ensuring equity across and between present and future generations (Pearce & Barbier, 2000), which should be a key consideration in developing a successful environmental policy. Thus, much academic and political discussion about designing sustainable economic frameworks is concerned with equitable and sustainable resource management (see e.g. Anthoff & Tol, 2010; Bretschger & Vinogradova, 2015; Lange et al., 2007). Given the finite supply of fossil fuels and the negative environmental consequences of fossil fuel extraction, transportation, and use, the current energy system is not sustainable and leads to social inequities, as low-income and marginalized communities are disproportionately affected by the associated environmental and health impacts (Bretschger & Valente, 2011). Implementing environmental policies that reduce the reliance on fossil fuels contributes to ensuring that future generations have the same access to resources and opportunities as the present generation. Additionally, technological progress is a safeguard for sustaining prosperity in a resource-constrained planet (see e.g. Bretschger, 2005; Borissov et al., 2019) and plays a vital role in making low-carbon energy solutions more affordable and accessible for all. Therefore, rather than focusing on penalizing environmentally harmful practices, policy can incentivize the development and adoption of sustainable practices to ensure that vulnerable regions and populations are not harmed. By promoting the transition to more sustainable consumption and production, policy accelerates clean innovation in energy production, transport, and buildings, which can in turn benefit countries and regions with limited resources through technological spillover effects (Acemoglu et al., 2014). One example is Kenya, which has made significant progress in improving energy access through the exploitation of renewable energy, particularly solar power. Whereas at the beginning of the century only about 15% of the population in Kenya had access to electricity, this number rose to over 71% by 2020.[2] Kenya's advances in renewable energy have also contributed to the economic development as the construction and operation of power plants has created job opportunities as well as boosted economic activity and living standards in the surrounding regions (Mariita, 2002).

Overall, environmental policies and green innovation play a significant role in addressing the pressing climate change challenges while supporting sustainable economic development across the globe.

1.2 The Mechanisms of Climate Policy

The prevailing market conditions lead to overconsumption and -production of goods that cause harmful effects and prevent economic agents from investing in clean energy resources and technologies. An effective and efficient environmental policy should aim to correct for both these positive and negative externalities. Thus, beyond reducing emissions, environmental policy must also be designed to promote technological development.

Standard economic theory predicts that if the relative price of fossil fuels increases, the demand for it decreases. Thus, increasing the relative price affects energy consumption patterns of consumers. Firms and households may be encouraged to save more energy, switch to more energy efficient machines and appliances, and replace fossil fuels for substitutes with lower relative prices. In the long run, firms have an incentive to invest in the development of technological innovation in order to decrease the use of the increasingly expensive factor. The concept of stimulating technological development by a change in factor prices was first proposed in 1932 by Hicks in *The Theory of Wages*. This has become known as the "induced innovation hypothesis" and states that "[a] change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind — directed to economizing the use of a factor which has become relatively expensive". The effects of a change in the relative price of energy sources thus can be twofold: It can lead to a change in energy consumption patterns and also impact the rate and direction of technological change by spurring innovation in renewables and energy efficiency. Given that environmental policy instruments such

[2] The World Bank, World Development Indicators (2023). Retrieved from `https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS`

as carbon pricing increase the relative price of environmental inputs, the induced innovation hypothesis suggests that environmental policy can stimulate the development of new technologies. Thus, there is a link between environmental policy and technological change.

The environmental literature has investigated the effects of carbon pricing on resource usage and innovation (see e.g. Dasgupta et al., 1980; Downing & White, 1986; Milliman & Prince, 1989; Popp, 2019). Carbon pricing has been found to be an effective and cost-efficient policy and thus an essential component of a policy mix that aims to steer technological change towards green energy and sustainable production processes – at least in theory (Acemoglu et al., 2012). The empirical evidence on the effects of carbon pricing, however, is mixed and the effectiveness depends on the nature and stringency of the policy as well as other factors such as characteristics of the economy and industry (Brännlund et al., 2009; Elkins & Baker, 2001). Consequently, the effects of carbon pricing on emissions and clean energy innovation is contingent on the particular context in which the policy is implemented.

1.3 The Mechanisms of Mergers & Acquisitions

Policy can stimulate the invention and adoption of less harmful technologies and promote sustainable energy behavior by setting economic incentives. Increasing pressure on companies to become more sustainable can also motivate environmental investments in the form of mergers and acquisitions (M&A). Firms increasingly engage in M&A in pursuit of growth opportunities to meet the demand for sustainable technologies and the challenges of resource scarcity (Fraunhoffer & Schiereck, 2012; Yoo et al., 2013). This trend is particularly evident in the energy sector, where global M&A activity is rising significantly (IMMA, 2021). The increasing demand for alternative energy sources has made renewable energy companies an attractive target for M&A with the aim of rapidly obtaining new products and markets. Thus, the acquisition of renewable energy companies constitutes a quick and effective way for firms to enter the renewable energy and cleantech sectors (Palmquist & Bask, 2016; Salvi et al., 2018). This opens up the path to sustainable development for companies, has a profound impact on corporate strategy and influences the post-acquisition innovation output.

On account of these developments, economists are paying increased attention to the impact of M&A and their consequences for innovation. The importance of innovation has also manifested itself among competition authorities. The existing literature reveals that a merger between two firms is generally a combination of positive and negative effects (Gilbert & Greene, 2014; Jullien & Lefouili, 2018; Katz & Shelanski, 2005). By combining the R&D efforts of different companies, mergers and acquisitions can create operational and financial synergies, allowing complementary resources, knowledge and skills to enhance innovation capabilities and enable the realisation of new technologies and products (Bena & Li, 2014; Hall, 1999). M&A can also negatively affect the innovation output of the involved firms. For example, increased market concentration can reduce incentives for innovation as there is less market pressure to differentiate and improve products. This notion that mergers dampen the incentives to innovate by lessening competition between two firms is often put forward by competition authorities and is explored in research dedicated to competition law (Baker, 2007; Gilbert & Newbery, 1982; Rapp, 1995). However, the effects of competition on innovation are often found to be ambiguous (see e.g. Aghion et al., 2005; Schmutzler, 2013) and whether M&A have positive or negative effects on innovation is dependent on a variety of factors, including the industry, the characteristics of acquirer and target firm, as well as the competitive landscape. Research on the effects of M&A in the context of innovation remains scare and no conclusive findings regarding the impact of M&A on environmental innovation can be drawn.

1.4 Outline of the Thesis

The thesis aims at broadening the existing knowledge around the impacts of government policies and the inducement of green innovation. While theoretical research has been conducted on these topics, gaps still exist in the empirical literature. Empirical research is required to test the theoretical considerations and verify their applicability in the real world. Collecting empirical data can uncover behavior, patterns and other important factors that are not apparent from theoretical models. As such, empirical studies are critical to complementing existing theoretical research, as they can support or refute theoretical hypotheses and provide a deeper understanding of real-world problems.

In the present thesis, I explore the mechanisms of climate policy and M&A in different empirical settings to advance research in the area of environmental economics and policy. To do so, the subsequent chapters of the thesis deal with the following three interlinked topics: green innovation, energy use and green energy innovation. In chapter 2, I consider the effects of climate policies on green innovation. The chapter evaluates the link between environmental regulation and green innovation in the context of regional emission trading systems, thereby expanding the empirical literature on the innovation inducement impact of environmental policy. Chapter 3 is devoted to evaluating the impact of environmental regulation on energy use. The chapter is co-authored with Lucas Bretschger and Melissa Newham. My contribution includes the development of the research question, data collection and processing, joint elaboration of the statistical analysis and its implementation. In chapter 4, I shift the focus from the effects of government actions to those of market transactions by empirically evaluating the effects of M&A on green innovation. The chapter comprises work co-authored with Melissa Newham, where my contribution includes formulating the research topic, collecting and compiling the necessary data, co-developing of the hypotheses and assisting in the statistical process. The main research questions addressed in each chapter are as follows:

- Chapter 2: How does the introduction of a regional emission trading system affect innovation in environmentally-friendly technologies?
- Chapter 3: What are the effects of a carbon tax on energy use and related emissions?
- Chapter 4: Do M&A of firms that own or apply green technologies induce acquiring firms to direct more of their innovation efforts towards green technologies?

The dissertation addresses the questions empirically based on the examples of Switzerland and the United States using diverse statistical methods. In the following sections, the empirical methods and the innovation measure employed are described, and the individual chapters of the dissertation are outlined in more detail.

1.5 Methods & Data

1.5.1 Empirical Methods

The selection of appropriate statistical methods is crucial for a reliable empirical analysis. Each chapter requires its own empirical strategy, as the statistical method depends on the empirical framework and the aim and purpose of the study. This section presents the empirical challenges and the selected methods used in each chapter to answer the different research questions.

In the second chapter, I draw on the synthetic control approach to empirically estimate the effectiveness of emission trading schemes in inducing green innovative activity as the method offers advantages relative to other commonly used identification strategies such as the difference-in-differences (DiD) method. The DiD method is a frequently applied policy evaluation tool when estimating the effect of an intervention at an aggregate level. However, the method relies on contrasting pre- and post-treatment outcomes across the treatment and control group, assuming that the outcomes prior to the treatment follow a parallel trend. Violation of the parallel trend assumption leads to a biased estimate of the causal effect, thereby making a DiD method unsuitable. The synthetic control method provides advantages as a research design method by relaxing the parallel trend assumption due to the construction of a counterfactual of the weighted average from a group of untreated units. This research method originally devised by Abadie & Gardeazabal (2003) and Abadie et al. (2010) has been described as "[...] the most important innovation in the policy evaluation literature in the last 15 years" (Athey & Imbens, 2017).

In the third chapter, we estimate policy-relevant treatment effects at the micro-level which requires a method that is designed for granular data. The main challenge in estimating the policy treatment effect stems from the fact that all entities in the available data are treated. Thus, we suffer from the fundamental problem of causal inference, which is also known as the missing data problem (Holland, 1986; Rubin, 1974). Hence, we do not observe the outcomes in the absence of the policy and there exists no control group to which the treatment group can be compared. Machine learning (ML) methods can address the problem of missing control groups that frequently arises in observational studies, by using the available data to estimate counterfactual outcomes. ML methods for policy evaluation have received much attention in recent years as they offer several promising features (e.g. Kleinberg et al., 2015; Künzel et al., 2019; Varian, 2014). ML methods are particularly beneficial as they are able to capture complex relationships between covariates and outcomes and process high-dimensional data. Hence, we use machine learning predictions as a counterfactual control scenario which allows for an accurate and precise estimation of micro-level policy effects.

In the fourth chapter, we evaluate the causal effects of M&A on innovation. The most common challenge of all empirical work dealing with the effects of M&A is the problem of endogeneity, as mergers and acquisitions are often the result of a strategic decision-making process. Further, as treatment occurs at different points in time, a statistical method is required that can accommodate the staggered nature of treatment. Hence, we select the staggered DiD framework as our identification strategy while considering acquiring firms and control for endogenous selection by using not yet treated entities as control observation as opposed to never treated entities to partially control for endogeneity.

1.5.2 Measuring Innovation Using Patent Data

The current literature proposes different measurements of innovation such as R&D expenditures, total factor productivity and patents. Following previous studies on induced innovation (e.g. Calel & Dechezleprêtre, 2016; Jaffe & Palmer, 1997; Noailly, 2012; Popp, 2002), this dissertation relies on patent data to measure innovative activities. A patent is an exclusive intellectual property right in exchange for disclosure of the creation. In order for an inventor to be granted a patent, the invention must constitute a technical novelty, involve an inventive step and be susceptible of industrial application. Each patent application must satisfy these three criteria as well as undergo a lengthy and costly procedure in order to be granted. These aspects imply that an invention protected by a patent constitutes an innovation, since a novelty and utility standard applies to the grant of such a right, and that this invention is expected to provide the applicants with future benefits that offset the expenses of the time and cost consuming procedure (Archibugi, 1992). These are the main indications of Schumpeter's (1939) commonly used distinction between the terms "innovation" and "invention". Schumpeter defines invention as the act of "intellectual creativity" with no economic significance, whereas an innovation refers to the introduction of a novel technical idea with commercial purpose. Thus, by this definition, granted patent applications represent innovation output and are an appropriate indicator to capture technological progress.

The use of patents as an indicator of innovation activity is well established. Patent data has been applied in numerous studies on a wide range of topics, and the advantages and disadvantages of the indicator have been debated since the 1990's (Archibugi, 1992; Desrochers, 1998; Griliches, 1990). Patent statistics are used as metric for innovation due to several advantages. One of them is the common availability of data over a long period of time (Archibugi, 1992; Griliches, 1990; OECD, 1994). All information is collected by patent offices and can be accessed via public web search engines. As the data is obtainable for all countries with a patent system, patents offer a high degree of spatial coverage and allow for cross-national comparisons. On top of that, patents provide detailed information about the invention. Patent documents contain a description of the invention, the name and address of the inventor and applicant, the technology field to which the invention relates as well as citations to other patents. This allows the evaluation of both the rate and the direction of technological change (Archibugi, 1992). Furthermore, it has been shown that there is a strong relationship between R&D spending and the number of patent applications (Griliches, 1990).

Patent statistics as innovation indicator also have drawbacks. One of the biggest shortcomings is that patent data may be an incomplete measure of innovation. On the one hand, not all inventions are patentable. Inventions that cannot meet the criteria for patentability but are nonetheless considered innovations are not reflected by the patent databases. On the other hand, not all inventions are being patented as there are alternative strategies to protect intellectual property (Pavitt, 1988). However, it has been found that there are only a few examples of economically significant inventions that have not been patented (Dernis et al., 2001). Another area of concern is that the propensity to apply for a patent differs significantly across technical fields, sectors and industries (Archibugi, 1992; Desrochers, 1998). Some technical fields or industries may experience more patent applications than others, which can lead to a skewed representation of the innovation rate. Studies have also revealed that patents can differ significantly in terms of their economic value (Lanjouw et al., 1998; Schankerman & Pakes, 1986). If the value distribution of patent is skewed, a simple patent count can be deceptive because highly valuable innovations are treated the same as innovations of little or no value.

Notwithstanding these limitations, patents are a widely accepted, popular indicator for innovation due to the availability of data over a long period at a highly disaggregated technological level which enables the research focus to be placed on green innovation (OECD, 1994) . In consequence, I employ patent statistics as indicator for innovation.

1.6 Contribution of the Thesis

1.6.1 Cap-and-Innovate

In recent years, California has assumed a leading role in addressing the climate crisis by enacting some of the nation's most ambitious climate measures. Extreme weather conditions in 1988 increased awareness of the greenhouse effect, leading to California passing its first climate change legislation (Franco et al., 2008). In June 2005, the Golden State established GHG emission reduction targets to reduce emissions to what the state emitted in the years 2000 and 1990 by 2010 and 2020, respectively, and to reduce emissions to 80 percent below 1990 levels by 2050. This was followed in 2006 by passing the Assembly Bill 32 (also known as AB 32 or California Global Warming Solutions Act of 2006) which put the emission targets into law. The passage of the bill made California the first state in the US to place legally binding, economy-wide emission targets. The AB 32 required the California Air Resources Board (CARB) to establish a scoping plan of regulatory and market mechanisms to achieve the reduction targets.

At the heart of CARB's Scoping Plan is the Cap-and-Trade Program which constrains firm-level emissions. The Cap-and-Trade applies to emissions that account for about 80% of the state's GHG emissions, thereby providing a strong economic incentive for significant investment in cleaner and energy-efficient technologies.

By empirically analyzing the effects of the Cap-and-Trade on the State's green innovation output, the chapter's findings enrich the literature on the innovation incentive effects of emission trading systems and quantitatively support the implementation of regional environmental policy. The paper thus contributes to a greater understanding of the role of local and regional policy in the achievement of sustainable development goals. For the economy to transition to a green economic pathway, successful policies at all levels of government are critical. Many US state governments are undertaking groundbreaking work in developing and implementing ambitious climate policies, thereby taking a leading role in promoting clean energy (Carley, 2011). Yet, research on climate policy has focused heavily on international political governance and the policy responses of national governments. Insights on the effects of regional policies are useful for other regional governments in setting their own climate policies. In this way, California's policies can serve as an example and pave the way for the adoption of similar programs in other US states as well as nationally.

1.6.2 Evaluation of Climate Policy Based on Machine Learning

In Switzerland, the introduction of a CO_2 tax has been discussed since the 1980s. The federal government has set the goal to reduce fossil fuel dependency and increase the share of renewable energies to guarantee a secure and reliable supply of environmentally sound energy. In 2000, the CO_2 Act came into force, setting reduction targets for the period 2008 – 2012 compared to 1990. On top of the goal of creating economical energy consumption and increased use of climate-friendly energy sources, Switzerland committed itself to reducing GHG emissions with the ratification of the Kyoto Protocol in July 2003. Due to the increasing deviation from the targeted reduction path, the Federal Council introduced a CO_2 tax in 2008. The tax is imposed on fossil thermal fuels (e.g. coal, heating oil, natural gas) when they are used by firms and households to generate heat, light or electricity and is indicated on invoices for purchases of thermal fuels. By increasing the price of fossil fuels, the levy is intended to set financial incentives for households and firms to switch from CO_2-intensive energy sources to low-CO_2 or CO_2-free alternatives.

Despite carbon taxation being a widely used policy instrument, there are a limited number of ex-post assessments of carbon taxes in the literature. Using machine learning to estimate the impacts of the Swiss CO_2 levy, this chapter expands the literature on carbon taxation. Taking a micro-level perspective, the paper provides insights into the effect of carbon taxation on energy use of business entities and the associated emissions from fossil fuels which can serve as a basis for future policy decisions and contribute to ongoing discussions on effective environmental policy instruments. Further, our study contributes to the emerging literature on the use of machine learning methods for causal policy analysis by providing an implementation of this novel approach that illustrates its use for estimating policy effects with real world data.

1.6.3 Learning by Buying

Instead of focusing exclusively on the price effects of mergers, competition authorities are increasingly taking innovation aspects into consideration in competition investigations. Predicting the impact of M&A on innovation is difficult because the evaluation is complicated by the interaction of several effects and depends on the characteristics of the respective markets. In antitrust economics, the question of whether mergers are helpful or harmful to investment in research and development (R&D) and innovation, and thus to the long-term welfare of consumers, remains unsettled.

Both M&A and innovation in climate-friendly technologies have become a business strategy to reduce environmental impacts and comply with environmental regulations, yet there is little research on the interrelationship between M&A and green innovation. Most existing studies in this field are limited to examining the overall impact on innovation without taking into consideration the direction of innovation. Considering the importance of green innovation in the reduction of emissions and the ongoing increase in M&A activity in the energy sector, it is crucial to understand how the consolidation of firms impacts the green innovation output. The importance of this topic is further underscored by the fact that the electricity sector is one of the largest contributors to global emissions. To this end, the chapter aims to fill the gap in the literature by studying the effects of M&A in the energy sector. To our knowledge, this is the first paper that empirically analyzes the effects of M&A on green innovation. The paper thereby contributes to the literature on the effects of M&A on innovation and on the drivers of green innovation.

Chapter 2

Cap-and-Innovate: Evidence of Regulation-induced Innovation in California

Chapter Abstract

California has adopted some of the strictest environmental regulations among US states, taking a climate leadership role at the subnational level. The paper applies the synthetic control method to evaluate the effects of California's Cap-and-Trade Program on environmental innovation. Using patent data and a weighted combination of other US states as counterfactual, I estimate the causal effect of the policy on innovative activity. The estimates show that the number of patents related to green technologies increased by approximately 22.5% after the implementation of the Cap-and-Trade regulation. A difference-in-differences approach yields comparable estimates and provides empirical evidence that the policy encouraged the development of alternative and energy conservation technologies. The results indicate that the introduction of regional climate policies can promote environmental innovation in the respective region.

2.1 Introduction

New technological developments play an important and decisive role in tackling long-term environmental problems. Scholars have therefore paid increasing attention to the nexus between environmental regulation and technological innovation. The idea that environmental policies may spur technological innovation dates back to the “induced innovation hypothesis” proposed by Hicks (1932). The hypothesis suggests that by increasing the relative price of environmental inputs, policies can induce innovation to economize on the relatively expensive input.[1] This notion has sparked considerable literature on the impact of environmental policies on the direction and rate of technological change.[2] The majority of empirical studies examining the link between environmental policy and innovation focus on national or transnational policy and there is scant research on the impact of regional climate policies. I fill this gap by providing an empirical analysis of the impact of regional environmental regulation on green innovation.

Many political, innovative ideas and pioneering policies are emerging and being adopted at the local level (Schreurs, 2008). Subnational climate change mitigation efforts can advance federal climate policy in that policymakers can benefit from local regulation by gaining knowledge and experience in adopting and enforcing policy instruments (Adler, 2005). This bottom-up policy approach is particularly evident in the United States, where the willingness of federal and state governments to tackle climate change has diverged in recent decades. As the federal government restrains its efforts to reduce greenhouse gas emissions, the actions of lower levels of government are taking on greater importance. Environmental action has increasingly shifted toward lower levels of government, with state and local policy makers setting emissions targets and implementing regulations (Lutsey & Sperling, 2008). As such, state governments have the ability to shape the course of political change at the national level or within other states. Consequently, scholars have emphasized the growing role of state and local government action in shaping US climate policy at the federal level (Rabe, 2004; Selin & VanDeveer, 2007).

California, which is projected to be the fourth largest economy in the world,[3] sets itself apart from other US states due to its unrivaled pioneering role in environmentalism. Since the 1980s, the Golden State has implemented the most innovative and stringent environmental policies. Due to its economic size and cross-border cooperations to reduce global emissions, the state is playing a global climate leadership role. California’s global influence is also evidenced by the term “California effect” invoked by Vogel (1997). The term describes the tendency for

[1] Porter further developed this idea and significantly contributed to the debate surrounding the link between environmental regulation and innovation by proposing the so-called Porter Hypothesis (Porter, 1991; Porter & van der Linde, 1995). The hypothesis asserts that well-designed and stringent environmental regulation can effectively spur innovation aimed at lowering the cost of the regulation compliance, thereby improving firm productivity and competitiveness.

[2] Earlier studies mainly involved theoretical models to compare the impacts of different environmental policy instruments on environmentally-friendly innovation (see e.g. Downing & White, 1986 and Milliman & Prince, 1989). The growing availability of data on innovation activities has brought forth a number of empirical studies analyzing the effects of environmental regulation on innovation (see Popp (2019) for an overview).

[3] https://www.weforum.org/agenda/2022/11/california-s-economy-may-surpass-germany-s-but-what-s-beneath-the-numbers/

environmental regulations to shift to the level of political jurisdictions with more stringent regulatory standards. It derives from the spread of stricter environmental regulations, which were first introduced by California and subsequently adopted in other US states.

In 2011, California adopted the first multi-sector Cap-and-Trade system in North America covering electricity generators, large industrial facilities, and fuel suppliers. The Cap-and-Trade is a key regulatory system for the state to respond to climate change and meet the state's greenhouse gas reduction goals. California's climate action can provide valuable lessons for the implementation and administration of state-wide emission trading systems and other market-based instruments. Understanding the impact of California's emission trading system is therefore of great significance to the achievement of the US climate goals as well as to the development of green technologies both domestically and in other parts of the world.

There is currently a limited body of research pertaining to subnational climate policy. The existing studies are largely focused on "carbon leakage" where firms shift their production to other regions with less stringent emission constraints. For example, Bushnell & Chen (2012) and Fowlie (2009) investigate the potential for leakage between US states, finding evidence of such leakage. It is argued that subnational climate policies are subject to larger carbon leakage rates than their federal counterparts as trade between states is less restricted. Related research examining the effects of "pollution havens" analyze how regional energy prices impact trade and the location of energy-intensive manufacturing facilities (see e.g. Aldy & Pizer, 2015; Fell & Maniloff, 2018; Kahn & Mansur, 2013). The general results suggest that stricter environmental regulations or higher energy prices in a region can lead to an increase in emission-intensive imports and a decrease in energy-intensive manufacturing in that area.

There are thus two opposing views on the effects of subnational climate action. Whereas the induced innovation hypothesis asserts that companies respond to environmental regulations by investing in green technology, the second view assumes that, in the case of asymmetric environmental policies within national borders, companies may react by relocating to regions with laxer regulation which potentially leads to carbon leakage. Against this background, the question arises whether the theory of induced innovation is applicable when considering subnational political regulation. I address this question by exploring the relationship between environmental regulation and green innovation on a regional level by estimating the effect of California's regional Cap-and-Trade system on green innovation.

The goal of this paper is to explore whether state-level policy promotes innovation within state borders. To analyze the impact of California's Cap-and-Trade program, I use patents as a measure for innovation and the synthetic control method (SCM) (Abadie & Gardeazabal, 2003; Abadie et al., 2010). The SCM aims to estimate treatment effects by constructing a counterfactual for the treated region using a weighted combination of control units. I find that the implementation of California's Cap-and-Trade increased innovative activity measured in patents related to climate change mitigation technologies by around 22.5%. I further perform a difference-in-differences (DiD) method on disaggregated patent data, revealing that the estimated effect is driven by an increase in patents related to alternative energy production and energy conservation. Therefore, this paper indicates that the policy measure encouraged the private sector to develop alternative and renewable energy technologies. The empirical findings provide evidence that regional emission trading systems spur innovation within state borders. These findings give insights into mechanisms that promote technological change, leading to valuable policy lessons. In a broader sense, the results of this paper deepen our understanding of the impacts of regional governments in combating climate change, which could have important ramifications for the role of regional governments in climate policy discussions.

This paper contributes to the literature in two important ways. First, I add to the induced innovation literature by extending the empirical evidence on the inducement impact of environmental regulation. While there is an extensive literature examining the relationship between environmental policy and innovation (see e.g. Popp, 2010 and Popp, 2019 for an overview), there exist only few empirical studies that specifically address the inducement effect of emission trading systems, most of which focus on the EU Emissions Trading System (Bel & Joseph, 2018; Borghesi et al., 2015; Calel & Dechezleprêtre, 2016; Popp, 2003; Taylor, 2012). With the emission trading system becoming an increasingly popular policy tool, evaluating its impact can provide useful insights for policy makers.

Second, this paper adds to the literature analyzing the role of subnational governments in combating climate change. It is increasingly recognised that research should address subnational climate policies to further our understanding of the challenges and effectiveness of implementing local and state climate measures (Linstroth & Bell, 2007; Lundqvist & Biel, 2013; Schreurs, 2008). Prior research in this field has focused on the development and implementation of innovative policy strategies and the diffusion of environmental policies (see e.g. Anderton & Setzer, 2018; de Oliveira, 2009; Mazmanian et al., 2008). However, little is known about the impact of state-level regulations on innovation, as existing studies focus on policies at the national or transnational level. In a recent paper, Popp (2020) highlights the significance of state and local government involvement in R&D efforts. Recognizing that the current political climate in the US suggests that climate policy progress is more likely to be made at the state and local level than at the federal level, Popp summarizes research on clean energy innovation to draw important lessons for state and local governments. I extend this line of research by providing quantitative evidence on the topic.

The remainder of this paper is organized as follows. Section 2 describes the empirical design and data used to estimate the impact of the policy on innovation. Subsequently, Section 3 presents the main findings. Section 4 concludes.

2.2 Empirical Analysis

2.2.1 Method

I implement the synthetic control approach originally introduced by Abadie & Gardeazabal (2003) and expanded in Abadie et al. (2010). The SCM estimates an unobserved counterfactual of the treated unit. This involves constructing a synthetic control unit as a weighted average of untreated states that is comparable with the treated unit before the policy intervention. This allows to compare outcomes of the treated unit with a synthetic counterfactual over time. The method has been applied by an increasing number of studies evaluating the impact of policy interventions (e.g. Andersson, 2019; Bretschger & Grieg, 2020; Bueno & Valente, 2019; Kreif et al., 2016; Leroutier, 2019) as it offers advantages compared to other traditional methods by allowing for the effects of unobserved variables to change over time (Kreif et al., 2016). Another advantage stems from the transparency of the weights assigned to each unit of the control group, providing a comprehensible construction of the estimated counterfactual of interest (Abadie et al., 2015). However, the SCM also presents some drawbacks and limitations, including the failure of the method to allow for the presence of spillover effects and the requirement that the outcome trajectory of the synthetic control must approximate that of the treated unit during the pre-treatment period (Abadie, 2021). The credibility of the result depends on achieving a good pre-intervention fit for the outcome variable between treated unit and synthetic control. The fit can be assessed graphically or measured by using the mean squared prediction error (MSPE).[4] Given a good fit, the difference in the outcome variable during the post-treatment period can be interpreted as the treatment effect.

The notation and proceeding of the paper follows the approach of Abadie et al. (2010). Let $t = 1, ..., T$ be the observed time period. Let T_0 denote the number of pre-intervention periods with $1 \leq T_0 < T$. In a case where forward looking economic agents react in advance of the policy intervention and there are signs of anticipation, Abadie (2021) recommends to "[...] backdate the intervention in the data set to a period before any anticipation effect can be expected, so the full extent of the effect of the intervention can be estimated". Thus, the beginning of the treatment period is set to begin with the passage of the bill in 2011 as anticipated regulations can encourage firms and organizations to invest in R&D prior to the first compliance period (Barbieri, 2015; Taylor et al., 2003).[5][6]

Let $J + 1$ be the states observed over the time period t with $J = 1$ being the state of California. The remaining J states are potential control units will be referred to as the “donor pool”. Control units in the donor pool are not affected by the treatment for any period t. The observed outcome variable of interest for a unit $i = 1, ..., J + 1$ at time t is given by Y_{it}. Correspondingly, let Y_{1t}^N and Y_{1t}^I be the outcome variable for California under no treatment and under treatment, respectively. Subsequently, the treatment effect can be denoted as:

[4] $\text{MSPE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

[5] Due to regulations being published before the effective implementation, inventions are developed beforehand to ensure that the requirements can be met which results in a rise in patent applications even before regulations were implemented.

[6] Adjusting the starting point of the treatment period to account for earlier anticipation does not have a significant impact on the results presented in the paper (see Appendix A.2).

$$\alpha_t = Y_{1t}^I - Y_{1t}^N \tag{2.1}$$

As the counterfactual Y_{1t}^N is unobserved, it has to be estimated. The estimation of the counterfactual is derived from the weighted average of control units Y_{jt} $(j = 2, ..., J+1)$ in the donor pool. Therefore:

$$\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt} \tag{2.2}$$

where $\sum_{j=2}^{J+1} w_j = 1$ and $0 \leq w_j \leq 1$. $\sum_{j=2}^{J+1} w_j$ is defined as a $(J \times 1)$ vector W of weights, such that each value of W represents a potential synthetic California. The vector W is obtained by minimizing the discrepancy of the pre-treatment characteristics of California and the donor pool. Formally, W is derived such that:

$$\|X_1 - X_0 W\| v = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{2.3}$$

where $X_1 = (Z_1', Y_{11}, ..., Y_{1T_0})$ denotes a $(k \times 1)$ vector of pre-treatment characteristics for California and $X_0 = (Z_j', Y_{j1}, ..., Y_{jT_0})$ is a $(k \times J)$ matrix for the untreated states. Z_i denotes the vector of predictors of Y_{it}. Analogous to Abadie & Gardeazabal (2003), let V be some $(k \times k)$ symmetric and positive semi definite matrix that assigns weights to pre-treatment variables in such a way as to minimize the mean square error for the pre-treatment periods.

2.2.2 Patent Data

The patent data is collected from the U.S. Patent and Trademark Office (USPTO) online database. The USPTO provides a publicly available data set, consisting of a complete history of patent applications for all states as of 1976.[7] For the analysis, I restrict the data to successful patent applications (i.e. granted patents) to ensure that the applications meet the requirements of novelty and marketability.[8]

As this paper focuses on green innovation, I rely on the "IPC Green Inventory" developed by the International Patent Classification (IPC) to conduct a targeted search for relevant patents.[9] The IPC is a classification system developed at the World Intellectual Property Organisation (WIPO). The IPC Green Inventory was established to facilitate searches for patents relating to Environmentally Sound Technologies (ESTs).

Figure 2.1a depicts the evolution of patent filings from 1976 until 2015 distributed by year of application in the US. Figure 2.1b graphs the development of patent filings for California. At the beginning of the century, both the US and California experience an increase in green patent applications. Towards the end of the observed period, however, the number of green

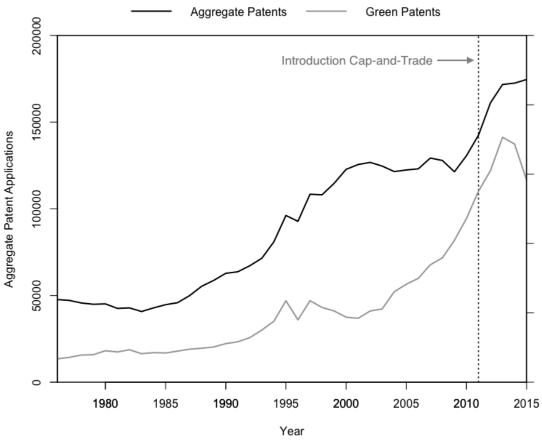
[7] Documentation updated on March 30, 2021.

[8] I discard all patents originating outside the US or in incorporated and unincorporated territories and military states from the dataset. Furthermore, I omit all patent documents with faulty or incomplete information.

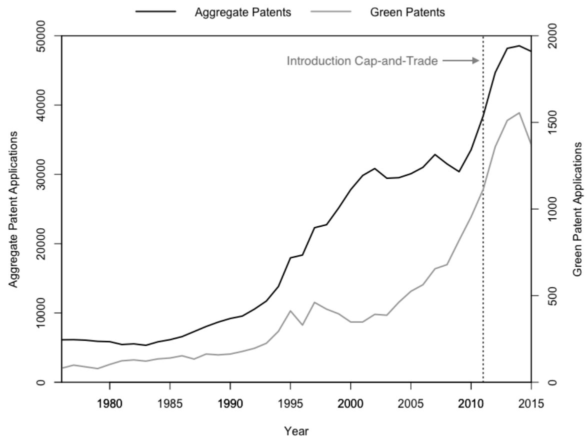
[9] The Green Inventory is one of several green patent classification systems. It is adopted in this paper due to being the most widely used classification in academic literature (Tanner et al., 2019).

patent application declines. This decreasing trend in green patent applications is in line with previous published results on the development of environmental innovation who recorded a decline in the number of patent applications this field (León et al., 2018; OECD, 2021; Urbaniec et al., 2021).[10]

Figure 2.1: Patent Filing Trends, 1976–2015



(a) US Patent Trends



(b) California Patent Trends

For each patent, I collect several bibliographic data including filing date, grant date, IPC code as well as details of the inventor/assignee and citation information.[11] I determine the patent origin by the residence of the inventor and the assignee. In the case of two or more entities residing in different states, I follow the OECD Patent Statistics Manual (2009) which suggest fractional counting, i.e. "sharing" the patent among the respective states to avoid double counting.[12] It has to be noted, however, that this approach can result in over- or underestimation of some states, as the different contributions to the inventive output of several inventors may not have equal weight. Further, I define the application date as the date of origin of the invention, as it is a good indicator of R&D activities and a more accurate approximation than the grant date due to the duration of the patent granting process (Griliches, 1990).

To account for differences in the importance and value of inventions, the patents are weighted using a logarithmic transformation of the number of forward citations.[13] This

[10]The studies report that patent filings in the field have declined for some technologies, notably patenting activity in alternative energy technologies. This development is not exclusive to the US but can also be observed in countries such as Germany, Japan and China. The reasons for this development are not entirely clear.

[11]Inventorship is independent of the assignment of a patent. The person(s) listed as an inventor on a patent application is determined by who conceived of the invention. In contrast, the assignee is defined as the entity that holds the property rights to the patent.

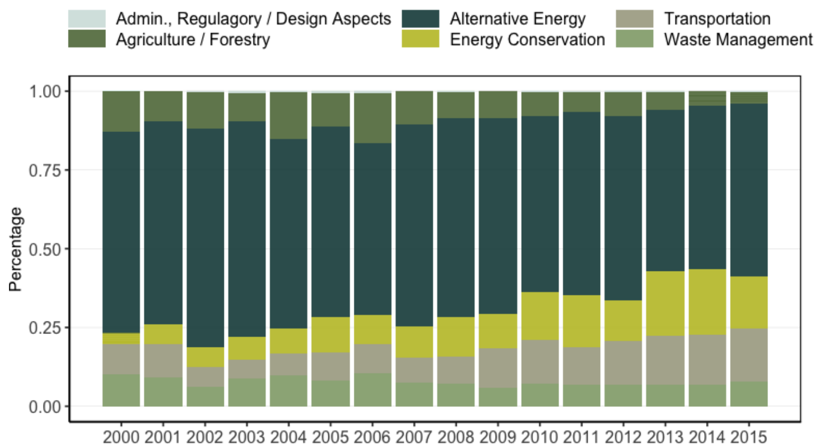
[12]This case can occur if either (i) there are two or more inventors; (ii) inventor and assignee differ; or (iii) there are multiple partial assignees of the patent property.

[13]Each patent application is multiplied by ln(2 + #forward citations). Because the number of citations increases over time as older patents have had more time to accumulate citations, only citations within the first five years of publication are counted to avoid bias (OECD, 2009). Studies have found that a citation window of the first five years following publication is a reasonable indicator for the number of citations received for

citation-weighted indicator overcomes the issue of the skewed distribution of patent values (OECD, 2009).[14] Thus, I determine the weighted number of patents per year for each US state based on the inventor's and assignee's state of residence, the application date and fractional counts. I then compute the patent count per 100'000 inhabitants for comparability between states.[15] Consequently, the outcome variable is given by the citation-weighted annual count of granted green patent applications per 100'000 inhabitants per state.

Based on the patent classification, green patents can be categorized in seven major areas: a) administrative, regulatory or design aspects; b) alternative energy production; c) agriculture/ forestry; d) energy conservation; e) transportation; f) nuclear power generation; and g) waste management.[16] Figure 2.2 depicts the percentage distribution of green patents in California per technological category.[17] Notably, patents related to alternative energy production and energy conservation represent the largest share of patent filings, reflecting the growing interest in technological advancements in this field such as solar, wind and hydro power since the late 1990s (WIPO, 2009). In comparison, only a small share of green patents pertain to agriculture/forestry and waste management. Examples of patents falling under these categories include innovations related to pesticide alternatives and reuse of waste materials. Green patents related to transportation include technologies related to hybrid vehicles or cosmonautic vehicles using solar energy. The smallest share relates to patents concerning administrative, regulatory or design aspects, such as patents on emissions trading.

Figure 2.2: Green Patent Filings in California by Technological Area, 2000–2015



each patent application as the majority of all citations occur during this period (Breschi et al., 2006; Narin & Olivastro, 1993).

[14] Several studies provide evidence that the number of citations a patent receives is a valid measure of the technological importance and value of an invention (Carpenter et al., 1981; Lanjouw & Schankerman, 1999; Trajtenberg, 1990).

[15] Due to California being extreme in the number of patent applications compared to other US states, there is not a weighted average of untreated states that can approximate the trajectory of the outcome variable in the pre-treatment period (see Appendix A.1.1). To circumvent this, I transform the outcome variable by taking the population size into account.

[16] Further details are given in Appendix A.1.4, Table A.3.

[17] Nuclear Energy Generation is not represented in the graph, as no patents were found for this category in the data set.

2.2.3 Covariates

The synthetic counterfactual is constructed based on a number of covariates X. Thus, I determine covariates of the outcome variable which can explain some of the variability in the dependent variable in the years before the intervention. Annual US state-level data for the selected covariates is collected from several federal bureaus for the period 2000–2015.[18] The data are described below and summarized in Appendix A.1.5, Table A.4.

I include the following state-level variables: GDP per capita; real GDP growth; exports (measured in total global merchandise exports); and total R&D expenditures (as a percentage of GDP). Further, I include science and engineering (S&E) indicators to control for differences in higher education, labor force and the importance of S&E in the economy across states. These are: the number of bachelor's degrees awarded in S&E fields (conferred per 1'000 individuals 18 to 24 years old); the percentage of a state's workforce employed in high science, engineering, and technology (SET) establishments; and the high SET employment establishments (as a percentage of all business establishments).[19] Descriptive statistics for all predictor variables based on the estimation sample are presented in Table 2.1.

Table 2.1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Max	Min
(ln) GDP per Capita	816	3.79	0.29	5.22	3.14
Real GDP Growth (1-year lag)	816	1.91	2.71	22.30	-8.80
Total Energy Average Price	816	17.20	5.31	40.15	6.69
R&D expenditure (% of GDP, 1-year lag)	764	2.21	1.47	8.08	0.27
Exports (% of GDP)	816	6.86	3.88	27.66	0.75
High SET Establishments	663	8.26	2.10	17.77	4.68
Employment in High SET (% of Total)	663	11.01	2.74	18.21	5.42
S&E BA Degrees (3-year lag)	663	17.24	7.52	62.65	5.13

Notes: Differences in the number of observations are due to heterogenous time periods. The variable R&D expenditures and the S&E Indicators are only available as of 2001 and 2003, respectively.

[18] Macroeconomic variables and crude oil prices affecting the entire national economy can be disregarded due to the nature of the empirical framework.

[19] S&E fields include the physical, life, earth, ocean, atmospheric, computer, and social sciences; mathematics; engineering; and psychology. High SET employment industries are defined as industries in which the proportion of employees in technology-oriented occupations is at least twice the average proportion for all industries.

2.3 Estimation & Results

I start by selecting the control units for the donor pool. The donor pool selection is subject to contextual requirements (Abadie, 2021). To employ the SCM, control units must be available for the donor pool that have not taken measures similar to the one studied. Thus, states that adopted any state-wide interventions similar to the Cap-and-Trade during the study period are discarded from the donor pool.[20] In addition, it is crucial that the control units are comparable to California in terms of outcome variable. This is necessary in order to compute a weighted average of the untreated units that can approximate the trajectory of the outcome variable for the treated unit before treatment.

I restrict the donor pool to states in the US. I discard from the donor pool the member states of the Regional Greenhouse Gas Initiative (RGGI), a mandatory Cap-and-Trade program for GHG emissions which was established in 2009 (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont).[21] I further discarded states that initially joined the Western Climate Initiative (WCI) (Arizona, Montana, New Mexico, Oregon, Utah and Washington).[22] Finally, I also discard the state of Missouri due to incomplete data on R&D expenditures. Consequently, the final donor pool consists of the remaining 33 states (including the District of Columbia).

To obtain a suitable comparison unit for evaluating the intervention effects on patent activity, a synthetic control is constructed as the weighted combination of US states in the donor pool to match the pre-treatment outcome. The weights w_j are estimated according to the algorithm developed by Abadie et al. (2010) and reported in Table 2.2. The displayed values represent the vector of weights W of each control state in the donor pool and indicate that the synthetic California is best reproduced by a combination of the District of Columbia, Hawaii, Idaho, Michigan, Texas and Virginia. The remaining states in the donor pool are assigned a weight of zero.

Table 2.3 displays the relative weights corresponding to each of the key predictor in the V matrix and the covariate-specific means for California and its synthetic counterpart in the pre-treatment period. The last column represents the simple average. The mean comparisons indicates that the state average does not provide a suitable control group due to large differences in pre-treatment characteristics. The synthetic counterfactual provides a better approximation of the factual situation.

[20] The SCM allows to disregard nationwide policy interventions in this setting as the outcome path of each state is uniformly affected.

[21] The state of Virginia effectively joined the RGGI on January, 2021. As the state was not yet a member of the initiative during the observation period and a possible anticipation effect does not reach back to the observed time period, Virginia is not eliminated from the donor pool.

[22] The WCI is a non-profit cooperation established in 2007. The goal of the WCI was to collectively implement emission policies to reduce GHG emissions to 15% below 2005 levels by 2020. In 2010, the WCI developed and published a greenhouse gas reduction strategy that included the introduction of a regional Cap-and-Trade program. Although all US states except California withdrew in November 2011, these states are excluded from the donor pool because the anticipated implementation of the WCI Cap-and-Trade program prior to the states' official withdrawal may bias the estimate.

Table 2.2: State Weights in Synthetic California

Weight	State	Weight	State
0.000	Alabama	0.000	Mississippi
0.000	Alaska	0.000	Nebraska
0.000	Arkansas	0.000	Nevada
0.000	Colorado	0.000	North Carolina
0.074	District of Columbia	0.000	North Dakota
0.000	Florida	0.000	Ohio
0.000	Georgia	0.000	Oklahoma
0.086	Hawaii	0.000	Pennsylvania
0.058	Idaho	0.000	South Carolina
0.000	Illinois	0.000	South Dakota
0.000	Iowa	0.000	Tennessee
0.000	Indiana	0.146	Texas
0.000	Kansas	0.335	Virginia
0.000	Kentucky	0.000	West Virginia
0.000	Louisiana	0.000	Wisconsin
0.300	Michigan	0.000	Wyoming
0.000	Minnesota		

Table 2.3: Predictor Means for Green Patent Filings

Variables	Weights	Treated	Synth.	Sample Mean
(ln) GDP per Capita	0.128	3.86	3.82	3.70
GDP Growth (1-year lag)	0.035	2.46	1.66	1.95
Total Energy Average Price	0.057	16.93	15.38	14.43
R&D expenditure (% of GDP, 1-year lag)	0.047	4.22	2.82	1.62
Exports (% of GDP)	0.246	6.99	6.92	6.23
High SET Establishments	0.124	10.02	9.77	7.97
Employment in High SET (% of Total)	0.205	13.56	13.51	10.48
S&E BA Degrees (3-year lag)	0.159	15.78	18.77	15.73

Notes: The predictor variable R&D expenditure is averaged over the period 2001–2015. High SET Establishments, Employment in High SET, and S&E BA degrees are averaged for the period 2003–2015. All remaining predictors are averaged for the 2000–2015 period. Data measurements are presented in Appendix A.1.5, Table A.1.5. The values of the sample mean are simple averages with equal weights assigned to each donor pool unit.

Figures 2.3 and 2.4 plot the key results from the synthetic control estimation. As noted in Section 2.2.1, the credibility of the synthetic control estimator depends on the MSPE and how closely the outcome path of the counterfactual follows that of the treated state. Thus, it lends great credibility to the synthetic control estimator if the synthetic counterfactual is able to closely track California's trajectory in the pre-treatment period and reproduce the values of the covariates. Figure 2.3 depicts the patent trajectories for both California and its synthetic counterfactual during the period 2000–2015. The synthetic California closely tracks the patenting trends of California before the introduction of the Cap-and-Trade, with a pre-treatment MSPE of 0.005. Thus, the synthetic counterfactual is able to approximate the treated unit closely.

Figure 2.3: Trends in Green Patent Filings: California vs. Synthetic California

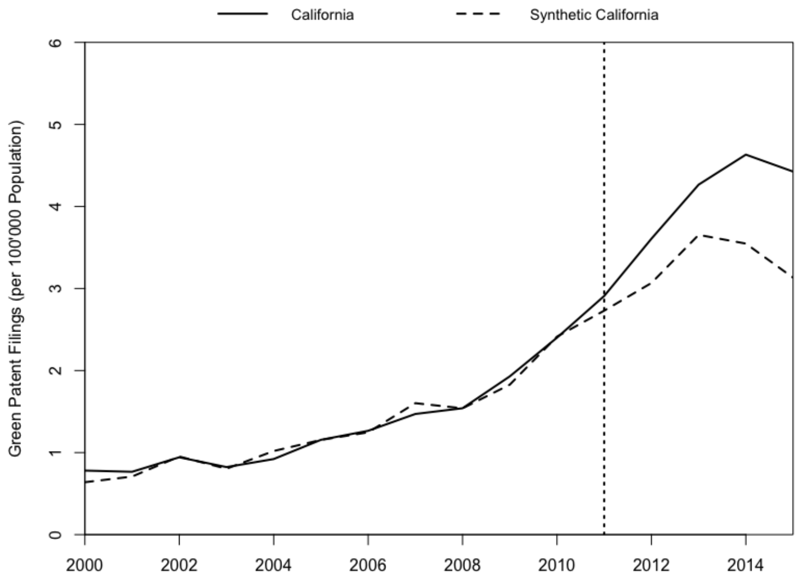
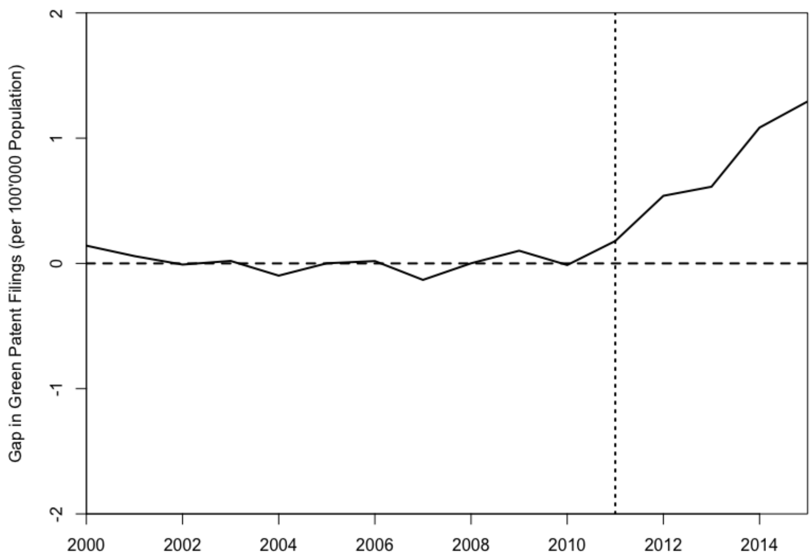


Figure 2.4: Green Patent Filings Gap between California and Synthetic California



The discrepancy between the two trajectories in the post-treatment period represents the treatment effect. The effect can be interpreted as the annual increase in successful green patent filings resulting from the passing of the bill. The figure indicates a positive effect of the policy on green patenting activity in California. Though both California and its counterfactual display a decline in green patent filings towards the end of the post-treatment period, the decline occurs later for California. This suggests that the introduction of the emission trading system counteracted the decline in green patent activity in early years by incentivizing businesses under the cap to develop environmentally-friendly technologies. Figure 2.4 visualizes the gap between the synthetic and treated California. I compute the average treatment effect as the average post-treatment percent gap.[23] I find that green innovation output in California increased by about 22.5% on average relative to the synthetic control in the observed time period.

2.3.1 Robustness Checks

To test the validity of the findings, a series of robustness checks is performed. Abadie et al. (2010) proposes three placebo tests to assess causal inference; "in-time", "in-space" and "leave-one-out" placebo tests.

For the in-time placebo test, the treatment is re-assigned to a date prior to the pre-treatment period, all else being equal. The purpose is to test whether this placebo treatment leads to a divergence in the outcome trajectory between California and the synthetic control. I shift the treatment to 2006 to assess whether the observed results are in fact not a result of the adoption of the passage of AB 32. Figures 2.5a and 2.5b show that the trajectories and estimated treatment effects largely correspond to those in the main analysis. Notably, the trajectories of California and its synthetic counterfactual do not diverge after 2006. Thus, randomly assigning the intervention to 2006 has no perceivable effect, alleviating doubts that the effect is owed to reasons other than the treatment.

For the in-space placebo, the treatment is iteratively re-assigned to each of the units in the donor pool, using the remaining units as control. Thus, the synthetic control is run 33 times. Comparing the results of these runs to the main specification provides indications of whether the gap associated with the actual synthetic control unit differs in size from the other 33 estimated gaps. The underlying rationale is to test whether a control unit experiences a similar or even greater increase in patent applications compared to its respective synthetic version. This would cast doubt on claims that the effect identified in the main specification is due to the policy intervention.

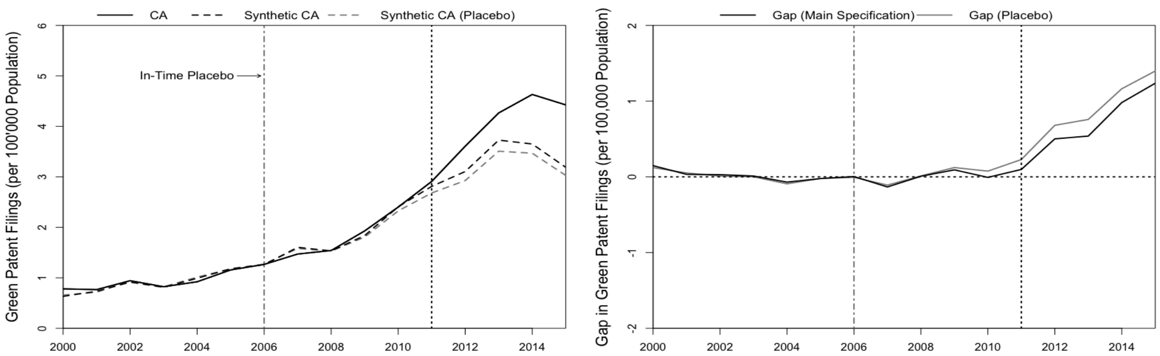
Figure 2.6 displays the results of the in-space placebo. The grey lines denote the estimated gaps between the control units in the donor pool and the corresponding counterfactual. The bold black line represents the gap between the treated and synthetic California. Figure 2.6a depicts the gaps for California and all 33 control states. It shows that for some specifications the synthetic control method is unable to accurately replicate the pre-treatment outcome

[23] The average post-treatment percent gap is computed as $\frac{1}{T-T_0}\sum_{t>T_0}\left(\frac{Y_{1t}^I-\hat{Y}_{1t}^N}{\hat{Y}_{1t}^N}\right)\times 100$

trajectory by using a convex combination (this is characterised by large deviations from the zero-gap line). While the median MSPE is 0.02, Michigan and Washington exhibit MSPEs of 2.237 and 2.268, respectively. This indicates a very poor fit and the lack of a combination of control units in the sample that accurately reflects the pattern of patent applications for these states.

Abadie et al. (2010) recommend the exclusion of control units with a high MSPE due to poor pre-treatment fit to achieve a meaningful comparison. In consequence, Figure 2.6b discards states with a MSPE equal or higher than four times the MSPE of California. Among the eighteen states remaining, the solid line from the main specification clearly stands out, depicting the largest increase in patent applications from 2011 onwards. I further calculate the ratio of post-treatment MSPE to pre-2011 MSPE for California and all states in the donor pool. The ratios serve to illustrate the differences in the magnitude of the pre- and post-intervention gap for California relative to the gaps obtained in the placebo tests, whereby a

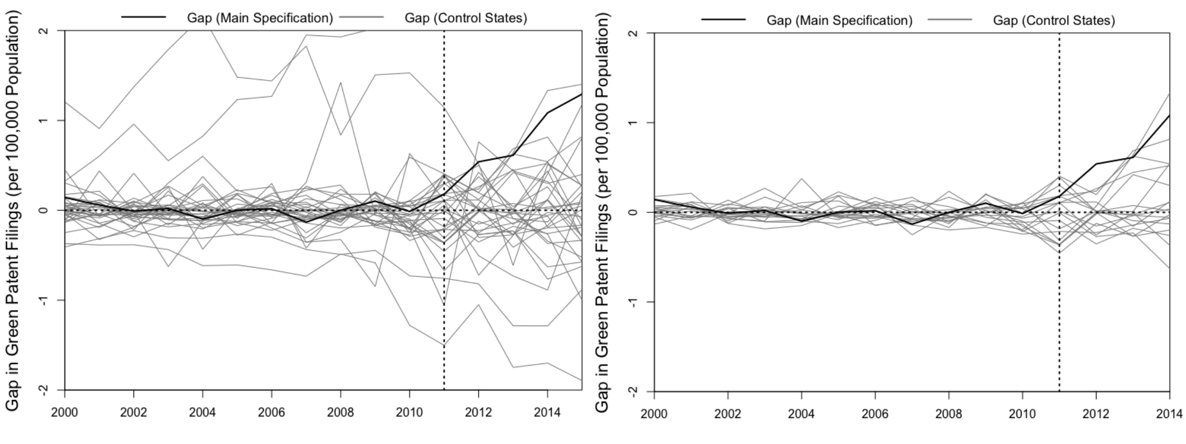
Figure 2.5: Green Patent Filings: In-Time Placebo Test



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

Figure 2.6: Green Patent Filings Gaps in California and Placebo Gaps in Control States

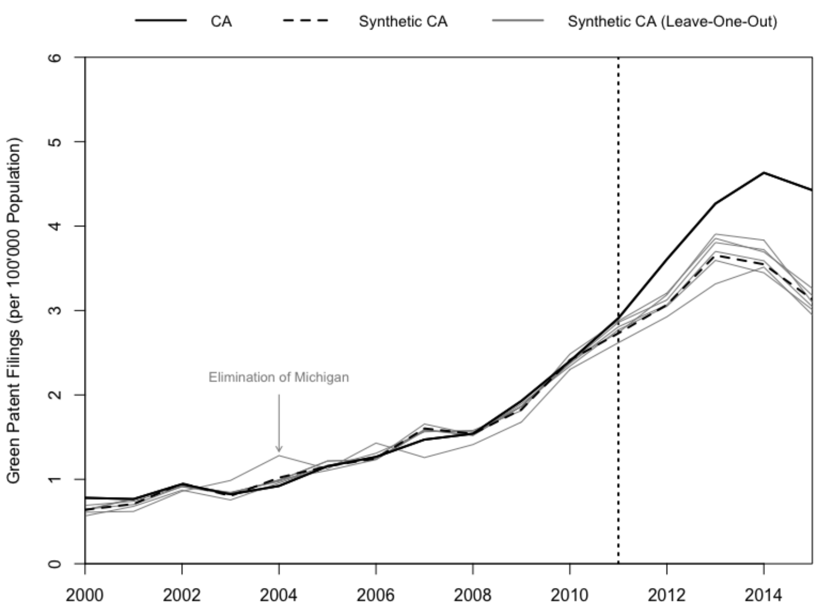


(a) Including all 33 Control States

(b) Including States with Small Pre-Intervention MSPE large ratio for California is indicative of a causal effect. I find that California clearly stands out among most of the 33 control states and has the largest MSPE ratio. Further, I calculate the probability of obtaining results of the magnitude of those obtained for California. That is, if one were to assign treatment at random, the probability of attaining a post/pre-intervention ratio this large is $1/34 = 0.03$. This ratio can be interpreted as the p-value at which the null hypothesis can be rejected (Abadie et al., 2010). Thus, the result is significant at the 5% level.

For the leave-one-out placebo test, the six control states with a positive weight w_j are iteratively eliminated from the donor pool to examine whether the main results are sensitive to the exclusion of one donor pool state. The objective is to assess the extent to which the main results in Figure 2.3 are driven by any particular control unit. Thus, I re-estimate the model excluding at each iteration one of the six states used to construct the synthetic counterfactual, namely Washington, Hawaii, Idaho, Michigan, Texas and Virginia. Figure 2.7 displays the results of the leave-one-out placebo test.

Figure 2.7: Green Patent Filings: Leave-One-Out Placebo Test



As can be seen from the figure, eliminating Michigan deteriorates the pre-treatment fit. A potential explanation for this outcome can be found in Table 2.4 which presents the detailed results of the placebo test. When omitting Michigan, the synthetic control assigns a high weight to the state of Minnesota which is not present in the baseline estimation. This impairs the predictive ability of the model (MSPE of 0.034) and the magnitude of the effect is likely overestimated (29%). The remaining leave-one-out estimations yield good fits and the resulting estimated treatment effects are comparable to the effect obtained in the main specification. This suggests that the leave-one-out estimates are robust to changes in the synthetic control state weights. The elimination of Washington, Idaho, Hawaii, Texas and Virginia provides us with a range for the estimated treatment effect, from an average increase in green patent filings of 17.1% (for the elimination of Washington) to 24.7% (for the elimination of Idaho).

Table 2.4: State Weights from the Leave-One-Out Placebo Test

	Washington	Hawaii	Idaho	Michigan	Texas	Virginia
Alabama	0.000	0.000	0.000	0.000	0.000	0.000
Alaska	0.000	0.000	0.000	0.000	0.000	0.000
Arkansas	0.000	0.000	0.000	0.000	0.000	0.000
Colorado	0.000	0.000	0.000	0.000	0.000	0.349
Washington	—	0.067	0.100	0.090	0.075	0.052
Florida	0.000	0.000	0.000	0.000	0.000	0.000
Georgia	0.000	0.000	0.000	0.000	0.000	0.000
Hawaii	0.000	—	0.000	0.000	0.032	0.071
Idaho	0.126	0.047	—	0.179	0.035	0.001
Illinois	0.000	0.000	0.000	0.000	0.000	0.000
Iowa	0.000	0.000	0.000	0.000	0.000	0.000
Indiana	0.146	0.000	0.000	0.000	0.000	0.000
Kansas	0.335	0.000	0.000	0.000	0.000	0.000
Kentucky	0.000	0.000	0.000	0.000	0.000	0.000
Louisiana	0.000	0.000	0.000	0.000	0.000	0.000
Michigan	0.317	0.316	0.302	—	0.327	0.241
Minnesota	0.103	0.000	0.001	0.600	0.000	0.045
Mississippi	0.000	0.000	0.000	0.000	0.000	0.000
Nebraska	0.000	0.000	0.000	0.000	0.000	0.000
Nevada	0.000	0.241	0.000	0.000	0.242	0.000
North Carolina	0.000	0.000	0.000	0.000	0.000	0.000
North Dakota	0.000	0.000	0.143	0.000	0.000	0.000
Ohio	0.000	0.000	0.000	0.000	0.000	0.000
Oklahoma	0.000	0.000	0.000	0.000	0.000	0.000
Pennsylvania	0.000	0.000	0.000	0.000	0.000	0.000
South Carolina	0.000	0.000	0.000	0.000	0.000	0.000
South Dakota	0.000	0.000	0.000	0.000	0.000	0.000
Tennessee	0.000	0.000	0.000	0.000	0.000	0.000
Texas	0.000	0.127	0.115	0.131	—	0.241
Virginia	0.455	0.201	0.337	0.000	0.288	—
West Virginia	0.000	0.000	0.000	0.000	0.000	0.000
Wisconsin	0.000	0.000	0.000	0.000	0.000	0.000
Wyoming	0.000	0.000	0.000	0.000	0.000	0.000
Estimated Effect	17.1%	18.6%	24.7%	29.0%	22.2%	18.5%
MSPE	0.009	0.004	0.006	0.034	0.005	0.003

I undertake several further sensitivity checks to examine the validity of the synthetic control estimates. In a first step, I extend the donor pool to include all US states. The resulting synthetic control estimates presented in Figure A.3 produce a fairly similar outcome. Note that the inclusion of the whole sample significantly changes the assigned weights yet does not significantly affect the estimated treatment effect. This indicates that the counterfactual outcome trajectory is not dependent on a particular combination of states.

In a second step, I re-assess the initial selection of the donor pool. I run the synthetic control including the states initially discarded from the donor pool due to the adoption of similar policies. Thus, I reproduce the estimation by including WCI and RRGI states. The results are presented in Figure A.5 and A.4, respectively. The outcome shows that in the case of a good pre-treatment fit, the main results are fairly robust to the undertaken modifications in the donor pool which is an encouraging finding, as it further confirms that the estimated treatment effect is not dependent on the donor pool selection.[24]

As a final robustness check, I re-run the baseline model using an alternative data set constructed by employing a different green patent classification system. The motivation for this robustness check is that the identification of green patents using filter-approaches based on classification systems is prone to errors, and data sets can differ greatly depending on the patent classification systems used to identify the relevant patents.[25] To ensure that the results do not depend on the chosen classification system, the SCM estimation is repeated with green patent applications as identified by the Y02 tagging scheme of the Cooperative Patent Classification (CPC) – a classification scheme for climate change mitigation and adaptation technologies policies analogous to the IPC Green Inventory. The results of the robustness check are shown in Figure A.6 illustrating a similar gap in green patent filings as found in Figure 2.4.

In any case, the placebo tests and the sensitivity analyses to the choice of donor pool states and classification system provide evidence that the main results are not driven by the selection of specific control units or patent identification scheme.

2.3.2 Supplementary Analysis

The above analysis finds that the average treatment effect is positive and significant at the 5% level. The selected methodology, however, does not allow to examine in which of the seven technology classes additional patents were filed, as it is not possible to determine which of the patent applications were induced by the introduction of the Cap-and-Trade. Hence, to assess whether the policy intervention has impacted the direction of technological change within the

[24]The inclusion of the WCI leads to a poor pre-treatment match indicating that there is no weighted average of untreated units in the donor pool that can approximate the pre-treatment trajectory of the outcome variable for the treated unit due to the high value assigned to the state of Washington. In contrast, the re-estimation with the RGGI produces a very similar outcome as the baseline results despite a notable change in the distribution of state weights.

[25]While the retrieval of relevant patent documents based on classification systems such as the IPC inventory enables and simplifies the identification of patents related to specific technologies, it has to be noted that this approach may lead to the inclusion of incorrect patent documents (Type I errors) or incomplete results (Type II errors) (Veefkind et al., 2012).

field of green innovation I apply a DiD approach at a more disaggregated level.[26] I split the patent data according to the seven areas of green innovation and set up the following model:

$$y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Treated_i \times Post_t + \beta_4 X_{it} + \varepsilon_{it} \tag{2.4}$$

where y_{it} is the weighted number of green patent filings per 100'000 population for state i at time t. $Treated_i$ and $Post_t$ are dummy variables. $Treated_i$ is equal to one for the treated unit and $Post_t$ is equal to one after the policy change. The DiD estimate is given by the coefficient β_3 which represents the average treatment effect. X_{it} is a vector of the control variables specified in the main analysis and ε_{it} is the error term. The regression results are presented in Table 2.5.

For patents related to administrative, regulatory or design aspects as well as agriculture/forestry, the coefficient of the interaction term is insignificant at a 5% level. This suggests that patent activity in those areas is not affected by the policy change and therefore exhibits no treatment effect. For patents related to transportation the estimated effect is also not statistically significant. This is in line with the statistical expectation, as the cap coverage expanded to transportation fuels only at the beginning of the second compliance period in 2015. This may have delayed the incentive to improve transportation technologies, whereby the anticipatory effects on innovation set in later for the particular technological area. Further, although for patents relating to waste management the coefficient is significant at a 10% level, the sign of the coefficient is negative. This is consistent with the fact that the initial cap does not directly cover agricultural and forestry nor waste management sources of emissions.

As can be seen in column three and four, the average treatment effect for patents related to alternative energy and energy conservation is positive and statistically significant. This shows that the policy intervention stimulated innovation in these technological areas. Moreover, this result indicates that the treatment effect found in Figure 2.3 is largely driven by an increase in patent filings relating to alternative energy technologies and energy conservation.

In the last column, I run the same regression model for the entire data set for a comparison of the DiD and SCM estimates. The obtained DiD estimates of the average treatment effect are positive and statistically significant at a 5% level. According to the model estimates, the policy change leads to an estimated average increase in green patent filings of 0.849 (per 100'000 population). The treatment effect as estimated using the synthetic control method corresponds to an average annual increase in patent filings by approximately 0.74 patent filings per 100'000 population.[27] Thus, the estimated average treatment effects obtained by the DiD present plausible magnitudes. Note, however, that the estimates obtained by DiD are larger than the SCM estimate. This difference in the estimated treatment effects may be attributable to the violation of the parallel trends assumption.

[26]Disaggregated analysis on patents related to nuclear power generation is unfeasible due to lack of patents in this area.

[27]The average treatment effect is computed as $\frac{1}{T-T_0}\sum_{t>T_0} Y_{1t}^I - \hat{Y}_{1t}^N$

Table 2.5: Difference-in-Differences Regression Estimates

	Admin., Regulatory / Design Aspects	Agriculture / Forestry	Alternative Energy	Energy Conservation	Transportation	Waste	Total
Treated × Post	−0.003	0.014	0.750***	0.237**	0.020	−0.172*	0.849***
	(0.002)	(0.047)	(0.078)	(0.060)	(0.204)	(0.098)	(0.314)
Treated	−0.002	−0.008	0.068	−0.157**	−0.616*	−0.456***	−1.172**
	(0.005)	(0.032)	(0.108)	(0.076)	(0.345)	(0.176)	(0.512)
Post	0.006	−0.050**	0.056	0.103**	0.203***	0.068*	0.386***
	(0.005)	(0.020)	(0.063)	(0.031)	(0.070)	(0.040)	(0.125)
ln GDP per Capita	0.017**	0.090***	0.230	−0.047	0.177*	0.408***	0.874**
	(0.008)	(0.024)	(0.175)	(0.066)	(0.107)	(0.157)	(0.373)
GDP Growth (1-year lag)	−0.001*	−0.001	0.005	0.005	0.007	0.007	0.022
	(0.001)	(0.002)	(0.008)	(0.004)	(0.006)	(0.006)	(0.019)
Total Energy Average Price	0.001	−0.002	−0.020**	−0.004	0.001	−0.020**	−0.046**
	(0.001)	(0.002)	(0.009)	(0.005)	(0.006)	(0.008)	(0.020)
R&D expenditure (% of GDP, 1-year lag)	0.003	0.026***	0.238***	0.318*	0.127***	0.189**	0.852***
	(0.002)	(0.006)	(0.057)	(0.039)	(0.165)	(0.080)	(0.243)
Exports (% of GDP)	−0.0001	0.0001	−0.014*	−0.007**	0.009	0.004	−0.008
	(0.002)	(0.001)	(0.008)	(0.003)	(0.007)	(0.007)	(0.015)
High SET Establishments	−0.002	0.012***	0.022	0.012**	0.002	0.003	0.048
	(0.001)	(0.003)	(0.021)	(0.005)	(0.010)	(0.015)	(0.030)
Employment in High SET (% of Total)	0.001	−0.008***	−0.034***	−0.012*	−0.031	−0.013	−0.098***
	(0.001)	(0.002)	(0.013)	(0.006)	(0.021)	(0.013)	(0.036)
S&E BA Degrees (3-year lag)	0.00003	0.007***	0.013**	−0.004*	−0.017*	−0.015**	−0.016
	(0.0004)	(0.001)	(0.005)	(0.002)	(0.009)	(0.006)	(0.016)
Constant	−0.059	−0.346***	−0.299	0.334	−0.595	−0.981**	−1.939**
	(0.037)	(0.082)	(0.490)	(0.252)	(0.391)	(0.496)	(0.832)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	377	442	442	442	442	442	442
Period	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015	2003 – 2015
Adjusted R^2	0.065	0.582	0.573	0.448	0.349	0.440	0.677

Notes: Heteroskedasticity-consistent standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01. Patent applications relating to administrative, regulatory or design aspects were only found for 45 states resulting in a lower number of observations in the first column. No patents related to that technological area were found in Arkansas, Hawaii, Mississippi, Vermont, West Virginia and Wyoming.

2.4 Conclusion

US states are undergoing great efforts to promote renewable and sustainable energy technologies within their borders by introducing regional climate and energy policies. Adopted in 2011, California‘s Cap-and-Trade program is aimed at reducing GHG emissions throughout the state as well as creating an economic incentive for investments in cleaner, more efficient technologies. In this paper, I empirically estimate the effect of the policy on the state’s green innovation output.

The estimates of the synthetic control method indicate that the implementation of the Cap-and-Trade system resulted in an increase in green patenting activity of approximately 22.5% over the 2011–2015 period. An additional DiD estimation suggests that this effect can largely be attributed to an increase in alternative energy and energy conservation technologies. Thus, this paper provides evidence that the policy has had a positive impact on environmental innovation.

The findings of this paper contribute to the policy debate on the significance of local and state government climate policies in achieving a sustainable transition to a green economy. Exploring the impacts of such policies is becoming increasingly important with federal governments continuing to cede policy responsibilities to lower levels of government. I find strong evidence that regional policies stimulate green innovation within state borders and have therefore the potential to contribute to the achievement of national and global climate goals.

Considering that market size may be a critical component for innovation-enhancing effects of local and state-level policies, further studies should be conducted to assess the impact of government interventions in different regions. Thus, future research should confirm the initial findings and evaluate long-term effects. In addition, further efforts may be undertaken to evaluate whether regional policies can evoke incentive effects in neighbouring regions as the enactment of state measures to promote renewable energies need not necessarily be limited to effects within the own state (Popp, 2020).

Chapter 3

Evaluation of Climate Policy Based on Machine Learning: The Case of Switzerland*

Chapter Abstract

Carbon taxes are the climate policy instrument favored by economists and a core element of government policies in many countries. Only a limited number of empirical studies have evaluated the effectiveness of the policy, typically using traditional econometric models that may not be suitable in the absence of a control group. To avoid these deficiencies, we use a novel machine learning approach for the case of Switzerland. We estimate the effects of the Swiss CO_2 levy on the energy use of business entities and emissions related to fossil fuels. Microeconomic data covers energy use of business establishments in the industry and service sector for the period 2000 – 2017. The findings provide evidence that the CO_2 levy decreased heating oil use while increasing the use of low-CO_2 and CO_2 alternatives. The results also suggest significant heterogeneity in the entities' reaction to the levy. The direction and magnitude of the effect depends on the initial user behavior and energy mix. Entities that regularly use heating oil are more responsive to tax changes than occasional users.

*This chapter represents joint work with Prof. Lucas Bretschger and Dr. Melissa Newham (CER-ETH Center of Economic Research at ETH Zurich)

3.1 Introduction

The high energy demand of modern civilization is a central concern in the agenda for sustainable development. Given the limited supply of non-renewable energy resources and their combustion being the biggest source of human-caused emissions, there is an urgent need for a transition towards a sustainable energy system. As a result, governments around the world are intensifying climate action and implementing energy conservation and energy substitution policies. The main objective of these policies is to encourage the use of renewable energy sources and prompt households and firms to adopt more energy-efficient behaviors.

One of the most widespread climate policy measures is carbon taxation. The introduction of a carbon tax, imposed on fossil fuels in proportion to their carbon content, makes carbon-intensive energy sources more expensive than low-carbon alternatives. Thus, increasing the relative price of fossil fuels through carbon taxation can induce substitution effects whereby economic agents switch to less carbon-intensive energy sources (Fuss, 1977; Halvorsen, 1977; Pindyck, 1979). However, empirical evidence on the impact of carbon taxes on energy use and emission reduction associated therewith is limited (see Green (2021) for a review). This study intends to extend the existing empirical evidence in this field by examining the case of Switzerland.

Switzerland introduced carbon taxation in 2008 by imposing a CO_2 levy on fossil combustible fuels such as heating oil and natural gas. Fossil fuels are used by companies to generate energy, i.e. for heat generation, in thermal plants for electricity generation or in combined heat and power plants. Starting at 12 CHF/tCO_2, the tax rate in Switzerland was gradually increased to 96 CHF/tCO_2 in 2020, making it one of the highest in the world (OECD, 2021). Using data of a sample survey carried out by the Swiss Federal Office of Energy (FOE), we analyze the energy usage behavior of business entities in the industrial and service sector in Switzerland. Taking into account the tax relief mechanisms of the Swiss regulatory framework, we construct a sample of business entities subject to the levy. Based on this sample, we estimate the impact of the Swiss CO_2 levy on the use of heating oil, the substitution process between polluting and less polluting fossil fuels and the level of carbon emissions from energy use.[1]

A few studies have evaluated the effects of the CO_2 levy in Switzerland. Müller et al. (2015) use a computable general equilibrium model to estimate the impact of the levy on CO_2 emissions for the period 2008–2014. The study concluded that the tax reduces CO_2 emissions from fossil fuels by 2.5% to 6% in the observed time period. In 2016, the FOEN examined the effects of the CO_2 levy on around 4'000 tax-liable and tax-exempt companies in a direct survey to gain insights into the decision-making processes of the involved businesses and their reduction efforts (Jakob et al., 2016). In general, it was found that firms' most common actions

[1]Operators of installations that emit a considerable amount of greenhouse gases can avoid the levy by committing to reduce their greenhouse gas emissions. In addition, operators of large greenhouse gas-intensive installations participate in the emissions trading system are thereby also exempt from the levy. However, our study focuses exclusively on the effects of the levy, as the available data does not provide information on which companies have entered reduction commitments, and the number of entities participating in the emissions trading system is insufficient to produce a reliable estimate.

were in the areas of selection of energy sources (e.g. switching from heating oil to gas or to district heating), adjusting space and process heating, and consideration of these decisions in operational and strategic planning. More recently, Leu (2018) empirically analyzes the policy using data from the same survey as our analysis but for the period from 1999 – 2016 by using panel data regression models to quantify the effects on energy use and GHG emissions. The study found that the levy initially had a limited impact on fossil fuel use, with a reduction of 1% compared to the pre-policy period, but by 2016 use had fallen by 13% compared to levels before the policy was introduced. The levy had a similar effect on total CO_2 emissions, which initially decreased by less than 1%, but by 2016 had decreased by 16% compared to levels before the introduction of the policy. We complement these studies by evaluating the impact of the Swiss climate policy using machine learning (ML) drawing on the approach proposed by Abrell et al. (2022) for policy evaluation. The empirical framework is used to test a set of hypotheses. In particular, we examine whether the effect of the policy varies across different groups of energy users. Our hypotheses are based on the notion that the impact of the carbon tax may vary depending on the energy mix used by the business entity and the frequency of fossil fuel use. These hypotheses are tested to determine the strength and direction of the policy's impact on different user groups and across different energy sources.

Due to the widespread implementation of the carbon tax in Europe and the imposition of measures affecting all business entities in Switzerland, no control group exists. The lack of a suitable control renders empirical methods such as difference in differences (DiD) and the synthetic control method (SCM) unfeasible.[2] Machine learning techniques can be used to perform counterfactual estimation in cases where a valid control group is unavailable, as ML models can be used for the construction of the counterfactual outcome, thus overcoming the missing data problem (Rubin, 1974). In addition, having disaggregated data on energy use of business entities, we are able to estimate the impact of the policy on different energy sources. This enables us to assess the impact on the use of energy sources with different carbon intensities. Following Abrell et al., we train a model to predict entity-level energy use under observed and counterfactual treatment. A causal inference of the treatment effect can then be established derived from the difference between the predicted observed outcome and the predicted counterfactual. To estimate energy use, we implement the Super Learner (SL) as introduced by Van der Laan et al. (2007), an ensemble machine learning method that creates a weighted combination of selected algorithms.

The findings in this paper indicate tax effects on energy usage behavior and reduction in fossil fuel related emissions. We find that the taxation on fossil combustible fuels induces a shift in energy use to less carbon-intensive alternatives. This substitution of energy sources is associated with a reduction in emissions. We further find that the policy effect depends on the energy mix and usage behavior of an entity, with business entities that regularly use heating oil exhibiting a greater reduction than non-regular users.

Our work makes an important contribution to the literature in two ways. First, the majority of econometric research on the impact of carbon taxes is based on macro- or sector-

[2]Reliably implementing these statistical methods would require a similar survey to be conducted in one or more other countries to obtain comparable data.

level data (for examples see Andersson, 2019; Bretschger & Grieg, 2020; Bruvoll & Larsen, 2004; Lin & Li, 2011; Murray & Rivers, 2015). There are only a limited number of studies providing plant- and firm-level evidence on the effects of carbon pricing on energy use and emission abatement from energy substitution (see e.g. Jo & Karydas, 2022; Marin & Vona, 2021; Martin et al., 2014). Ellerman & McGuinness (2008) use a panel regression and power plant-data on emissions from the United Kingdom to estimate the effect of the EU ETS. Annual average emission rates were calculated using predicted and counterfactual emissions. Wagner et al. (2014) rely on propensity score matching and regression to analyze firm- and plant-level data on French manufacturing firms to examine the impact of the EU ETS. The composition of emissions in terms of fuel share is used to estimate emission abatement caused by changes in the fuel mix. The present paper adds to this literature by using micro-level data across different industries thereby providing additional empirical evidence on the effects of carbon pricing policies. Moreover, we contribute to the scarce empirical evidence on emission abatement from fuel switching.

Second, the paper contributes by applying a novel machine learning approach for evaluating climate policy impacts. The use of ML methods for causal inference and applications related to energy economics has gained popularity in recent years (e.g. Athey & Imbens (2016); Hill (2011); Kleinberg et al., 2015; Künzel et al., 2019; Mullainathan & Spiess, 2017; Varian, 2014).[3] ML offers several advantages for causal inference in the evaluation of policy measures. These include the capability of capturing non-linear relationships in the data to build more accurate models, and the ability to build flexible models. ML algorithms are able to autonomously select the best performing model, thereby improving the accuracy of the predictions. ML has been particularly beneficial in settings where no control group is available. For example, Bertoni et al. (2021) apply multinominal choice framework to estimate the counterfactual behavior of farmland units to estimate the greening impact of the Common Agricultural Policy reform. Other examples include Burlig et al. (2020) and Fabra et al. (2022) who implement event study approaches with ML. Their approaches consist of training a ML model using pre-treatment data to predict post-treatment counterfactual outcomes. Recently, Abrell et al. (2022) developed and implemented a ML approach using observations from both the pre- and post-treatment period to train a ML model. They apply the approach to analyze the impact of the UK carbon tax by employing the LASSO algorithm. With the present paper, we add to this literature by adopting the policy evaluation approach proposed by Abrell et al. using the SL algorithm.

The study is divided into six sections, including this introduction. Section 2 describes Switzerland's climate policy. Section 3 develops a series of hypotheses to be tested. Section 4 presents the data and corresponding descriptive statistics. Section 5 provides a description of the methodology. Section 6 presents the empirical results obtained. Section 7 discusses the results and concludes.

[3] Ghoddusi et al. (2019) provide a review of recently published articles on the energy economics/finance applications of ML methods.

3.2 Swiss Climate Policy

Under the Kyoto Protocol, Switzerland pledged to reduce its greenhouse gas emissions by 20% below the 1990 level by 2020 with sectoral targets for transport, buildings and industry. In order to meet these targets, the Swiss government enacted the CO_2 Act in 2000, which mandated the introduction of the CO_2 levy.[4] Additionally, large scale energy users are required by cantonal energy legislation to conduct an analysis of their energy usage and implement reduction measures to save energy. The levy and the cantonal energy policy are outlined in more detail below.

CO_2 Levy

The levy was introduced in 2008 in conjunction with the Swiss emissions trading scheme (CH-ETS). It covers emissions from fossil heating and process fuels and is indicated on invoices for purchases of thermal fuels. Oil products for transportation purposes (e.g. gasoline and diesel) are not subject to the levy. Also not affected by the levy are wood and biomass, as they are considered CO_2-neutral.

Under the levy, the government sets a price that emitters must pay for each metric ton of CO_2 they emit. The tax was designed to be increased if CO_2 emissions from fuels do not decrease sufficiently to prospectively meet emission reduction targets set out in the Kyoto Protocol. The rate of the levy was initially set at CHF 12 per ton of CO_2. As the level of actual CO_2 emissions from heating and process fuels exceeded the stipulated threshold values, the rate was increased to 36 CHF/ tCO_2 for 2010–2013 and further increased to 60 CHF/tCO_2 for 2014–2015, 84 CHF/tCO_2 for 2016–2017 and 96 CHF/tCO_2 for 2018–2021.

The levy is designed as an incentive tax. The level of the levy for each energy source depends on the respective carbon content: the higher the carbon content during combustion of an energy source, the higher the levy. An example is the combustion of heating oil and natural gas. Heating oil has a higher emission factor than natural gas, leading to higher CO_2 emissions per TJ than natural gas. As a result, the level of levy is higher for heating oil. The tax rate levels for each energy source can be calculated using emission factors. The emission factors that are used in this paper and the calculated tax rate levies are displayed in Table 3.1. The policy instrument therefore sets financial incentives for households and firms to reduce their fossil fuel consumption and switch from CO_2 intensive energy sources to low-CO_2 or CO_2-free alternatives. This can be achieved in a variety of ways, e.g. through the increased use of low-carbon emitting technologies, through changes in process and production methods or through changes in heating.

About two thirds of the revenues from the levy are redistributed by the federal government to the citizens and the economy.[5] The remaining third of the revenue (max. CHF 200

[4] Along with the levy, the CO_2 Act contains a range of other reduction measures, namely the Buildings Programme and emission regulations for new cars and light commercial vehicles. The Buildings programme is a national programme that provides financial support for energy efficient renovations and the use of renewable energies. The majority of the disbursements concern real estate under private ownership of natural persons. Fund grants may be obtained upon request. In 2010, only 4.4% of the total requests originated from legal entities (in 2016, they accounted for 16.1%).

[5] In 2015, a sum of about 236 million francs was distributed to the economy. In 2019, it amounted to 439

million as of 2010, max CHF 300 million as of 2013, and max CHF 450 million as of 2018) is used to support energy-efficient building renovations and renewable heating energy through the building programme. The share of revenue from the CO_2 levy paid by the population is redistributed on a per capita basis to all residents of Switzerland, regardless of their individual consumption. The revenue from the levy paid by the economy is redistributed to all employers in proportion to the settled AHV payroll of their employees.[6] Thus, emission-intensive companies tend to be burdened more by the tax than labor-intensive companies.

Table 3.1: Tax Rate Level of Levy per Energy Source, 2008–2022

		2008–2009	2010–2013	2014–2015	2016–2017	2018–2022
		CHF per ton of CO_2				
		12	**36**	**60**	**84**	**96**
	Emission Factor (tCO_2 / TJ)	CHF per TJ				
Heating Oil Medium/Heavy	77.0	884.40	2’653.20	4’422.00	6’190.80	7’075.20
Heating Oil Extra Light	73.7	824.00	2’772.00	4’620.00	6’468.00	7’392.00
Natural Gas	56.6	679.20	2’037.60	3’396.00	4’754.40	5’433.60

Notes: Calculations are based on emission factors. Information on emission factors is provided by the FOE. Under the Federal Office for the Environment, other liquid fuels are not permitted if they higher or different emissions than extra light heating oil. Thus, the same emission factor and tax rate level is used for other liquid fuels as for light heating oil.

Depending on the size and nature of the installation, an operator can request to be exempted from the levy. In return, the installation operators must enter a reduction commitment or participate in the CH-ETS. This applies to firms that would be severely burdened by the tax and thereby severely impaired in their international competitiveness. Small and medium-sized installations producing large amounts of greenhouse gases can enter a reduction commitment. Larger, carbon-intensive entities are obligated to participate in the emission trading scheme and are subsequently exempted from the levy.

As a consequence, companies differ in terms of exemption regime depending on the sector and yearly emitted CO_2 levels. A distinction can be made between five categories as presented in Table 3.2. An evaluation of the CO_2 levy must take this environmental policy mix into account.

million francs.

[6]During the first commitment period 2008–2012, the revenue was redistributed only to levy-paying companies. As of 2013, all companies receive the redistribution even if they are exempt from the levy.

Table 3.2: Levy Exemption Regimes in Swiss Federal Climate Policy

	Description	Levy Exemption Regime
1	Firms with installed capcaity of 20 MW and more (engaged in an activity referred to in Annex 6 of the CO_2 Ordinance) **with emissions ≥ 25'000 tonnes of CO_2 equivalents per year**	Obligatory participation in the CH-ETS
2	Firms with installed capcaity of 20 MW and more (engaged in an activity referred to in Annex 6 of the CO_2 Ordinance) **with emissions < 25'000 tonnes of CO_2 equivalents per year**	Voluntary participation in the CH-ETS or reduction commitment
3	Firms with an installed capacity of between 10 and 20 MW (engaged in an activity referred to in Annex 7 of the CO_2 Ordinance)	Voluntary participation in the CH-ETS or reduction commitment
4	Firms with an installed capacity below 10 MW (and engaged in an activity referred to in Annex 7 of the CO_2 Ordinance) **with emissions > 100 tonnes of CO_2 equivalents per year**	Reduction commitment
5	Firms **with emissions ≤ 100 tonnes of CO_2 equivalents per year**	None

Notes: Annex 6 and 7 can be found in the Ordinance of 30 November 2012 for the Reduction of CO_2 Emissions (CO_2 Ordinance) available at `https://www.bafu.admin.ch/`.

Cantonal Energy Policy

With the revision of the federal energy law in 2007, the cantons are mandated to implement a "large consumer model" known as Grossverbrauchermodell (GVM). The GVM stipulates that establishments with an annual heat consumption of more than 5 GWh or an annual electricity use of over 0.5 GWh are required to analyze their energy use and take reasonable measures to reduce consumption.[7] This measure is specifically targeted at promoting a more efficient use of energy by large-scale energy users on a cantonal level.

[7]This corresponds to an annual heat consumption of more than 18 TJ and an annual electricity use of more than 1.8 TJ.

3.3 Hypotheses

In the following analysis, we focus on a number of contingencies that may be crucial for assessing the impact of carbon taxation on energy use. Based on prior work in the field, we formulate a series of hypotheses to be tested using our novel methods.

Standard economic theory predicts that carbon taxation affects the behavior of households and firms. Carbon taxes levied on fossil fuels in proportion to their carbon content raise the price of carbon-intensive energy sources relative to low-carbon alternatives. Thus, by raising the price of heating oil relative to other sources of energy, taxation is expected to induce both a decrease in the use of heating oil and an increase in natural gas or other energy sources. We aim to replicate this theoretical prediction using our ML approach. In addition, we expect the effects induced by the levy to be contingent on the tax level. Thus, the higher the tax rate, the more entities react with a change in energy use. Hence, we posit the following hypothesis:

Hypothesis 1 (H1) *With an increasing tax rate, the use of high carbon energy source decreases and the use of low-carbon alternatives increases when all the other determinants of energy use are held constant.*

Inter-company differences in energy usage patterns may lead to differences in the effect of carbon taxation. Thus, when evaluating the effects of a CO_2 levy, energy usage patterns may be considered.

The degree and form of impact of a carbon tax may vary due to differences in heating oil usage and associated costs and benefits of adapting energy demand. Entities with a regular demand for heating oil face a higher tax burden in relation to the total costs, which increases the financial benefit of tax avoidance. As a result, regular heating oil consumers may be more sensitive to carbon taxation than irregular users.

Further, the nature and extent of substitution opportunities between energy sources are essential to the analysis of fossil fuel reduction mechanisms (Steinbuks, 2012). Hence, the impact and behavioral choices of entities prompted by the levy depend on the entity's scope of action. Substituting heating oil used for production or process purposes for other energy sources requires technological substitution possibilities and technical flexibility. The feasibility of implementing changes in the production process or replacement of energy-related equipment may therefore depend on historical energy usage patterns. Entities that already include natural gas and alternative energy resources in their energy mix may be able to shift away from heating oil more easily than entities that relied entirely on heating oil until the introduction of the tax. Thus, fuel-switching and fuel-saving possibilities may vary. However, if the switching potential is exhausted, further reductions in heating oil use might be limited.

In consequence, it may be relevant to take into account entity-specific differences between energy usage patterns when considering the effects of a carbon tax. Taking this into consideration, we hypothesize:

Hypothesis 2 (H2) *Entities that regularly use heating oil are more responsive to tax changes than occasional users when all the other determinants of oil use are held constant.*

Hypothesis 3 (H3) *Entities that have used low-carbon and carbon-free alternatives before the implementation of the carbon tax policy are more responsive to tax changes than the average entity, independent of the regularity of oil use.*

Further, theoretical research finds that a carbon tax can effectively reduce emissions due to inter-fuel substitution (Agostini et al., 1992; Delarue et al., 2008; Morrison & ten Brink, 1993; Karki et al., 2006). By replacing more polluting energy sources with lower-polluting alternatives, the energy mix becomes cleaner, leading to a reduction in emissions. Consequently, fuel switching induced by carbon taxation can be a cost-effective and quick way to achieve carbon reductions (Wilson & Staffell, 2018). Accordingly, we hypothesize:

Hypothesis 4 (H4) *Energy substitution gradually decreases CO_2 emissions with a growing carbon tax rate.*

3.4 Data & Descriptives

The empirical analysis is based on entity-level data that was collected annually in the period 1999–2020 in the course of a survey on the “energy consumption in industry and the service sector” carried out by the Swiss Federal Office of Energy (SFOE). In the survey, business entities were asked to report the annual usage quantity for each energy source (i.e. electricity, fossil fuels, gaseous fuels and others). With heating oil and natural gas being subject to the levy, the focus of this analysis is placed on these main energy sources. The energy sources industrial waste, local and district heating as well as wood are grouped together and labeled as “other energy sources”. The entities are classified into 19 different industry groups (the industrial sector contains 12 subsectors, the service sector contains 7 subsectors as presented in Table A.5). The survey yielded an annual average of 5’224.82 respondents, and the average entity participated 4.81 times. The annual entity-level data is measured in terajoules (TJ), which allows a comparison between energy sources in a common energy unit. For the empirical estimation we use log-transformed values.[8] Besides questions on energy use, the survey included questions on basic characteristics (number of employees, gross floor space).

Beyond the data provided by the survey, we include variables that may affect energy use. We include prices for the respective energy sources to control for market-driven price changes. Further, we use the number of heating degree days per year as a weather-based index on the heating energy requirements. Considering that energy research activities may effect energy use through innovative solutions and technological improvements, public spending on Swiss energy research is included as control variable. At last, we include an index for energy efficiency to control for the progress in energy efficiency and the related energy savings. Table 4.2 presents information for the variables included in the analysis.

3.4.1 Sample

To construct our final sample, we make use of emission estimates and the guidelines for CO_2 tax exemption of the FOE to determine tax liability. As such, we classify entities that are not eligible for a tax exemption as subject to the levy. The proceedings are discussed below.

As detailed in Section 3.2, entities that emit more than 25’000 tCO_2e per year are obliged to participate in the CH-ETS and in consequence are exempt from the levy. Business entities that emit less than 25’000 tCO_2e but more than 100 tCO_2e have the option to be exempted from the levy during the commitment period 2013–2020 by voluntarily participate in the CH-ETS or by committing to reducing their greenhouse gas emissions in return. Decisive for this are the emissions in the years leading up to the commitment period 2013–2020. It follows that all business entities with yearly emissions $\leq$ 100 tCO_2e in the years prior to 2013 are subject to the levy (see Table 3.2). Consequently, we use a classification approach based on this exemption regime: We estimate the CO_2 emissions of a business entity by multiplying

[8] For analytical reasons, we convert it to megajoules (MJ) (1 TJ = 1’000’000 MJ) before the log transformation of the data.

the amount of energy used with the fuel-specific CO_2 emission factor. On the basis of these calculations, we identify entities in the sample with average annual CO_2 emissions $\leq$ 100 tCO_2e before the introduction of the policy as subject to the levy.[9] As annual observations are not available for every business entity, we classify as subject to the levy those entities for which the average annual CO_2 emissions from energy use in the period 2008 – 2012 are equal or less than 100 TCO_2.[11]. We further remove "large users" that are subject to cantonal energy policy (i.e. GVM). Applying this strategy results in a sample of 3'561 entities that can be classified as being subject to the levy covering the years 2000–2017.[12] Summary statistics for the sample are displayed in Table 3.3.

Table 3.3: Summary Statistics

	Pre-policy *n = 13'240*			Post-policy *n = 13'005*		
	Mean	St. Dev	Median	Mean.	St. Dev.	Median.
Heating Oil (ln)	7.86	6.22	11.74	6.37	6.40	8.19
Natural Gas (ln)	2.67	5.16	0.00	3.59	5.75	0.00
Electricity (ln)	12.03	1.49	12.21	12.43	1.41	12.69
Other Energy Sources (ln)	1.90	4.62	0.00	2.58	5.32	0.00
Total Energy Consumption (ln)	13.18	1.29	13.40	13.44	1.22	13.67
GFS	1919.39	5853.11	1000.00	2402.07	3458.68	1427.00
FTE	9.20	87.49	2.00	12.51	41.99	4.00
PTE	28.48	100.56	15.00	40.71	74.35	22.00
EE	112.77	5.86	110.38	130.52	9.67	129.49
EF	180.32	13.97	184.22	214.61	47.95	200.78
HDD	4193.81	134.50	4183.88	4236.17	195.07	4286.58
Oil Price	46.63	12.66	54.00	59.87	13.46	63.20
Electricity Price	14.30	1.04	13.90	13.66	1.16	13.80
Gas Price	4.32	0.64	4.20	5.08	0.41	5.19
GDP per Capita	76946.95	2974.26	76784.64	82942.09	1569.34	82997.69

[9]The CO_2 equivalents of an entity are determined on the basis of the following greenhouse gas emissions: i) energetic CO_2 emissions from the combustion of fossil regular fuels and ii) fossil waste fuels and/or geogenic process emissions.[10] The sample survey, however, does not provide any information on the second category, thereby the classification is conducted solely on the basis of the stated energy-related CO_2 emissions. Nevertheless, this approach is warranted by the fact that energy-related emissions from Swiss firms account for a predominant share of a firm's or facility's total greenhouse gas emissions. Thus, whilst this method is fraught with uncertainties, we argue that it provides a sufficiently good representation of the entity's situation.

[11]Entities for which we do not have observations in this period are automatically dropped. We further drop entities for which we do not have any observations in the pre-treatment period. In addition, we drop entities pertaining to the cement and concrete sector as our sample does not provide a representative number of entities for this industry group.

[12]Outliers and inconsistent observations were removed from the data set. Missing values for the variables FTE, PTE and GFS were imputed by using the k-Nearest Neighbors imputation method.

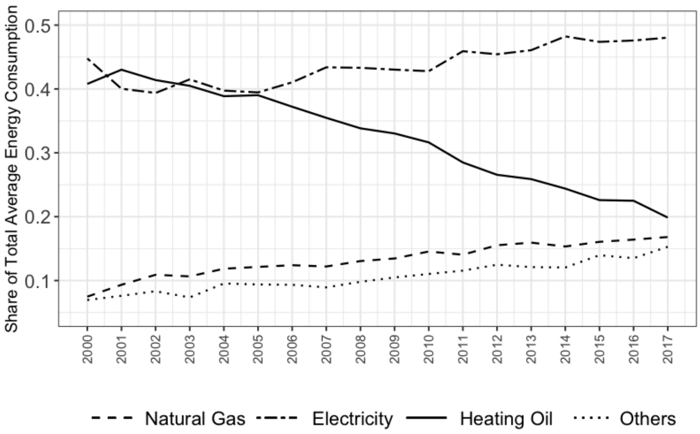
Table 3.4: Description of Variables Used for the Analysis

Variable	**Description**
Energy Consumption (in MJ)	
Electricity	Net electricity use
Heating oil	Heating oil extra light, heating oil medium/heavy and other liquid fuels
Natural gas	Natural gas
Other Energy Sources	Industry waste, local / district heating and wood
Facility characteristics	
Industry group	19 industry groups (as described in Table A.5)
Number of full-time employees (FTE)	Employees with an employment ratio $\geq$ 90%
Number of part-time employees (PTE)	Employees with an employment ratio $<$ 90%
Gross floor space (GFS)	Measured in m^2
Other explanatory variables	
Heating oil price	(Real) price excl. CO_2 levy[1)]
Gas price	(Real) price excl. CO_2 levy[1)]
Electricity price	(Real) price[1)]
Heating Degree Days (HDD)	Sum of differences between outside air temperature and target indoor air temperature (20°C) for all heating days of the year[2)3)]
Public spending on energy research (EF)	Total spending on energy research in the fields of energy efficiency, renewable energies, nuclear energy and energy policy fundamentals (2 years lag)[4)]
Energy Efficiency (EE)	Index on the basis of GDP/end-use energy consumption[4)]
GDP per capita	GDP in constant 2015 US Dollars[5)]

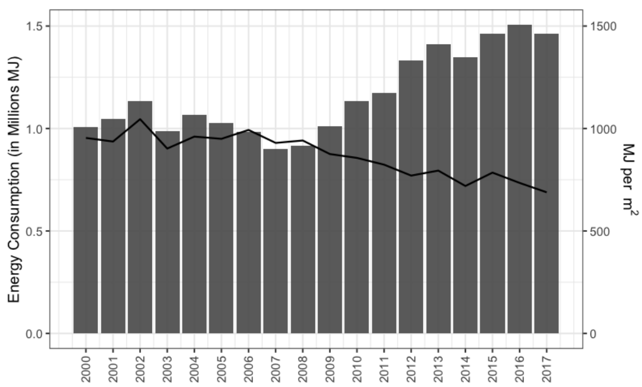
[1)] Source: Overall energy statistics (Swiss Federal Office of Energy, 2021), Tab. 39
[2)] A heating day is defined as a day with a daily mean temperature of less than 12°C
[3)] Source: Meteo Swiss
[4)] Source: Federal Statistical Office (2022)
[5)] Source: World Bank

Figure 3.1 illustrates the mean energy use for this sample. Figure 3.1a depicts the average share of energy use by source. Heating oil was one of the predominant energy sources at the beginning of the century, but the share of energy use for heating oil has declined steadily over time. This trend coincides with an increase in average use for all other energy sources. Consequently, the energy mix of the business entities in the sample has changed drastically in this time period: While the average share of heating oil dropped from roughly 41% to under 20%, the average share of natural gas grew from 7% to roughly 17%. Other energy sources followed a similar development, with their share increasing from 7% to 15%. Further, we observe an increase in average total energy consumption (see Figure 3.1b). Total mean energy use per square meter of floor space, however, declined since the introduction of the levy in 2008.

Figure 3.1: Trends in Energy Use, 2000–2017



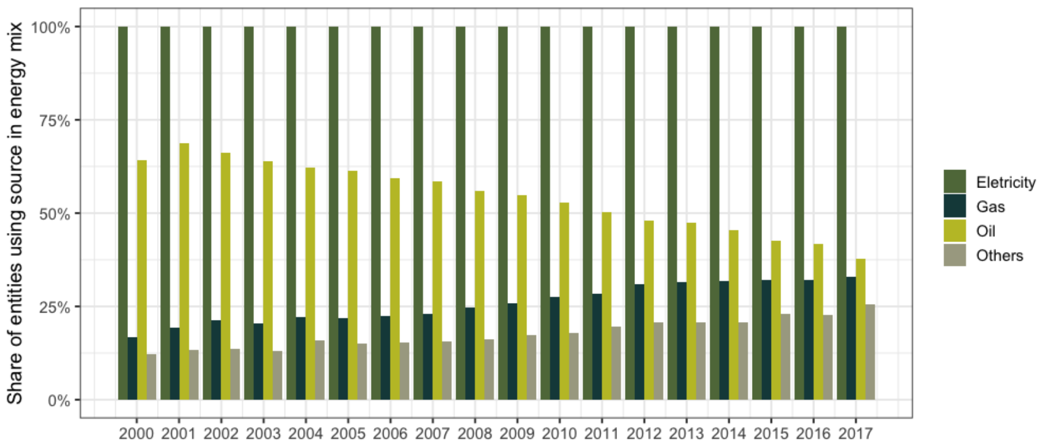
(a) Share of Energy Use per Source



(b) Total Average Energy Use

We further consider the distribution of energy source use by looking at the share of entities in the sample that use each energy source. Figure 3.2 illustrates the annual share of firms that include each energy source in their energy mix.[13] We find that all of the entities in the sample use electricity. More than 60% of the entities used heating oil at the beginning of the period. However, this share declined significantly over the course of time, falling to below 40% in 2017. For natural gas and other energy sources, on the other hand, an rise in the shares can be observed. Thus, we find that increasingly more entities are including these energy sources into their energy mix while heating oil is being phased out of the energy mix.

Figure 3.2: Distribution of Energy Source Usage

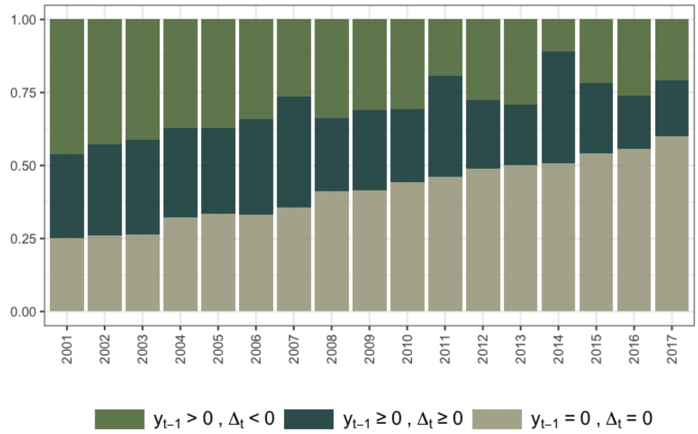


On a more in-depth examination of the annual changes in the heating oil at the entity level, three patterns can be observed in our data: Entities either (i) use less than in the period before ($y_{t-1} > 0, \Delta_t < 0$); (ii) use more or the same than in the period before ($y_{t-1} \geq 0, \Delta_t \geq 0$); or (iii) remain at zero use (($y_{t-1} = 0, \Delta_t = 0$). Figure 3.5 graphically illustrates these patterns. We observe a high share of business entities that remain at zero heating oil use from one year to the next, with this share increasing over the entire period. The annual share of entities that increase their heating oil use from one year to the next also decreases over time, indicating that entities are gradually abandoning the use of heating oil. In the same vein, the annual percentage of entities that experience a negative change in their heating oil use increases. Most of them remain at a positive usage level, with only a small proportion of entities ceasing heating oil use completely from one year to the next.

Given the percentage of business entities that do not use heating oil in a given year, it is apparent that not all entities in our sample regularly use heating oil prior to the introduction of the levy. Establishments may be affected to a varying extent by the levy depending on their energy usage patterns. As a result, the entities in our sample can be categorized into three groups according to their energy use before the introduction of the levy: Occasional oil users who have used heating oil at least once before the introduction of the levy; regular oil users, who have used heating oil in every observed year before the introduction of the levy; and non

[13] Figure A.9 provides a detailed illustration of the trends in energy mix over time.

Figure 3.3: Annual Changes in Heating Oil Use



oil users who have not used heating oil in any of the observed years before the introduction of the levy. Table 3.5 provides an overview of the energy usage patterns, including the allocation between industry and the service sector. The largest share in our dataset is regular oil users, which are equally distributed between industry and the service sector. Non oil users constitute another large share in our data, i.e. more than a third of the companies in our sample do not use heating oil.

We also find differences within these groups regarding pre-treatment natural gas use. While only a small share of regular heating oil users use natural gas before 2008, this share is much greater for occasional users and for non-users. Hence, entities that regularly use heating oil therefore use natural gas considerable less frequently. Conversely, entities that do not or only occasionally use heating oil frequently use natural gas. We find a similar pattern for other energy sources. Again, only a small share of regular heating oil users use other energy sources while the share is notably bigger for occasional users and for non-users.

Table 3.5: Heating Oil Usage Patterns (Pre-Treatment)

Occasional oil users		**Regular oil users**		**Non oil users**	
346 entities		1’902 entities		1’313 entities	
2’911 observations		14’367 observations		8’967 observations	
(43% industrial sector, 57% service sector)		(51% industrial sector, 49% service sector)		(40% industrial sector, 60% service sector)	
Pre-Levy Energy Mix:	Freq.	Pre-Levy Energy Mix:	Freq.	Pre-Levy Energy Mix:	Freq.
Oil + Electricity	35.8%	Oil + Electricity	88.7%	Electricity	23.8%
Oil + Electricity + Gas	37.9%	Oil + Electricity + Gas	5.7%	Electricity + Gas	43.5%
Oil + Electricity + Others	22.3%	Oil + Electricity + Others	5.4%	Electricity + Others	28.9%
All	4.0%	All	0.2%	Electricity + Gas + Others	3.8%

3.5 Methodology

3.5.1 Model

The empirical strategy follows the approach proposed by Abrell et al. (2022) for policy evaluation in setting where no suitable control group exists. We define energy use y of entity i in period t as a function:

$$y_{it} = f_i(x_{it}, k_{it}, z_t) + \epsilon_{it} \tag{3.1}$$

where x_{it} and k_{it} are vectors of observed and unobserved controls, respectively. z_t is the continuous treatment variable, i.e. the levy. z_t^0 is the levy rate zero (no treatment). ϵ_{it} is a random noise with mean zero and variance σ_ϵ^2. ϵ_{it} is independent of controls and treatment: $\epsilon_{it} \perp (x_{it}, k_{it}, z_t) \, \forall \, i, t$. We assume that controls affect energy use via the function $f_i(x_{it}, k_{it}, z_t)$ and that the function f_i is autonomous to changes in the treatment.

The objective of this study is to identify the effect on energy use y caused by the government intervention. Let y_{1it} be the energy use of entity i under treatment and let y_{0it} be the energy use without treatment. The treatment effect can then be calculated as $\theta = y_{1it} - y_{0it}$. To identify the impact of treatment on the outcome variable, the following assumptions have to hold true:

1. Observed control variables are independent of the changes in the treatment variable:

   $x_{it} \perp z_t$

2. Unobserved control variables are conditionally independent to changes in the treatment variable given the observed controls:

   $k_{it} \perp z_t | x_{it}$

Assumption 1 rules out effects of the treatment on observed control variables. If the assumption doesn't hold, there would be an indirect effect on the outcome, which would, in turn, bias the estimated treatment effect. Assumption 2 rules out effects of the treatment on unobserved control variables once observed control variables are controlled for. Otherwise, there would be an indirect effect biasing the estimated treatment effect.

Given that all business entities in Switzerland are subject to one of the three policy instruments, there is no untreated control sample y_{0it} available to estimate the impact of the levy. Thus, the estimation of the causal effect using standard statistical approaches is hampered due to the lack of couterfactual outcome (Holland, 1986; Rubin, 1974). Thus, we use supervised machine learning to obtain an estimator $\hat{f}_i$ for f_i to produce reliable out-of-sample predictions for the outcome variable under the observed and counterfactual treatment:

$$\hat{y}_{it} = \hat{f}_i(x_{it}, k_{it}, z_t) + \epsilon_{it} = y_{it} + \xi_{it}(x_{it}, k_{it}, z_t) + \epsilon_{it} \tag{3.2}$$

where ξ_{it} is the prediction error which is unobserved in the case of the counterfactual outcome. As a result, the estimated treatment effect can be computed as: $\hat{\theta} = \hat{y}_{1it} - \hat{y}_{0it}$. The estimated treatment effect is unbiased if the following assumption is satisfied:

3. The prediction errors are independent of the treatment:
   $\xi(x_{it}, k_{it}, z_t) = \xi(x_{it}, k_{it}, z_t^0) = \xi(x_{it}, k_{it})$

Given this and $E[\epsilon_{it}] = 0$, the estimated treatment effect $\hat{\theta}$ is unbiased, i.e. $E[\hat{\theta}] = 0$.

Additionally, we impose two further assumptions on the properties of our data for the feasibility of the applied estimation strategy:

4. The variation in the level of treatment and controls over time is sufficiently large

5. Each combination of the counterfactual treatment and control variables has been observed (thus $Prob[z|x_{it}] > 0$)

Assumption 4 is imposed because variation is needed for ML algorithms to detect patterns and relationships between variables. If variation over time is insufficient, the algorithm may not be able to accurately capture the effect of the treatment. Therefore, assuming sufficient variation in the level of treatment and controls over time is necessary for ML algorithms to produce reliable estimates of the treatment effect. Assumption 5, the “positivity” or “covariate overlap” assumption (Samii et al., 2016) is necessary as ML algorithms may not perform well on combinations of variables that were not observed during training. Therefore, it is uncertain how well the estimated models generalize to unseen observations. We assume that all combinations of z and x are within the range of the observed data.

3.5.2 Empirical Implementation

The empirical implementation requires us to obtain a precise estimate of the energy use at the entity level. To estimate f_i, we use facility characteristics as well as the covariates presented in Table 4.2. Further, we include entity and industry group fixed effects.

As we do not know the functional form of f_i and restrain from restricting the relationship by assuming a functional form, we estimate the relationship directly from the data. Therefore, we can treat estimation as a prediction task, and use any algorithm suited for prediction. This excludes standard OLS regression because this method breaks down when accounting for many (often) correlated covariates. In this case, OLS overfits the data, inducing variance inflation and sign reversal. To avoid the risk of overfitting and increase prediction accuracy without restricting functional forms, we use a machine learning method to obtain an estimator of f_i. We make use of the Super Learner (SL) ensemble machine learning algorithm as outlined in Van der Laan et al. (2007). The method is described in the subsequent section.

Impact on energy use. In order to estimate the impact of the levy on entity-level energy use, we need to obtain predictions for energy use with and without treatment, i.e. $\hat{y}_{1it}$ and $\hat{y}_{0it}$. For this, we employ the SL algorithm to train a model including a continuous treatment variable z_t indicating the tax levy. The prediction model is trained on untreated observations (i.e. before the introduction of the levy where the tax rate is equal to zero) and treated observations (i.e. after the introduction of the levy). This model is then used to predict actual, observed and counterfactual, unobserved outcomes for the period 2000–2017.

To simulate untreated, unobserved outcomes after 2008, we assign the treatment variable the value of zero for the entire time period, everything else remaining unchanged. The resulting predictions are our counterfactual. By estimating $\hat{y}_{1it}$ and $\hat{y}_{0it}$, the difference between the two values can be calculated to determine the treatment effect, i.e., the difference in energy use relative to the counterfactual situation in the absence of the levy.

Impact on CO_2 emissions from the combustion of fossil fuels. The impact of the levy on emissions from energy-related fossil fuel use can be assessed based on the estimated energy use. To estimate the emission abatement, we calculate emissions under observed and unobserved outcome using the emission factors in Table 3.1. Thus, we obtain the amount of emissions resulting from fossil fuel use by multiplying energy use with the respective emission factors. Aggregating the sum of emissions from heating oil and natural gas over all periods t yields the total emissions from the use of fossil fuels:

$$\hat{E}_i = \sum_t e^{oil} \times \hat{y}_{it}^{oil} + \sum_t e^{gas} \times \hat{y}_{it}^{gas} \tag{3.3}$$

The emission abatement can then be computed as the difference between total emissions in the case with and without levy.

3.5.3 The Super Learner Algorithm

The Super Learner is an algorithm that minimizes the cross-validated risk with respect to an appropriate loss function. In other words, the SL uses cross-validation to create an optimal weighted convex combination of candidate prediction algorithms, the so-called base learners. The approach has proven to perform asymptotically as well as or better as its best performing candidate learner (Van Der Laan & Dudoit, 2003; Van der Laan et al., 2006). In the following, we summarize the SL algorithm as detailed in the paper by Van der Laan et al..

Let $U_i = (Y_i, X_i), i = 1, ..., n$ be the data set where Y is the outcome variable of interest and X is a p-dimensional set of covariates. The objective of the SuperLearner is to estimate the function $\psi_0(X) = E(Y|X)$. The function $\psi_0(X)$ can be defined as the minimizer of the expected loss:

$$\psi_0(X) = \underset{\psi}{\operatorname{argmin}}\, E[L(U, \psi(X))] \tag{3.4}$$

where L is a loss function. Predictions of n observations are constructed as follows: Let $\mathcal{L}$ be a collection of base learners with cardinality $K(n)$. The idea is to fit each algorithm in $\mathcal{L}$ on the entire data set to estimate $\hat{\Psi}_k(X), k = 1, ..., K(n)$. The weight vector α is then determined such that it minimizes the cross-validated risk of the candidate estimator $\sum_{k=1}^{K} \alpha_k \hat{\Psi}_k$ with $\sum_{k=1}^{K} \alpha_k = 1$ and $\forall \alpha_k >= 0$, over all allowed combinations of α:

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \sum_{i=1}^{n} (Y_i - \alpha_k \hat{\Psi}_k)^2 \tag{3.5}$$

The SuperLearner fit is then given by:

$$\hat{\Psi}(X)_{SL} = \sum_{k=1}^{K} \hat{\alpha}\hat{\Psi}_k \tag{3.6}$$

We make use of the R package "SuperLearner" to implement the algorithm. The following base learners are selected: random forests (Breiman, 2001), gradient boosting (Chen & Guestrin, 2016), regularized regression (Friedman et al., 2010).

Gradient Boosting. Gradient boosting refers to a tree-based ensemble method. Ensemble methods are learning algorithms where multiple models, also known as base learners, are trained to combine the predictions to improve the overall accuracy of the model results. In gradient boosting the base learners are trained sequentially wherein each subsequent base learner uses information from previous models to provide more accurate estimates. One implementation of such gradient boosted decision trees is the XGboost (eXtreme Gradient Boosting) algorithm developed by Chen & Guestrin (2016). It is a novel boosting-based ensemble learning that offers efficient computational performance and sparsity aware split-finding. R provides the "xgboost" package to implement the algorithm.

Random forest. As in the case of gradient boosting, random forest is an ensemble machine learning technique. The algorithm proposed by Breiman (2001) is an extension of the bagging method introduced by Breiman (1996). Each tree in the ensemble is built using a bootstrap sample of the data. At each node in a tree, the splitting criteria is selected from a subset of predictors randomly chosen at that note. The main idea behind random forest is to reduce variance by training on different samples drawn with replacement. Thus, random forests often achieve high accuracy and reduces the risk of overfitting by averaging the results of different decision trees trained on randomly drawn subsets. We use the "ranger" R package to implement Breiman's algorithm.

Regularized Regression. Regularized linear regression is a regression method that includes a regularization penalty. The regularization constrains or shrinks the coefficient estimates towards zero. This constraint discourages complex models to avoid over-fitting. This is done by adding a penalty that is the squared magnitude of the coefficients to the loss function (ridge regression) or a penalty equal to the absolute value of the magnitude of the coefficients (LASSO regression). We implement regularized regression by using the "glmnet" R package.

To sum up, we have a versatile set of algorithms which are weighted by the SL algorithm such as to minimize the cross-validated risk.

3.6 Estimations & Results

3.6.1 Preliminary Analysis

Our machine learning approach estimates the causal effects of the policy measured on a continuous scale. To corroborate this, we estimate a regression model including dummy variables to measure the impact of each tax rate on energy use as compared to pre-treatment. This allows to evaluate the effect of the increasing tax rate. Therefore, for each tax rate we include a dummy variable that takes the value 1 for the respective years, and 0 otherwise. The results of the regression estimations are presented in Table 3.6. The results indicate that the CO_2 levy had a negative impact on heating oil use (column 1), and a positive impact on the use of all other sources of energy (column 2–4). Notably, the coefficients show that the effect gradually increases with the increase in the tax rate. The dummy coefficients thereby confirm that the effect of the levy increases when the tax rate is raised which validates the use of a continuous variable in our ML-based estimation approach.

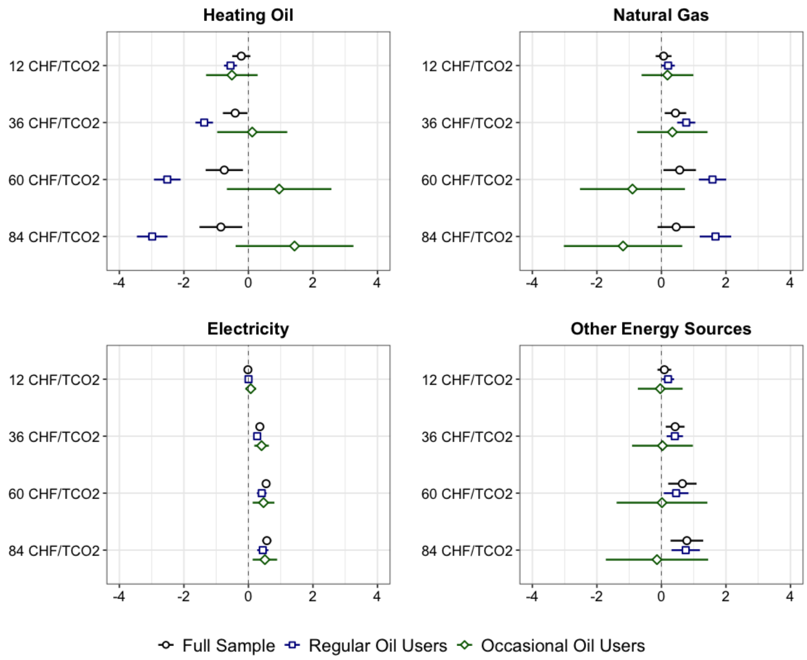
Table 3.6: Regression Results (Full Sample)

	Dependent variable:			
	ln Heating Oil	ln Natural Gas	ln Electricity	ln Others
	(1)	(2)	(3)	(4)
12 CHF/tCO_2	−0.221	0.067	−0.016	0.090
	(0.143)	(0.125)	(0.030)	(0.109)
36 CHF/tCO_2	−0.411**	0.435**	0.354***	0.425***
	(0.195)	(0.170)	(0.041)	(0.148)
60 CHF/tCO_2	−0.748**	0.566**	0.548***	0.650***
	(0.295)	(0.257)	(0.062)	(0.224)
84 CHF/tCO_2	−0.854**	0.458	0.571***	0.789***
	(0.339)	(0.296)	(0.072)	(0.258)
Observations	26,245	26,245	26,245	26,245
R^2	0.069	0.044	0.211	0.123
Adjusted R^2	0.068	0.043	0.210	0.123
Entity FE	YES	YES	YES	YES
GROUP FE	YES	YES	YES	YES
FIRM CONTROLS	YES	YES	YES	YES

Note: The constant term and control variables are estimated but not reported.
*p<0.1; **p<0.05; ***p<0.01

To assess whether the regularity of use leads to differences in the direction and magnitude of treatment effects, we repeat this regression for regular users and occasional users separately. Quantifying the effect for the two user groups sheds light on how causal effects may differ across usage patterns. Figure 3.4 compares the dummy coefficients obtained for the full sample, occasional users and regular users. Our findings show that the results in Table 3.6 are mainly driven by the latter. Entities that regularly use heating oil react strongly to the taxation of fossil fuels by simultaneously reducing heating oil use and increasing natural gas

Figure 3.4: Regression Results, Coefficient Comparison of Different Samples



use, i.e. inter-fuel switching. Further, for this user group we see a smaller but positive effect in the use of electricity and other energy sources. For occasional users, on the other hand, the effects are mostly insignificant.

Next, we examine whether the pre-levy energy mix of entities affect usage behavior. For this, we evaluate whether entities that have used natural gas in pre-treatment period react differently to the introduction of the levy relative to entities who have only relied on heating oil. The regression model can be written as follows:

$$y_{it} = \beta_0 + \beta_1 Gas_i + \beta_2 Post_t + \beta_3 Gas_i \times Post_t + \beta_4 X_{it} + \varepsilon_{it} \tag{3.7}$$

where y_{it} is the heating oil use of entity i at time t. Gas_i is a dummy variable which is equal to one if entity i has used natural gas during the pre-treatment period and equal to zero otherwise. $Post_t$ is an indicator variable for time t and is equal to one if the observation occurs after the introduction of the levy and equal to zero in the previous periods. Thus, the interaction term $Gas_i \times Post_t$ takes the value of one for observations for "gas users" in the post-treatment period. The corresponding estimated coefficient β_3 can be interpreted as the effect of the levy on gas users. X_{it} represents the control variables as specified in the main analysis and ε_{it} is the error term. We run the equivalent regression for other energy sources:

$$y_{it} = \beta_0 + \beta_1 Other_i + \beta_2 Post_t + \beta_3 Other_i \times Post_t + \beta_4 X_{it} + \varepsilon_{it} \tag{3.8}$$

The regression results are reported in Table 3.7. We find that entities that have used natural gas in the pre-treatment period have a significantly lower heating oil use in the post-treatment period compared to entities that only use electricity and other energy sources. Thus, the findings show that entities are characterized by stronger decreases in heating oil if the entity used natural gas already in the pre-treatment period. For other energy sources, this only holds true for regular users, however, we find that this effect is less pronounced.

Table 3.7: Regression Analysis

	Dependent variable:			
	ln Heating Oil			
	Regular Oil Users		Occasional Oil Users	
	(1)	(2)	(3)	(4)
Gas × Post	−2.938***		−2.948***	
	(0.212)		(0.431)	
Others × Post		−0.121		0.100
		(0.236)		(0.488)
Gas	−0.164		−0.769**	
	(0.154)		(0.298)	
Others		−0.167		−0.209
		(0.164)		(0.337)
Post	−0.004	−0.154	0.469	−0.810**
	(0.094)	(0.095)	(0.413)	(0.400)
Observations	14,367	14,367	2,911	2,911
R^2	0.145	0.119	0.131	0.091
Adjusted R^2	0.144	0.118	0.123	0.083
Entity FE	YES	YES	YES	YES
GROUP FE	YES	YES	YES	YES
FIRM CONTROLS	YES	YES	YES	YES

*p<0.1; **p<0.05; ***p<0.01

3.6.2 Machine Learning

We proceed by evaluating the size of the policy effect on energy use for both the full sample and the regular users subsample using our machine learning approach.[14] Separate models are estimated for each sample. We start by performing hyperparameter optimization by training the SL on the entire sample. To tune the hyperparameters of each individual learner, we define a range of possible values for each tuning parameter and run the models for every combination of hyperparameters specified to select the tuning parameters that minimize the mean squared error.[15]

To estimate energy use in observed and unobserved outcomes, we need an estimator $\hat{f}_i$ that provides reliable out-of-sample predictions. Therefore, we proceed by evaluating the out-

[14]To obtain accurate and reliable predictions, an adequate sample size is required. With a small sample size, machine learning may result in overfitting and produce unreliable predictions. Due to the low number of occasional users in our sample, we are unable to perform model estimations for this subsample that provide reliable results.

[15]For the selection of tuning parameters we do not use cross-validation as this is computationally costly. We try the following range of values: Using the ranger algorithm, we tune two hyperparameters, the number of predictors that are sampled at each split (mtry $\in \{10, 20, 50, 100, 120\}$ and the minimal node size (min.node.size $\in \{3, 4, 5\}$). For the XGboost algorithm we tune the number of trees (ntrees $\in \{500, 1000, 1500\}$, the minimal node size (min.node.size $\in \{3, 4, 5\}$) and the learning rate or shrinkage (eta $\in \{0.1, 0.15, 0.2, 0.25, 0.3\}$). For the regularized regression, we tune the elastic net mixing parameter ($\alpha \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$).

of-sample prediction performance. For this, the respective data set is randomly split into a training and test set with an 80/20 split. The training data is used to fit the SL model using a 10-fold cross-validation. This model is then used to to predict energy use y_{it} of the unseen test set which allows us to evaluate the out-of-sample prediction performance. This process is done for the prediction of each energy source individually. The results are displayed in Table 3.8.

Table 3.8: Out-of-sample Prediction Performance

	Heating Oil	Natural Gas	Electricity	Other Energy Sources
		Full Sample		
RMSE	2.000	1.981	0.351	1.711
MdAE	1.115	0.900	0.195	0.444
R^2	0.920	0.930	0.949	0.927
		Regular Oil User		
RMSE	1.748	1.485	0.293	1.144
MdAE	0.584	0.199	0.173	0.109
R^2	0.900	0.917	0.968	0.912

The R-squared values across all models are relatively high, indicating that a high proportion of the variance in the values of the dependent variable y_{it} can be explained by the independent variables x_{it}. Root Mean Square Error (RMSE) is a measure of accuracy and is the standard deviation of the prediction errors, indicating how far the predictions deviate from the true values.[16] The median absolute error (MdAE) evaluates the precision of the predictive performance and is a robust measure of how spread out the prediction errors are.[17] For both metrics, values closer to zero represent better fitting models. The normalized RMSE values range from 0.02 to 0.11, indicating a high prediction accuracy out-of-sample.

In a next step, the SL is trained using the selected hyperparameters for the three base learners using 10-cross-validation.[18] As mentioned in Section 3.5.3, the weights for each algorithm are chosen so as to minimise a predictive loss function. Across all models, the best predictive algorithms are glmnet and ranger.[19]

Based on the resulting predictions, the treatment effect can be estimated as described in Section 3.5.2. The estimated treatment effects for the full sample are presented in Table 3.9. Notably, the effect varies substantially over time depending on the tax rate. We find that for the first two years after the introduction of the levy, at a tax rate of 12 CHF/tCO_2, the effect on heating oil and natural gas was relatively low, averaging -8.2% and $+3.4\%$, respectively, compared to the counterfactual situation without a levy. In the subsequent years, during which the tax rate was successively increased, the effects on heating oil and

[16] RMSE $= \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$, Normalized RMSE $= \frac{RMSE}{(Max-Min)}$
[17] MdAE $= median(|\hat{y}_i - y_i|, ..., |\hat{y}_n - y_n|)$
[18] The following hyperparameters are selected: mtry = 120, min.node.size=3, ntrees=1500, eta=0.1, $\alpha = 0$.
[19] See Table A.9 for an overview of the weights assigned to each model.

natural gas are considerably greater. Raising the tax to 84 CHF/tCO_2, the estimated effect amounts to -43.9% and $+19.7\%$, respectively, suggesting a magnifying effect associated with the tax rate. In other words, an increase in the tax rate of 1 CHF/tCO_2 leads to an average decrease in heating oil use of $\sim 0.59\%$ and an average increase in natural gas use of $\sim 0.26\%$.

In column 6, we compute how the change in energy mix affects emissions. The estimates indicate that the tax has led to considerable emission reductions when compared to the situation without CO_2 levy. According to the results, the average entity-level emission reduction amounted to -3.9% for the first two years after the introduction of the levy and increased to an average of -14% in 2016 and 2017 at a levy rate of 84 CHF/tCO_2. On average, the carbon tax led to a reduction in energy-related emissions of -7.5% in the period 2008–2017 for business entities in the sample due to the switch to the less carbon-intensive alternative natural gas.

Table 3.9: Average Impact of the CO_2 Levy on Energy Use (Full Sample)

	Heating Oil	Natural Gas	Electricity	Other Energy Sources	Emissions
12 CHF/tCO_2	-8.21%	3.38%	0.7%	0.6%	-3.9%
36 CHF/tCO_2	-22.1%	11.0%	2.2%	2.8%	-7.7%
60 CHF/tCO_2	-33.7%	15.4%	3.4%	4.1%	-11.3%
84 CHF/tCO_2	-43.9%	19.7%	4.7%	5.3%	-14.0%

Table 3.10 reports the estimated treatment effects for regular users. We find that, on average, heating oil reduction is greater for regular users when compared to the full sample. Entities that regularly use heating oil on average reduce its consumption by -13.6% at the lowest tax rate in the years immediately after introduction of the policy. At a levy rate of 84CHF/tCO_2, the average reduction in heating oil usage amounts to -60.9% compared to the counterfactual situation without the levy. In addition, we see a significantly stronger increase in natural gas and other energy sources for regular oil users relative to the full sample. Regular users exhibit an average increase in natural gas usage of 64% and other energy sources usage up to 33% relative to the untreated case. These results strongly suggest that regular users are substituting heating oil for natural gas and other energy sources. Electricity use, however, remains roughly stable. The results find that the introduction of the carbon tax led to a very low impact on the use of electricity (0.2–0.9%) for regular users. Thus, the increase in electricity found in Table 3.9 is seemingly driven by occasional users or non-users. On average, the carbon tax led to a reduction in energy-related emissions of -13% in the period 2008–2017 for regular users in the sample due to the energy substitution.

Table 3.10: Average Impact of the CO_2 Levy on Energy Use (Regular Oil User)

	Heating Oil	Natural Gas	Electricity	Other Energy Sources	Emissions
12 CHF/tCO_2	-13.6%	11.5%	0.2%	5.6%	-9.6%
36 CHF/tCO_2	-33.9%	41.4%	0.6%	18.8%	-14.3%
60 CHF/tCO_2	-49.4%	49.1%	0.7%	22.4%	-14.7%
84 CHF/tCO_2	-60.9%	64.0%	0.9%	33.1%	-18.1%

3.6.3 Sensitivity Analyses

We carry out a number of robustness checks to ensure validity of our results. In Appendix A.2.5 we explore the sensitivity of our results regarding the classification approach used to determine tax liability which ultimately defines our sample. First, we use an alternative approach whereby we identify entities in the sample with annual CO_2 emissions $\leq$ 100 tCO_2 in each observation after the introduction of the tax as subject to the levy.[20] Thus, we construct an alternative sample where all firms emit less than 100 tCO_2 in every period after 2008 and re-estimate the treatment effects (see Table A.10).[21] The results are robust and do not depend on the classification approach chosen in the main specification. We also re-estimate our models without this restriction, only excluding very high emitters ($>$ 25'000 tCO_2) as those are in the emission trading system (see Table A.11).[22] Overall, these estimates are comparable to those in the main specification, with natural gas exhibiting a small discrepancy. This may be due to the fact that this sample includes entities that are covered by the reduction measures and are therefore not subject to the tax. The reaction to the reduction commitment may differ from the reaction to the tax, resulting in different policy impacts.

[20]The restriction to at least one observation in the pre-treatment period and the exclusion of large users remains in place.

[21]This alternative sample has more stringent restrictions and is therefore smaller than the full sample.

[22]See footnote 20.

3.7 Discussion & Conclusions

Previous empirical research examining the impact of carbon taxation on energy use and emissions has predominantly focused on the effects at the macroeconomic or sectoral level. This paper extends the current body of research by studying the effects of carbon taxation on energy use, energy substitution and energy-related emissions at the microeconomic level; the level of entities is even below the firm level as firms typically include multiple entities at different locations.

The results of the regression models and machine learning estimations in Table 3.6 and 3.9 indicate support for **H1**. The findings reflect a significant decrease in heating oil and a significant increase in natural gas and other energy sources as a result of the policy, with the effect becoming more pronounced as the tax rate is raised. The estimations of the SL also find that electricity does not react strongly to the carbon tax. This is in line with previous research findings showing that electricity is a poor substitute for fossil fuels (Hyland & Haller, 2018; Fuss, 1977; Pindyck, 1979; Steinbuks, 2012).

Our results of the regression models further show that there is considerable variation in the magnitude of the effect, depending on the historical energy usage behaviour of the entities. We find that entities that regularly use heating oil react strongly to the introduction of the levy. Conversely, for occasional users we do not find significant effects on the use of fossil fuels. This is in line with the idea that entities who use heating oil regularly face higher financial incentives to switch away from heating oil, supporting **H2**. In addition, we find that entities that were already using natural gas prior to the imposition of the CO_2 levy reduced their heating oil use to a greater extent than entities that did not exhibit this usage pattern (see Table 3.7). This holds true for both regular and occasional oil users and is in line with the idea that entities who have natural gas at their disposal are more flexible in terms of substituting heating oil in response to increases in the relative price. This finding indicates a substitution between heating oil and natural gas. Such a substitution pattern is not observed for other energy sources. While our ML estimates reveal an uptick in the use of other energy sources due to the policy, we do not observe a larger decline in heating oil use among entities that were already using these energy sources prior to the introduction of the levy compared to those that were not. These findings suggest that natural gas is a readily available alternative to heating oil, rendering it a viable option for businesses. Other energy sources such as industrial waste or district and local heating systems on the other hand may not be as immediately accessible, or the reduction potential through the switch to other energy sources may already be exhausted, making further reductions through switching no longer possible. Thus, while our results provide support for **H3** in the context of natural gas, we do not find evidence that it holds true for other energy sources.

Further, we find supporting evidence for **H4**. We estimate that switching to the less carbon-intensive alternative, natural gas, resulted in an average entity-level reduction of CO_2 emissions from the combustion of fossil fuels of approximately -7.5% in the period 2008–2017. For entities that exhibited regular heating oil usage before the introduction of the levy we find that this effect is even more pronounced and amounts to -13% emission reduction attributable to policy-induced fuel switching.

The results of this analysis can be compared to other studies in this field. Ellerman & McGuinness (2008) empirically assess impact of the European Union Emissions Trading Scheme (EU ETS) carbon pricing on the plant-level CO_2 abatement as a result of fuel switching using power plant data on UK. They find that the carbon price increased natural gas utilization between 19% to 24%, while coal utilization decreased by 16% to 18%, resulting in an annual emission abatement of roughly 8-12% due to fuel switching. Similarly, Wagner et al. (2014) find that the policy has resulted in a significant reduction in GHG emissions within ETS plants, of 20%, relative to non-ETS plants which is mainly driven by a decrease in carbon intensity of the fuel mix in ETS plants. The results of these studies are therefore roughly in the same order of magnitude. Variations in the magnitude of the estimated impact may be attributable to multiple factors, including differences in the level of the tax rate, varying empirical settings and estimation methods.

In summary, the empirical analysis shows that business entities in the industry and service sector respond to the introduction of the fossil fuel tax by amending the energy mix used. This leads to a less carbon-intensive energy mix which in turn reduces emissions. The estimated effects provide new evidence on fossil fuel use under carbon taxation that can be useful in designing policies to reduce emissions of energy-related GHG emissions. The implications of these findings extend to research, policy, and practice, which will be discussed in the following subsections.

3.7.1 Implications for Research

First, this study evaluates the impact of carbon taxation on entity-level energy use. A company's economic performance and competitiveness can be affected by carbon taxation as it increases production costs. Assessing the micro-level impact of carbon taxation can help policymakers moderate the potentially negative effects on competitiveness and promote a level playing field. Further, it offers insights on how business entities and firms respond to environmental policies and can provide a more accurate estimate of impacts by accounting for inter-firm differences. In this way, micro-level policy analysis deepens the understanding of how policy measures affect the behavior of companies.

Second, this study examines the impact of carbon pricing on businesses with different oil usage patterns, thereby enriching research by considering heterogeneity across energy usage patterns. Further research could explore the importance of the energy mix for fuel switching opportunities, as emphasized in this study.

Third, this paper complements the research on carbon taxation by applying a new machine learning approach to evaluate the effectiveness of this policy in reducing fossil fuel use and emissions. Future studies can build upon and expand the current findings to develop more accurate and efficient policy evaluation methods. Furthermore, the ML approach can be applied to evaluate the effectiveness of other environmental policies, broadening the scope of policy analysis and improving our understanding of the impact of policies on firms.

3.7.2 Implications for Policy & Practice

The CO_2 levy is one of the Swiss government's key instruments for curbing carbon emissions. It is therefore essential to assess how the levy has performed up until now in order to determine whether the climate policy measures are taking effect. The findings show that the increase of the tax rate had a significant positive impact on the reduction of emissions of business entities. This implies that the Swiss government can accelerate the decarbonization in the industrial and service sector by raising the tax rate, thereby creating incentives for entities to switch to low-carbon energy sources.

While there is general consensus on the need to transition away from fossil fuels, there is disagreement on the best course of action to achieve this transition. One view is that resorting to intermediates such as gas instead of renewable energy sources such as wind and solar can help phase out the use of carbon-intensive energy sources in the short term. However, an alternative view claims that relying on intermediates can delay the final transition to fully clean and secure energy sources, and therefore the direct transition to clean energy sources should be prioritized. Both perspectives in this contentious debate offer valid arguments — resorting to intermediate sources of fossil fuels constitutes a quick way to curb emissions, however, the approach poses the risk of hampering the advancement of renewable technologies and possibly resulting in another lock-in, e.g. due to gas-based infrastructure. Furthermore, our findings reveal that occasional oil users are not sufficiently incentivised to reduce heating oil use under the current tax rate. With an increase in the tax rate, one may be able to target these entities and reduce their heating oil use.

In sum, the findings of substituting heating oil with natural gas by implication entail that there is further action necessary to completely abandon the use of fossil fuels and avoid further carbon lock-ins. Thus, although the CO_2 levy has led to a reduction in heating oil use and energy-related emissions, higher levy rates are required for the decarbonization of the economy. The analysis also revealed that business entities reduce their use of heating oil to a greater extent when alternatives are available. Strengthening the promotion of renewable and climate-friendly alternatives can therefore accelerate the transition away from heating oil. Accordingly, in line with Acemoglu et al. (2012), an increase in levy rates in combination with other policy instruments, e.g. strengthened measures to promote renewable energy, is advisable.

On 13 June 2021, the Swiss electorate voted on an amendment on the Federal Act on the Reduction of Greenhouse Gas Emissions (CO_2 Act). The revised law was designed to strengthen Switzerland's efforts to reduce greenhouse gas emissions and combat climate change. Under the revised CO_2 Act, the maximum tax rate on fossil thermal fuels would have been raised from 120 to 210 CHF/tCO_2. However, Swiss voters rejected legislation by a vote of 51.59% to 48.41%. There is concern that the maximum rate foreseen by the current law is insufficient to achieve the required emission reductions and that an increase in the maximum tax rate must be considered.

3.7.3 Research Limitations & Prospects

Several limitations to our analysis should be noted. To begin with, we do not allow for anticipatory effects. If entities react before the levy, or if certain anticipatory measures are introduced before the formal implementation of the levy that otherwise would not have been introduced in the absence of the policy intervention, the estimates may be biased.

Another limitation of the study is attributable to our applied classification strategy. In the analysis, entities are classified as subject to the levy on the basis of their calculated emissions. This allows us to examine only those entities that emit less than 100 CO_2 per year. Entities that exceed this threshold but do not make use of tax exemption regime by entering into reduction measure agreements are also subject to this tax. However, our estimation of the policy impact does not account for these entities as we are not able to reliably identify those. If there are heterogeneous regulatory effects in the quantity of emissions, this may constitute a source of bias in our estimates.

The lack of available data presents another limitation. The data needed to precisely evaluate the effects of a government policy requires a comprehensive set of variables on relevant entity characteristics as well as data on potential confounding factors. The available data on energy use of Swiss business entities collected by the survey pose substantial challenges for data analysts. These challenges include missing information on important variables such as productivity, profits or the degree of control over the energy use of the building. A big political concern is the negative impact of carbon taxation on firms' productivity and competitiveness. The increase in the relative cost of fossil fuels can negatively affect industries reliant on these fuels and reduce the competitiveness of a country, sector or firm. In view of the principal-agent problem, it is important to consider whether the business entity owns the building in which it is located or merely rents it, as this can have a significant impact on the incentives and decision-making processes related to energy use.[23] To conduct a fully comprehensive study of these impacts, additional variables must be made available.

3.7.4 Overall Conclusions

With the ratification of the Paris Agreement in 2017, Switzerland has committed to halving its emissions from GHG by 2030 in comparison with 1990 levels. The CO_2 levy is a key element of Switzerland's strategy to achieve this climate goal. The levy was introduced in 2008 on fossil combustible fuels to set incentives for firms and households to use less carbon-intensive energy sources and to thus reduce CO_2 emissions.

This paper provides empirical evidence on the effects of the Swiss CO_2 levy based on micro-level data on energy use. The unavailability of a control group and the exemption regimes from the levy complicated the analysis, requiring a well-chosen statistical method and an identification of the entities subject to the levy on the basis of emitted emissions.

[23]In cases where a businesses are tenants, they may have little control over energy use and influence over how heating and cooling systems are maintained and operated, as the building owner is responsible for managing these systems. Moreover, it is less likely that tenants will invest in energy-efficient improvements or adopt energy-saving practices.

Using a machine-learning approach, we estimate the effects of the levy on energy use and emissions from the combustion of fossil fuels.

Our results indicate that the carbon tax successfully lead to a reduction in the use of heating oil from business entities, while simultaneously increasing the use of natural gas and other energy sources. These findings suggest that the CO_2 levy stimulates a substitution from heating oil towards less CO_2-intensive energy sources, with an associated reduction in entity-level emissions. Beyond these empirical findings, our findings suggest that there is heterogeneity in reaction to the introduction of the Swiss CO_2 levy. We find that the direction and magnitude of the effect depends on the initial usage behavior and energy mix.

Chapter 4

Learning by Buying: The Impact of Mergers on Green Innovation*

Chapter Abstract

Achieving the green transition requires investment and innovation in green technologies. However, due to path dependencies in innovation, established firms may be slow to develop clean technologies. Mergers and acquisitions (M&A) are one strategy for firms to gain access to new knowledge. Applying a comprehensive dataset of M&A deals in the US power and utilities sector between 1981 and 2017, we document a steep rise in "green acquisitions" - involving target firms engaged in renewable energy and clean technologies - in the last two decades. We then analyze the impact of M&A on the subsequent innovation activities of acquiring firms. We find that green technological acquisitions – involving target firms that possess intellectual property related to sustainable technologies – significantly increase the green innovation output of acquiring firms post-acquisition, providing evidence of "learning by buying" in green technologies.

*This chapter represents joint work with Dr. Melissa Newham (CER-ETH Center of Economic Research at ETH Zurich)

4.1 Introduction

Achieving the green transition while maintaining economic growth requires that firms undertake green innovation i.e. invest in research and development (R&D) related to sustainable and low-carbon technologies. However, due to path dependencies in innovation, established firms may be slow to develop new technologies. Mergers and acquisitions (M&A) are one strategy for firms to gain access to new knowledge.[1] Could M&A with "green firms" - that own or apply green technologies - induce acquiring firms to direct more of their innovation efforts towards green technologies? Applying a detailed dataset of M&A activity in the US power and utilities sector combined with firm-level patent data, we address this question.

Mergers and acquisitions can affect the innovation output of merging firms by altering both their incentives and ability to innovate (Jullien & Lefouili, 2018; Shapiro, 2011). The sign of the impact, at the firm or industry level, depends on the interplay between a number of factors. In certain situations, increases in market power post-merger dampen the incentives to invest in R&D (Arrow, 1962). However, these negative effects can be offset by the presence of research synergies and spillovers in knowledge and learning.[2] Thus, the effect of M&A on innovation in a specific setting is an empirical question. Existing empirical research predominately analyzes the biotech and pharmaceutical industry (e.g. Cunningham et al., 2021; Haucap et al., 2019). Research on how M&A affect the direction of innovation is scant and there has been no study analyzing how mergers affect green innovation in particular.[3] We fill this gap by empirically analyzing the impact of M&A on the extent and nature of subsequent innovation activities of acquiring firms in the electric power sector; a sector where the promotion of green innovation is paramount to curb greenhouse gas emissions.

The electric power sector has experienced a significant rise in M&A activity worldwide since 1985 (IMMA, 2021). Increasingly, firms are undertaking M&A with renewable energy firms to widen their energy portfolio, acquire new technologies and achieve CO_2 reduction goals set by climate change policies (Fraunhoffer & Schiereck, 2012; Yoo et al., 2013). This pursuit of M&A may spur the development of climate-friendly technologies at the firm level due to path dependency. In the automobile industy, Aghion et al. (2016) show that firms with a history of green innovation activities, as well as firms that have had more exposure to green innovations from other firms, are more likely to direct their research efforts to climate-friendly innovations in the future. One mechanism contributing towards this path dependency is that firms learn by doing (Arrow, 1962).

Acquisitions may similarly affect firms' green innovation paths as exemplified by the merger between Vivint Solar Inc, a large provider of residential solar systems, and Solmetric Corpora-

[1] A merger combines two or more firms into one new legal entity, typically with a new name. An acquisition, also known as a takeover, entails one firm purchasing another outright. The acquired firm may retain its name and operate as a subsidiary of the acquirer or it may be incorporated into the acquiring firm. In this article, we use the two terms interchangeably.

[2] As it stands, the relationship between mergers and innovation is hotly contested in economics. For a recent discussion of the literature see Gilbert (2020). Relatedly, there is a body of literature that studies how the level of competition affects innovation (e.g. Acemoglu & Akcigit, 2012; Aghion et al., 2005).

[3] Lambertini et al. (2017) examine the relationship between competition and green innovation in an oligopolistic market model. This study is related to the literature on merger effects as mergers between two rival firms may increase market concentration and lessen competition.

tion, a manufacturer of photovoltaic system installation tools and software, in 2014. Solmetric filed its first patent in 2005 when it invented a shade measurement device to assist the design and installation of solar panels. Since then, the company was granted seven additional patents by the United States Patent and Trademark Office (USPTO), four of which were classified as technologies or applications related to climate change mitigation or adaptation ("green patents"). Whilst the acquirer Vivint Solar had no patents prior to 2014, following the acquisition, Vivint Solar registered two new green patents in 2015 and 2016, citing Solmetric's patents. Through the acquisition, the acquiring company was also able to expand its product range by offering photovoltaic installation software products and devices.[4]

As recognized in the literature, the effect of an acquisition on the innovation output of the merging firms ex-post is conditional on the technological input acquired in the transaction (Ahuja & Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006). Consequently, our analysis distinguishes between different types of M&A and categorizes deals based on the technological input provided by the target. Further, we distinguish between target companies engaged in green vs. conventional business activities. Drawing on the theory of path dependence in environmental innovation (Aghion et al., 2016, 2019) and the existence of high technological spillovers for green technologies (Dechezleprêtre et al., 2014; Martin & Verhoeven, 2022), we argue that "green technological acquisitions" - involving innovative targets engaged in sustainable technologies - have the potential to impact positively on the green innovation activities of the acquiring firm via learning and R&D spillovers.

To test this claim, we construct a detailed panel dataset of firms engaging in M&A in the US power and utilities sector between 1980 and 2017. Data on M&A events is combined with data on patent applications filed by the merging parties pre- and post acquisition from the USPTO. By identifying patents related to climate change mitigation and adaption technologies using the Cooperative Patent Classification (CPC) Y02-tagging scheme, we are able to separate between green and conventional technologies. This allows us to categorize deals into "green technological acquisitions" (such as the Vivint-Solmetric deal) and "conventional technological acquisitions." It further enables us to specifically analyze the impact of mergers on green innovation by estimating the effect on green patents filed by the acquiring firm subsequent to the transaction.

The empirical set-up involves staggered treatment as firms in the sample experience a merger/acquisition at different points in time. We adopt a differences-in-differences framework, implementing two-way fixed effects regressions. The identification of causal effects of M&A on subsequent innovation output represents a challenging task due to the fact that the potential innovation outcomes that would have been realized in the absence of the consolidation would likely have occurred contemporaneously with the merger decision. Firms' research activities and the probability that they will seek to engage in an acquisition may both be influenced by the respective characteristics of the firms which can create endogeneity issues. Identifying the causal effect of M&A on innovation is further complicated by the fact that firms select into acquiring. We address this concern by limiting the control group to acquiring

[4] Vivint Solar Inc, Form S-1 Registration Statement, *EDGAR.*, Securities and Exchange Commission, 2016, https://www.sec.gov/Archives/edgar/data/1607716/000119312514321739/d716029ds1.htm.

firms that have not yet acquired/merged. However, it should be noted that despite the efforts made to account for endogeneity, the fundamental limitation of the approach employed in this paper is that the decision to merge is largely determined by factors that are not observable. Thus, the potential still remains that the correlation between mergers and innovation outcomes it attributable to other sources of unobserved heterogeneity.

Our data shows that since the year 2000 there has been a steep rise in acquisitions involving green target firms. In line with the theory of path dependence in environmental innovation, energy firms in our sample with a higher existing stock of patents relating to green (conventional) technologies are more likely to file new green (conventional) patents. Controlling for knowledge stocks at the firm-level, amongst other variables, we find that green technological acquisitions indeed promote further green innovation as evidenced by an increase in the likelihood that the acquiring firm will file a green patent post-acquisition. Conversely, conventional technological mergers do not significantly impact on conventional innovation nor green innovation. These results are consistent with the notion that green technologies are associated with larger knowledge spillovers than conventional technologies (see Dechezleprêtre et al., 2014; Martin & Verhoeven, 2022), and point towards research synergies between target and acquirer firms with regard to green technologies in particular. In sum, the findings suggest that acquiring firms exhibit "learning by buying" in green innovation.

Although the endogeneity concerns may not be completely resolved, the empirical results of this study nevertheless provide a basis for discussion and highlight the need for further attention to the impact of M&A on green innovation. The findings suggest that, when considering green innovation, the commonly held notion that mergers have a negative effect on innovation may not hold true. Across all model specifications, the acquisition of green targets (both technological and non-technological) exhibit a positive effect on the subsequent green innovation output of the acquirer. Consequently, a general conclusion from this paper is that a distinction should be made between conventional and green innovation when analyzing M&A effects. This research contributes to two strands of literature. Firstly, we contribute to the literature on the drivers of green innovation. In the face of climate change, identifying and understanding drivers of green innovation is crucial. Previous research has identified a number of factors which impact on green innovation including environmental regulation (e.g. Lanjouw & Mody, 1996; Noailly, 2012), R&D subsidies (e.g. Howell, 2017), energy prices (e.g. Popp, 2002), existing stock of knowledge (e.g. Aghion et al., 2016; Popp, 2002) and corporate governance (Amore & Bennedsen, 2016). We add to this literature by highlighting the role of M&A.

Secondly, we contribute to the literature addressing the impact of mergers on innovation. Previous empirical research on the topic has predominantly focused on the biotech and pharmaceutical industry (e.g. Cunningham et al., 2021; Haucap et al., 2019; Ornaghi, 2009). In this industry, Haucap et al. (2019) find that average patenting and R&D of the merged entity and its rivals declines in post-merger periods. Conversely, using an economy-wide sample of firms, Bena & Li (2014) find that acquirers with prior technological linkage to their target firms generate more patents post-merger, concluding that synergies obtained from combining innovation capabilities are important drivers of acquisitions. Whereas previous research has used overall innovation as the outcome of interest, we delineate innovation output further by looking at the direction of innovation in terms of green vs. conventional patents, and explore the implications of M&A in the power and utilities sector.

The remainder of this paper is organized as follows. Section 2 provides background information and describes the data. Section 3 describes the trends in M&A in the US energy sector. Section 4 describes the methodology used to analyze the impact of M&A on innovation. Section 5 presents results. Section 6 provides a discussion of our results and the policy implications thereof. Section 7 concludes.

4.2 Background & Data

4.2.1 The Power & Utilities Sector

The power and utilities sector includes establishments that perform one or more of the following activities: (1) operate electricity generation facilities (powered by fossil fuels, gas, wind, solar and other power sources); (2) operate transmission systems that convey the electricity from the generation facility to the distribution system; and (3) operate distribution systems that convey electricity to the final consumer.

Historically, US power utilities were vertically integrated, i.e. utilities were responsible for all three of these activities. Utilities were subject to regulations dictating electricity prices and services by the Federal Energy Regulatory Commission and state regulators. Under this traditional regulated structure, utilities were operating as monopolies. While firms benefited from economies of scale in production, it has been argued that the regulated framework and lack of competition lead to a dearth of technological progress in the industry in the last half of the 20$^{\text{th}}$ century (Willis & Philipson, 2018).

Nowadays, there are only a few utilities in the US operating under this traditional scheme. Structural and regulatory reforms beginning in the 1990s led to a vertical separation of electricity retailing, distribution and generation in many states and measures were taken to promote competition in the industry (Borenstein & Bushnell, 2015). Although deregulation was expected to boost innovation, a study by Sanyal & Ghosh (2013) finds no marked increase in electric technology innovation in the years that followed. This is attributable, among other things, to the fact that technology and innovation in the electric power sector have some unique characteristics. Market failures associated with energy R&D investments, indivisibility and spillovers are more pronounced than in other industries, leading firms to under-invest in energy R&D (Jamasb & Pollitt, 2008).[5] The large-scale operations of established power firms also contribute to technological lock-in at the firm and industry level, leading to slow technological progress (Unruh, 2000).

In recent years, US utilities and power generators have been faced with further industry transformations, driven by the shale revolution as well as the increasing significance of renewables and energy storage resources, among other factors. These developments have led companies to use M&A as one strategy to adapt to ongoing changes in the market (Adams et al., 2021).

The developments and characteristics of the industry described in the preceding paragraph make the power and utilities industry an interesting industry in which to study the effects of M&A on green innovation. Increased utilization of clean electricity is crucial for the reduction of greenhouse gas emissions. To meet the energy demand through renewable energy sources, technological advancements are needed (IEA, 2020). Given that advances in energy technologies are critical to mitigating climate change but are hampered by market failures, it is important to understand whether recent trends in M&A are encouraging or further hindering

[5] Jamasb & Pollitt (2008) present a review of the literature on R&D and innovation to identify the potential causes of the decline in R&D spending in the post-liberalisation electricity sector.

the development of such technologies.

4.2.2 M&A Data

For our analysis we construct a unique dataset that combines data on relevant acquisition events and firm-level innovation activity. To obtain M&A data, information from two sources were combined; M&A reports by Datastream and accessed via Refinitiv Eikon, and the Zephyr M&A database provided by Bureau von Dijk. From these sources, we collect data on deals taking place in the period 1981 – 2017 which pertained to US firms, falling under the NAIC Classification *2211 – Electric Power Generation, Transmission and Distribution*, undertaking acquisitions of US firms.[6,7] We focus on M&A occurring up until the year 2017 as this provides us with a sufficiently long post-acquisition time window in which to observe the effects on innovation.

For each acquisition event, information is provided on the date of completion, the name of the acquiring firm, the name of the target firm, and further information about firms such as NAICS codes and a business description. Additionally for each firm, for all available years, we collect financial data from Compustat accessed through the Wharton Research Data Services (WRDS) platform. Our sample is then restricted to M&A deals for which financial data on the acquiring firm is available.[8] This yields a sample comprising of 482 individual deals. As firms enter (through incorporation) and exit (through mergers and dissolution) over time, we have an unbalanced panel.

4.2.3 Patent Data

As a measure of firms' (green) innovation activities, we use granted patent applications. This approach is common in the literature analyzing innovation as the data provides detailed information on the technological field of the innovation which allows, in our case, for a differentiation between conventional and green innovation (Archibugi, 1992). Furthermore, patents are considered a good proxy for innovative output because there is a strong relationship between R&D spending and the number of patent applications (Griliches, 1990).

For each firm in our sample we obtain the complete patenting history for the period 1970 until 2021 from the USPTO accessed through Patentsview. Names of the merging firms are matched to patents using the name of the patent "assignee" at issue, which is the company that owns legal rights related to the patent.[9] We allocate patents to firms in the year in

[6] An overview of the NAICS codes and corresponding code descriptions can be found in Table A.12.

[7] Deals classified as exchange offers and buybacks along with acquisition in which only certain certain assets were acquired (such as subdivisions, facilities, projects or specific assets and acquisitions of less than 80% of shares) are excluded. Further, we exclude three-way mergers and joint ventures as well as deals involving firms owned by the government and undisclosed deals. Finally, we exclude three large conglomerate firms that have significant business activities and patents related to other industries (General Electric, BWX Technologies and General Dynamics).

[8] In effect this means that we include acquiring firms that were publicly listed at some point in time. Target firms, in contrast, can be both public or private.

[9] Further information on the construction of the data set is provided in Appendix A.3.3.

which the patent was filed (submitted), as opposed to published, as the publication process can take up to five years. The matching procedure results in a total of 1270 successful patent applications.[10] For each identified patent, bibliographic data is extracted including the filing date and technological classes assigned to the patent.

We separate between patents pertaining to green vs. conventional technologies on the basis of the CPC Y02-scheme (Veefkind et al., 2012).[11, 12] The Y02 class identifies "technologies or applications for mitigation or adaptation against climate change", which we refer to as "green patents." We refer to all patents which are not green as "conventional patents." On the basis of the Y02-tagging scheme, 44% of the patents matched to firms in our sample qualify as green patents. In addition to patent counts, we construct measures that summarize firms' existing knowledge stocks, including total accumulated green and conventional patents as well as discounted accumulated green and conventional patents at the firm-year level.[13]

4.2.4 M&A Classification

Firms in the energy sector undertake M&A for a variety of reasons. As recognized in the literature (e.g. Ahuja & Katila, 2001), the effects on innovation subsequent to the acquisition are dependent, among other things, on the motive behind the deal and, associated therewith, the characteristics of the targeting firm. Our analysis thus distinguishes between different types of M&A.

First, we distinguish between technological and non-technological M&A by classifying acquisitions of targets with a patent history of at least one patent as technological acquisitions, and non-technological acquisitions otherwise. The underlying reason for this distinction is that the impact is likely to depend on the assets acquired in the transaction and the objectives of the deal. Acquisitions with the intent of gaining access to technology can supply acquirers with knowledge in new fields, enhancing and shaping the future innovative activities of the company (Denicolò & Polo, 2021; Jullien & Lefouili, 2018). In contrast, M&A motivated by other reasons, such as geographical expansion or access to a new customer base, may not necessarily provide new technological inputs and can therefore be expected to have little impact on an acquirer's ability to innovate. Although, such non-technological acquisitions may nevertheless affect the firm's innovation incentives via, for example, increased market power.[14]

[10] Only successful patent applications, i.e. granted patents, are included in the data set. This ensures that the inventions are novel and marketable as the requirements concerning novelty, inventive step and industrial applicability must be met for the granting of a patent.

[11] The CPC is an internationally compatible classification system for technical documents such as patent publications jointly developed by the European Patent Office (EPO) and the USPTO.

[12] Recent studies making use of the Y02-scheme to study innovation at the firm-level include Calel (2020) and Calel & Dechezleprêtre (2016).

[13] Discounted knowledge stocks are calculated using a perpetual inventory method. We follow the literature and apply a depreciation rate of 15% (Aghion et al., 2016; Haucap et al., 2019). Patent counts start in 1970 at the earliest.

[14] Market power can dampen incentives to innovate due to the monopolist's interest in protecting the status quo (the "replacement effect") (Tirole, 1988). The effect can move in the opposite direction, if market power increases the ability to appropriate the benefits of inventions (Gilbert & Greene, 2014).

Second, we distinguish between "green" and "conventional" businesses depending on whether the target is active in the renewable energy sector or owns green patents.[15] In comparison to conventional technologies, green technologies are associated with high knowledge spillovers, larger than the dirty technologies that they replace (Dechezleprêtre et al., 2014; Martin & Verhoeven, 2022; Noailly & Shestalova, 2017). One reason being that green technologies are at an earlier stage of development and thus benefit from steep learning curves associated with new technological fields.[16] Due to the internalization of R&D externalties post-merger there is a positive impact on the incentives of the merged entity to invest in R&D post-merger (Jullien & Lefouili, 2018). Further, the presence of R&D externalities and learning spillovers contributes towards path dependence in environmental innovation (Aghion et al., 2019). By providing environmentally-friendly inputs, we argue that the acquisition of green technological firms has the potential to direct the nature of technical innovation at the firm-level towards clean technologies. Hence, even among technological acquisitions, the impact on innovation is likely to depend on the nature of the technological knowledge acquired in the transaction.

In consequence, we classify deals into four different categories based on the technological input provided by the target and the type of firm acquired as presented in Table 4.1. The most frequent type of acquisition is conventional non-technological which accounts for 74% of deals, followed by green non-technological acquisitions.

Table 4.1: Classification of M&A

	Technological	**Non-Technological**
Conventional	**Conv-T** Acquisition of firm with conventional patents (and no green patents) N= 30	**Conv-NT** Acquisition of a firm without any patents N=357
Green	**Green-T** Acquisition of firm with green patents (may also have conventional patents) N=22	**Green-NT** Acquisition of renewable energy firm without any patents N=73

As discussed, many mechanisms interact to determine the sign of the effect of an acquisition on the innovative output of the firm. This makes predictions on the overall sign of the effect difficult. However, owing to larger knowledge spillovers for green technologies we expect that the impact of a green technological acquisition on innovation will be more positive that the impact of a conventional technological acquisition. Further we hypothesize that green

[15]Renewable firms are identified on the basis of the industry information as well as a search of the firm description using keywords associated to renewable energy.

[16]There are several reasons why knowledge spillovers may be greater for green technologies (Dechezleprêtre et al., 2014). Additional reasons are that green technologies are more novel/radical than the dirty technologies that they replace; green patents have more general applications than dirty inventions; and environmental regulation pushing green innovation can amplify spillovers.

technological acquisitions may allow the acquirer to obtain and further develop clean technologies, as exemplified by the Vivint-Solmetric deal detailed in the introduction, leading to a positive impact on green innovation. In contrast, green non-technological acquisitions may be undertaken for reasons other than technological ones, such as capacity expansion, market entry and portfolio diversification.[17, 18] Hence we expect the impact of green non-technological acquisitions on green innovation to be weaker.

Table 4.2 provides an overview of the key variables in the data and their definitions.

[17]An example a green non-technological acquisition in our sample is the acquisition of US Geothermal Inc by Ormat Technologies Inc in 2019 which was undertaken with the intent to increase geothermal capacity. See `https://investor.ormat.com/news-events/news/news-details/2018/Ormat-Closes-Acquisition-Of-US-Geothermal/default.aspx`.

[18]Green non-technological acquisitions also provide opportunities to diversify the energy portfolio by including renewables as exemplified by NRG Energy Inc's acquisition of Pandoma Wind Power LLC in 2006 which marked NRG Energy's entrance into the wind generation market. See `https://investors.nrg.com/news-releases/news-release-details/nrg-energy-inc-completes-acquisition-padoma-wind-power-llc`.

Table 4.2: Variables

Variable	**Description**
Event[1]	
MA	Indicator for acquisition event
MA_Green	Indicator for green acquisition (technological and non-technological)
MA_Green_T	Indicator for green technological acquisition
MA_Green_NT	Indicator for green non-technological acquisition
MA_Conv	Indicator for conventional acquisition (technological and non-technological)
MA_Conv_T	Indicator for conventional technological acquisition
MA_Conv_NT	Indicator for conventional non-technological acquisition
deal_year	Year in which acquisition event occurs
Innovation[2]	
patents	Number of total patents assigned to the firm
green_patents	Number of green patents assigned to the firm
conv_patents	Number of conventional patents assigned to the firm
dpatentstk	Discounted total knowledge stock
dgreenpatentstk	Discounted green knowledge stock
dconvpatentstk	Discounted conventional knowledge stock
Financials[3]	
ln_at	Log of total value of assets (in mil. $)
ln_emp	Log of number of company workers (in thousands)
ln_revt	Log of gross income received from all divisions (in mil. $)
ln_che	Log of cash and short-term investments (in mil. $)
Firm information[4]	
I_renewable	Indicator for firm active in the renewable energy sector
I_generation	Indicator for firm primarily engaged in the generation of electricity
I_transmission	Indicator for firm primarily engaged in the transmission of electricity
I_distribution	Indicator for firm primarily engaged in the distribution of electricity
company_age	Age of company in years
never_listed	Indicator for private firm that was at no point publicly listed

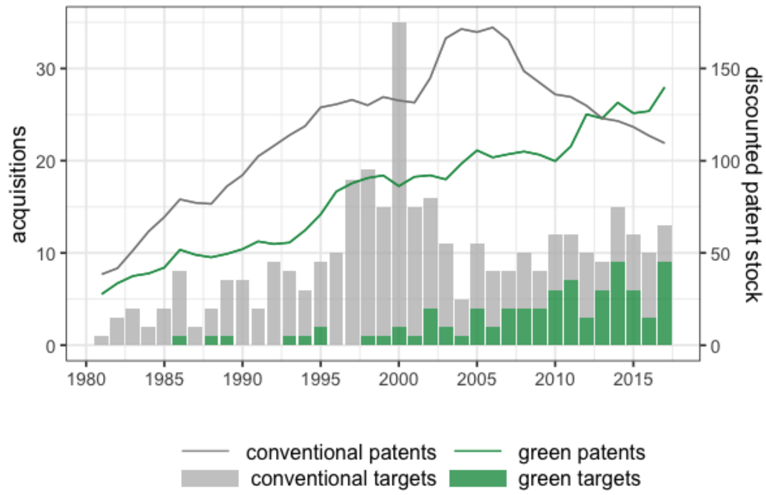
Notes: Indicator variables take on the value 1 if the specification in the description holds true, 0 otherwise. Discounted knowledge stocks are calculated using a perpetual inventory method such that patent stock $PS_{it} = (1-\delta)PS_{i,t-1} + P_{it}$, where the knowledge depreciation rate, δ, is set to 15%. Data is collected from the following sources:
[1] Source: Datastream, Zephyr
[2] Source: USPTO
[3] Source: Compustat
[4] Source: Datastream, Zephyr and keyword search

4.3 Descriptive Analysis

In this section we explore and describe the trends in M&A activity in the electric power industry. Figure 4.1 depicts the evolution of the number of green and conventional acquisitions between 1981 and 2017.[19] It also illustrates the evolution of the discounted green and conventional patent stock for all acquirers and targets in the sample.

The figure illustrates the technological progress and shift towards green technologies that has taken place in the industry. While the stock of green patents starts at a lower level than the stock of conventional patents, it trends upwards quickly. The discounted stock of green patents catches up and exceeds that of conventional patents after 2010. Similar trends have been observed in patent activity in the European electricity generation sector by Noailly & Smeets (2015) who find evidence that technology gap between patents related to renewable energy technologies and fossil fuel energy technologies has become smaller over the period 1978 – 2006.

Figure 4.1: Acquisitions and Discounted Patents Stocks Overtime (1981–2017)



The figure shows that following the restructuring and deregulation of the market, the sector experienced an increase in the number of M&A transactions in the mid 1990s, reaching a peak in the year 2000. Further, companies have increasingly been acquiring green targets. While most transactions carried out between 1981 and 2006 involved conventional targets, the number of transactions involving green targets, both with and without technological input, has increased in recent years. In the last 10 years of the observation period (2007–2017), on average, roughly 50% of M&A deals involved green targets (see Figure 4.2).

[19]A small number of firms engage in multiple mergers per year. For a cleaner depiction of trends, we aggregate events to the firm-year level.

Figure 4.2: Share of Acquisitions Types Overtime

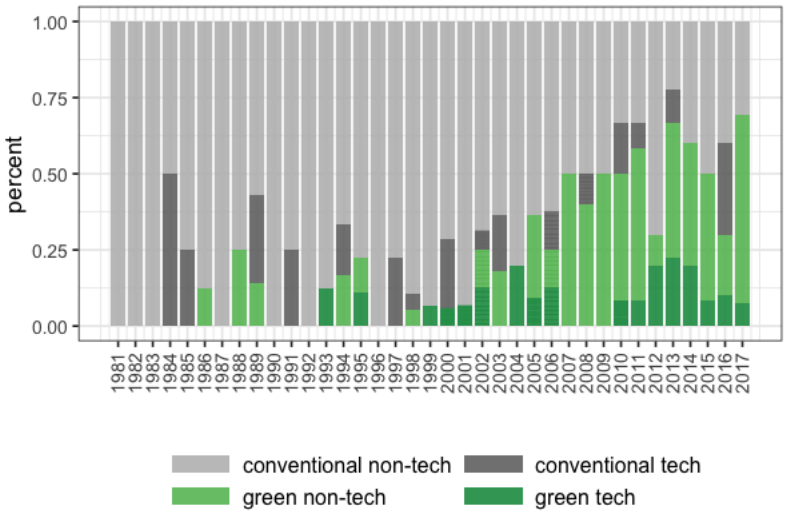


Table 4.3 compares acquirer and target characteristics in the year directly before the acquisition. Acquirer firms in our sample are on average larger (in terms of e.g. assets and employees) and more well-established (in terms of years since foundation).[20] 77% of targets in our dataset are private firms that were never publicly listed, whereas by construction, all acquiring firms in our dataset are at some point in the sample period publicly listed. Looking at the innovation output of firms, we find that acquirers are also characterized by higher levels of patent stocks and patenting activity, for both green and conventional patents.

Table 4.3: Summary Statistics for Acquirer and Target Pre-Acquisition

VARIABLES	Acquirer Mean	Acquirer Obs.	Target Mean	Target Obs.	Difference
patents	0.095	482	0.025	482	0.071***
dpatentstk	0.614	482	0.138	482	0.476***
greenpatents	0.035	482	0.006	482	0.029*
dgreenpatentstk	0.244	482	0.039	482	0.205***
convpatents	0.06	482	0.019	482	0.041**
dconvpatentstk	0.37	482	0.1	482	0.27***
I_renewable	0.299	482	0.168	482	0.131***
I_generation	0.282	482	0.095	482	0.187***
I_transmission	0.133	482	0	482	0.133***
I_distribution	0.585	482	0.249	482	0.336***
never_listed	0	482	0.774	482	–0.774***
company_age	23.929	482	6.5	482	17.429***
ln_at	7.86	416	7.15	90	0.71***
ln_emp	1.521	414	0.986	90	0.536***
ln_revt	7.004	416	6.493	90	0.51**
ln_che	4.169	416	2.919	90	1.25***

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$.

[20] Missing financial data for certain firms and years explains discrepancies in observation counts.

We further compare acquiring firms in terms of transactions undertaken. Table 4.4 presents the average characteristics of the acquirers of each type of target in the year directly before the merger. Several interesting patterns are visible. Acquirers of technological targets have higher patent stocks and more employees. In particular, acquirers of green technological targets have both higher discounted green patent stocks and discounted conventional patent stocks when compared to the average acquirer for other types of targets. Further, acquirers of green firms are more likely to be involved in renewable energy: All acquirers of green non-technological target companies in our sample are also active in the renewable energy sector; among acquirers of green technology companies, 45% are active in renewables, compared to 16% and 10% for acquirers of conventional non-technological and conventional technological acquisitions, respectively.

Table 4.4: Acquirer Characteristics by Acquisition Type

	Green-NT	Green-T	Conv-NT	Conv-T
VARIABLES	mean	mean	mean	mean
patents	0.123	0.0909	0.0812	0.200
dpatentstk	0.481	1.947	0.498	1.342
greenpatents	0.0274	0.0455	0.0308	0.100
dgreenpatentstk	0.247	0.873	0.156	0.820
convpatents	0.0959	0.0455	0.0504	0.100
dconvpatentstk	0.234	1.074	0.341	0.522
I_renewable	1	0.455	0.162	0.100
I_generation	0.589	0.591	0.210	0.167
I_transmission	0.0137	0	0.171	0.0667
I_distribution	0.397	0.409	0.619	0.767
company_age	18.05	24.50	24.75	28
deal_year	2010	2007	2001	2001
ln_at	7.128	9.037	7.856	8.496
ln_emp	1.126	1.903	1.544	1.792
ln_revt	5.883	7.856	7.102	7.544
ln_che	4.400	5.634	4.003	4.387

In sum, there has been a rise in green acquisitions in recent years, both in absolute number and as a share of total M&A activity in the electric power industry. At the same time, the gap between conventional and green patenting in the industry has become smaller, with green patenting overtaking conventional patenting in the last years. We note that acquirers in our sample display different characteristics on average depending on the type of target that they acquire. As these characteristics may also drive firms' innovation activities, it is important to control for these confounding factors when analyzing the impact of M&A on innovation, which we now turn our attention to.

4.4 Empirical Strategy

We aim to quantify both the average effect of a M&A event on acquiring firms innovation activities, as well as explore heterogeneous effects across different types of acquisitions. There are several reasons, both practical and conceptual, as to why we focus our attention on effects on the *acquiring* entity as opposed to targets or the combined entity. First, the availability of more complete data on acquiring firms allows us to control for a larger set of confounding factors. Many targets are private companies and hence financial data for these firms is not available. Second, many targets are merged into the acquirer ceasing to exist as a stand-alone entity post-acquisition. Finally, the effect of being acquired on targets is likely to be more prone to endogeneity concerns because acquirers may select targets with promising yet unpatented research.[21] As we are interested in how the (technological) assets acquired affect new innovation due to potential R&D spillovers and synergies, we argue that the focus on acquiring firms is appropriate.

The empirical set-up involves staggered treatment as firms in the sample experience an acquisition at different points in time. To assess the effects on the acquiring firm we adopt a differences-in-differences framework, implementing two-way fixed effects regressions. Our baseline regression specification takes the following functional form,

$$I\_(green/conv)patent_{it} = \beta_0 + \sum_{k=1}^{k} \beta_k MA_{kit} + \gamma X_{it-1} + \eta_i + \mu_t + \epsilon_{it}$$

where the binary dependent variable $I\_(green/conv)patent$ captures the registration of at least one new patent (green or conventional) by acquirer i in year t. That is, the dependent variable I_patent captures the filing of any patent, $I\_greenpatent$ captures the filing of a green patent, $I\_convpatent$ captures the filing of a conventional patent. We use binary outcome variables as the vast majority of firms file a maximum of one patent per year (see Figure A.11 and A.12 in the Appendix). In a robustness check, we use the log of patent counts.

MA_{kit} is a dummy variable indicating the acquisition type $k \in K$, with the corresponding coefficient vector β_k being the treatment effect of interest. K depends on the model specification and can either be {MA}, {MA_Green, MA_Conv} or {MA_Green_T, MA_Green_NT, MA_Conv_T, MA_Conv_NT}. Each observation in the sample experiences only one merger event, thus treatments are always mutually exclusive at the firm-level. The relevant treatment variable is equal to 1 for x years after the year in which the acquisition takes place, and equal to 0 otherwise. In the main specification x is 3 years.[22] Post-acquisition observations after x periods are dropped. In a robustness check, we vary this time period.

X_{it-1} is a vector of time varying firm characteristics, measured in $t-1$, including dis-

[21] There is still the remaining concern that acquirers may patent the target's promising work shortly after the acquisition under their own name, however patenting (under the acquirer's name) may also be made possible precisely because of access to funds and resources provided by the acquirer. Moreover, our analysis focuses on a time window of three years after the merger year, not only immediate effects.

[22] This time period is comparable to the existing literature. In Ornaghi (2009) the specification is estimated up to three years after the merger, and in Haucap et al. (2019) up to fours years.

counted patent stock and financial controls. To account for path dependency in the nature of innovation, we control separately for green patent stock and conventional patent stock. η_i are firm fixed effects and μ_t are year fixed effects. Year fixed effects account for changes in regulation and economic conditions that affect all firms similarly in a given year.[23] By including firm fixed effects, we control for time-constant unobserved firm characteristics and estimate the average within-firm effects of acquisitions. Standard errors are clustered at the year level to account for within-year correlation and heteroscedasticity.[24] Given the substantial number of fixed effects included in our analysis, we use ordinary least squares (OLS) as the primary estimation method.[25]

Similarly to other empirical studies on the effects of M&A, our analysis faces the challenge of identification. Identifying the causal effect of M&A on innovation is complicated by the fact that firms select into acquiring and that firms may already take into account current and expected changes in innovation when making acquisition decisions. In order to address the concern of selection into acquiring the control group is constructed to only consist of acquirers that have not yet acquired (i.e. not yet treated), as opposed to never treated, on the grounds that these firms are most similar to the treated firms. A similar approach is taken by other recent studies on the effects of M&A including Affeldt & Kesler (2021) and Blonigen & Pierce (2016). The rationale for this identification strategy relies on the assumption that, conditional on the included control variables and fixed effects, the treated and not yet treated firms should not differ in future innovative performance, if it were not for the merger itself.[26]

The occurrence of multiple acquisitions by the same firm in quick succession poses another challenge for identification. In such cases, it is not possible to clearly isolate the effects of individual mergers. Estimation of the treatment effect of acquisitions using the specification above therefore requires a clean time window, both before and after the merger, in which the firm does not undergo any other major changes that are not captured by the included covariates. In our data, more than half of the deals are part of a chain of successive acquisitions. Hence, we develop a novel strategy to make use of acquisitions that take place consecutively, provided that they occur sufficiently far apart (in time), and excluding them otherwise.[27] Our rule for the inclusion of a M&A event is that there needs to be a minimum of six years between the events. In the three years immediately preceding the event and in the three years

[23]Popp et al. (2010) and Popp (2019) provide an extensive review of the literature examining the linkage between innovation and varying policy instruments. Duso et al. (2019) analyze the impact of competition policy in energy markets.

[24]Due to changes in technological developments and regulation overtime which may affect firms' innovation activities, it is unlikely that error terms in our analysis would be independent over time.

[25]The advantage of OLS is that it is by construction better suited to accommodate a large number of fixed effects and can also estimate coefficients of groups where every member of the group has the same value for the dependent variable. Logit and probit models fail in our setting given that patenting is a rare event, we have a limited number of mergers within each merger category type, and a large number of fixed effects. Consequently, when using logit or probit regression with four merger categories the included fixed effects perfectly predict the outcome for many observations.

[26]An alternative approach in the literature on the effects of M&A is to use propensity score matching to select a suitable control group (e.g. Haucap et al., 2019; Ornaghi, 2009), however this approach faces the limitation that while matched control firms will be similar with regard to observable characteristics, unobserved differences remain a concern.

[27]Previous research has excluded firms that engage in other M&A (Haucap et al., 2019; Szücs, 2014).

following the event no other deal should take place. The firm is given a new identifier for each time window around one M&A event which recognizes the changes that firms undergo after merging. The fixed effects included in the model are associated with the new firm identifier. In a few cases acquirers engage in more than one transaction in the same year.[28] For these cases, we aggregate observations to the firm-year level.[29] Thus, we obtain a sample of firms where each firm undertakes one acquisition, and we have a clean window of at least three years before the acquisition, and a clean window of at least three years after the acquisition, in which we observe the firm.

The implementation of the procedure described above leaves us with 100 merger events for which we have complete data for all variables. Table 4.5 provides summary statistics for the final panel dataset used in the regression analysis.

Table 4.5: Summary Statistics for Acquirers in the Final Sample

VARIABLES	Mean	Std. Dev	Min	Max	Obs
I_patents	0.058	0.234	0	1	2228
I_greenpatents	0.025	0.155	0	1	2228
I_convpatents	0.034	0.18	0	1	2228
ln_patents	0.062	0.28	0	2.944	2228
ln_greenpatents	0.022	0.147	0	1.792	2228
ln_convpatents	0.046	0.238	0	2.944	2228
dpatentstk	0.845	4.113	0	51.516	2228
dgreenpatentstk	0.263	1.713	0	28.963	2228
dconvpatentstk	0.583	3.157	0	51.516	2228
ln_company_age	2.704	0.829	0.693	4.625	2228
ln_at	7.109	2.245	0	11.676	2228
ln_revt	6.152	2.197	0	10.346	2228
ln_emp	1.301	0.931	0	3.804	2228
ln_che	2.934	1.879	0	8.292	2228

[28]This is not the norm. For 76% of events, the event is the only one for that year for a firm.

[29]We sum the patents of the targets and use the same criteria as described in Table 4.1 to define acquisition types. The combined target is considered to be engaged in the renewable sector if at least half the targets are renewable.

4.5 Results

We begin by quantifying the average effect of a merger event (MA) on the three outcomes variables of interest. The results are presented in Table 4.6. In columns 1-3 firm fixed effects are excluded in order to shed more light on how the control variables are associated with patenting activity.[30] Firm fixed effects are included in columns 4-6.

Consistent with path-dependency in the direction of innovation, Table 4.6 indicates that discounted green patent stock is a highly significant predictor of green patenting activity (column 2) and discounted conventional patent stock is a highly significant predictor of conventional patenting activity (column 3). The number of employees is positively associated with patenting. Company age is on average negatively correlated with green patenting activity, but positively correlated with conventional innovation, indicating that younger firms are more likely to undertake green innovation.

After the inclusion of fixed effects, we find a negative and significant effect of mergers on the average patenting probability (column 4) and on the probability to patent in conventional technologies (column 6).

Table 4.6: Results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	I_patents	I_greenpatents	I_convpatents	I_patents	I_greenpatents	I_convpatents
MA	-0.0139	0.00217	-0.0161	-0.0375***	-0.00755	-0.0299**
	(0.0130)	(0.0112)	(0.00975)	(0.0137)	(0.0108)	(0.0115)
dgreenpatentstk	0.0414***	0.0395***	0.00187	0.0181	0.00296	0.0151
	(0.00551)	(0.00503)	(0.00526)	(0.0140)	(0.0190)	(0.0174)
dconvpatentstk	0.0225***	0.00121	0.0213***	0.00838	0.000398	0.00799
	(0.00470)	(0.00167)	(0.00454)	(0.00880)	(0.00411)	(0.00843)
ln_company_age	-0.0177*	-0.0207***	0.00302	0.0288	0.0189	0.00988
	(0.00891)	(0.00653)	(0.00635)	(0.0232)	(0.0201)	(0.0179)
ln_emp	0.0358***	0.0197**	0.0162*	0.0102	0.0229	-0.0127
	(0.0109)	(0.00805)	(0.00856)	(0.0264)	(0.0164)	(0.0218)
All controls	yes	yes	yes	yes	yes	yes
Observations	2228	2228	2228	2228	2228	2228
R-squared	0.302	0.238	0.184	0.473	0.379	0.294
Company FE	no	no	no	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Notes: The binary dependent variable is equal to one when observation i files at least one patent (columns 1 and 4), or at least one green patent (columns 2 and 5), or at least one conventional patent (columns 3 and 6) in year t. The variable MA is a binary indicator equal to one for the three years subsequent to the merger. Fixed effects for each firm (Company FE) and year (Year FE) are included as indicated. The constant term and control variables are estimated but not reported. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

[30] Firm level fixed effects will absorb most of the variation due to control variables such as discounted green patent stock and the financial controls if these variables are relatively constant over time.

Next, we consider the impact of green and conventional acquisitions separately. Table 4.7 reveals that the average negative effect of M&A observed in Table 4.6 is driven by conventional acquisitions (column 1). The acquisition of green targets has a positive (although not significant effect) on green innovation (column 2) and a negative effect on conventional innovation (column 3).

Table 4.7: Results by Target Type I

	(1)	(2)	(3)
VARIABLES	I_patents	I_greenpatents	I_convpatents
MA_Green	-0.0196	0.0499	-0.0695**
	(0.0256)	(0.0338)	(0.0314)
MA_Conv	-0.0408***	-0.0182**	-0.0226**
	(0.0140)	(0.00868)	(0.0107)
All controls	yes	yes	yes
Observations	2228	2228	2228
R-squared	0.473	0.381	0.295
Company FE	yes	yes	yes
Year FE	yes	yes	yes

Notes: The binary dependent variable is equal to one when observation i files at least one patent (column 1), or at least one green patent (column 2), or at least one conventional patent (column 3) in year t. The variable MA_Green(Conv) is a binary indicator equal to one for the three years subsequent to a Green (Conventional) merger. The constant term and control variables are estimated but not reported. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Exploring these heterogeneous effects further, we separate green technological acquisitions from green non-technological acquisitions and conventional technological acquisitions from non-technological conventional acquisitions. As shown in Table 4.8, the negative effect of acquisitions on the probability to patent is driven by conventional non-technological mergers (column 1). Turning our attention to green innovation (column 2), we find that green technological mergers increase the probability of filing a green patent post-merger. On average, the probability to file at least one green patent in a given year in the three years subsequent to a merger is 9 percentage points higher after a green technological merger, ceteris paribus. The unconditional probability to file at least one green patents in a given year for firms that eventually engage in green technological acquisitions is 0.25, hence an increase in the probability to patent by 9 percentage points represents a large impact in terms of economic magnitude. Green non-technological mergers have a positive although not statistically significant effect on green patenting. Conventional non-technological mergers, which often expand acquirers' generative capabilities in conventional technologies, lead to a decline in green patenting post-merger. Finally, green non-technological mergers, which often expand acquirers' generative capabilities in renewable energy and do not provide new technological inputs, lead to a decline in conventional patenting post-merger (column 3).

Table 4.8: Results by Target Type II

VARIABLES	(1) I_patents	(2) I_greenpatents	(3) I_convpatents
MA_Green_T	0.0575	0.0935**	-0.0360
	(0.0540)	(0.0355)	(0.0283)
MA_Green_NT	-0.0395	0.0395	-0.0789**
	(0.0355)	(0.0443)	(0.0355)
MA_Conv_T	-0.0785	-0.0190	-0.0595
	(0.0588)	(0.0388)	(0.0370)
MA_Conv_NT	-0.0332**	-0.0178**	-0.0154
	(0.0125)	(0.00798)	(0.0118)
All controls	yes	yes	yes
Observations	2228	2228	2228
R-squared	0.474	0.382	0.296
Company FE	yes	yes	yes
Year FE	yes	yes	yes

Notes: The binary dependent variable is equal to one when observation i files at least one patent (column 1), or at least one green patent (column 2), or at least one conventional patent (column 3) in year t. The variable MA_Green(Conv)_T(_NT) is a binary indicator equal to one for the three years subsequent to a Green (Conventional) Tech (Non-Tech) merger. The constant term and control variables are estimated but not reported. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Our results are broadly robust across a number of specifications as documented in Appendix A.3.5. In Table A.14 we use the log of patents as the main outcome variable. Our results remain qualitatively very similar. In Table A.15 we explore the sensitivity of our results regarding green innovation to different time windows. We find a significant positive effect when we measure the impact of the acquisition within a period of 2, 3 or 4 years. If we limit the effect to 1 year post-acquisition, the coefficient carries the same sign but loses statistical significance.

In Table A.16 we limit the sample to data from the year 2000 on. This excludes data from the 1990s when the US power industry was undergoing substantial structural transformation and, as shown earlier, is roughly the time when the trend toward green acquisitions begins. To ensure sufficient observation periods prior to the acquisition, we consider deals that take place from 2004 onward. This results in a much smaller sample. Our finding that green technological acquisitions promote green patenting remains positive and significant at the 5% level. The negative effect of green non-technological acquisitions on conventional innovation remains significant. However, the negative effect of conventional non-technological mergers on green innovation loses significance.

Taken together, the key finding that green technological acquisitions promote green patenting activity among acquirers is very robust. In the following section we interpret our results in greater detail and discuss the policy implications.

4.6 Discussion

While previous studies have empirically examined the impact of mergers on innovation, the focus has been almost exclusively on innovation in general rather than focusing specifically on green innovation. The present work broadens our knowledge on the effects of acquisitions on acquirers' innovation rate and direction by taking the target firm's innovation history into account.

The results indicate that when characteristics of the acquired company are not accounted for, on average, acquisitions have a negative impact on subsequent innovation output. However, this masks considerable heterogeneities in the sign and magnitude of the effect depending on the nature of the acquisition. In particular, green technological acquisitions - involving target firms with a history of green patenting activity - induce further green innovation by the acquiring entities. Conversely, conventional technological mergers do not significantly impact on conventional innovation nor green innovation. This is consistent with the notion that green technologies are associated with larger knowledge spillovers than conventional technologies, providing more opportunities to learn, and points towards significant research synergies between target and acquirer firms with regard to green technologies. Further, we find that green non-technological acquisitions are associated with a decline in conventional patenting. Potential explanations for this finding include that firms investing in renewable power generation capacity scale back on conventional innovation or that organizational disruptions caused by the acquisition negatively impact the innovation output.[31]

An implication of the findings for research is that empirical studies disregarding heterogeneity in treatment effects may miss crucial effects of M&A on post-merger patent output. In particular, the present analysis reveals that it is essential to account for differences in the knowledge stock of target firms in order to accurately estimate the impact on the acquirers' innovative activities.

The findings also have implications for policy geared towards supporting green innovation, and for competition authorities who are increasingly interested in assessing the innovation impact of mergers in addition to price effects.[32] Firstly, our findings indicate that competition authorities should pay closer attention to the nature of the acquired knowledge stock when evaluating mergers. Secondly, we shed light on a positive aspect of mergers and acquisitions owing to the potential to drive the development of new green technologies. Recently academics and policymakers have expressed concerns about potential "killer acquisitions" - where incumbent firms acquire innovative targets purely to shut down their research and preempt future competition. These concerns are founded in a recent study which, using data from the pharmaceutical industry, estimates that "killer acquisitions" account for 5-7% of M&A (Cunningham et al., 2021). In contrast, our findings temper such concerns for the power and

[31] M&A can entail a disruption of business routines causing the integration of the target to require considerable managerial time and resources, thus negatively affecting the innovation output (Hitt et al., 1991).

[32] In particular policy interest on mergers and innovation has centered around the pharmaceutical industry. For example, in May 2021, the European Commission (EC) fined the company Merck KGAA EUR 7.5m for a failure to disclose an R&D project while pursuing the acquisition of Sigma-Aldrich in 2015 (European Commission, 2021).

utilities sector and draw attention to the positive effects of M&A on green innovation. This is a crucial insight in view of the fact that encouraging technological change in the energy sector is a pressing issue and hampered by specific market failures.

4.7 Conclusion

In this paper, we construct a panel dataset by combining data comprising of merger events in the power and utility sector between 1981 and 2017 with firm level patent and financial data. Applying a differences-in-differences framework with two-way fixed effects we estimate the effect of acquisitions on the subsequent innovative output of the acquiring entity. Distinguishing between different types of M&A, we find that green technological acquisitions - involving target firms with a history of green patenting activity - substantially increase the probability that the acquiring entity files a green patent in the post-acquisition period. This points towards significant knowledge spillovers and research synergies between merging firms with regard to green technologies in particular. In short, acquiring firms exhibit “learning by buying” in green innovation.

We see several interesting avenues to extend this work. Further research can explore whether learning by buying in green innovation is present in other industries, such as the transportation and buildings industries where technological progress is also crucial to tackling climate change. Future research can make greater use of the information provided by patents to examine the development of clean technologies arising from green acquisitions in more detail, i.e. by including patent citations or more granular information on the technological classes of patents (e.g. wind, solar, energy storage). Finally, as this study emphasizes the crucial role of technological progress in combating climate change, researchers can link these insights with data on greenhouse gas emissions to estimate the carbon reducing effect of green acquisitions.

Appendix

A.1 Appendix: Chapter 2

A.1.1 State-level Trends in Green Patent Activity

As the US states differ greatly in economic size, there is great disparity in the number of patents among the individual states. California is by far the largest state in the US and as such has the largest number of patents. Thus, California is extreme in the values of the outcome variable, such that the values cannot be closely approximated by states in the donor pool (see Figure A.1). In these cases, transformations to the outcome variable are necessary to employ the SCM (Abadie, 2021). By calculating the number of green patent applications per 100'000 population, the differences between California and the states in the donor pool are less pronounced (see Figure A.1.1).

Figure A.1: Total Number of Green Patent Filings, 2000–2015

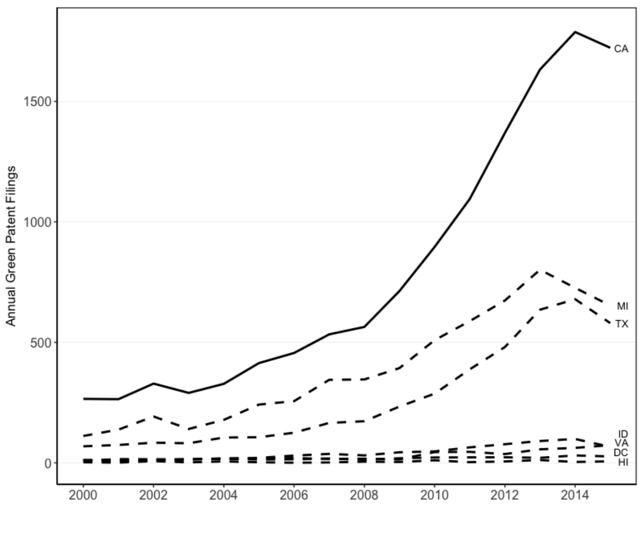
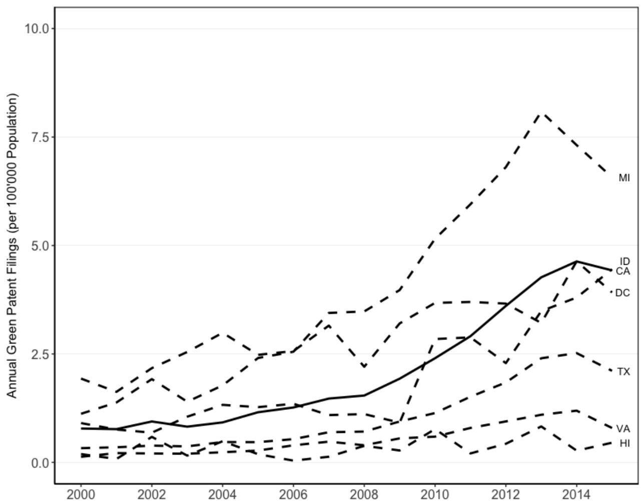


Figure A.2: Green Patent Filings (per 100'000 Population)

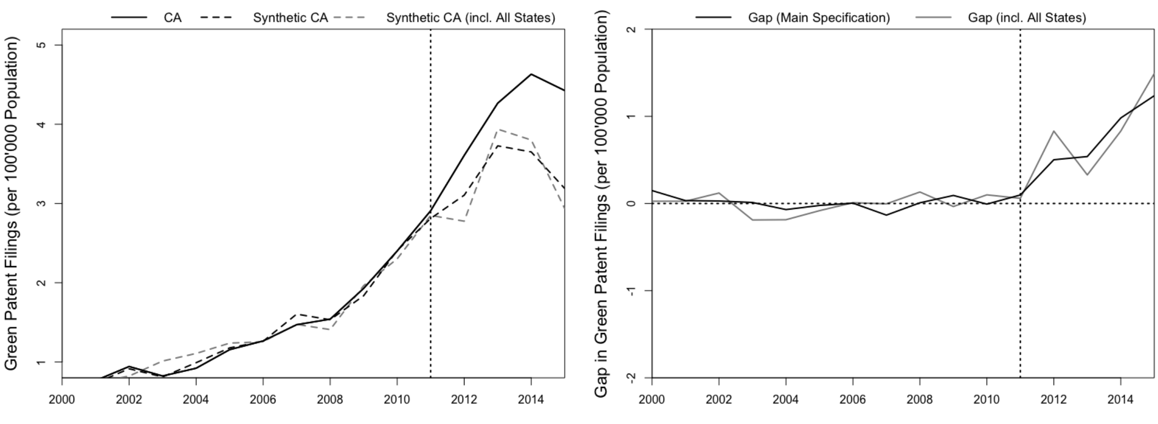


A.1.2 Further Robustness Checks

A.1.2.1 Choice of Donor Pool

For further robustness checks, modifications are made in terms of the donor pool from which the synthetic California is constructed. Predictor variables are chosen as for the main specification discussed in Section 2.2.2.[1] The corresponding weights of control units can be found in Table A.1.

Figure A.3: Robustness Check: Including All US States

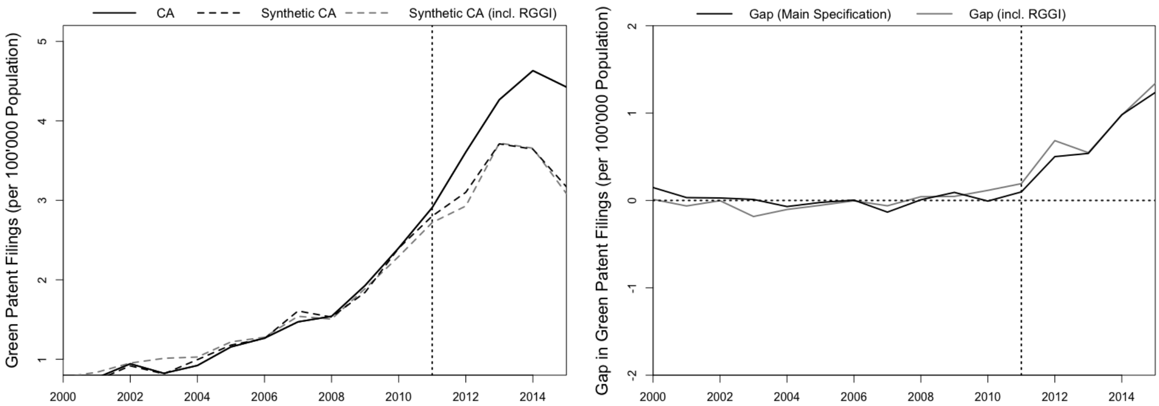


(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

[1]There is no data on R&D for the state of Minnesota in the year 2010. The NA value is ignored in the estimation.

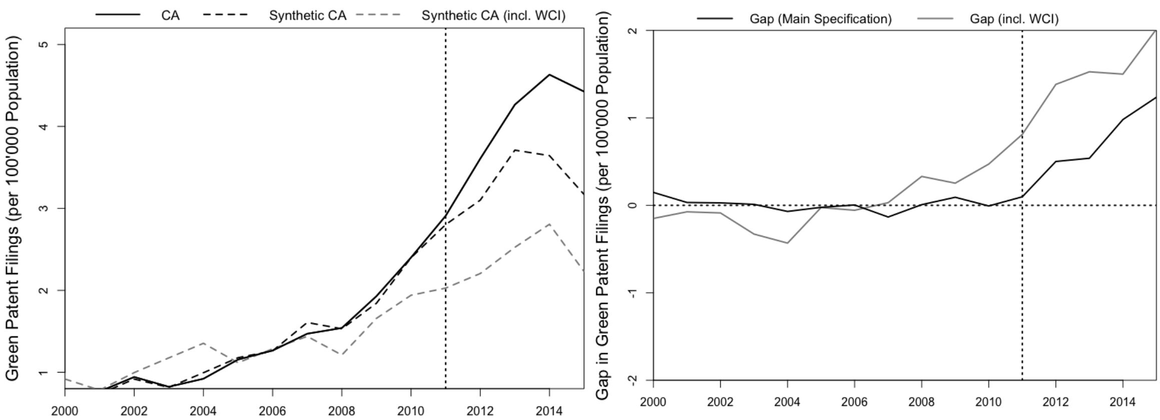
Figure A.4: Robustness Check: Including Members of the RGGI in Donor Pool



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

Figure A.5: Robustness Check: Including Former Members of the WCI in Donor Pool



(a) Trends in Green Patent Filings

(b) Green Patent Filings Gap

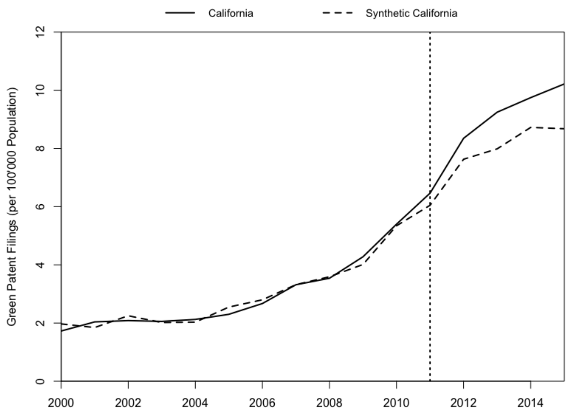
Table A.1: State Weights in Synthetic California (Robustness Checks)

	Weights		
State	Incl. All US States	Incl. WCI	Incl. RGGI
Alabama	0.001	0.000	0.000
Alaska	0.002	0.000	0.000
Arizona	0.001	0.000	—
Arkansas	0.001	0.000	0.000
Colorado	0.001	0.000	0.000
Connecticut	0.006	—	0.001
Delaware	0.061	—	0.000
District of Columbia	0.012	0.337	0.000
Florida	0.001	0.000	0.000
Georgia	0.001	0.000	0.000
Hawaii	0.00	0.117	0.000
Idaho	0.001	0.000	0.000
Illinois	0.001	0.000	0.000
Indiana	0.001	0.000	0.000
Iowa	0.001	0.000	0.000
Kansas	0.001	0.000	0.000
Kentucky	0.000	0.000	0.000
Louisiana	0.001	0.000	0.000
Maine	0.000	—	0.000
Maryland	0.099	—	0.279
Massachusetts	0.363	—	0.311
Michigan	0.001	0.000	0.155
Minnesota	0.001	0.000	0.000
Mississippi	0.000	0.000	0.000
Missouri	0.001	0.000	0.000
Montana	0.001	0.000	—
Nebraska	0.001	0.000	0.000
Nevada	0.056	0.000	0.107
New Hampshire	0.001	—	0.000
New Jersey	0.001	—	0.000
New Mexico	0.142	0.013	—
New York	0.001	—	0.000
North Carolina	0.001	0.000	0.000
North Dakota	0.001	0.109	0.000
Ohio	0.001	0.000	0.000
Oklahoma	0.001	0.000	0.000
Oregon	0.001	0.000	—
Pennsylvania	0.001	0.000	0.000
Rhode Island	0.001	—	0.000
South Carolina	0.001	0.000	0.000
South Dakota	0.001	0.001	0.000
Tennessee	0.001	0.000	0.000
Texas	0.231	0.000	0.146
Utah	0.001	0.000	—
Vermont	0.000	—	0.000
Virginia	0.001	0.000	0.000
Washington	0.000	0.422	—
West Virginia	0.000	0.000	0.000
Wisconsin	0.001	0.000	0.000
Wyomning	0.001	0.000	0.000

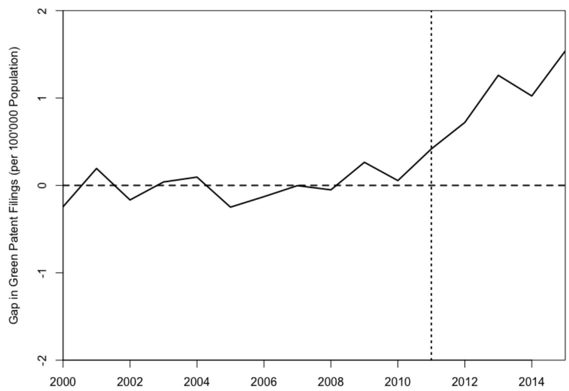
A.1.2.2 Choice of Patent Classification System

For the robustness check, I select all patents issued between 2000 and 2015 that pertain to the Y02 class and re-estimate the synthetic control model using the resulting data set. Figure A.6 reports the results of the estimation. It is evident that the CPC Y02-tags schema returns significantly more results than the Green Inventory. Nevertheless, the illustrations show that the number of green patent filings of California and its synthetic counterpart show a similar progression as those in the main specification.

Figure A.6: Robustness Check: Identifying Green Patents Using the CPC



(a) Trends in Green Patent Filings



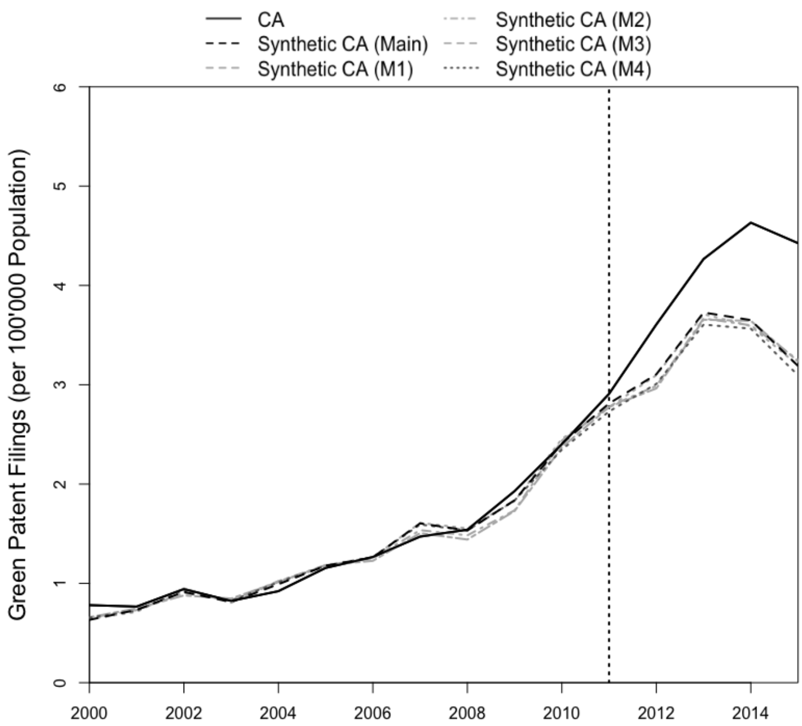
(b) Green Patent Filings Gap

A.1.3 Alternative Treatment Periods

Table A.2: Alternative Treatment Periods

Indication	Modification	Estimated Effect
M1	Treatment is set to 2010	20.8%
M2	Treatment is set to 2009	21.3%
M3	Treatment is set to 2008	21.4%
M4	Treatment is set to 2007	23.5%

Figure A.7: Alternative Treatment Periods



A.1.4 IPC Green Inventory

Table A.3: Topics of WIPO's Green Inventory (WIPO, 2020)

Topic	Sub-Topic
Administrative, Regulatory or Design Aspects	Commuting (e.g. High-occupancy vehicle lanes, teleworking, etc.); Carbon / emissions trading (e.g. pollution credits); Static structure design
Alternative Energy Production	Bio-fuels; Integrated gasification combined cycle; Fuel cells; Pyrolysis or gasification of biomass; Harnessing energy from manmade waste; Hydro energy; Ocean thermal energy conversion; Wind energy; Solar energy; Geothermal energy; Other production or use of heat, not derived from combustion (e.g. natural heat); Using waste heat; Devices for producing mechanical power from muscle energy
Agriculture/ Forestry	Forestry techniques; Alternative irrigation techniques; Pesticide alternatives; Soil improvement
Energy Conservation	Storage of electrical energy; Power supply circuitry; Measurement of electricity consumption; Storage of thermal energy; Low energy lighting; Thermal building insulation, in general; Recovering mechanical energy
Nuclear Power Generation	Nuclear engineering; Gas turbine power plants using heat source of nuclear origin
Transportation	Vehicles in general; Vehicles other than rail vehicles; Rail vehicles; Marine vessel propulsion; Cosmonautic vehicles using solar energy
Waste Management	Waste disposal; Treatment of waste; Consuming waste by combustion; Reuse of waste materials; Pollution control

A.1.5 Data Sources

Table A.4: Data Sources

Variable	Measured in	Source
Employment in High SET Establishments	Percentage of Total Employment	US Census Bureau
Available at: `https://ncses.nsf.gov/indicators/states/indicator/high-set-employment-to-total-employment`		
Exports (Total Merchandise)	Percentage of GDP	Foreign Trade Division, U.S. Census Bureau
Available at: `http://tse.export.gov/tse/`		
GDP per Capita	Thousands of 2020 USD	US Bureau of Economic Analysis
Available at: `https://www.bea.gov/data/gdp/gdp-state`		
High SET Establishments	Percentage of All Business Establishments	US Census Bureau
Available at: `https://ncses.nsf.gov/indicators/states/indicator/high-set-to-all-business-establishments`		
Patent Data	Citation-Weighted Count	United States Patent and Trademark Office
Available at: `https://www.patentsview.org/download/`		
Real GDP growth (1-year lagged)	Percent change from preceding period	US Bureau of Economic Analysis
Available at: `https://www.bea.gov/data/gdp/gdp-state`		
R&D performed	(% of GDP)	National Center for Science and Engineering Statistics
Available at: `https://ncses.nsf.gov/indicators/states/indicator/rd-performance-to-state-gdp`		
S&E BA Degrees (3-years lagged)	Per 1'000 Individuals 18–24 Years Old	US Department of Education
Available at: `https://ncses.nsf.gov/indicators/states/indicator/se-bachelors-degrees-per-1000-18-24-year-olds`		
State Population Estimates	Count	US Census Bureau
Available at: `https://www.census.gov/programs-surveys/popest.html`		
Total Energy Average Price	2020 USD per Million Btu	US Energy Information Administration
Available at: `https://www.eia.gov/state/seds/seds-data-complete.php?sid=US`		

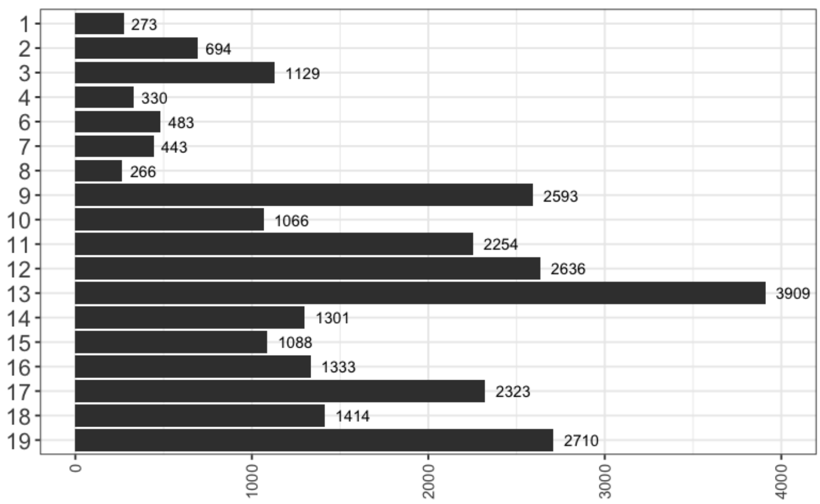
A.2 Appendix: Chapter 3

A.2.1 Industry Groups

Table A.5: Industry Groups

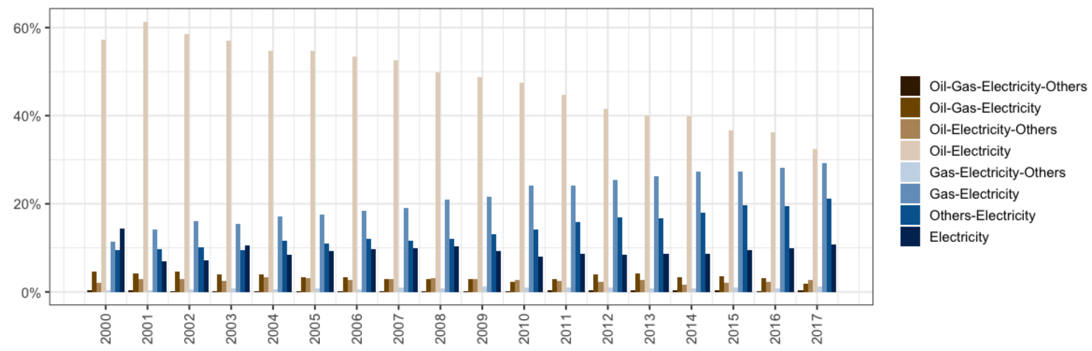
	Industrial Sector		*Service Sector*
1	Food	13	Commerce
2	Textile / Leather	14	Hospitality
3	Paper / Printing	15	Lending / Insurance
4	Chemicals / Pharmaceuticals	16	Administration
5	Cement / Concrete	17	Schooling
6	Other non-ferrous minerals	18	Health care & social services
7	Metal / Iron	19	Other services
8	Non-ferrous metals		
9	Metal / Appliances		
10	Machinery		
11	Other Industries		
12	Construction		

Figure A.8: Number of Entities per Industry Group in the Sample



A.2.2 Energy Mix

Figure A.9: Energy Mix of Entities



A.2.3 Types of Consumers

Table A.6: Summary Statistics Regular Oil User

	Pre-policy n = 7'362			Post-policy n = 7'005		
	Mean	St. Dev	Median	Mean.	St. Dev.	Median.
Heating Oil (ln)	12.73	1.11	12.90	10.86	4.67	12.73
Natural Gas (ln)	0.54	2.46	0.00	1.61	4.21	0.00
Electricity (ln)	11.97	1.48	12.16	12.36	1.39	12.59
Other Energy Sources (ln)	0.55	2.62	0.00	1.11	3.71	0.00
GFS	1742.50	2642.16	1004.00	2274.41	3125.96	1400.00
FTE	7.50	98.61	2.00	10.24	33.63	3.00
PTE	24.16	41.69	14.00	33.67	51.31	20.00

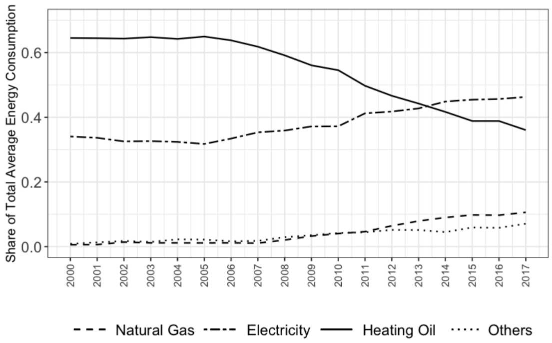
Table A.7: Summary Statistics Occasional Oil User

	Pre-policy n = 1'614			Post-policy n = 1'297		
	Mean	St. Dev	Median	Mean.	St. Dev.	Median.
Heating Oil (ln)	6.43	6.23	9.92	3.65	5.58	0.00
Natural Gas (ln)	4.02	6.02	0.00	5.59	6.46	0.00
Electricity (ln)	12.11	1.45	12.28	12.65	1.33	12.93
Other Energy Sources (ln)	2.25	4.91	0.00	3.30	5.78	0.00
GFS	1824.83	2676.08	958.00	2607.97	5517.90	1450.00
FTE	8.10	47.10	2.00	10.65	18.59	4.00
PTE	33.52	75.77	15.00	51.57	94.21	27.00

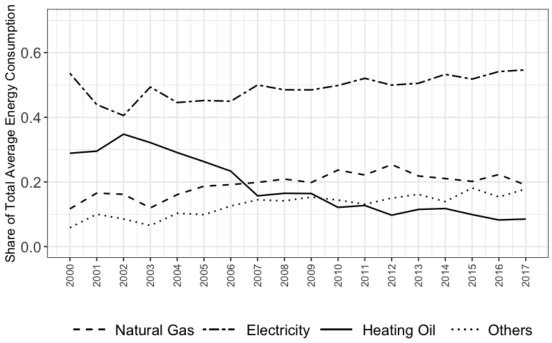
Table A.8: Summary Statistics Non Oil User

	Pre-policy n = 4'264			Post-policy n = 4'703		
	Mean	St. Dev	Median	Mean.	St. Dev.	Median.
Heating Oil (ln)	0.00	0.00	0.00	0.45	2.28	0.00
Natural Gas (ln)	5.83	6.31	0.00	5.99	6.39	0.00
Electricity (ln)	12.10	1.52	12.28	12.47	1.45	12.78
Other Energy Sources (ln)	4.09	6.12	0.00	4.57	6.42	0.00
GFS	2260.60	9563.22	980.00	2535.44	3175.27	1491.00
FTE	12.55	78.26	3.00	16.39	55.43	4.00
PTE	34.02	161.74	15.00	48.20	93.58	23.00

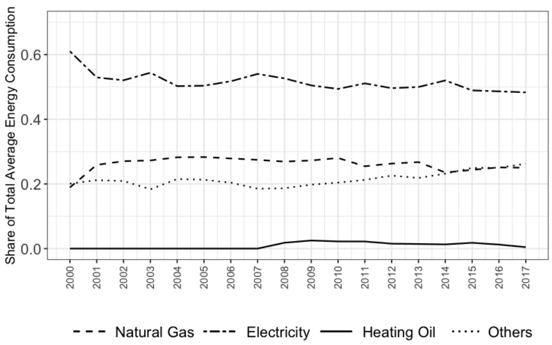
Figure A.10: Share of Energy Use per Source, 2000–2017



(a) Regular Oil User



(b) Occasional Oil User



(c) Non Oil User

A.2.4 Further Figures and Tables

Table A.9: SL Weights

	Heating Oil	Natural Gas	Electricity	Other Energy Sources
	Full Sample			
glmnet	0.953	0.677	0.794	0.720
ranger	0.047	0.323	0.126	0.280
XGboost	0.000	0.000	0.080	0.000
	Regular Oil Users			
glmnet	0.432	0.158	0.735	0.051
ranger	0.568	0.842	0.256	0.949
XGboost	0.000	0.000	0.009	0.000

A.2.5 Sensitivity Analysis

Table A.10: Sensitivity Analysis: Alternative Sample incl. Entities with Annual CO_2 Emissions $\leq$ 100 tCO_2

	Heating Oil	Natural Gas	Electricity	Other Energy Sources
	Full Sample			
12 CHF/tCO_2	-5.6%	2.6%	0.5%	0.6%
36 CHF/tCO_2	-15.4%	9.1%	1.7%	2.7%
60 CHF/tCO_2	-23.9%	12.8%	2.6%	4.1%
84 CHF/tCO_2	-31.9%	16.5%	3.7%	5.6%
	Regular Oil Users			
12 CHF/tCO_2	-14.3%	15.7%	0.1%	4.3%
36 CHF/tCO_2	-34.9%	42.8%	0.3%	15.2%
60 CHF/tCO_2	-49.1%	42.2%	0.4%	19.1%
84 CHF/tCO_2	-60.7%	55.1%	0.6%	32.3%

Table A.11: Sensitivity Analysis: Alternative Sample incl. Entities with Annual CO_2 Emissions $\leq$ 25'000 tCO_2

	Heating Oil	Natural Gas	Electricity	Other Energy Sources
	Full Sample			
12 CHF/tCO_2	-7.8%	1.5%	0%	1.8%
36 CHF/tCO_2	-21.4%	3.5%	0%	5.3%
60 CHF/tCO_2	-32.8%	3.1%	0%	7.3%
84 CHF/tCO_2	-42.6%	3.9%	0%	9.8%
	Regular Oil Users			
12 CHF/tCO_2	-13.1%	7.6%	0.0%	5.4%
36 CHF/tCO_2	-32.7%	25.4%	0.2%	22.8%
60 CHF/tCO_2	-47.0%	31.8%	0.2%	26.5%
84 CHF/tCO_2	-59.1%	42.9%	0.0%	39.0%

A.3 Appendix: Chapter 4

A.3.1 NAICS Industry Group 2211 – Electric Power Generation, Transmission and Distribution

Table A.12: NAICS Codes that Fall Under 2211

Category	**NAICS Code**	**Description**
Generation	221111	Hydroelectric Power Generation
	221112	Fossil Fuel Electric Power Generation
	221113	Nuclear Electric Power Generation
	221114	Solar Electric Power Generation
	221115	Wind Electric Power Generation
	221116	Geothermal Electric Power Generation
	221117	Biomass Electric Power Generation
	221118	Other Electric Power Generation
Transmission	221121	Electric Bulk Power Transmission and Control
Distribution	221122	Electric Power Distribution

A.3.2 Y02 Tagging Scheme - Technologies or Applications for Mitigation or Adaptation Against Climate Change

Table A.13: CPC Subsection Y02

Subclass	Description
Y02A	Technologies for adaption to climate change
Y02B	Climate change mitigation technologies related to buildings
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies
Y02E	Reduction of greenhouse gas emissions, related to energy generation, transmission or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

A.3.3 Construction of the Data Set

We construct a unique data set by combining our sample of mergers with patent and financial data. The patents granted to firms in our sample are identified by matching assignee names to the company names. This matching process presents some challenges. Spelling mistakes and affiliations between entities complicates the attribution of patents to a particular company (OECD, 2009). Moreover, the merger data only provides the company name at the time of the merger. However, changes in enterprise names may have occured over time. Thus, cleaning and preparing a list of company names is necessary. The following steps were undertaken:

– Internet research has been conducted to compile a list of former and subsequent names taken on by these entities before and after the merger, respectively.

– Inclusion of abbreviated company name

– Standardizing different expressions (e.g. “Corp” and “Corporation”)

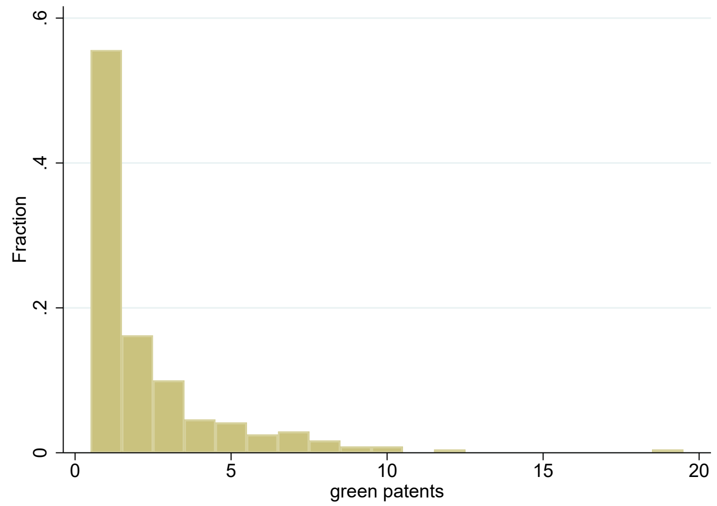
– Removal of suffixes as “Gmbh” or “Inc.”

– Removal of punctuation

The prepared list of cleaned and standardized company names is then matched to standardized company names extracted from the patent data using a approximate string matching to allow for spelling errors, missing characters and slight variations of the entity name. The matches obtained were validated by examining each match individually and identifying and removing faulty matches. We further remove reissue patent applications. The resulting data set comprises patent applications granted by the USPTO and assigned at issue to the firms in our sample.

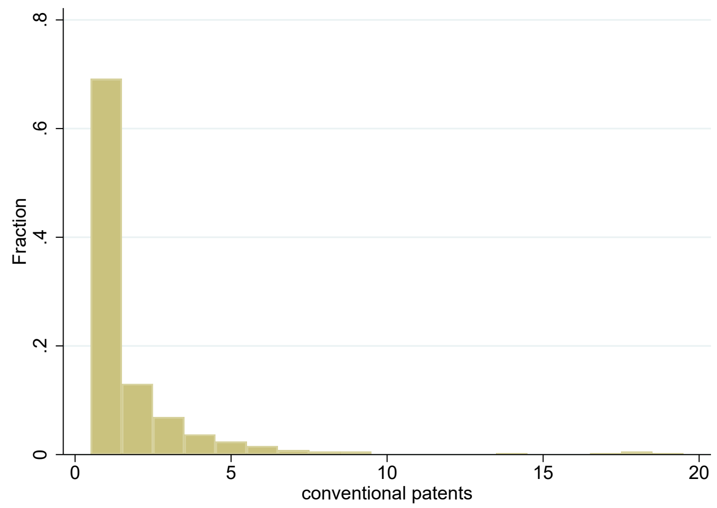
A.3.4 Additional Figures

Figure A.11: Histogram Green Patents



Notes: Sample of firm-years where green patents > 0

Figure A.12: Histogram Conventional Patents



Notes: Sample of firm-years where conventional patents > 0

A.3.5 Additional Tables

Table A.14: Results - Log Outcome

VARIABLES	(1) ln_patents	(2) ln_patents	(3) ln_greenpatents	(4) ln_greenpatents	(5) ln_convpatents	(6) ln_convpatents
MA	-0.0241*		-0.00563		-0.0195	
	(0.0134)		(0.00930)		(0.0123)	
MA_Green_T		0.0820		0.0647**		0.0318
		(0.0501)		(0.0304)		(0.0418)
MA_Green_NT		-0.00443		0.0340		-0.0331
		(0.0348)		(0.0326)		(0.0379)
MA_Conv_T		-0.0521		0.00244		-0.0543
		(0.0586)		(0.0436)		(0.0337)
MA_Conv_NT		-0.0266**		-0.0170*		-0.0126
		(0.0131)		(0.00864)		(0.0111)
dgreenpatentstk	0.00194	0.00253	-0.00809	-0.00767	-0.00352	-0.00328
	(0.0253)	(0.0253)	(0.0226)	(0.0226)	(0.0220)	(0.0221)
dconvpatentstk	0.00619	0.00628	6.67e-05	-1.25e-05	0.00526	0.00542
	(0.0161)	(0.0161)	(0.00389)	(0.00388)	(0.0154)	(0.0154)
ln_company_age	0.0157	0.0131	0.0156	0.00970	0.00345	0.00579
	(0.0234)	(0.0243)	(0.0163)	(0.0176)	(0.0208)	(0.0204)
ln_at	0.0437***	0.0447***	-0.00167	-0.00297	0.0458***	0.0479***
	(0.0123)	(0.0135)	(0.00919)	(0.0101)	(0.0116)	(0.0122)
ln_revt	-0.0139	-0.0158	-0.00408	-0.00488	-0.00730	-0.00857
	(0.0150)	(0.0151)	(0.0107)	(0.0107)	(0.0120)	(0.0119)
ln_emp	-0.00233	-0.00338	0.0167	0.0176	-0.0163	-0.0182
	(0.0239)	(0.0247)	(0.0123)	(0.0130)	(0.0208)	(0.0211)
ln_che	0.000157	0.000207	-0.00278	-0.00286	0.00295	0.00308
	(0.00510)	(0.00513)	(0.00279)	(0.00284)	(0.00475)	(0.00479)
I_distribution	-0.241**	-0.228**	0.0472	0.0806	-0.308***	-0.323***
	(0.102)	(0.112)	(0.0658)	(0.0747)	(0.0974)	(0.0988)
I_transmission	-0.163	-0.151	0.0516	0.0828	-0.227**	-0.242**
	(0.102)	(0.112)	(0.0641)	(0.0729)	(0.0933)	(0.0956)
I_renewable	0.0935*	0.0895*	0.0503	0.0382	0.0517	0.0581
	(0.0476)	(0.0465)	(0.0301)	(0.0262)	(0.0429)	(0.0419)
Constant	-0.0223	-0.0281	-0.0531	-0.0700	0.0241	0.0324
	(0.0674)	(0.0714)	(0.0470)	(0.0507)	(0.0566)	(0.0576)
Observations	2228	2228	2228	2228	2228	2228
R-squared	0.513	0.514	0.402	0.404	0.476	0.477
Company FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log(all/green/conventional patents + 1) filed by observation i in year t. The variable MA is a binary indicator equal to one for the three years subsequent to the merger. The variable MA_Green(Conv)_T(_NT) is a binary indicator equal to one for the three years subsequent to a Green (Conventional) Tech (Non-Tech) merger. Fixed effects for each firm (Company FE) and year (Year FE) are included. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A.15: Results - Effect on Green Patents for Different Time Windows

VARIABLES	(1) deal year	(2) 1 year	(3) 2 years	(4) 3 years	(5) 4 years
MA_Green_T	0.0634	0.176	0.153**	0.0935**	0.0658*
	(0.0897)	(0.153)	(0.0584)	(0.0355)	(0.0342)
MA_Green_NT	0.0485	0.0768	0.0726	0.0395	0.0355
	(0.0626)	(0.0625)	(0.0472)	(0.0443)	(0.0396)
MA_Conv_T	-0.0776**	-0.0397	-0.0443	-0.0190	-0.0270
	(0.0369)	(0.0329)	(0.0281)	(0.0388)	(0.0357)
MA_Conv_NT	-0.0256**	-0.0170*	-0.0191**	-0.0178**	-0.0108
	(0.0111)	(0.00928)	(0.00829)	(0.00798)	(0.00920)
dgreenpatentstk	0.00740	0.00741	0.00775	0.00367	0.00102
	(0.0192)	(0.0190)	(0.0190)	(0.0189)	(0.0189)
dconvpatentstk	0.000617	0.000559	0.000777	0.000383	0.000559
	(0.00408)	(0.00407)	(0.00406)	(0.00409)	(0.00406)
ln_company_age	0.0230	0.0216	0.0189	0.0122	0.00703
	(0.0233)	(0.0229)	(0.0213)	(0.0211)	(0.0203)
ln_at	-0.00620	-0.00786	-0.00373	-0.000974	-0.000412
	(0.0103)	(0.0105)	(0.0106)	(0.0111)	(0.0116)
ln_revt	-0.00504	-0.00508	-0.00268	-0.00828	-0.0115
	(0.0139)	(0.0142)	(0.0136)	(0.0127)	(0.0140)
ln_emp	0.0304	0.0307	0.0228	0.0232	0.0247
	(0.0198)	(0.0190)	(0.0178)	(0.0171)	(0.0168)
ln_che	-0.00401	-0.00397	-0.00401	-0.00393	-0.00424
	(0.00369)	(0.00365)	(0.00347)	(0.00335)	(0.00332)
I_distribution	0.0866	0.106	0.0648	0.0906	0.107
	(0.106)	(0.0974)	(0.0858)	(0.0903)	(0.0825)
I_transmission	0.0936	0.111	0.0750	0.0955	0.108
	(0.104)	(0.0957)	(0.0843)	(0.0883)	(0.0798)
I_renewable	0.0641	0.0654	0.0611*	0.0550*	0.0283
	(0.0455)	(0.0415)	(0.0335)	(0.0276)	(0.0286)
Constant	-0.0839	-0.0916	-0.0766	-0.0856	-0.0864
	(0.0778)	(0.0720)	(0.0608)	(0.0614)	(0.0541)
Observations	2043	2043	2138	2228	2296
R-squared	0.391	0.393	0.403	0.382	0.372
Company FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes

Notes: The dependent variable is a binary indicator equal to one when observation i files at least one green patent in year t. The variable MA_Green(Conv)_T(_NT) is a binary indicator equal to one for the year of the Green (Conventional) Tech (Non-Tech) merger (column 1), one year subsequent to the merger (column 2), two years subsequent to the merger (column 3), three years subsequent to the merger (column 4), and four years subsequent to the merger (column 5). Fixed effects for each firm (Company FE) and year (Year FE) are included. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A.16: Results - Sample After 2000

VARIABLES	(1) I_patents	(2) I_patents	(3) I_greenpatents	(4) I_greenpatents	(5) I_convpatents	(6) I_convpatents
MA	-0.0472*		0.00278		-0.0499***	
	(0.0241)		(0.0223)		(0.0138)	
MA_Green_T		0.0514		0.113**		-0.0618
		(0.0690)		(0.0428)		(0.0380)
MA_Green_NT		-0.0484		0.0425		-0.0909***
		(0.0467)		(0.0502)		(0.0305)
MA_Conv_T		-0.159		-0.0574		-0.101
		(0.140)		(0.104)		(0.0844)
MA_Conv_NT		-0.0381*		-0.0171		-0.0210
		(0.0212)		(0.0165)		(0.0190)
dgreenpatentstk	0.00770	0.00901	0.0130	0.0144	-0.00532	-0.00538
	(0.0157)	(0.0154)	(0.0218)	(0.0218)	(0.0175)	(0.0183)
dconvpatentstk	-0.00179	-0.00148	0.00131	0.00138	-0.00309	-0.00285
	(0.0102)	(0.0102)	(0.00218)	(0.00222)	(0.00995)	(0.00996)
ln_company_age	0.0150	0.0120	0.0405	0.0275	-0.0255	-0.0155
	(0.0433)	(0.0485)	(0.0367)	(0.0417)	(0.0301)	(0.0312)
ln_at	0.0477	0.0502*	0.00588	0.00411	0.0418	0.0461
	(0.0278)	(0.0284)	(0.0217)	(0.0227)	(0.0282)	(0.0284)
ln_revt	-0.0209	-0.0264	-0.00484	-0.00732	-0.0161	-0.0191
	(0.0294)	(0.0289)	(0.0222)	(0.0209)	(0.0203)	(0.0216)
ln_emp	0.0483	0.0501	-0.0105	-0.00808	0.0588	0.0582
	(0.0758)	(0.0746)	(0.0284)	(0.0280)	(0.0676)	(0.0668)
ln_che	0.0117	0.0141	-0.000604	0.000109	0.0123	0.0140
	(0.0112)	(0.0121)	(0.00617)	(0.00732)	(0.0107)	(0.0111)
I_distribution	-0.287**	-0.278*	-0.0504	0.00421	-0.236**	-0.282***
	(0.117)	(0.136)	(0.117)	(0.135)	(0.0897)	(0.0945)
I_transmission	0.273	0.266	0.377	0.396	-0.104	-0.130
	(0.283)	(0.292)	(0.302)	(0.312)	(0.211)	(0.212)
I_renewable	0.214	0.212	0.0525	0.0260	0.161	0.186
	(0.186)	(0.185)	(0.0617)	(0.0513)	(0.178)	(0.180)
Constant	-0.302	-0.292	-0.0906	-0.0694	-0.211	-0.223
	(0.185)	(0.187)	(0.0712)	(0.0678)	(0.175)	(0.176)
Observations	671	671	671	671	671	671
R-squared	0.511	0.515	0.456	0.462	0.335	0.339
Company FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is a binary indicator equal to one when observation i files at least one patent (columns 1 and 2), or at least one green patent (columns 3 and 4), or at least one conventional patent (columns 5 and 6) in year t. The variable MA is a binary indicator equal to one for the three years subsequent to the merger. The variable MA_Green(Conv)_T(_NT) is a binary indicator equal to one for the three years subsequent to a Green (Conventional) Tech (Non-Tech) merger. The sample is limited to observations from 2000 on, and mergers occurring from 2004 on. Standard errors displayed in parentheses are robust and clustered at the year level. $***p < 0.01, **p < 0.05, *p < 0.1$.

References

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, *59*(2), 391–425. doi: 10.1257/jel.20191450

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, *105*(490), 493–505. doi: 10.1198/jasa.2009.ap08746

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), 495–510. doi: 10.1111/ajps.12116

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American economic review*, *93*(1), 113–132. doi: 10.1257/000282803321455188

Abrell, J., Kosch, M., & Rausch, S. (2022). How effective is carbon pricing?—a machine learning approach to policy evaluation. *Journal of Environmental Economics and Management*, *112*, 102589.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American economic review*, *102*(1), 131–66.

Acemoglu, D., Aghion, P., & Hémous, D. (2014). The environment and directed technical change in a north–south model. *Oxford Review of Economic Policy*, *30*(3), 513–530.

Acemoglu, D., & Akcigit, U. (2012). Intellectual property rights policy, competition and innovation. *Journal of the European Economic Association*, *10*(1), 1–42.

Adams, K., Andrade, J., Boufarah, B., Glass, B., Culbertson, M., Platt, B., … Fetaih, S. (2021). *Power & utilities sector evolution: Unlocking value through M&A.* Retrieved from `https://www2.deloitte.com/content/dam/Deloitte/us/Documents/mergers-acqisitions/power-and-utilities-sector-evolution.pdf`

Adler, J. H. (2005). Jurisdictional mismatch in environmental federalism. *NYU Envtl. LJ*, *14*, 130.

Affeldt, P., & Kesler, R. (2021). Big Tech Acquisitions—Towards Empirical Evidence. *Journal of European Competition Law & Practice*, *12*(6), 471–478.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, *120*(2), 701–728.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, *124*(1), 1–51.

Aghion, P., Hepburn, C., Teytelboym, A., & Zenghelis, D. (2019). Path dependence, innovation and the economics of climate change. *Handbook on Green Growth*.

Agostini, P., Botteon, M., & Carraro, C. (1992). A carbon tax to reduce CO2 emissions in Europe. *Energy Economics*, *14*(4), 279–290.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197–220.

Aldy, J. E., & Pizer, W. A. (2015). The competitiveness impacts of climate change mitigation policies. *Journal of the Association of Environmental and Resource Economists*, *2*(4), 565–595.

Amore, M. D., & Bennedsen, M. (2016). Corporate governance and green innovation. *Journal of Environmental Economics and Management*, *75*, 54–72.

Andersson, J. J. (2019). Carbon taxes and CO_2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy*, *11*(4), 1–30. doi: 10.1257/pol.20170144

Anderton, K., & Setzer, J. (2018). Subnational climate entrepreneurship: innovative climate action in California and São Paulo. *Regional Environmental Change*, *18*, 1273–1284.

Anthoff, D., & Tol, R. S. (2010). On international equity weights and national decision making on climate change. *Journal of Environmental Economics and Management*, *60*(1), 14–20.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: A review. *Science and public policy*, *19*(6), 357–368. doi: 10.1093/spp/19.6.357

Arrow, K. J. (1962). *Economic welfare and the allocation of resources for invention.* Princeton University Press.

Athey, S., & Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, *113*(27), 7353–7360.

Athey, S., & Imbens, G. W. (2017). The state of applied econometrics: Causality and policy evaluation. *Journal of Economic perspectives*, *31*(2), 3–32.

Baker, J. B. (2007). Beyond Schumpeter vs. Arrows: Antitrust fosters innovation. *Antitrust LJ*, *74*, 575.

Barbieri, N. (2015). Investigating the impacts of technological position and European environmental regulation on green automotive patent activity. *Ecological Economics*, *117*, 140–152. doi: 10.1016/j.ecolecon.2015.06.017

Bel, G., & Joseph, S. (2018). Policy stringency under the European Union Emission trading system and its impact on technological change in the energy sector. *Energy Policy*, *117*, 434–444.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, *69*(5), 1923–1960.

Bertoni, D., Aletti, G., Cavicchioli, D., Micheletti, A., & Pretolani, R. (2021). Estimating the cap greening effect by machine learning techniques: A big data ex post analysis. *Environmental Science & Policy*, *119*, 44–53.

Blonigen, B. A., & Pierce, J. R. (2016). *Evidence for the effects of mergers on market power and efficiency* (Tech. Rep.). National Bureau of Economic Research.

Borenstein, S., & Bushnell, J. (2015). The US electricity industry after 20 years of restructuring. *Annual Review of Economics*, *7*(1), 437–463.

Borghesi, S., Cainelli, G., & Mazzanti, M. (2015). Linking emission trading to environmental innovation: evidence from the Italian manufacturing industry. *Research Policy*, *44*(3), 669–683.

Borissov, K., Brausmann, A., & Bretschger, L. (2019). Carbon pricing, technology transition, and skill-based development. *European Economic Review*, *118*, 252–269.

Brännlund, R., Lundgren, T., et al. (2009). Environmental policy without costs? A review of the Porter hypothesis. *International Review of Environmental and Resource Economics*, *3*(2), 75–117.

Breiman, L. (1996). Bagging predictors. *Machine learning*, *24*(2), 123–140.

Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5–32.

Breschi, S., Tarasconi, G., Catalini, C., Novella, L., Guatta, P., & Johnson, H. (2006). Highly cited patents, highly cited publications, and research networks. *CESPRIBOCCONI UNIVERSITY, http://ec. europa. eu/invest-in-research/pdf/download_en/final_report_hcp. pdf (Accessed: 17/08/2016).*

Bretschger, L. (2005). Economics of technological change and the natural environment: How effective are innovations as a remedy for resource scarcity? *Ecological Economics*, *54*(2-3), 148–163.

Bretschger, L., & Grieg, E. (2020). Exiting the fossil world: The effects of fuel taxation in the UK. *Economics Working Paper Series*, *20*. doi: 10.3929/ethz-b-000410578

Bretschger, L., & Valente, S. (2011). Climate change and uneven development. *The Scandinavian Journal of Economics*, *113*(4), 825–845.

Bretschger, L., & Vinogradova, A. (2015). Equitable and effective climate policy: Integrating less developed countries into a global climate agreement. *International Economics and Economic Policy*, *12*, 437–467.

Brown, M. A. (2001). Market failures and barriers as a basis for clean energy policies. *Energy policy*, *29*(14), 1197–1207.

Bruvoll, A., & Larsen, B. M. (2004). Greenhouse gas emissions in Norway: do carbon taxes work? *Energy Policy*, *32*(4), 493–505.

Bueno, M., & Valente, M. (2019). The effects of pricing waste generation: A synthetic control approach. *Journal of Environmental Economics and Management*, *96*, 274–285. doi: 10.1016/j.jeem.2019.06.004

Burlig, F., Knittel, C., Rapson, D., Reguant, M., & Wolfram, C. (2020). Machine learning from schools about energy efficiency. *Journal of the Association of Environmental and Resource Economists*, *7*(6), 1181–1217.

Bushnell, J., & Chen, Y. (2012). Allocation and leakage in regional cap-and-trade markets for CO2. *Resource and Energy Economics*, *34*(4), 647–668.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy*, *12*(3), 170–201.

Calel, R., & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the European carbon market. *Review of economics and statistics*, *98*(1), 173–191.

Carley, S. (2011). The era of state energy policy innovation: A review of policy instruments. *Review of Policy Research*, *28*(3), 265–294.

Carpenter, M. P., Narin, F., & Woolf, P. (1981). Citation rates to technologically important patents. *World Patent Information*, *3*(4), 160–163. doi: 10.1016/0172-2190(81)90098-3

Cassiman, B., Colombo, M. G., Garrone, P., & Veugelers, R. (2005). The impact of M&A on the R&D process: An empirical analysis of the role of technological-and market-relatedness. *Research Policy*, *34*(2), 195–220.

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785–794). doi: 10.1145/2939672.2939785

Cloodt, M., Hagedoorn, J., & Van Kranenburg, H. (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy*, *35*(5), 642–654.

Cunningham, C., Ederer, F., & Ma, S. (2021). Killer acquisitions. *Journal of Political Economy*, *129*(3), 649–702.

Dasgupta, P., Heal, G., & Stiglitz, J. E. (1980). *The taxation of exhaustible resources.* National Bureau of Economic Research Cambridge, Mass., USA.

Dechezleprêtre, A., Martin, R., & Mohnen, M. (2014). *Knowledge spillovers from clean and dirty technologies.* (CEP Discussion Papers CEPDP1300 Centre for Economic Performance LSE)

Delarue, E., Voorspools, K., & D'haeseleer, W. (2008). Fuel switching in the electricity sector under the EU ETS: review and prospective. *Journal of Energy Engineering*, *134*(2), 40–46.

Denicolò, V., & Polo, M. (2021). Mergers and innovation sharing. *Economics Letters*, *202*, 109841.

de Oliveira, J. A. P. (2009). The implementation of climate change related policies at the subnational level: An analysis of three countries. *Habitat international*, *33*(3), 253–259.

Dernis, H., Guellec, D., & Van Pottelsberghe, B. (2001). Using patent counts for cross-country comparisons of technology output. *STI-Science Technology Industry Review*(27), 129–146.

Desrochers, P. (1998). On the abuse of patents as economic indicators. *The Quarterly Journal of Austrian Economics*, *1*(4), 51. doi: 10.1007/s12113-998-1026-z

Downing, P. B., & White, L. J. (1986). Innovation in pollution control. *Journal of environmental economics and management*, *13*(1), 18–29. doi: 10.1016/0095-0696(86)90014-8

Duso, T., Seldeslachts, J., & Szucs, F. (2019). The impact of competition policy enforcement on the functioning of EU energy markets. *The Energy Journal*, *40*(5).

Elkins, P., & Baker, T. (2001). Carbon taxes and carbon emissions trading. *Journal of economic surveys*, *15*(3), 325–376.

Ellerman, A. D., & McGuinness, M. (2008). CO2 abatement in the UK power sector: evidence from the EU ETS trial period.

European Commission. (2021, 5). *Commission fines Sigma-Aldrich EUR 7.5 million for providing misleading information during Merck takeover investigation.* https://ec.europa.eu/commission/presscorner/detail/en/IP_21_2181.

Fabra, N., Lacuesta, A., & Souza, M. (2022). The implicit cost of carbon abatement during the covid-19 pandemic. *European Economic Review*, *147*, 104165.

Fell, H., & Maniloff, P. (2018). Leakage in regional environmental policy: The case of the regional greenhouse gas initiative. *Journal of Environmental Economics and Management*, *87*, 1–23.

Fowlie, M. L. (2009). Incomplete environmental regulation, imperfect competition, and emissions leakage. *American Economic Journal: Economic Policy*, *1*(2), 72–112.

Franco, G., Cayan, D., Luers, A., Hanemann, M., & Croes, B. (2008). Linking climate change science with policy in California. *Climatic Change*, *87*(1), 7–20.

Fraunhoffer, R., & Schiereck, D. (2012). Consolidation of the energy sector, potential synergies, and realized shareholder value–survey and new insights from top managers' perceptions. *Problems and Perspectives in Management*, *10*(2), 81–92.

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of statistical software*, *33*(1), 1.

Fuss, M. A. (1977). The demand for energy in Canadian manufacturing: An example of the estimation of production structures with many inputs. *Journal of econometrics*, *5*(1), 89–116.

Ghoddusi, H., Creamer, G. G., & Rafizadeh, N. (2019). Machine learning in energy economics and finance: A review. *Energy Economics*, *81*, 709–727.

Gilbert, R. J. (2020). *Innovation matters: Competition policy for the high-technology economy.* MIT Press.

Gilbert, R. J., & Greene, H. (2014). Merging innovation into antitrust agency enforcement of the Clayton Act. *Geo. Wash. L. Rev.*, *83*, 1919.

Gilbert, R. J., & Newbery, D. M. (1982). Preemptive patenting and the persistence of monopoly. *The American Economic Review*, 514–526.

Gillingham, K., Newell, R. G., & Pizer, W. A. (2008). Modeling endogenous technological change for climate policy analysis. *Energy Economics*, *30*(6), 2734–2753.

Green, J. F. (2021). Does carbon pricing reduce emissions? a review of ex-post analyses. *Environmental Research Letters*, *16*(4), 043004.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*(4), 1661–1707.

Hall, B. (1999). Mergers and R&D revisited. In *Prepared for the quasi experimental methods symposium, econometrics laboratory, US Berkeley.*

Halvorsen, R. (1977). Energy substitution in US manufacturing. *The Review of Economics and Statistics*, 381–388.

Haucap, J., Rasch, A., & Stiebale, J. (2019). How mergers affect innovation: Theory and evidence. *International Journal of Industrial Organization*, *63*, 283–325.

Hicks, J. (1932). *The theory of wages.* London: Macmillan.

Hill, J. L. (2011). Bayesian nonparametric modeling for causal inference. *Journal of Computational and Graphical Statistics*, *20*(1), 217–240.

Hitt, M. A., Hoskisson, R. E., Ireland, R. D., & Harrison, J. S. (1991). Effects of acquisitions on R&D inputs and outputs. *Academy of Management Journal*, *34*(3), 693–706.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American statistical Association*, *81*(396), 945–960.

Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review*, *107*(4), 1136–64.

Hyland, M., & Haller, S. (2018). Firm-level estimates of fuel substitution: an application to carbon pricing. *The Energy Journal*, *39*(6).

IEA. (2020). *Energy technology perspectives 2020.* IEA, Paris. Retrieved from `https://www.iea.org/reports/energy-technology-perspectives-2020`

IMMA. (2021). *Merger and acquisition statistics.* Retrieved from `https://imaa-institute.org/mergers-and-acquisitions-statistics/`

IPCC. (2022). *Climate change 2022: Impacts, adaptation, and vulnerability. contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change* (H.-O. Pörtner et al., Eds.). Cambridge, UK and New York, NY, USA: Cambridge University Press.

Jaffe, A. B., & Palmer, K. (1997). Environmental regulation and innovation: A panel data study. *Review of economics and statistics*, *79*(4), 610–619. doi: 10.1162/003465397557196

Jakob, M., Rosskopf, Y., Kendall, I., Looser, R., Remo, F., Reiter, U., & Hoff, O. (2016). Wirkungsabschätzung CO2-Abgabe auf Brennstoffe. Direktbefragungen zur Abschätzung der Wirkung der CO2-Abgabe auf Unternehmensstufe. *TEP Energy und Rütter Soceco im Auftrag des Bundesamtes für Umwelt, Bern.*

Jamasb, T., & Pollitt, M. (2008). Liberalisation and R&D in network industries: The case of the electricity industry. *Research Policy*, *37*(6-7), 995–1008.

Jo, A., & Karydas, C. (2022). Firm heterogeneity, industry dynamics and climate policy. *CER-ETH–Center of Economic Research at ETH Zurich, Working Paper*, *23*, 378.

Jullien, B., & Lefouili, Y. (2018). Horizontal mergers and innovation. *Journal of Competition Law & Economics*, *14*(3), 364–392.

Kahn, M. E., & Mansur, E. T. (2013). Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics*, *101*, 105–114.

Karki, S., Mann, M. D., & Salehfar, H. (2006). Substitution and price effects of carbon tax on CO2 emissions reduction from distributed energy sources. In *2006 power systems conference: Advanced metering, protection, control, communication, and distributed resources* (pp. 236–243).

Katz, M. L., & Shelanski, H. A. (2005). Merger policy and innovation: Must enforcement change to account for technological change? *Innovation policy and the economy*, *5*, 109–165.

Kleinberg, J., Ludwig, J., Mullainathan, S., & Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review*, *105*(5), 491–495.

Kreif, N., Grieve, R., Hangartner, D., Turner, A. J., Nikolova, S., & Sutton, M. (2016). Examination of the synthetic control method for evaluating health policies with multiple treated units. *Health economics*, *25*(12), 1514–1528. doi: 10.1002/hec.3258

Künzel, S. R., Sekhon, J. S., Bickel, P. J., & Yu, B. (2019). Metalearners for estimating heterogeneous treatment effects using machine learning. *Proceedings of the national academy of sciences*, *116*(10), 4156–4165.

Lambertini, L., Poyago-Theotoky, J., & Tampieri, A. (2017). Cournot competition and "green" innovation: An inverted-U relationship. *Energy Economics*, *68*, 116–123.

Lange, A., Vogt, C., & Ziegler, A. (2007). On the importance of equity in international climate policy: An empirical analysis. *Energy Economics*, *29*(3), 545–562.

Lanjouw, J., & Schankerman, M. (1999). *The quality of ideas: Measuring innovation with multiple indicators.* National bureau of economic research Cambridge, Mass., USA. doi: 10.3386/w7345

Lanjouw, J. O., & Mody, A. (1996). Innovation and the international diffusion of environmentally responsive technology. *Research Policy*, *25*(4), 549–571. doi: 10.1016/0048-7333(95)00853-5

Lanjouw, J. O., Pakes, A., & Putnam, J. (1998). How to count patents and value intellectual property: The uses of patent renewal and application data. *The Journal of Industrial Economics*, *46*(4), 405–432. doi: 10.1111/1467-6451.00081

León, L. R., Bergquist, K., Wunsch-Vincent, S., Xu, N., Fushimi, K., et al. (2018). *Measuring innovation in energy technologies: Green patents as captured by WIPO's IPC green inventory* (Vol. 44). WIPO.

Leroutier, M. (2019). Carbon pricing and power sector decarbonisation: The impact of the UK carbon price floor. In *6th FAERE annual conference.*

Leu, T. (2018). The impact of the Swiss climate policy instruments on the energy consumption and greenhous gas emissions in the industry and the service sector: evidence from an ex-post evaluation of microdata. In *IEPPEC 2018: International energy policy & programme evaluation conference, Vienna (Austria), 25-27 june 2018.*

Lin, B., & Li, X. (2011). The effect of carbon tax on per capita CO2 emissions. *Energy policy*, *39*(9), 5137–5146.

Linstroth, T., & Bell, R. (2007). *Local action: The new paradigm in climate change policy.* UPNE.

Lundqvist, L. J., & Biel, A. (2013). *From Kyoto to the town hall: making international and national climate policy work at the local level.* Routledge.

Lutsey, N., & Sperling, D. (2008). America's bottom-up climate change mitigation policy. *Energy policy*, *36*(2), 673–685.

Mariita, N. O. (2002). The impact of large-scale renewable energy development on the poor: environmental and socio-economic impact of a geothermal power plant on a poor rural community in Kenya. *Energy Policy*, *30*(11-12), 1119–1128.

Marin, G., & Vona, F. (2021). The impact of energy prices on socioeconomic and environmental performance: Evidence from French manufacturing establishments, 1997–2015. *European Economic Review*, *135*, 103739.

Martin, R., De Preux, L. B., & Wagner, U. J. (2014). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, *117*, 1–14.

Martin, R., & Verhoeven, D. (2022). Knowledge spillovers from clean and emerging technologies in the uk.

Mazmanian, D. A., Jurewitz, J., & Nelson, H. (2008). California's climate change policy: The case of a subnational state actor tackling a global challenge. *The Journal of Environment & Development*, *17*(4), 401–423.

Milliman, S. R., & Prince, R. (1989). Firm incentives to promote technological change in pollution control. *Journal of Environmental Economics and Management*, *17*(3), 247–265. doi: 10.1016/0095-0696(89)90019-3

Morrison, M. B., & ten Brink, P. (1993). The cost of reducing CO2 emissions: A comparison of the German and UK power sectors. *Energy policy*, *21*(3), 284–295.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87–106.

Müller, A., Schoch, T., Mattmann, M., Thalmann, P., Vielle, M., & Hulliger, B. (2015). *Wirkungsabschätzung CO2-Abgabe, Synthese* (Tech. Rep.).

Murray, B., & Rivers, N. (2015). British Columbia's revenue-neutral carbon tax: A review of the latest "grand experiment" in environmental policy. *Energy Policy*, *86*, 674–683.

Narin, F., & Olivastro, D. (1993). Patent citation cycles. *Library Trends*, *41*(4), 700–709.

Noailly, J. (2012). Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation. *Energy Economics*, *34*(3), 795–806. doi: 10.1016/j.eneco.2011.07.015

Noailly, J., & Shestalova, V. (2017). Knowledge spillovers from renewable energy technologies: Lessons from patent citations. *Environmental Innovation and Societal Transitions*, *22*, 1–14.

Noailly, J., & Smeets, R. (2015). Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. *Journal of Environmental Economics and Management*, *72*, 15–37.

Nordhaus, W. D. (1994). *Managing the global commons: the economics of climate change* (Vol. 31). MIT press Cambridge, MA.

OECD. (1994). *The measurement of scientific and technological activities using patent data as science and technology indicators: Patent manual.* Paris: OECD Publishing.

OECD. (2009). *OECD patent statistics manual.* Paris: OECD Publishing, Paris. doi: 10.1787/9789264056442-en.

OECD. (2021). *Patents in environment-related technologies: Technology indicators.* doi: 10.1787/e478bcd5-en

Ornaghi, C. (2009). Mergers and innovation in big pharma. *International Journal of Industrial Organization*, *27*(1), 70–79.

Palmquist, S., & Bask, M. (2016). Market dynamics of buyout acquisitions in the renewable energy and cleantech sectors: An event study approach. *Renewable and Sustainable Energy Reviews*, *64*, 271–278.

Pavitt, K. (1988). Uses and abuses of patent statistics. In *Handbook of quantitative studies of science and technology* (pp. 509–536). Elsevier.

Pearce, D. W., & Barbier, E. (2000). *Blueprint for a sustainable economy.* Earthscan.

Pigou, A. C. (1920). *The economics of welfare.* Macmillan.

Pindyck, R. S. (1979). Interfuel substitution and the industrial demand for energy: an international comparison. *The Review of Economics and Statistics*, 169–179.

Popp, D. (2002). Induced innovation and energy prices. *American economic review*, *92*(1), 160–180.

Popp, D. (2003). Pollution control innovations and the Clean Air Act of 1990. *Journal of Policy Analysis and Management*, *22*(4), 641–660. doi: 10.1002/pam.10159

Popp, D. (2010). Innovation and climate policy. *Annu. Rev. Resour. Econ.*, *2*(1), 275–298.

Popp, D. (2019). Environmental policy and innovation: A decade of research. *International Review of Environmental and Resource Economics*, *13*(3-4), 265–337.

Popp, D. (2020). Promoting clean energy innovation at the state and local level. *Agricultural and Resource Economics Review*, *49*(2), 360–373.

Popp, D., Newell, R. G., & Jaffe, A. B. (2010). Energy, the environment, and technological change. *Handbook of the Economics of Innovation*, *2*, 873–937. doi: 10.1016/S0169-7218(10)02005-8

Porter, M. (1991). America's green strategy. *Scientific American*, *264*, 168.

Porter, M., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of economic perspectives*, *9*(4), 97–118.

Rabe, B. G. (2004). *Statehouse and greenhouse: The emerging politics of American climate change policy.* Brookings Institution Press.

Rapp, R. T. (1995). The misapplication of the innovation market approach to merger analysis. *Antitrust LJ*, *64*, 19.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and non-randomized studies. *Journal of educational Psychology*, *66*(5), 688.

Salvi, A., Petruzzella, F., Giakoumelou, A., et al. (2018). Green M&A deals and bidders' value creation: the role of sustainability in post-acquisition performance. *International Business Research*, *11*(7), 96–105.

Samii, C., Paler, L., & Daly, S. Z. (2016). Retrospective causal inference with machine learning ensembles: An application to anti-recidivism policies in Colombia. *Political Analysis*, *24*(4), 434–456.

Sanyal, P., & Ghosh, S. (2013). Product market competition and upstream innovation: evidence from the US electricity market deregulation. *Review of Economics and Statistics*, *95*(1), 237–254.

Schankerman, M., & Pakes, A. (1986). Estimates of the value of patent rights in European countries during the post-1950 period. *The economic journal*, *96*(384), 1052–1076.

Schmutzler, A. (2013). Competition and investment—a unified approach. *International Journal of Industrial Organization*, *31*(5), 477–487.

Schreurs, M. A. (2008). From the bottom up: local and subnational climate change politics. *The Journal of Environment & Development*, *17*(4), 343–355.

Schumpeter, J. A. (1939). *Business cycles* (Vol. 1). New York: McGraw-Hill New York.

Selin, H., & VanDeveer, S. D. (2007). Political science and prediction: What's next for US climate change policy? *Review of Policy Research*, *24*(1), 1–27.

Shapiro, C. (2011). Competition and innovation: Did Arrow hit the bull's eye? In *The rate and direction of inventive activity revisited* (pp. 361–404). University of Chicago Press.

Steinbuks, J. (2012). Interfuel substitution and energy use in the UK manufacturing sector. *The Energy Journal*, *33*(1).

Szücs, F. (2014). M&A and R&D: Asymmetric effects on acquirers and targets? *Research Policy*, *43*(7), 1264–1273.

Tanner, A. N., Faria, L., Moro, M. A., Iversen, E., Østergaard, C. R., & Park, E. K. (2019). Regional distribution of green growth patents in four nordic countries: Denmark, Finland, Norway and Sweden. *Technical University of Denmark (DTU).*

Taylor, M. R. (2012). Innovation under cap-and-trade programs. *Proceedings of the National Academy of Sciences*, *109*(13), 4804–4809. doi: 10.1073/pnas.1113462109

Taylor, M. R., Rubin, E. S., & Hounshell, D. A. (2003). Effect of government actions on technological innovation for SO2 control. *Environmental Science & Technology*, *37*(20), 4527–4534. doi: 10.1021/es034223b

Tirole, J. (1988). *The theory of industrial organization.* MIT press.

Trajtenberg, M. (1990). *Economic analysis of product innovation: The case of ct scanners* (Vol. 160). Harvard University Press.

Unruh, G. C. (2000). Understanding carbon lock-in. *Energy Policy*, *28*(12), 817–830.

Urbaniec, M., Tomala, J., & Martinez, S. (2021). Measurements and trends in technological eco-innovation: Evidence from environment-related patents. *Resources*, *10*(7), 68.

Van Der Laan, M. J., & Dudoit, S. (2003). Unified cross-validation methodology for selection among estimators and a general cross-validated adaptive epsilon-net estimator: Finite sample oracle inequalities and examples.

Van der Laan, M. J., Dudoit, S., & van der Vaart, A. W. (2006). The cross-validated adaptive epsilon-net estimator. *Statistics & Decisions*, *24*(3), 373–395.

Van der Laan, M. J., Polley, E. C., & Hubbard, A. E. (2007). Super learner. *Statistical applications in genetics and molecular biology*, *6*(1). doi: 10.2202/1544-6115.1309

Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, *28*(2), 3–28.

Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., & Thumm, N. (2012). A new EPO classification scheme for climate change mitigation technologies. *World Patent Information*, *34*(2), 106–111. doi: 10.1016/j.wpi.2011.12.004

Vogel, D. (1997). Trading up and governing across: transnational governance and environmental protection. *Journal of European public policy*, *4*(4), 556–571.

Wagner, U. J., Muûls, M., Martin, R., & Colmer, J. (2014). The causal effects of the European Union Emissions Trading Scheme: evidence from French manufacturing plants. In *Fifth world congress of environmental and resources economists, instanbul, turkey.*

Willis, H. L., & Philipson, L. (2018). *Understanding electric utilities and de-regulation.* CRC Press.

Wilson, I. G., & Staffell, I. (2018). Rapid fuel switching from coal to natural gas through effective carbon pricing. *Nature Energy*, *3*(5), 365–372.

WIPO. (2009). *Patent-based technology analysis report - alternative energy technology.* Retrieved from `https://www.wipo.int/edocs/plrdocs/en/landscape_alternative_energy.pdf`

Yoo, K., Lee, Y., & Heo, E. (2013). Economic effects by merger and acquisition types in the renewable energy sector: An event study approach. *Renewable and Sustainable Energy Reviews*, *26*, 694–701.