Essays on the Economics of Competition and Innovation under Environmental Regulation

Dissertation

zur Erlangung des akademischen Grades
"doctor rerum politicarum"

an der Fakultät für Wirtschafts- und Sozialwissenschaften
der Ruprecht-Karls-Universität Heidelberg

vorgelegt von
Albert Roger Figuerola
geboren am 25. Januar 1987 in Barcelona

im Juli 2022

Tag der Disputation: 25.10.2022
Betreuer und Erstgutachter: Prof. Timo Goeschl, Ph.D., Universität Heidelberg
Zweitgutachter: Prof. Carlos J. Serrano, Ph.D., HEC Paris & Universitat Pompeu Fabra
Drittprüferin: Prof. Dr. Jale Tosun, Universität Heidelberg

A Ascensión Figuerola i Miquel Roger,
els meus pares.

Acknowledgements

First and foremost, I would like to thank my supervisor Prof. Timo Goeschl for his guidance, support, and advice during all these years.

I am grateful to Prof. Carlos J. Serrano for accepting to be an external examiner for this dissertation.

I would like to thank Prof. Bernhard Ganglmair for his support, feedback, advice, and inspiring talks. I am indebted to Prof. Ulrich J. Wagner for early guidance in my dissertation, advice, and feedback. Further, I am thankful to Georg Licht for his direct and indirect support during all these years at ZEW.

I would like to thank my former colleagues and friends from ZEW, in particular: Claudio Baccianti, Philipp Massier, Florence Blandinières, Wolfgang Habla, Nikolas Wölfing, and Sebastian Voigt. We shared many good and bad moments together, but at the end, we still had a good time.

To my friends in Mannheim, especially, Martina, Kathrin, and Eleonora. Many thanks for the great time together, the laughs, trips, nice moments, inspiration, and for cheering me up. To my friends in Barcelona and abroad. Thank you for your support.

To my family. Thank you for being there all these years.

Finally, I would like to thank my parents for being always an example of ethics, work, perseverance, and resilience, and, of course, for their support and unconditional love. This thesis is dedicated to them.

Albert Roger
Mannheim, July 2022

Contents

1 Introduction

Sustainable technologies such as renewable energies, electric cars, and energy-efficient processes lie at both the core of the energy transition and of the fight against climate change. Environmental economics is concerned with mechanisms to internalize negative externalities; a market that would not take these externalities into account would produce them in excess. Environmental regulations provide incentives to internalize these externalities and, by doing so, they might influence the direction of technological change. In addition, technological change suffers from the public goods problem, as the innovator cannot appropriate all the value that he has generated. Therefore, without policies supporting R&D, there would be suboptimal levels of innovation produced. Environmental innovations face, therefore, a double externality, which requires intervention from policymakers. Environmental regulations can provide incentives to induce innovation and direct technological change. The intuition behind this mechanism stems from Hicks (1932), who argued that relative changes in the costs of input factors induce innovation that makes efficient use of the most expensive factor of production. This notion has been since then further developed by others, including Acemoglu (1998; 2002) and Acemoglu et al. (2012). Newell et al. (1999) and Popp (2002) have evaluated this theory in the context of environmental innovation. More recently, Aghion et al. (2016) have further studied the impact of environmental regulation on the direction of technological change, scrutinizing the effect of taxes that target CO_2 emissions on innovations in the automobile sector.

Climate change is caused by greenhouse gases, such as CO_2. Once these gases are emitted into the atmosphere, they disperse and accumulate, transforming a local negative externality into an externality on a global scale. This makes the abatement of CO_2 and other pollutants a public good because the benefits of reducing emissions have both nonrival and nonexcludable properties (Murdoch and Sandler, 1997). International environmental agreements (IEAs) are the central regulatory instrument in order to solve global environmental externalities. However, IEAs have a self-enforcing nature themselves, since countries can always withdraw themselves from the agreement once signed (Barrett, 1994). This characteristic of IEAs defines both the types of environmental regulations pledged and their stringency. Consequently, studying the interaction between IEAs and the direction of technological change is particularly important, as these agreements lie at the core of the climate change challenge. Aside from work by Dekker et al. (2012) and Dugoua (2021), this interaction has not been fully empirically explored.

International environmental agreements are key to solving global environmental problems. Negotiating the agreement, however, is often a lengthy process. This is primarily because countries that sign and ratify the agreements might face certain costs, while their benefits remain often more uncertain, netted out from the avoided environmental damages. Quantifying the impact of IEAs on technological change would therefore be a major step towards reducing the uncertainty surrounding future environmental agreements, although doing so is not a trivial task. In this dissertation, I study how environmental regulations impact incentives to innovate for competing clean and dirty technologies. I examine this under the framework of international environmental agreements, and I specially focus on the cases of the Montreal Protocol on Substances that Deplete the Ozone Layer and one of its amendments, the Kigali Amendment. In order to analyze the effect of environmental regulations on incentives to innovate, I focus on two dimensions that have received little attention in environmental innovation, namely the timing of technological change and the value of innovations, as measured by the value of patents.

Timing is particularly relevant in the analysis of the impact of international environmental agreements on technological change. There are three main factors in the analysis that have a time component. First, agents that are party to international environmental agreements (i.e., countries) have incentives to anticipate their behavior (Aufhammer et al., 2005); however, if the agreement is too lenient, its impact on technological change could be delayed. Second, technological change is slow: there is often a time gap or lag between the emergence of a new problem and the creation of an idea to solve it. This lag may be particularly large if the idea's authors pursue publication or if the new technology is embodied in a product that must be produced. Third, the market's expectations affect clean and dirty technologies differently. Considering that dirty technologies are initially more advanced, in a technology transition towards clean technologies, they will respond to shocks on their short-term market, while clean technologies will be more reactive to shocks regarding their long-term market (Dechezleprêtre and Hémous, 2022). This is especially relevant for international environmental agreements, since their signature, as a shock, might be interpreted differently by clean and dirty technology producers as their time horizons differ.

1 Introduction

Historically, the value of patents has been studied from different perspectives. Starting with the work of Scherer (1965) showing that values of innovations are highly skewed, the drivers of this skewness have been further studied by many scholars. One approach to study patent value has explored the validity of several proxies for value stemming from patent characteristics such as citations, family size, or renewal years (Griliches, 1990; Trajtenberg, 1990; Harhoff et al., 1999; Pakes and Schankerman, 1984). A second approach has exploited the stock market's reaction to patent grant announcements to compute the value of granted patents (Pakes, 1985; Hall et al., 2005; Kogan et al., 2017). Finally, a third approach has used patent renewal decisions to compute the monetary value of patents, using a structural method (Pakes and Schankerman, 1984; Pakes, 1986; Lanjouw, 1998; Deng, 2011; Serrano, 2018). In this dissertation, I focus on the first and third approaches.

This dissertation is divided into two parts. In the first part, I develop and adapt two new methods to study the impact of an environmental regulation on patent value. First, I develop a dynamic discrete choice model of patent renewal under uncertain environmental regulation. Together with a synthetic control group, this approach allows me to quantify the monetary impact of an environmental regulation on patent value. This new method allows me to estimate the technological gains and losses engendered by an environmental regulation. Second, I adapt the nonparametric model of van den Bergh et al. (2020) to study the impact of an environmental regulation on patent renewal, a proxy for patent value. I examine this impact in the context of the Kigali Amendment to the Montreal Protocol. This method allows me to estimate the average treatment effects on conditional survival probabilities of clean and dirty patents around the signature of the agreement. This new approach to the analysis of patent renewal rates enables me to explore the impact of an international environmental agreement on technological change and on the timing of technological change.

In the second part, I apply the methods that I developed and adapted in the first part. First, I quantify the technological gains and losses induced by the Kigali Amendment to the Montreal Protocol. This permits me to further shed light on the technological incentives that countries face as they ratify international environmental agreements. Second, I apply the nonparametric model that I adapted to patent data in the first part to scrutinize the impact of the Montreal Protocol on Substances that Deplete the Ozone Layer and its early amendments on the value of clean and dirty technologies, proxied by patent renewals.

This enables me to shed further light on the various hypotheses regarding the original drivers of the Protocol.

Synopsis

This dissertation is divided into four chapters. In Chapter 2, I develop a method for quantifying the technological gains and losses induced by an environmental regulation. To do this, I develop a model of patent renewal under environmental regulation uncertainty and combine it with a synthetic control method approach. My model builds upon the dynamic discrete choice models of patent renewal that were developed by Serrano (2018) and Deng (2011), and adds to these models by incorporating the possibility of being affected by an environmental regulation. This method enables me to estimate the monetary impact of an environmental regulation on patent value. It builds upon several assumptions, including monotonicity of the likelihood of the environmental regulation, which is intuitive for stock pollutants, and unidirectionality of positive and negative shocks for clean and dirty technologies, respectively. The method presupposes the existence of three similar groups of patents (clean, dirty, and not affected) that likely would have had similar renewal patterns in the absence of the environmental policy. Furthermore, it also assumes the existence of positive and negative shocks on the value of clean and dirty patents, which are proxied by abnormal hazard rates compared to the hazard rates of patents that are not affected by the regulation. My method has the typical caveats and limitations of synthetic control group methods and simulated method of moments structural estimations, which I discuss further in the chapter. In Chapter 4, I provide an example of an empirical application of this method. This chapter adds to the literature in several manners. First it contributes to the literature on patent renewal models, since it is the first model of its kind that incorporates uncertain environmental regulation. Second, it contributes to the literature on structural methods for quantifying the monetary impact of environmental policies by introducing the first method combining a structural model and a synthetic control group.

In Chapter 3, I study the impact of international environmental agreements on the timing and direction of technological change. I study the impact of the signature of the Kigali Amendment to the Montreal Protocol on incentives to innovate. I focus especially on the value of clean and dirty patents. To do this, I construct a self-curated dataset of patents which mention chemical substances that are regulated under the Kigali Amendment or the Montreal Protocol, as well as patents that mention substances that can be used as refrigerants. This enables me to create a dataset of dirty patents, clean patents mentioning the clean substitutes to the regulated substances as well as non-regulated patents. Furthermore, I adapt the nonparametric duration model of van den Bergh et al. (2020) to the patent renewal framework. This allows me to estimate the average treatment effects on the conditional survival probabilities capturing differences in the hazard rates between treatment and control groups before, at the moment of, and after the signature of the Amendment. I find that the Kigali Amendment to the Montreal Protocol had first a negative impact on the value of dirty patents, although only almost significant at a 5 percent level. Furthermore, I also find that the Amendment had a positive and statistically significant impact at the 5 percentage level on the value of clean patents, although the effect occurred some time after the negative shock. This chapter adds to the literature in several ways. First, because this work proposes a new way to estimate shocks on patent value using patent renewal data, it makes a contribution to the literature on patent valuation. Second, it contributes to studies on innovation by constructing a unique dataset of regulated patents and patents related to their substitute technologies. Third, it also adds to the literature on innovation by proposing a new method to select patents mentioning chemical substances. Fourth, it contributes to the literature on international environmental agreements and the direction of technological change, by studying the impact of the most recent and successful international environmental agreement targeting a greenhouse gas. Finally, it also contributes to the literature on environmental innovation and directed technological change by studying for the first time the difference in response curves of clean and dirty technologies to a regulatory change.

In Chapter 4, I quantify the technological gains and losses induced by an international environmental agreement. To do this, I use the method developed in Chapter 2 and implement it to study the monetary gains and losses in patent value engendered by the Kigali Amendment to the Montreal Protocol. To estimate the gains and losses I employ the dataset that I constructed in Chapter 3. Before implementing my method, I discuss the plausibility of the method's assumptions and present the existing empirical evidence upon which my method builds. Using counterfactual simulations, I find that the Amendment generated average total gains ranging between 1600 Euro and 50,000 Euro, while I find that it induced only small average total losses of up to 200 Euro. Afterwards, I discuss the goodness-of-fit as well as, robustness checks, measurement errors and limitations related to my estimates. This work makes several key contributions to the literature. First, it contributes to the literature on structural models in environmental economics, by providing the first estimates from a novel structural patent renewal model with environmental uncertainty and its combination with a synthetic control approach. Second, it contributes to the literature on international environmental agreements and provides evidence for the self-enforcing rationale of Barrett (1994). Finally, it also contributes to the literature on international environmental agreements and directed technological change by providing the first estimates of the technological gains and losses induced by an environmental agreement.

In Chapter 5, I examine the impact of the Montreal Protocol and its successive amendments on patent value, using patent renewal as a proxy. For this chapter, I built a unique dataset of European patents which mention substances that are regulated under the Protocol and clean patents citing their substitutes used in refrigeration. I employ the nonparametric duration approach adapted from van den Bergh et al. (2020) in Chapter 3 and compute the average treatment effects on the conditional survival probabilities. Furthermore, I use a new identification strategy to differentiate between patents applied for in a period before discussions on the Montreal Protocol had started and patents applied while discussions on the Protocol were ongoing, to shed further light on the different hypotheses regarding the drivers of the Protocol. My results support the hypothesis of Barrett (1994) arguing that benefits were higher than costs, as well as arguments made by Sunstein (2007), who stated that the industry had already started developing substitute technologies before the signature of the Protocol. Furthermore, my results also support the rationale of Dugoua (2021) regarding the increasing stringency of the successive amendments to the Protocol, but contradict the claims of Benedick (1998) by providing evidence showing that firms had already partially anticipated the agreement and started moving before it was signed. My results should be interpreted with caution, however, since they rely on a relatively small sample. Future research should expand on this analysis by incorporating data from additional countries. This work contributes to the literature in several ways. First, it contributes to the literature on international environmental agreements and the Montreal Protocol by providing further evidence on the different hypotheses regarding its success. Second, it contributes to the literature on international environmental agreements and the direction of technological change by computing the impact of an agreement on the value of clean and dirty patents. Finally, it contributes to research on the Montreal Protocol by exploiting a new patent dataset and a novel identification strategy to study the impact of an environmental regulation on the direction of technological change.

2 Method for Quantifying the Monetary Impact of an Environmental Regulation on Patent Value*

2.1 Introduction

The urgency of global warming requires us to accelerate the speed of the energy transition. Traditionally environmental innovation has studied the direction of technological change and how incentives might affect it. The current situation requires us, however, to go a step beyond those type of questions and rather focus on studying the drivers of the speed of directing technological change, i.e. of the rate of technological change. For this we need to provide answers to questions related to the costs and benefits of directing technological change. This work will focus on how environmental regulation might affect the value of existing clean and dirty patents. This is particularly relevant if we want to understand the impact of environmental regulation on the rate of technological change.

As argued by Langer et al. (2022), studying the drivers of the rate of clean versus that of dirty innovation is key for understanding what shifts the technological equilibrium towards a sustainable technology path. Studying the determinants of the private value of clean and dirty technologies is essential assessing what shifts the relative growth path (Langer et al., 2022). In their work, Langer et al. (2022) focus on the role of financial constraints (related to the Great Recession of 2010) in the private value of clean and dirty patents. For this, they use the Kogan et al. (2017) approach to measure patent value, which is based on the stock market reaction to the grant event of a patent.

In this paper, I will study the drivers of green versus dirty innovation by examining how environmental regulations impact on the private value of existing patents, depending on

---

*I would like to thank Victor Aguirregabiria, Bernhard Ganglmair, Timo Goeschl, Wolfgang Habla, François Laisney, Bettina Peters, Mar Reguant, Imke Reimers, John Rust, Carlos Serrano, Kenneth Simons, and Ulrich Wagner for their helpful feedback and comments. Furthermore, I would like to thank all participants to ZEW seminars, Econometric Society DSE 2018, MaCCI Annual Conferences 2020 and 2021, EAERE-ETH Winter School 2019, AURÖ 2019, MaCCI IO Day 2019, TECHNIS 2020, AERE 2020, Summer School on Data Algorithms for Science, Technology & Innovation Studies 2020, Mannheim Energy Conference 2021, IX IEB Symposium, and WIPE 2021. The usual disclaimer applies.

their environmental characteristics. In doing so, I add to the literature in several ways. First, since I focus on the influence of an environmental regulation on the value of clean and dirty technologies, it could help us quantify the double externality that environmental innovations are suffering. Namely, the combination of the underinvestment in abatement technologies in the lack of environmental regulations added to the suboptimal level of R&D expenditures due to the inability of the innovator to capture all benefits from innovation. The second advantage lies in focusing on the impact on already existing R&D assets. This has a clear advantage compared to the Kogan et al. (2017) approach, that I focus on innovations whose value has been evaluated several times after their grant date and does not depend solely on the stock market expectations at the grant moment. Finally, by analyzing the change in value of already existing clean and dirty R&D assets, I can shed light on how the lack of environmental regulation undervalues clean innovations and overvalues dirty ones. In order to implement my method, I develop a theory of patent renewal under uncertain exogenous regulation. My model builds upon the work of Serrano (2018), where he further develops the framework of Pakes (1986) by disentangling the parameters governing the process of internal growth returns from the returns that are external to the patent holder, which in his case are due to patent trade. In my model the external shock to the patent returns is due to an environmental regulation, which is exogenous to the patent holder. Since the main objective of this work is to estimate the monetary impact of an environmental regulation on patent value, I will shortly summarize the main challenges of my estimation method and how I overcome them.

As econometricians, we don't observe the moment when a patent is regulated. We can know at most that some patents belonging to a certain group might have received a shock during their life cycle compared to similar patents not affected by the environmental regulation. Therefore, I will focus on evaluating the effect of the regulation from the moment it was introduced onwards. Since we are performing a structural estimation and the information on when the regulation affects a certain patent is not on a unit level anymore but on a group level, then we cannot use anymore the patents that might have been affected by the regulation to estimate any other parameters besides the regulation shocks. The intuition behind this is that the lack of information on the treatment at the unit level requires us to treat partially the structural estimation as a regression since we face the fundamental problem of causal inference. For this, I will combine the structural estimation with a synthetic control group approach. The intuition for this method is to use a structural dynamic discrete choice model in the spirit of an integrated assessment model in order to generate counterfactuals. Holland et al. (2016) use an integrated assessment model to compute health damages resulting from a change in emissions of local pollutants. Instead, I use a dynamic discrete choice model to compute counterfactuals, where the first step would be the "calibration" of the integrated assessment model, in my case the structural estimation of the dynamic discrete choice model without environmental regulation with patents that have not been affected by the regulation. Then in the second step I estimate the deviations from the generated counterfactuals of the first step with a structural model of patent renewal allowing for environmental regulation.

This chapter is divided in the following sections, first I present the literature review, then the modelling framework with the main theoretical assumptions, and finally I expose the mechanics of the estimation routine including a discussion of the measurement error.

2.2 Literature Review

This work builds upon three different strands of the literature. The first one is the development of measures for patent valuation. The second one is on patent renewal and patent renewal models for assessing patent value, which could be considered as a sub-strand of the first one but that can be treated as an independent strand and is the main literature upon which this work builds. The third and final strand of the literature of this paper is on counterfactual generation and synthetic controls.

The literature on measures of patent valuation started with Scherer (1965), Schmookler (1966) and Griliches (1981; 1984) using patent counts for accounting for how innovative the output of a firm or industry was. Scherer (1965) found that the distribution of patent value is highly skewed. Therefore and since then several measures have been developed to disentangle the heterogeneity of patent value such as patent citations (backward and forward), references to scientific literature, renewal years, surveys, family size (i.e. in how many countries a patent has been granted), number of claims, patent scope, and the relation between firm's market value and patent value. The relation between patent citations and economic value started being studied by Griliches (1990), Trajtenberg (1990), Albert et al. (1991). Harhoff et al. (1999) used a survey to ask patent holders for the amount at which they would have been willing to sell their patent. They find that more valuable patents are cited more. Scherer and Harhoff (2000) using survey data further analyze the skewness of the private patent value distribution. Furthermore, the work of Hall et al. (2001) was a methodological milestone regarding the use of patent citations. Harhoff et al. (2003) provide estimates of the private value of patents using survey data and find evidence that patents with more references (to the scientific literature or other patents), with more forward citations, and patents in opposition or annulment procedures are of higher value. Lerner (1994) provides evidence that broader patents, in terms of patent scope proxied by International Patent Classification are more valuable. Lanjouw and Schankerman (2004) use additional measures for patent quality, besides citations, such as family size and the number of claims, creating a composite measure they find that it is a good predictor for a patent to be kept active more years. Nevertheless, Gambardella at al. (2008) combining survey data with patent characteristics correlated with patent value find that the typical measures used (i.e. citations, claims, references, and family size) capture only a little part of the variation associated with patent value, suggesting that there is a need for further research. Recent evidence from Abrams et al. (2018) contradicts prior work suggesting that more valuable patents are more cited and find instead that there is an inverted-U shape relationship, where high end patents are less cited than average ones.

Within the strand of the literature of patent valuation it is important to dedicate a special mention to the works relating patenting activity and stock market valuation. This last line of the research, that was initiated among others with the work of Pakes (1985), was later extended by Austin (1993), Hall et al. (2005), and Nicholas (2008). More recently it has been further developed by Kogan et al. (2017), creating a new way of assessing the value of patents through stock market expectations. This method has also recently been used in environmental economics by Langer et al. (2022) to compare the impact of financial constraints on the value of clean and dirty innovations. They find that financial constraints have reduced the relative share of clean versus dirty innovations because clean innovations were perceived to be riskier. Also, recent works by Dechezleprêtre et al. (2021a; 2021b) use the approach of Hall et al. (2005) to compare the value of firm level clean and dirty innovations. They find that clean innovations are more valuable than dirty ones.

The second strand of the literature is on patent renewal models which started with the early works on patent renewal of Pakes and Schankerman (1984), Pakes (1986), Lanjouw (1998), and Schankerman (1998). This literature is split between the deterministic models and the stochastic ones. It started with the deterministic patent renewal model of Pakes and Schankerman (1984), further developed in Schankerman and Pakes (1986) and in Schankerman (1998), and the deterministic model of Sullivan (1994). Putnam (1996) and later Deng (2007) modelled the international patent application with a deterministic evolution of returns. Finally, the stochastic models, which are also the class of model that I use in my work, started with the work of Pakes (1986), further developed by Lanjouw (1998), the nonparametric approach of Pakes et al. (1989), the model of international patent application of Deng (2011), and the model incorporating the option to trade a patent of Serrano (2018) (although first working paper dates from 2005). It is important to make a special mention to two works, Bessen (2008) and Schankerman (1998). The first one, because using a version of the Pakes and Schankerman (1984) patent renewal model he controls for patent characteristics and finds that patents with more citations and litigated patents are more valuable. The second paper, because it is the first work studying the impact of a shock on patent returns using a patent renewal model (although a deterministic one). In particular he uses a version of the Schankerman and Pakes (1986) model to study the oil shock of 1973 on the decay rate of patents in France for different technology groups. This last paper would be the closest in the literature to the aim of my work, although I build upon the stochastic modelling framework of Serrano (2018) for it.

The last strand of the literature upon which this work stands is on counterfactual generation and synthetic controls. This literature started with the work of Abadie and Gardeazabal (2003) estimating the economic cost of the Basque Country conflict, through a synthetic control region without conflict, further developed in Abadie et al. (2010). The fundamental problem of not having a good control available is relatively common in environmental economics since many regulations are first of their kind. Recently several works in this field have further implemented this approach for generating counterfactuals in the spirit of synthetic controls in different ways like integrated assessment models (Holland et al. 2016) or machine learning approaches (Burlig et al. 2020, Abrell et al. 2022).

2.3 Model

In this section I present a model of patent renewal under uncertain exogenous environmental regulation. The section is divided in two parts, first I provide an overview of the model intuition and then I present its mechanics.

2.3.1 Model Intuition

In my model the agent is a patent holder that each period, a, indicating patent age, decides whether to renew or not a patent. In order to make this decision he takes into account the current realization of different state variables as well as the expectations on their future realizations. The framework follows the spirit of the reformulation of the patent renewal model of Pakes (1986) by Serrano (2018). In particular each period a the agent observes the renewal fees c_a, the current per period returns x_a, and he also observes if he has received an information regarding the regulatory state of his technology, i.e. if the technology is affected or not by the regulation that is under discussion σ_a.

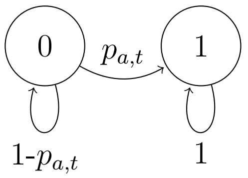


Figure 2.1: Evolution of environmental regulation

In this setting the patent holder can be in two possible states at any age. As shown in the figure 2.1, patent holders might be in state ”0” ($\sigma_a = 0$), where they are not regulated. From this state he can transition with probability $p_{a,t}$ to state ”1”, where he is regulated ($\sigma_a = 1$). The probability of being regulated ($p_{a,t}$) is increasing in patent age a and accross patent cohorts t. When moving to that state, the patent holder readjusts his per period returns x_a by an external factor g^e, such that in the first period when he receives the information on his regulatory status σ_a he takes the decision of whether to renew the patent or not given his new per period returns y_a, defined as $y_a = g^e x_a$. Similar to Serrano (2018), g^e is a random variable drawn each period from a truncated exponential distribution with parameters γ_e, δ_e, and σ_e (see equation 2.1). The distribution of g^e captures whether the regulation affects positively patent returns σ_e, depreciates them by an additional factor δ_e, or makes the technology obsolete γ_e, bringing them to zero.

$$F^{g^e}(g^e) = \begin{cases} 1-\gamma^e & if\ g^e = 0 \\ 1-\gamma^e+\gamma^e\left[1-exp\left(\frac{-\delta_e}{\sigma^e}\right)\right] & if\ g^e = \delta_e \\ 1-\gamma^e+\gamma^e\left[1-exp\left(\frac{-g^e}{\sigma^e}\right)\right] & if\ g^e > \delta_e \end{cases} \tag{2.1}$$

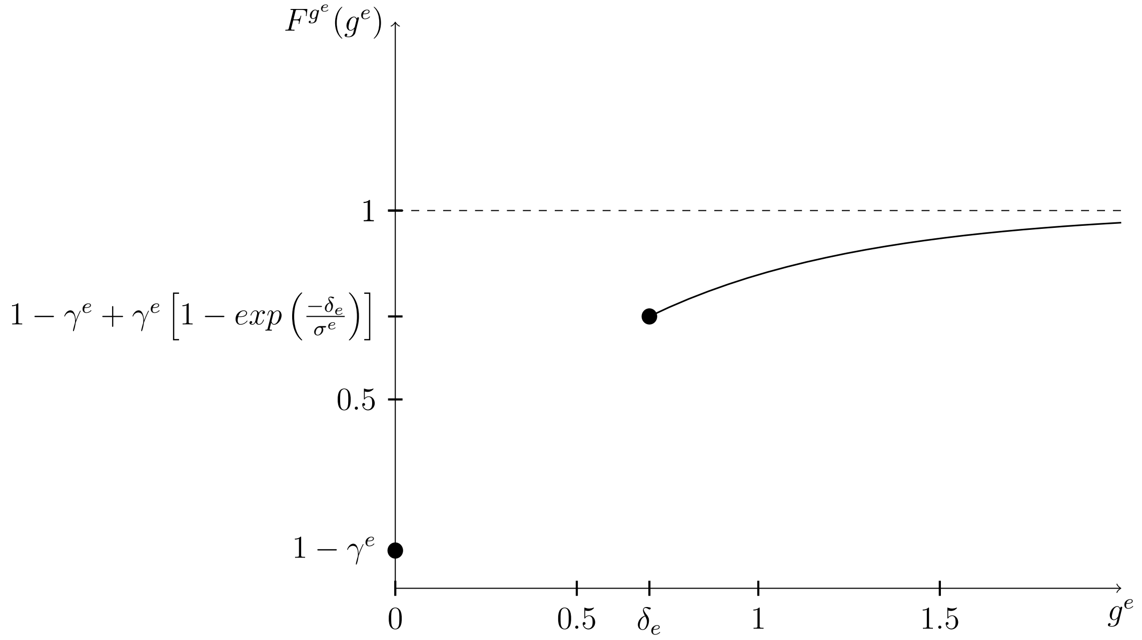


Figure 2.2: Representation of $F^{g^e}(g^e)$ (with $\gamma^e = 0.9$, $\delta_e = 0.7$, and $\sigma^e = 0.6$)

2.3.2 Model

Patent renewal model without environmental regulation

My patent renewal model incorporates the framework of Serrano (2018) without allowing for patent transfer. Patent holders annually need to decide whether to renew a patent or not. In order to be able to make this decision, they are informed about their current per period returns x_a and form expectations about their future internal growth return g^i as shown in equation (2.2) taking into account all information available in age a, Ω_a. The evolution of patent returns follows equation (2.3), where next period patent returns are equal to the current period ones times the internal growth factor g^i. Each period this internal growth factor is drawn from a mixture with CDF F^{g^i} (equation 2.4). This mixture captures the fact that patents might either become obsolete with probability $1-\gamma_i$, or depreciate with a factor δ^i or learn new uses which improves their per period returns by g^i_a. In case a patent becomes obsolete it gets into an absorbing state of zero per period returns. The model of Serrano (2018), like that of Pakes (1986), incorporates age-reducing learning opportunities σ^i_a, i.e., it accounts for the fact that learning new uses for inventions gets harder the older a patent is (equation 2.5). New learning opportunities are captured by the parameters ϕ, representing upside opportunities, and σ^i representing internal growth returns.

$$V(x_a) = max\{0\,,\, x_a + \beta\, E[V(x_{a+1})|\Omega_a] - c_a\} \tag{2.2}$$

$$x_{a+1} = g^i_a x_a \tag{2.3}$$

$$F^{g^i}(g^i_a) = \begin{cases} 1-\gamma^i & if\ g^i_a = 0 \\ 1-\gamma^i+\gamma^i\left[1-exp\left(\frac{-\delta_i}{\sigma^i_a}\right)\right] & if\ g^i_a = \delta_i \\ 1-\gamma^i+\gamma^i\left[1-exp\left(\frac{-g^i_a}{\sigma^i_a}\right)\right] & if\ g^i_a > \delta_i \end{cases} \tag{2.4}$$

$$\sigma^i_a = \sigma^i \phi^{a-1} \tag{2.5}$$

Patent renewal model with increasing external regulation threat

Having introduced the patent renewal model, I now present the details of how I introduce environmental regulation into such a framework. The state variable that takes into account that the patent holder might be informed that his patent is regulated in age a, σ_a, stems from a Bernoulli trial. The variable σ_a can only take two values $\{0, 1\}$, with "1" expressing that a patent holder is told that he is regulated, and occurs with probability $p_{a,t}$, a probability that is changing with age a and across patent cohorts t. Once a patent holder is regulated he does not change his state. Equations (2.6) show the evolution of the regulatory state.

$$\begin{cases} Pr(\sigma_{a+1} = 1 | \sigma_a = 0) = p_{a+1,t} \\ Pr(\sigma_{a+1} = 0 | \sigma_a = 0) = 1 - p_{a+1,t} \\ Pr(\sigma_{a+1} = 1 | \sigma_a = 1) = 1 \end{cases} \tag{2.6}$$

Assumption 1

The probability of being regulated $p_{a,t}$ is weakly increasing over time, i.e. in a and t such that:

$$\begin{cases} p_{a-1,t} \leq \ p_{a,t} \\ p_{a,t-1} \leq \ p_{a,t} \end{cases} \tag{2.7}$$

A typical example of an environmental regulation fulfilling Assumption 1 would be one concerning stock pollutants.

Assumption 2

Patent holders do not anticipate environmental regulation.

$$\begin{cases} E[p_{a+1,t} | \sigma_a = 0] = 0 \\ E[p_{a+1,t} | \sigma_a = 1] = 1 \end{cases} \tag{2.8}$$

Assumption 2 might seem relatively strong, but it is in line with the work of Schankerman (1998), where agents do not anticipate the oil shock. In my case the plausibility of the assumption will have to be justified in the empirical implementation. A field of further research could be relaxing this assumption with the help of either some survey data or some prediction method, such as machine learning.

Having seen how one could model patent renewal and environmental regulation independently, I now combine the two models. To do so, I first need to specify the state variables of my model. Each period, the agent (patent holder) observes the per period returns realized x_a, the per period returns that she would receive had she been regulated y_a, and her regulatory status σ_a. The econometrician, instead, only observes if he has renewed a patent or not, the probability of being regulated $p_{a,t}$, and whether she belongs to Treatment Groups (T_1, T_2) or the Control Group (C). Given this setting, I have to consider the decision the agent faces depending on whether he is regulated or not.

Before being regulated

I first consider the decision problem the patent holder faces before being regulated ($\sigma_a = 0$). In this case, she not only has to form expectations about future realizations of per period returns but also needs to take into account future probabilities of being regulated.

$$V(x_a, y_a, \sigma_a) = max\{0\,,\ x_a + \beta\, E_{x,y,\sigma}[V(x_{a+1}, y_{a+1}, \sigma_{a+1})] - c_a\} \tag{2.9}$$

with $x_{a+1} = g_a^i x_a$

The patent holder will form expectations only taking into account the probability of being regulated next period.

$$\begin{aligned} E_{x,y,\sigma}[V(x_{a+1}, y_{a+1}, \sigma_{a+1})] =\ & p_{a,t}\ E_{x,y}[V(x_{a+1}, y_{a+1})] \\ & + (1 - p_{a,t})\ E_{x,y,\sigma}[V(x_{a+1}, y_{a+1}, \sigma_{a+1})] \end{aligned} \tag{2.10}$$

After being informed of the regulation

Two aspects need be considered in case the agent is informed of the regulation ($\sigma_a = 1$), first how being regulated affects the patent holder and also from where he obtains the information to know how regulation affects him.

I start with the information on how the regulation affects the technology owned by the patent holder. I model this information shock in a similar manner as Serrano (2018) models the arrival of transfer opportunities. In this case, I consider that the information on how the regulation affects the patent holder stems from last period's policy discussions. That is, the information shock took place in the previous period but since the patent holder is only informed to be regulated in the current period, he takes the draw g^e from the last period to rescale his current per period returns. This random variable g^e is drawn from the mixture with CDF F^{g^e} and represents the external growth returns, where with a certain probability returns either become zero (probability $1 - \gamma_e$), depreciate by an additional factor δ_e, or grow by a factor g^e, where the parameter σ^e measures the mean of the improvement factor. These draws are independent of patent age a.

I will now explain how being regulated affects him. In case the patent owner is informed to be regulated, the external growth returns factor g^e only affects him in the first period, in which he is regulated, thereby generating a change in levels of per period returns. For exposition purpose I define the variable α_a indicating whether his regulatory status changed from the last period to the current one. After this period the agent faces the simplest decision model of patent renewal: he then decides based only on the expected realization of his internal growth returns g^i.
At the introduction of the regulation, i.e., when $\sigma_a = 1$ and $\sigma_{a-1} = 0$, then $\alpha_a = 1$
$x_{a+1} = g^i_a y_a$ with $y_a = g^e x_a$

$$V(x_a, y_a) = max\{0\,,\, y_a + \beta\, E_x[V(x_{a+1})] - c_a\} \tag{2.11}$$

After the continuation of the regulation, i.e., when $\sigma_a = 1$ and $\sigma_{a-1} = 1$, then $\alpha_a = 0$
$x_{a+1} = g^i x_a$

$$V(x_a) = max\{0\,,\, x_a + \beta\, E_x[V(x_{a+1})] - c_a\} \tag{2.12}$$

Positive and negative impacts

The distribution of F^{g^e} presented in equation (2.1) is a general form of the impact of the environmental regulation on the current per period returns. Assuming that patent returns have been affected either positively or negatively, depending on the type of innovation, I will define two distributions stemming from the CDF of equation (2.1). In particular I define $F^{g^e,dirty}$ as the CDF of the random variable capturing the negative impact of the environmental regulation on the patent per period returns. Similarly I define $F^{g^e,clean}$ as the CDF of the random variable capturing the positive impact on patent returns.

Assumption 3 Regarding the CDFs of positively and negatively affected patents, I assume that $\gamma^e_{dirty} < \gamma^e_{clean} \leq 1$, $\delta^e_{clean} = 1$, and $\sigma^e_{dirty} < \sigma^e_{clean}$. Furthermore I assume that some of these parameters have fixed values, i.e.: $\sigma^e_{dirty} = 0$, $\gamma^e_{clean} = 1$, and $\delta^e_{clean} = 1$.

A direct consequence of Assumption 3 is that we can rewrite the CDFs of $F^{g^e,dirty}$ and $F^{g^e,clean}$ in the following simplified forms.

$$F^{g^e,dirty}(g^e) = \begin{cases} 1-\gamma^e_{dirty} & if\ g^e = 0 \\ 1-\gamma^e_{dirty} + \gamma^e_A \left[1 - exp\left(\frac{-1}{\sigma^e_{dirty}}\right)\right] & if\ g^e = 1 \end{cases} \tag{2.13}$$

So, we can simplify it to:

$$F^{g^e,dirty}(g^e) = \begin{cases} 1-\gamma^e_{dirty} & if\ g^e = 0 \\ 1-\gamma^e_{dirty} + \gamma^e_A & if\ g^e = 1 \end{cases} \tag{2.14}$$

$$F^{g^e,clean}(g^e) = 1 - exp\left(\frac{-g^e}{\sigma^{e,clean}}\right) \quad with\ g^e \geq \delta^e_{clean} \tag{2.15}$$

Proposition 1: Given the set of assumptions stated in Assumption (3) and the fact that g^e_a is a positive bounded random variable $g^e_a \in [0, B]$, then the CDF $F^{g^e,clean}$ first-order stochastically dominates the CDF $F^{g^e,dirty}$. This implies that:

$$F^{g^e,clean}(g^e) \leq F^{g^e,dirty}(g^e) \tag{2.16}$$

Proposition 2: For a certain patent age a, cohort t, and level of current per period returns x_a, given that $F^{g^e,clean}(g^e) \leq F^{g^e,dirty}(g^e)$, then $V^{clean}_a \geq V^{dirty}_a$.

Propositions 1 and 2 as well as their proofs build upon the works of Serrano (2018) and Ganglmair and Reimers (2019).

2.4 Estimation Method

In this section I present the estimation method, which is divided in three parts. First, I present the estimation challenges and the main statistics that I can build of existing data. Second, I present the estimation routine, which consists of two steps. Finally, I define and formalize the different sources of measurement error.

2.4.1 Estimation Challenge

The objective of the estimation is to recover estimates of the following vector of 18 parameters $\omega = (\gamma_i, \sigma^i, \phi^i, \delta_i, \gamma^e_{dirty}, \sigma^e_{clean}, \mu, \sigma_R, b_{C,1}, b_{C,2}, b_{C,3}, b_{C,4}, b_{C,5}, b_{C,6}, b_{C,7}, b_{C,8}, b_{C,9}, b_{C,10})$, where as in Pakes (1986), I assume a fixed discount factor β of 0.9. Particularly important are the parameters γ^e_{dirty} and σ^e_{clean}, which are responsible for quantifying the monetary impact of the environmental regulation on patent value.

Unitary patent data does not contain information regarding whether an environmental regulation has affected or not a particular patent. That is, the information regarding when an environmental regulation might have affected a particular patent and whether the impact of the regulation has been positive or negative to the value of that patent (proxied by patent renewal) is not directly available in the patent data. If this information was available I could have used the hazard rates of the patents that were to be regulated, but hadn't been yet, to estimate all parameters except γ^e_{dirty} and σ^e_{clean}, and the hazard rates of those patents that are regulated to estimate γ^e_{dirty} and σ^e_{clean}. Nevertheless the only information available to the econometrician is at best, what is presented in Proposition 3.

Proposition 3: Given some external empirical evidence, there exists either a positive or a negative significant shock (or both) on the patent returns of the patents of the Treatment Group in year Υ. The Treatment Group being defined as a group of patents similar in all characteristics to another group of patent (Control Group), except that the latter is not affected by the regulation.

Given that the best available information for the econometrician regarding when the regulation affected certain patents is summarized in Proposition 3, I develop a method assuming the existence of three groups of patents. Namely, two Treatment Groups $T = \{1\}$ and $T = \{2\}$, and a Control Group $C = \{0\}$, built upon supporting empirical evidence that patents from $T = \{1\}$ have been affected negatively by the environmental regulation and patents of $T = \{2\}$ positively compared to the Control Group $C = \{0\}$.

Fundamental Problem of Causal Inference: Need for a Synthetic Control

Taking the data framework described above, one cannot use the patents from the Treatment Group to identify the structural parameters driving patent renewal in the absence of environmental regulation since we don't know what would have been the fate of the Treatment Group patents' had there been no regulation. We are therefore facing the fundamental problem of causal inference. In order to solve this problem we need to take a synthetic control group approach and simulate what would have been the renewal pattern of the Treatment Group patents in the absence of an environmental regulation.

Construction of Estimation Statistics

Since I want to perform an estimation using a simulated method of moments (SMM) approach in the spirit of Deng (2007), I need to build the simulated and the sample hazard rates. I build two types of hazard rates from two different groups of patents that I use to estimate my parameters. First I compute the simulated hazard rate for those patents that cannot be directly affected by the regulation $\pi^s_{nr}(a,t)$ to elapse at a given age a being from cohort t. I compute the sample equivalent $\pi_{nr}(a,t)$ using the patents from the Control Group as described above. Second I compute the simulated hazard rate for age a of the patents that could have been affected by the regulation $\pi^s_r(a,t)$. For these patents I compute the sample equivalent using the patents of the Treatment Groups.

In the model presented in the former section, I am considering two types of decision problems, depending on whether or not the external growth returns factor needs to be taken into account in the decision to renew the patent. For this reason, I define two types of cutoff values. First for the patents that cannot be regulated, we have only one type of cutoff value $\hat{x}^{nr}_a$. Second for the patents that might have been regulated, we have two cutoff values $\hat{x}^r_a$ and $\hat{y}^r_a$, the latter being the cutoff returns in the period where the patent holder receives the information that he is regulated τ. Finally, before estimating the model I specify the simulated hazard rates for the two types of patents (following Deng (2011) and Serrano (2005)).

I define the initial draw of per period returns specific to cohort t, where $b_{C,t}$ is the cohort-specific coefficient of the cohort dummy D_t.

$$x_{t,1} = exp(b_{C,t}D_t + \xi) \tag{2.17}$$

$$\xi \sim N(\mu, \sigma_R^2) \tag{2.18}$$

Hazard rates for non regulated patents

As in Serrano (2005) and Deng (2011), I first define the proportion of patent holders renewing the patent at age a from cohort t, for the non-regulated patents as:

$$1 - H_{a,t}(\hat{x}_{t,a}^{nr}) = Pr\Big\{x_{t,a}^{nr} \geq \hat{x}_{t,a}^{nr}, x_{t,a-1}^{nr} \geq \hat{x}_{t,a-1}^{nr}, ..., x_{t,1}^{nr} \geq \hat{x}_{t,1}^{nr}\Big\} \tag{2.19}$$

Where $H_{a,t}(\hat{x}_{t,a}^{nr})$ is the CDF of the returns $x_{t,a}$ given the initial distribution of returns of $x_{t,a=1}$ and the conditional distribution of growth returns of g^i. So it is the probability that the random variable $x_{t,a}^{nr}$ is below $\hat{x}_{t,a}^{nr}$ in period a. Now I compute the hazard rate as the proportion of patents expiring at age a and cohort t from those having renewed for the same cohort until age $a - 1$.

$$\pi_{nr}^{s}(a,t) = \frac{H_{a,t}(\hat{x}_{t,a}^{nr}) - H_{a-1,t}(\hat{x}_{t,a-1}^{nr})}{1 - H_{a-1,t}(\hat{x}_{t,a-1}^{nr})} \tag{2.20}$$

Hazard rates for patents that can be regulated

For the patents that can be regulated I summarize the possible states in which a patent holder can be by the variable j, which can take three values, $\{1, 2, 3\}$ in a given cohort t and age a, with:

$$\begin{cases} j = 1 & \equiv \quad \sigma_{t,a} = 0 \\ j = 2 & \equiv \quad \sigma_{t,a} = 1, \alpha_{t,a} = 1 \\ j = 3 & \equiv \quad \sigma_{t,a} = 1, \alpha_{t,a} = 0 \end{cases}$$

With this I can define the following proportions of patent holders not paying the renewal fees in age a and cohort t, being in state 1, 2 or 3 and having been in the former periods in some state $j \in \{1, 2, 3\}$.

$$\begin{cases} H_{a,t}(\hat{x}^r_{t,a}, 1) = & Pr\Big\{x^r_{t,a,1} \leq \hat{x}^r_{t,a,1}, x^r_{t,a-1,j} \geq \hat{x}^r_{t,a-1,j}, ..., x^r_{t,1,j} \geq \hat{x}^r_{t,1,j}\Big\} \\ H_{a,t}(\hat{y}^r_{t,a}, 2) = & Pr\Big\{y^r_{t,a,2} \leq \hat{y}^r_{t,a,2}, x^r_{t,a-1,j} \geq \hat{x}^r_{t,a-1,j}, ..., x^r_{t,1,j} \geq \hat{x}^r_{t,1,j}\Big\} \\ H_{a,t}(\hat{x}^r_{t,a}, 3) = & Pr\Big\{x^r_{t,a,3} \leq \hat{x}^r_{t,a,3}, x^r_{t,a-1,j} \geq \hat{x}^r_{t,a-1,j}, ..., x^r_{t,1,j} \geq \hat{x}^r_{t,1,j}\Big\} \end{cases} \tag{2.21}$$

I define the proportion of patent holders renewing a patent at age a from cohort t, for those patent holders that are not regulated, ($j = 1$), as:

$$\begin{split} 1 - H_{a,t}(\hat{x}^r_{t,a}, p_{a,t}, \sigma_{t,a} = 0) = Pr\Big\{x^r_{t,a} \geq \hat{x}^r_{t,a}, x^r_{t,a-1} \geq \hat{x}^r_{t,a-1} \\ , ..., x^r_{t,1} \geq \hat{x}^r_{t,1}\Big\} \end{split} \tag{2.22}$$

I define the proportion of patent holders renewing a patent at age a from cohort t, for those patent holders that are regulated in age $\tau = a$, ($j = 2$), as:

$$\begin{split} 1 - H_{a,t}(\hat{x}^r_{t,a}, \hat{y}^r_{t,a}, p_{a,t}, \sigma_{t,a} = 1, \alpha_{t,a} = 1) = Pr\Big\{y^r_{t,a} \geq \hat{y}^r_{t,a}, ... \\ , x^r_{t,1} \geq \hat{x}^r_{t,1}\Big\} \end{split} \tag{2.23}$$

I define the proportion of patent holders renewing a patent at age a from cohort t, for those patent holders that have been regulated at age $\tau < a$, ($j = 3$), as:

$$\begin{aligned} 1 - H_{a,t}(\hat{x}^r_{t,a}, \hat{y}^r_{t,a}, p_{a,t}, \sigma_{t,a} = 1, \alpha_{t,a} = 0) =& Pr\Big\{ x^r_{t,a} \geq \hat{x}^r_{t,a}, ..., \\ & y^r_{t,\tau} \geq \hat{y}^r_{t,\tau}, ..., x^r_{t,1} \geq \hat{x}^r_{t,1} \Big\} \end{aligned} \tag{2.24}$$

I define the proportion of patent holders renewing a patent at age a from cohort t, for the regulated patents, as:

$$1 - H_{a,t}(\hat{x}^r_{t,a}, \hat{y}^r_{t,a}, p_{a,t}, \sigma_{t,a}, \alpha_{t,a}) = 1 - [H_{a,t}(\hat{x}^r_{t,a}, 1) + H_{a,t}(\hat{y}^r_{t,a}, 2) + H_{a,t}(\hat{x}^r_{t,a}, 3)] \tag{2.25}$$

Now I compute the hazard rate as the proportion of patents expiring at age a and cohort t from those having renewed for the same cohort until age $a-1$.

$$\pi^s_r(a,t) = \frac{H_{a,t}(\hat{x}^r_{t,a}, \hat{y}^r_{t,a}, p_{a,t}, \sigma_{t,a}, \alpha_{t,a}) - H_{a-1,t}(\hat{x}^r_{t,a-1}, \hat{y}^r_{t,a-1}, p_{a-1,t}, \sigma_{t,a-1}, \alpha_{t,a-1})}{1 - H_{a-1,t}(\hat{x}^r_{t,a-1}, \hat{y}^r_{t,a-1}, p_{a-1,t}, \sigma_{t,a-1}, \alpha_{t,a-1})} \tag{2.26}$$

2.4.2 Estimation Routine

For the estimation of my model I proceed in two steps. In the first step I estimate all parameters except the ones governing my regulatory shocks γ^e_{dirty} and σ^e_{clean}, for this I use the patents from my Control Group sample N_0. In the second step I estimate the two remaining parameters using my Treatment Group patents N_1 and N_2[1]. For both, the first and the second steps I only use the moments from the year Υ of the empirically shown shock onwards.

First Step: Structural Estimation of the Control Group parameters

In the first step I solely estimate the parameters related to g^i and the cohort-specific dummies of the initial draw of per period returns using the patents from the Control Group. With this, I estimate the following vector of parameters: $w_C = (\gamma_i,\ \sigma^i,\ \phi^i,\ \delta_i,\ \mu,\ \sigma_R,\ b_{C,1},\ b_{C,2},\ b_{C,3},\ b_{C,4},\ b_{C,5},\ b_{C,6},\ b_{C,7},\ b_{C,8},\ b_{C,9},\ b_{C,10})$. For this I do a first structural estimation using only the patents from my Control Group N_0.

---

[1] Note that $N = N_0 + N_1 + N_2$

Equations (2.20) and (2.26) provide the moment conditions for the estimation, as shown in equation (2.27). As in Deng (2011) I stack up the hazard probabilities for all cohort-age-type as simulated by the model into an a vector $\pi(\omega_C)$. I compute the sample equivalents of those simulated hazards and stack them into a vector π_{N_0}, where N_0 is the sample size.

$$E\Big[\pi_{N_0} - \pi(\omega_C)\Big] = 0 \tag{2.27}$$

I then estimate the model with the SMM estimator $\hat{\omega}_N^C$ of the true parameter vector ω_o^C. With:

$$\hat{\omega}_N^C = \underset{\omega^C}{arg\ min} || \pi_{N_0} - \widetilde{\pi_{N_0}}(\omega_C) ||_{W_N(\omega_C)} \tag{2.28}$$

$$W_N(\omega_C) = diag(\sqrt{n/N}) \tag{2.29}$$

, where, as in Deng (2011), $\widetilde{\pi}(\omega)$ is the vector of the simulated estimates given the parameters ω_C. $W_N(\omega_C)$ is a semi-definite weighting matrix. For computational purposes I follow Deng (2007) and Lanjouw (1998), and instead of using the inverse of the asymptotic variances of the moment conditions or the simulated estimates as a weighting matrix, I use their proposed substitute (see equation 2.29). It is a semi-definite weighting matrix, where n is the relative size of the cell versus the size of the whole sample N.

Assumption 4

I assume that patents from my Treatment Groups (T_1, T_2) would have had a similar renewal pattern compared to the patents from the Control Group, had there been no regulation.

This implies that the parameters of the internal growth returns g^i are the same for regulated and non-regulated patents and that the cohort-specific initial draw of per period returns is also identic. Therefore I can assume the estimated vector of parameters from my first step $\hat{\omega}^C$ for the second step.

Assumption 5

I assume that the first step solution $\hat{\omega}^C$ must be able to accommodate the second step shock following the ex-ante provided evidence, i.e.:

$$\begin{cases} \gamma^e_{dirty} < 1 & if\ a\ negative\ significant\ shock\ exists \\ \sigma^e_{clean} > 0 & if\ a\ positive\ significant\ shock\ exists \end{cases}$$

Second Step: Structural Estimation of the Impact of the Environmental Regulation - Deviations from the Control Group Simulations

Following Assumption 4, I use the parameter estimates from the first step and take them as given to perform the second structural estimation using only the patents from my treatment groups (T_1, T_2) to estimate the parameters capturing the positive and the negative impact: $\omega_T = (\hat{\omega}_C, \gamma^e_{dirty}, \sigma^e_{clean}) = (\gamma^e_{dirty}, \sigma^e_{clean})^2$. As for the first step, I compute the sample equivalents of the simulated hazards and stack them into a vector π_{N_T}, where $N_T = N_1 + N_2$.

$$E\Big[\pi_{N_T} - \pi(\omega_T)\Big] = 0 \tag{2.30}$$

I then estimate the model with the SMM estimator $\hat{\omega}^T_N$ of the true parameter vector ω^T_o. With:

$$\hat{\omega}^T_N = \underset{\omega^T}{arg\ min} ||\pi_{N_T} - \widetilde{\pi_{N_T}}(\omega_C)||_{W_N(\omega_T)} \tag{2.31}$$

Nevertheless, given that the objective of the estimation is to disentangle the unobserved heterogeneity due to the environmental regulation, we need to do further adjustments. For this reason I propose to use a new weighting matrix, with the following formula:

$$W_N(\omega_T) = diag(\sqrt{w^T_{t,a}}) \tag{2.32}$$

Where T refers to the treatment type ("1" for the Treatment Group patents possibly affected negatively "*dirty*", and "2" for the Treatment Group patents possibly positively affected "*clean*"), a to the patent age, and t to the patent cohort. Furthermore j refers to

---

[2] We use $\hat{\omega}_C$ estimated in the first step.

the 3-digit level main patent IPC (International Patent Classification) class, and $n^T_{t,a,j}$ to the number of patents still alive at a certain patent age a, from a given cohort t, and from a specific IPC class j .

$$w^T_{t,a} = \alpha^T \beta^T_t \Big(\frac{\gamma_{t,1} n^T_{t,a,1} + ... + \gamma_{t,j} n^T_{t,a,j} + ... + \gamma_{t,J} n^T_{t,a,J}}{N} \Big) \tag{2.33}$$

With:

$$\alpha^T = \frac{N - N_0}{2} \frac{1}{N_T} \tag{2.34}$$

$$\beta^T_t = \frac{N^0_t}{N_0} \frac{N_T}{N^T_t} \tag{2.35}$$

$$\gamma_{t,j} = \frac{N^0_{t,j}}{N^0_t} \frac{N^T_t}{N^T_{t,j}} \tag{2.36}$$

This new weighting matrix aims at doing three types of adjustments. First with α^T, I adjust for the relative weight of the samples N_1 and N_2 versus N_0, such that the contribution of the moments related to N_1 and N_2 is for each $\frac{N-N_0}{2}$. The second adjustment done through β^T_t aims at having the same cohort contribution for the cohorts of the Treatment and Control Groups. Finally the adjustment done with $\gamma_{t,j}$ seeks to control for the IPC class composition within each cohort between each one of the Treatment Groups and the Control Group. I adjust for the relative contribution of the IPC class j to the cohort t of the sample N^T with respect to the relative contribution of the IPC class j of the cohort t of the Control Group.

2.4.3 Measurement Error

The estimation method that I have just presented allows us to overcome the fundamental problem of causal inference and provide a first order approximation to the impact of the environmental regulation on patent value. Yet, this approximation comes at a cost, i.e. the measurement error. In order to understand to which extent this error might influence our results, I will explain the two parts that compose it.

The first component of the measurement error is the structural error stemming from the inability of a structural model to perfectly generate the empirical moments even with ideal patent data, i.e. without the need for a synthetic control. The second component is the error due to the use of a synthetic control approach. This is illustrated in equation (2.37), where the first term in the right handside represents the structural error and the second term the synthetic control group error, whereas the left handside is the current error from this method.

$$\begin{aligned} ||\pi_{N_T} - \widetilde{\pi_{N_T}}(\hat{\omega}_C, \gamma^e_{dirty}, \sigma^e_{clean})|| = & ||\pi_{N_T} - \widetilde{\pi_{N_T}}(\omega_T^{real})|| + \\ & ||\widetilde{\pi_{N_T}}(\omega_T^{real}) - \widetilde{\pi_{N_T}}(\hat{\omega}_C, \gamma^e_{dirty}, \sigma^e_{clean})|| \end{aligned} \tag{2.37}$$

As presented in Andrews et al. (2017) parameter estimates from moment estimations, among others from simulated method of moments estimations, can be sensitive to the selected moments used. Given that my method combines a structural model and a synthetic control group approach, with the two sources of error just mentioned, a further robustness check of the estimation results in the spirit of Andrews et al. (2017) could be highly valuable. It could help us disentangle whether the monetary impact estimated by the model is mainly driven by the results of some specific cohorts or if it is an average effect across the different ones.

Finally, the modelling choice of the negative impact can also contribute to the structural error. Given the general functional form of the external per period returns $F^{g^e}(g^e)$ (see Equation 2.1), there are two ways of modelling a negative impact, either through an additional depreciation rate δ_e or through the obsolescence rate γ_e. Schankerman (1998) decided to model the oil shock through an additional depreciation rate, I instead chose the obsolescence rate γ_e for one reason. Namely, that this method aims at capturing a shock in one year, which is easily modelled and rationalized through γ_e than through δ_e. The latter could lead to increased hazard rates in the years following the shock but has the advantage of easily capturing smaller shocks that would lead instead to $\gamma_e = 1$.

2.5 Conclusion

In this chapter I propose a method to estimate the technological monetary impact of an environmental regulation on patent value. My method builds upon the work of Serrano (2018) and combines a structural model with a synthetic control approach to generate control group counterfactuals. This approach needs several assumptions such as monotonicity of environmental policy or the lack of patent holder expectations regarding the upcoming regulation. The first assumption is easy to hold in stock pollutants' settings and could allow us to transpose the method to other events with a "point of no return" nature. Regarding the second assumption, it could be relaxed with some additional data, such as survey data. The third assumption would be difficult to relax since identification requires the existence of a shock in time for each type of technology, which could hardly be positive and negative at the same time for the same type of technology. Only the functional form of the negative shock could be modified as suggested in the measurement error section. The fourth and fifth assumptions are more difficult to relax since they help us overcome the fundamental problem of causal inference.

There are three points that are worth being remembered regarding the use of this method. A first point is that this method is empirical and as such it needs to build upon empirical evidence, therefore it requires a thorough analysis of the impact of the regulation on different proxies for patent value, like patent citations or patent renewal. In this sense any additional evidence regarding the impact of the environmental regulation on patent value, through other methods, like the Kogan et al. (2017) approach or others, can only provide further robustness to the potential findings. A second point is that this method could contribute to quantify the double externality that environmental innovations are suffering in the lack of an environmental regulation. Finally, it is worth remembering that the validity and robustness of the estimation results depends on two main points: the accuracy of the first step estimation and the sensitivity of the parameters to particular moments, in particular for the second step. Therefore, in any implementation it would be crucial to discuss these two issues. In the next chapters I will first provide empirical evidence of the impact of an environmental regulation on difference measures of patent value (Chapter 3) and present an implementation of this method in Chapter 4, given the empirical evidence and the dataset presented in Chapter 3.

2.6 Appendix: Proofs

2.6.1 Proofs of Proposition 1 and Proposition 2

Proposition 1: Given the set of assumptions stated in Assumption (3) and the fact that g_a^e is a positive bounded random variable $g_a^e \in [0, B]$,then the CDF $F^{g^e,clean}$ first-order stochastically dominates the CDF $F^{g^e,dirty}$. This implies that $F^{g^e,clean}(g^e) \leq F^{g^e,dirty}(g^e)$.
Proof:

In order to prove first-order stochastic dominance one only needs to show that the CDF $F^{g^e,clean}(g^e)$ lies on or to the right of the CDF $F^{g^e,dirty}(g^e)$. For this to be true, we can take $g^e = 1$, where $F^{g^e,dirty}(g^e = 1) = 1$ and $F^{g^e,clean}(g^e = 1) = 0$.

Proposition 2: For a certain patent age a, cohort t, and level of current per period returns x_a, given that $F^{g^e,clean}(g^e) \leq F^{g^e,dirty}(g^e)$, then $V_a^{clean} \geq V_a^{dirty}$.
Proof:

Knowing that:

$$\begin{aligned} E[V_{a+1}^{dirty}] =& E[V_{a+1}^{dirty}(x_{a+1}, y_{a+1}, \sigma_{a+1}|\sigma_a)] \\ =& \iint V_{a+1}^{dirty}(x_{a+1}, y_{a+1}, \sigma_{a+1}) f_a^i(g^i) f_{a,t}^{e,dirty}(g^e) dg^i dg^e \end{aligned}$$

Then

$$E[V_{a+1}^{clean}] \geq E[V_{a+1}^{dirty}]$$

Which implies by the definition of the value function:

$$V_a^{clean} = max\{0\, ,\, x_a + \beta\, E_{x,y,\sigma}[V^{clean}(x_{a+1}, y_{a+1}, \sigma_{a+1})] - c_a\} \tag{2.38}$$

That by symmetry:

$$V_a^{clean} \geq V_a^{dirty}$$

3 International Environmental Agreements and the Timing and Direction of Technological Change: Evidence from the Kigali Amendment*

3.1 Introduction

Today, we are facing a tremendous environmental challenge as we have never seen before. Germany needs to reduce its emissions by 65 percent by 2030 and achieve net greenhouse gas neutrality by 2045 (BMUV, 2021). Similarly, the EU has pledged to reduce emissions by 55 percent by 2030 and achieve greenhouse gas neutrality by 2050 (EU COMM, 2021). To meet these targets and achieve emission reductions, clean technologies are key. Moreover, it is not sufficient to direct innovation towards clean technologies, this process needs to be accelerated.

Since Hicks (1932), we know that environmental regulation by the increasing prices of dirty factor inputs would induce innovation towards more efficient utilization of those factors. Recently, Aghion et al. (2016) showed that an increase in fuel prices directed technological change from dirty to clean technologies by generating a negative effect on dirty innovations and a positive one on clean technologies. However, little is known about the timing of these effects and, in particular, of the relative shifts of dirty versus clean technologies.

Relative shifts in the direction of technological change are important since they are associated with the relative growth of clean versus dirty innovations and are the key to ensure a sustainable technology path (Langer et al., 2022). Research has shown that clean innovation responds to higher energy prices within a range of five years (Dechezleprêtre and Hémous, 2022). However, little is known of the relative response. Only the intuition that clean and dirty technologies are affected in a different manner from the market's

---

*I would like to thank Florence Blandinières, Thorsten Doherr, Robert Germeshausen, Timo Goeschl, Georg Licht, Mar Reguant, Carlos Serrano, and Ulrich Wagner for their helpful feedback and comments. Furthermore, I am grateful to Geert Boedt from the European Patent Office for providing latest update from PATSTAT on renewal data. The usual disclaimer applies.

"short-termism" (Dechezleprêtre and Hémous, 2022), i.e., that clean technologies' market is on the long-run whereas dirty technologies' one is on the short-run. This paper aims to shed further light on this question by providing first evidence. To do this, I study the timing of the shocks on the incentives to innovate in clean and dirty technologies for the case of an international environmental agreement (IEA).

In particular, I study the impact of an IEA on incentives to innovate, i.e., how the signature of the Kigali Amendment (2016) to the Montreal Protocol affected the private value of clean and dirty innovations over time. To do this, I build a unique dataset of patents citing dirty substances that are regulated under the Kigali Amendment and patents mentioning their clean substitutes. Furthermore, I adapt a nonparametric duration framework developed by van den Bergh et al. (2020), to patent data, which allows me to study the temporal dimension of the IEA's impact on clean and dirty incentives to innovate.

This paper is organized in the following manner. In sections 2 and 3, I summarize the existing literature and introduce the regulatory framework of study. In section 4, I present the dataset and descriptive statistics. In section 5, I describe the different empirical analyses performed in the paper, first using a panel event study framework and later within a nonparametric duration model setting. Finally, I summarize my findings in section 6.

3.2 Literature Review

This chapter is linked with four strands of the existing literature. First, to the literature on directed technological change, which builds upon the work of Hicks (1932), followed by, among others, Acemoglu (1998; 2002), and Acemoglu et. al (2012). Early evidence on directed technological change and environmental regulation is provided by Lanjouw and Mody (1996), Brunnermeier and Cohen (2003), and specifically on directed technological change driven by energy prices by the works of Newell et al. (1999) and Popp (2002). Newell et al. (1999) develop a method for testing Hicks' induced innovation hypothesis using product characteristics of durable goods and energy prices. Popp (2002) focuses on patent data of energy efficient innovations and estimates the effect of energy prices on patents. He finds a positive effect of prices and the quality of previous knowledge on clean innovations. More recently this literature has been extended with the works of Calel and Dechezleprêtre (2016) and Aghion et al. (2016). The formers studying the impact of the European Union Emissions Trading System (EU ETS) on technological change provide evidence that it increased clean innovations. Aghion et al. (2016) scrutinizing the impact of higher fuel prices on clean and dirty innovations in the automotive industry find that higher prices lead to fewer dirty innovations and more clean ones. Furthermore, they simulate the required increases in carbon taxes such that innovations in clean technologies reach dirty innovations.

The second strand of the literature to which my work relates is the timing of directed technological change. As discussed previously, this issue has not been directly studied yet. Recently, however, Hémous and Dechezleprêtre (2022) have summarized the main results on the innovation's reaction to an increase in energy prices, which they obtained from findings of diverse works on energy prices and the direction of technological change. Gathering the so far found patent-to-price elasticities they conclude that the reaction of clean innovations on a price increase occurs within the first five years.

The third strand of the literature that my work is related to includes the study of the relation between IEAs and the direction of technological change. This last strand is scarce and consists of the works of Dekker et al. (2012) and Dugoua (2021). In their seminal paper, Dekker et al. (2012) study the impact of an IEA on the direction of technological change. They find that the Convention on Long-Range Transboundary Air Pollution provided incentives for firms to innovate in clean technologies by reducing investment uncertainty. More recently Dugoua (2021) studied the impact of the signature of the Montreal Protocol on innovation employing a synthetic control group method. Using patents and scientific articles as proxies for inventive activity, the author finds that the IEA induced clean innovations.

Finally, my work is also related to the still sparse literature on clean patent valuation. Hall and Helmers (2013) study the differences in value of pledged patents under the "Eco-Patent Commons" to other patents of the same firm or technology field. Using various proxies for patent value within patent characteristics, they find that pledged patents have a similar value to other patents of the same firm but a lower value than other patents in the same field. Dechezleprêtre et al. (2021a; 2021b) in their work use the Hall et al. (2005) market-based patent valuation approach and find that clean innovations have higher value than dirty ones comparing renewable energy generation and electric cars innovations versus fossil fuel energy production and combustion engines ones. Finally, Langer et al. (2022) use in their recent paper the Kogan et al. (2017) patent valuation approach to study the impact of financial constraints on the value of clean and dirty innovations. They find that a shock on financial constraints reduced the relative share of clean versus dirty technologies since the former were perceived to be riskier.

3.3 Regulatory Framework: The Kigali Amendment to the Montreal Protocol

The Kigali Amendment to the Montreal Protocol was signed on October 15, 2016 and entered into force on January 1, 2019. The primary goal of the Kigali Amendment was to phase-down and phase-out a particular family of greenhouse gases known as hydrofluorocarbons (HFCs). HFCs are gases with refrigerant properties widely used in air-conditioning and refrigeration devices, but with a high 100-year global warming potential (Appendix 1.1 Annex F). They belonged to a group of greenhouse gases targeted by the Kyoto Protocol (UNFCCC, 1997), with limited success. They were principally developed to replace substances regulated under the Montreal Protocol on Substances that Deplete the Ozone Layer (Montreal Protocol) (Sun and Ferris, 2018). The Montreal Protocol was signed in 1987 and enforced in 1989. It aimed at phasing-out ozone-depleting substances (ODSs), such as the chlorofluorocarbons (CFCs). Some of the initial substitutes, the hydrochlorofluorocarbons (HCFCs), were still ODSs with a smaller ozone depleting potential and had to be replaced by other substances, including the HFCs. In a letter to the President of the United States in June 15. 2009, the ambassadors of The Federated States of Micronesia, Republic of Marshall Islands, Republic of Fiji Islands, and Papua New Guinea asked Barack Obama to regulate and phase down HFCs under the Montreal Protocol (as reported in the online newspaper *Inside Climate News* (Sassoon, 2009)). Since then, discussions on the possible regulation of the HFCs under the Protocol took place at regular policy meetings, which finally led to the agreement achieved in 2016. By November 2017, the minimum threshold for enforcement of 20 countries was achieved, and in 2018, it was ratified by the European Union. Nevertheless, it was not until 2021 that through a joint statement, the U.S. and China pledged to implement it (DOS, 2021). In Appendix 1.1, I list the substances regulated under the Montreal Protocol and in Appendix 4, I provide the phase-down schedules for HCFCs and HFCs.

3.4 Data

3.4.1 Dataset Construction

Patent Selection

The goal of my analysis is to study the impact of the signature of the Kigali Amendment on patent value, proxied by the renewal decision and the number of forward citations. For this purpose what is key is to have two comparable patent groups one that is affected by the regulation and another that is not. In order to identify patents that are affected by the regulation I will exploit the fact that patents cite chemical substances and that the Kigali Amendment aimed at phasing down and out some particular greenhouse gases developed as replacement solution for substances that had to be phased out under the Montreal Protocol.

Therefore, my starting point will be to query the substances targeted by the Kigali Amendment, which I report in Appendix 1 (UNEP, 2019). From those substances I will only focus on the ones used as refrigerants. Substances that can be used as refrigerants are clearly defined and listed in technical standards such as the ANSI/ASHRAE[1] Standard 34-2019 (ASHRAE, 2019). I also list in Appendix 1 substances included in the refrigerant's standard. Furthermore, the technical standard provides an additional key information for my analysis, namely it includes not only the refrigerating substances that were regulated under the Kigali Amendment but also their potential replacements, i.e. alternative substances that can also be used as refrigerants but are not regulated under the Kigali Amendment. Combining these two sources of information will allow me to identify not only the negative effect of the environmental regulation on the patents citing pollutants but also the positive one on patents citing potential substitutes.

---

[1] ANSI stands for the "American National Standards Institute" and ASHRAE refers to the "American Society of Heating, Refrigerating and Air-Conditioning Engineers".

Molecular Formula	$C_4H_2F_6$
Condensed Formula	$CF3CH = CHCF3$
Chemical Name	trans-1,1,1,4,4,4-hexafluoro-2-butene
Trade / Technical Name	R-1336mzz(E)

Table 3.1: Main types of chemical substances names

SMILES	$C(=CC(F)(F)F)C(F)(F)F$
Isomeric SMILES	$C(=C/C(F)(F)F)\ C(F)(F)F$
InChI	$InChI = 1S/C4H2F6/c5-3(6,7)1-2-4(8,9)10/h1-2H$
InChI Key	NLOLSXYRJFEOTA-UHFFFAOYSA-N

Table 3.2: Chemical Substances machine-readable names

For doing this the first and key step is to find all patents that cite certain chemicals. In particular for the case of the Kigali Amendment, I will restrict my attention to the substances regulated by the Montreal Protocol that have been used as refrigerants, which includes some CFCs, HCFCs and HFCs. In order to collect all the patents mentioning substances regulated under the Montreal Protocol, I first obtain the provided molecular formula or condensed formula together with the technical name from the Handbook of the Montreal Protocol (UNEP, 2019)[2]. In Table 3.1. I provide an overview of the main types of chemical names that substances can have, which are also the ones that I use for my data selection. Furthermore, a chemical substance might have different isomers that cannot be differentiated from the list provided by the Handbook of the Montreal Protocol but that would have been also regulated by it. Therefore, I use the molecular formula or condensed formula provided together with the technical name to query PubChem[3][4]. I identify the

---

[2] Chemical substances can be written in several ways, e.g.: they have a chemical name (trans-1,1,1,4,4,4-hexafluoro-2-butene), a molecular formula ($C_4H_2F_6$), and might also have a condensed formula ($CF_3CH = CHCF_3$) and a trade or technical name (R-1336mzz(E)).

[3] PubChem is a database built out of three different interlinked databases: ”PubChem Substance”, ”Pubchem BioAssay”, and ”PubChem Compound”. The ”PubChem Substance” database provides information given by individual contributors on chemical substances. Then PubChem has created an automatic process to compile the information provided by the individual contributors into a unique database. The ”PubChem Compound” database is generated first checking the validity of the chemical structure provided by the contributors and then normalizing the chemical representations thereby creating a unique standardized chemical structure. Once this standardized chemical structure is created they compute some general molecular properties such as the molecular weight and generate further chemical identifiers such as SMILES and InChI (Kim et al., 2016).

[4] SMILES stands for ”Simplified Molecular-Input Line-Entry System” and was developed in 1986

corresponding molecule in PubChem and download all patents linked through the InChI Key[5] from Patentscope. Then I also identify all possible stereoisomers[6] from this molecule and download all the patents via Patentscope. Similarly, I select the patents related to any substance that can be used as a refrigerant using the list of possible refrigerants from the ANSI/ASHRAE Standard 34-2019 (ASHRAE, 2019) (see Appendix 1). In Table 3.2 I provide examples of the most common machine-readable chemical names, which I use to differentiate between different isomers and stereoisomers.

Treatment and Control Groups

My primary data source are granted patents filed at the European Patent Office (EPO) extracted from the database (PATSTAT) and the computed patent-specific characteristics from the OECD patent datasets (Squicciarini et al., 2013). For my dataset construction I will focus on European patents renewed in Germany and from some C and F IPC[7] classes. I first select all European patents with renewal fees paid in Germany citing the regulated substances (i.e. substances listed in Appendix 1.1 Annex F) that are also listed as refrigerants in the ANSI/ASHRAE Standard 34-2019 (Appendix 1.2) and having either a C or a F IPC class as their main class. This gives us a set of patents citing regulated substances under the Kigali Amendment, which I define as T_I and a vector of their IPC classes that I list in Appendix 2.

---

by David Weininger at the U.S. Environmental Research Laboratory. It encodes stereochemistry in a human-readable way and is used as a general-purpose chemical nomenclature (SMILES, 2020, July 10) (O'Boyle, N.M., 2012).

[5] The InChI stands for "International Chemical Identifier" and was developed in 1999 together by the IUPAC (International Union of Pure and Applied Chemistry) and the National Institute of Standards and Technology (NIST). The InChI aims to provide a unique identifier for chemical substances (O'Boyle, N.M., 2012) (IUPAC, 2020, July 10). The InChI Key is a compact chemical identifier derived from the InChI that has always only 27 characters (Heller et al., 2015).

[6] I identify the stereoisomers by selecting all the molecules having the same SMILES as the original molecule identified previously but having a different Isomeric SMILES, i.e. those having isotopic and chiral specifications (SMILES, 2020, July 10).

[7] IPC stands for International Patent Classification, C section includes Chemistry and Metallurgy, and F section includes Mechanical engineering, lighting, heating, weapons, and blasting.

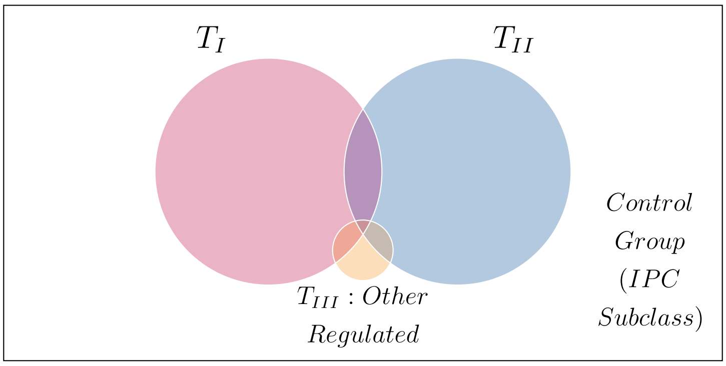


Figure 3.1: Treatment and Control Groups

Before defining my treatment and control groups I will define three sets of patents citing chemical substances in relation to T_I, i.e. T_{II}, and T_{III}, and will build my treatment and control groups with respect to them. The set T_{II} comprises those patents mentioning refrigerant substances not regulated under the Montreal Protocol, i.e. those patents that would be potentially positively affected by the Amendment's negotiations (substances from Appendix 1.2 that don't appear in Appendix 1.1). Finally, the last set of patents is T_{III}, which corresponds to patents mentioning substances regulated under the Montreal Protocol that are not HFCs (i.e. substances from Appendix 1.1 others than the ones included in Annex F). Using these three sets I define my treatment groups as: the set $T_1 = T_I \backslash ((T_I \cap T_{II}) \cup (T_I \cap T_{III}))$[8] is my treatment group of the dirty pollutants and the set $T_2 = T_{II} \backslash ((T_I \cap T_{II}) \cup (T_{II} \cap T_{III}))$ is the treatment group of the clean substitutes. Using these sets, I identify the control group as those patents similar to the ones affected by the Kigali Amendment. For this I exploit patent classification and focus on patents of sections C and F. In particular I define my control group as those patents in the 4-digits IPC subclasses of the sections F and C of the patents in T_I that are not included in my treatment groups T_1 and T_2, and that don't cite substances in T_{III} (see in Appendix 2, Table 3.7 the list of IPC subclasses). Figure 3.1 shows a schematic representation of my treatment and control groups.

Multiple Correspondence Analysis In order to have more dimensions for comparing patents in the empirical analysis, I will first perform a multiple correspondence analysis

---

[8] The intersections are due to the fact that one patent might potentially cite substances from different groups.

with IPC subclass co-classification. Patents are classified into several IPC subclasses, normally they have an "F" subclass, which is their main subclass and the remaining ones. IPC subclass co-classification of the remaining subclasses besides the "F" subclass can capture to some extent the technology type of the invention. Nevertheless, the main challenge in exploiting this information is that some patents can be co-classified into hundreds of patent subclasses. Therefore, in order to exploit that valuable information, I will project the discrete IPC co-classification into five continuous dimensions through the multiple correspondence analysis. In my case I project 566 co-classification dummies from sections A, B, C, D, E, F, G, and H.

Exact Matching After the Multiple Correspondence Analysis, I perform a Coarsened Exact Matching (CEM) using as matching variables: Application Year and IPC class dummies (see Table 3.8 in Appendix 2 for a list of the IPC Classes used for the matching). In order to perform the matching, I proceed in the following manner, first I do an exact matching between the patents from T_1 and T_2. I build Application Year – IPC class bins and keep only those having at least one patent from each one of the two groups. Afterwards, in a second step, I select all the patents from my control group T_0 belonging to the Application Year – IPC class bins kept from the first step (a list of the resulting dataset with the number of patents per bin is available in Appendix 3).

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.008	0.080	−0.266	0.407
Dim 2		0.005	0.060	−0.543	0.237
Dim 3		−0.002	0.005	−0.033	0.026
Dim 4		0.003	0.025	−0.145	0.163
Dim 5		−0.023	0.051	−0.148	0.198
Grant Lag		2,294.896	987.860	468	5,685
Inventors		4.022	2.407	1	16
Applicants		1.097	0.316	1	4
Family Size		17.140	15.694	1	93
Sample Size	835				

Table 3.3: Descriptive Statistics: Treatment Group T_1

3.4.2 Descriptive Statistics

After performing the Multiple Correspondence Analysis (MCA) and the Coarsened Exact Matching (CEM), I will present the dataset that I will use for my empirical analyses. In this paper I perform two empirical analyses on the impact of the environmental regulation on patent value, one using forward citations as a proxy for patent value and the other exploiting patent renewal, i.e. patent age, as a proxy for patent value. As a result from the two pre-treatment methods, i.e. MCA and CEM, I have now three comparable sets of European patents renewed in Germany, which have been applied for between 1997 and 2006. In particular, I have the set of patents that have been potentially negatively affected by the environmental regulation, i.e. the ones that cite some pollutant (HFC), T_1. I have the set of patents citing some of the chemical substitutes T_2, and the set of similar patents citing none of those types of chemical substances, which are my control group T_0.

In Tables 3.3, 3.4, and 3.5 I present the descriptive statistics from the three types of patents. Starting with a measure of the ex-ante patent value, i.e. the number of inventors, we can see that dirty patents (T_1) have more inventors than clean ones (T_2) and the control group ones (T_0). This is confirmed by the analysis of the family sizes, where dirty patents have also larger family sizes than clean ones and control group ones., i.e. also pointing out to a higher ex-ante value. It is interesting to note that clean patents, which should be the most novel technology have the smallest families of all. A hypothetical explanation for this phenomenon could be that in the lack of environmental economic incentives (i.e. environmental regulations), there are less incentives to innovate in clean technologies. Note that this refers to the ex-ante value, i.e. the value at the patent application moment, which corresponds to 1997 to 2006, hence several years before the Kigali Amendment. Regarding the number of applicants and grant lags, our three sets of data are fairly similar. Concerning the five MCA dimensions, values are not very different between the three types of patents. Nevertheless, it is interesting to notice that extreme values for the control group patents are much larger than the ones of T_1 and T_2, which could mean that the large sample of patents from that group has a larger degree of unobserved heterogeneity, which these five dimensions could help us control for. We will see in the empirical analyses if this hypothesis is confirmed.

If we now proceed to a technology class comparison, as the one presented in Figure 3.2,

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.086	0.062	−0.168	0.413
Dim 2		−0.014	0.093	−0.614	0.486
Dim 3		−0.00000	0.008	−0.040	0.096
Dim 4		0.004	0.083	−0.874	0.431
Dim 5		0.006	0.060	−0.148	0.503
Grant Lag		2,278.194	996.228	582	6,572
Inventors		3.348	1.930	1	18
Applicants		1.077	0.312	1	4
Family Size		9.632	7.308	1	136
Sample Size	1,056				

Table 3.4: Descriptive Statistics: Treatment Group T_2

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		−0.009	0.085	−0.329	0.762
Dim 2		−0.001	0.071	−1.003	1.178
Dim 3		0.0002	0.077	−0.063	9.540
Dim 4		−0.001	0.078	−2.968	0.664
Dim 5		0.006	0.071	−0.230	1.161
Grant Lag		2,286.081	995.016	265	6,840
Inventors		3.472	2.197	1	31
Applicants		1.100	0.381	1	13
Family Size		12.713	11.005	1	269
Sample Size	23,204				

Table 3.5: Descriptive Statistics: Control Group T_0

we can see that the patent classes distributions are fairly similar for the patents from the treatment groups T_1 and T_2. We can observe a gathering of patents in classes C07, C08, and C09, which correspond to, "Organic Chemistry" (C07), "Organic Macromolecular Compounds" (C08), and "Dyes, paints, polishes, natural resins, adhesives, and compositions otherwise not provided for" (C09). In particular, we can see that the peak for dirty patents T_1 and control group patents is the same (C07), whereas the one for clean group patents is C08. Furthermore, we notice a peak of control group patents in C12, which is not present neither for T_1 nor for T_2, and that would provide further evidence on the unobserved heterogeneity mentioned previously regarding technological classification. It will be therefore essential for the analyses to control for patent classes.

Comparing the distribution of patent counts across patent cohorts (application year), we see that all three groups have a similar increasing trend in the number of patents applied for (Figure 3.3). Interestingly, we see that the number of patents applied for from the dirty patents is the lowest across all and in the last three years it recovers and reaches the level of the clean patents. On the opposite, we observe that clean patents (T_2) and control group ones follow a similar trend across all cohorts. A possible hypothesis for this could come from the origin of the pollutants that I am analyzing. Namely, HFCs were developed as a replacement for other substances that depleted the ozone layer. As one can see in Appendix 1.1., the HFCs listed in Annex F have a corresponding 100-Year Global Warming Potential but no Ozone-Depleting-Potential like CFCs from Annexes A and B or HCFCs from Annex C. This means that as such they were seen as a clean solution to the environmental problem that the Montreal Protocol aimed at addressing and therefore considered as a clean technology between 1997 and 2006. Clean patents from T_2, instead were already seen as clean technologies from the beginning of the Montreal Protocol in 1987, and between 1997-2006 they were already considered to be clean. I consider patents citing HFCs as dirty technology because they were addressed as such from 2016 onwards under the Kigali Amendment.

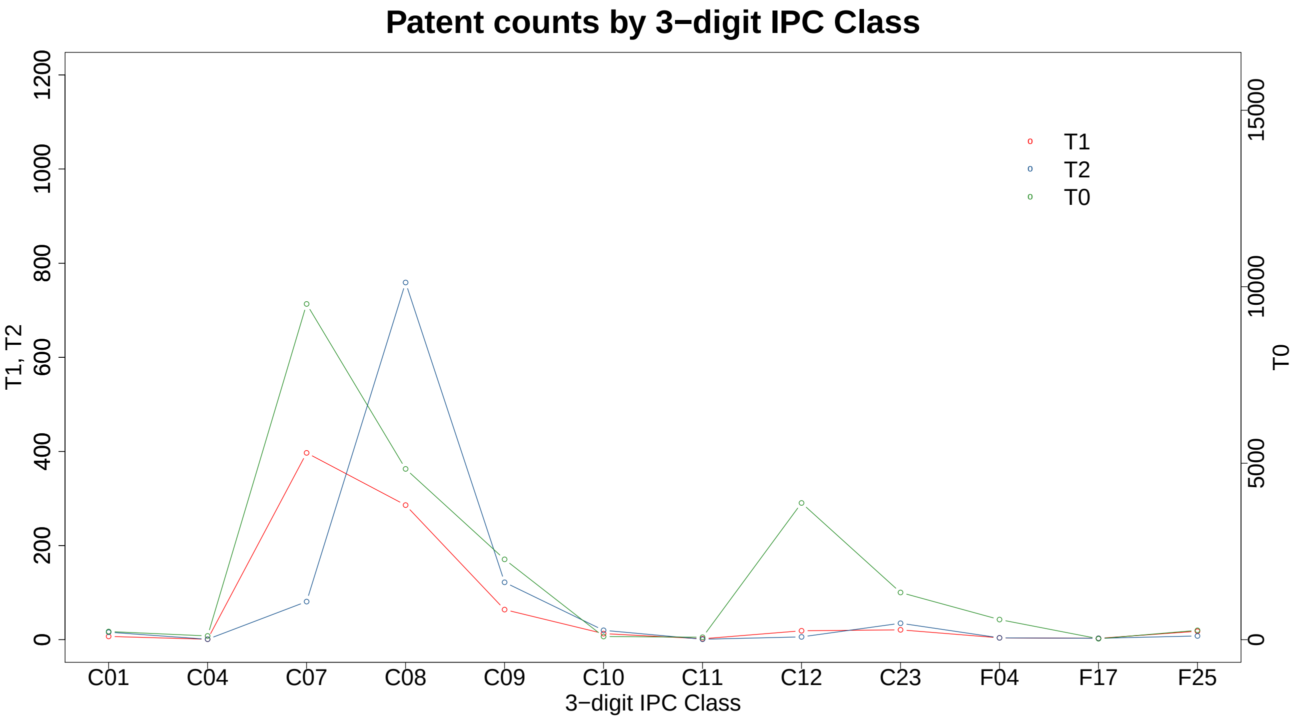


Figure 3.2: Patent counts by 3-digit IPC Class

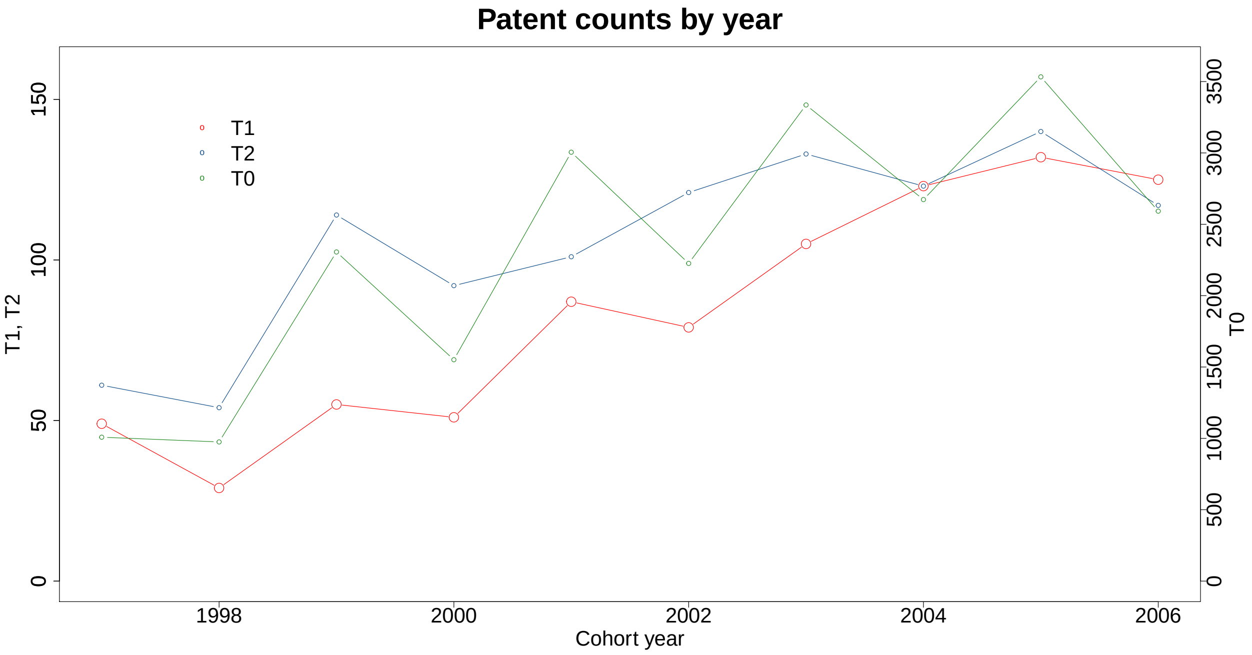


Figure 3.3: Patent counts by cohort year

3.5 Empirical Analysis on the Impact of the Kigali Amendment on Patent Value

3.5.1 Forward Citations Evidence: Panel Event Study

As a first step I use a panel event study in order to analyze the impact of the Kigali Amendment on patent value (proxied by yearly forward citations). In particular I do two independent studies taking as the baseline year 2008. In the first one I compare the patents from the substitutes T_2 with those patents that cannot be regulated (T_0). While in the second study I compare the patents potentially affected negatively by the future regulation, i.e. those from T_1, to the patents from the control group (T_0). I implement the panel event study using Clarke and Tapia-Schythe (2021).

Evidence on Clean Technologies In this first panel event study of clean technologies (T_2) compared to the control group ones (T_0) I include 10 lags, 5 leads, and control for patent validity, i.e. if the patent is still active or not, the five MCA dimensions, grant lag, number of applicants, number of inventors, class fixed effects, application year fixed effects, and year fixed effects.

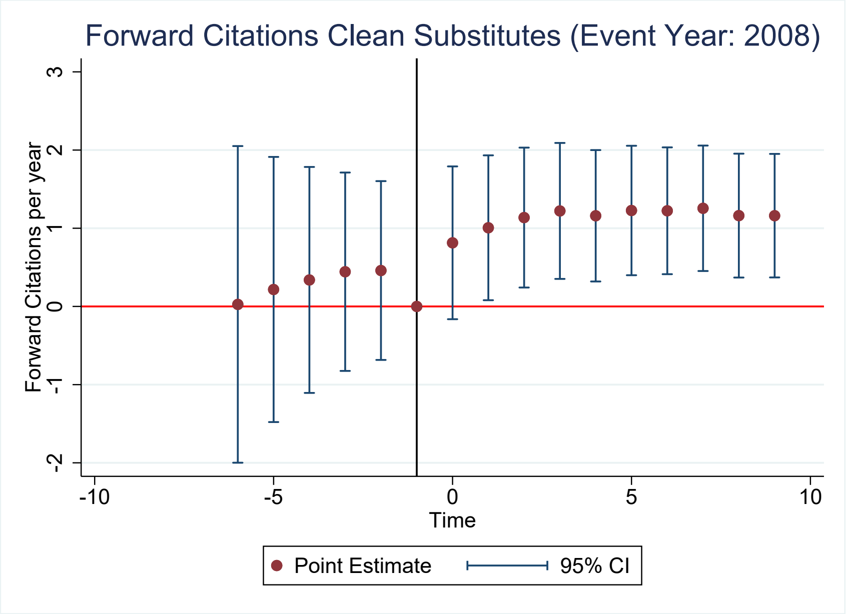


Figure 3.4: Panel Event Study Evidence of the Impact of the Kigali Amendment on Clean Technologies (baseline: 2008)

$$y_{it} = \alpha + \sum_{j=1}^{10} \beta_j (Lag\ j)_{it} + \sum_{k=2}^{6} \beta_k (Lead\ k)_{it} + \lambda_t + X'_{it}\Gamma + \epsilon_{it} \tag{3.1}$$

The estimates from the regression are shown in Figure 3.4 and allow us to see that the negotiations seem to have had a positive significant effect on forward citations, i.e. on patent value, and that this effect has been increasing over time. The exact results from this estimation can be found in the Table 3.10 of Appendix 3.

If we scrutinize the estimation results, one can see that we find all ex-ante control variables significant at 0.1 percent except two of them. The grant lag is not significant, which is in line with the descriptive statistics findings as the values across the three groups were similar. Similarly, Dim 3 from the MCA is not significant, which coincides with the descriptive statistics' observations. In the previous sections, we noticed that extreme values for some dimensions of the MCA were very different between the three groups, and Dim 3 was the variable where this difference appeared to be clearer. Analyzing the leads and the lags, I don't find any lead significant, which would point towards no difference in the forward citations pattern before the event. Conversely I find a positive significant impact (at a 5 percent level) on the lags starting at the second lag, which from the fourth lag onwards becomes significant at a 1 percentage level. It seems, therefore, that clean technologies' patents gained in value from 2010 onwards, with the largest effect in 2016, which coincides with the year of the Amendment.

Evidence on Dirty Technologies The second panel event study compares the patents expected to be affected negatively by the Kigali Amendment (T_1) to the control group patents (T_0). The baseline, the control variables, as well as the number of leads and lags are the same as for the first panel event study.

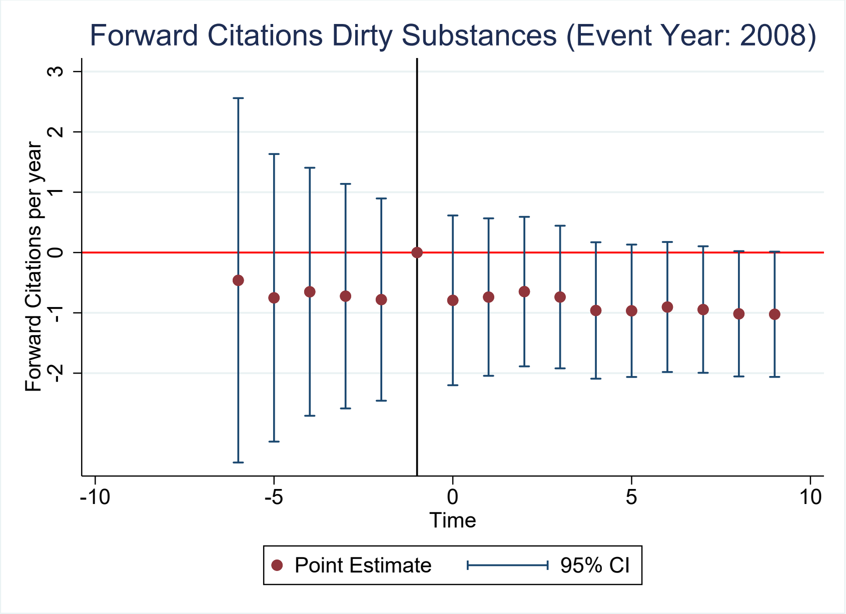


Figure 3.5: Panel Event Study Evidence of the Impact of the Kigali Amendment on Dirty Technologies (baseline: 2008)

$$y_{it} = \alpha + \sum_{j=1}^{10} \beta_j (Lag\ j)_{it} + \sum_{k=2}^{6} \beta_k (Lead\ k)_{it} + \lambda_t + X'_{it}\Gamma + \epsilon_{it} \tag{3.2}$$

The results from the second panel event study are very similar to the ones from the clean technologies, in particular regarding the ex-ante controls. I find that the same controls as in the first panel event study are significant at the same percentage level, and that they have the same signs, i.e. Dim 4, Dim 5, and the number of applicants are negative, whereas the remaining ones are positive. A more interesting result is, however, the analysis of the leads and lags. As in the first study I find no effect of the leads, but now this can be also extended to the lags. Only the last two lags are almost negatively significant at a 5 percent, but still fail to reject the null hypothesis.

Summing up my findings, the panel event study has provided first evidence that the Kigali Amendment seems to have positively affected the value of clean technologies from 2010 onwards with a peak in 2016. This would be in line with the rationale of the impact of an international environmental agreement, which would have a positive effect on clean technologies. Conversely, evidence on dirty technologies remains unclear although they seem to take a negative trend over time. Finally, the proposed set of controls, except for the grant lag, seem to be relevant in capturing the otherwise unobserved heterogeneity in patent value, including most of the dimensions from the MCA.

3.5.2 Patent Renewal Evidence: Nonparametric Duration Analysis

Duration Analysis Framework

From the previous section we have seen that the Kigali Amendment seems to have generated a positive impact on the patent value (proxied by forward citations) of clean technologies, whereas evidence on its impact on the value of dirty technologies remains inconclusive. In this section, I will try to shed further light on this by analyzing another dimension capturing patent value, i.e. patent renewal. Once a patent is granted, patent holders in Europe need to pay an annual fee in order to keep their patent rights. Since it is costly for the innovator to keep the rights on the invention, it follows that keeping a patent is a proxy for the value of private patent rights. Given this setting a natural approach to analyze a renewal decision is a duration analysis. In particular, intuitively we would be interested in the average treatment effects of the policy, i.e. the Kigali Amendment, on the hazard rate at the treatment moment. Nevertheless, this is not a straightforward effect to analyze without further assumptions, since depending on the framework of analysis subpopulations might vary after treatment between comparison groups biasing our estimates. Furthermore, and as pointed out by the panel event study, the effect might be diluted, i.e. it might not directly happen at the moment of the change in policy regime but could instead be delayed. If this is the case of the policy that we are studying, then the moment (treatment year) of the policy analysis might drive the conclusions from our results, hence as econometricians we would be very much interested in capturing the fate of the patents over time after the regulatory change. In this regard, van den Bergh et al. (2020) have developed a nonparametric approach that overcomes the two mentioned challenges if some changes are done to apply it into a patent framework. In this section I summarize the main results, assumptions and notations from the work of van den Bergh et al.(2020), explain how I adapt their model to patent renewal data, and present the results of my analysis.

Notation Van den Bergh et al.(2020) focus in their paper on analyzing two magnitudes of the impact of a policy on duration data. Namely, the impact of a policy at some t_0 duration on the hazard rate and the impact on the conditional survival probability over some period $[t_0, t_1)$. They focus specially on the causal impact of a policy that starts at some time $s \in \mathbb{R}_+ = [0; \infty)$ after inflow or is not treated at all, i.e. $s = \infty$.

Definitions They define $\mathcal{A} = \{\mathbb{R}_+\} \cup \{\infty\}$, and to each treatment $s \in \mathcal{A}$ corresponds a random variable $T(s) \geq 0$, that corresponds to the potential duration outcome if it gets treatment s. In terms of interpretation, s can be understood as the individual elapsed duration at which the unit is exposed, which in my case would correspond to the patent age. They define two potential treatments $s, s' \in \mathcal{A}$ with the corresponding potential outcomes distributions $T(s)$ and $T(s')$. The differences between the two potential outcome distributions would correspond to the treatment effects. In their paper they focus on the average effects of the treatments on the individual exit rates (i.e. on the hazard rates) and on the individual conditional hazard probabilities.

They define the distribution function of the potential outcome $T(s)$, $F_{T(s)}$, which is a

function of the time t, the unit inflow. Then they define the integrated hazard rate $\Theta_{T(s)}$, as $\Theta_{T(s)}(t) = -log(1 - F_{T(s)}(t))$, and the corresponding hazard rate $\theta_{T(s)}$[9]. With this they define two main types of treatment effects that we will analyze:
The individual additive effect on the hazard rate at t:

$$\theta_{T(s')}(t) - \theta_{T(s)}(t) \quad for\ t \geq 0\ \ s', s \in \mathcal{A} \tag{3.3}$$

The individual multiplicative effect on the hazard rate at t:

$$\frac{\theta_{T(s')}(t)}{\theta_{T(s)}(t)} \quad for\ t \geq 0\ \ s', s \in \mathcal{A} \tag{3.4}$$

Before-after Data Framework Bias As they argue, in the literature, the main approach to a duration treatment effect analysis has been a before-after data framework (i.e. taking only cohorts before the policy introduction and after the policy introduction), with X as the observable characteristics and V as the unobservable ones. Such a framework would lead to the following treatment effects[10]:

$$\theta_{T(0)}(t|X, V) - \theta_{T(\infty)}(t|X, V) \tag{3.5}$$

Below I show a Lexis Diagram of this framework (Figure 3.6), with c_1, ..., c_N being the cohorts from their inflow moment up to the last surviving specimen and τ^* the moment of the policy change.:

---

[9] In the interest of clarity this does not include all the formal derivation steps. As mentioned at the beginning of the section, it aims only at providing the main concepts to help the reader understand the work performed in this paper.

[10] ∞ stands for never treated.

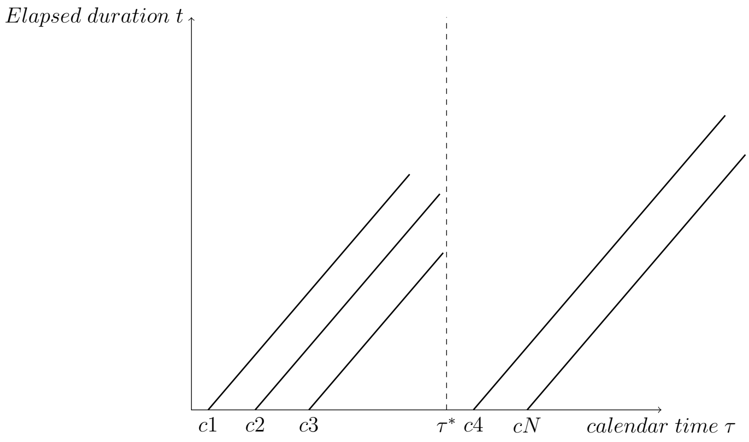


Figure 3.6: Lexis Diagram Before-after Data Framework

Their motivation for moving from a before-after framework to a setting with ongoing spells is that such a framework leads to biased results due to the changing composition of the comparison subpopulation in unobserved characteristics V. Therefore the average treatment effects of interest are not nonparametrically identified.

Ongoing Spells Data Framework The advantage of a data framework with ongoing spells at the treatment moment is that it allows us to take into account the changing composition of the surviving subpopulations for the estimation. By defining a new concept of average treatment effects in this framework van den Bergh et al. (2020) identify nonparametrically the instantaneous average treatment effects and the average treatment effects on the conditional survival probabilities, which are the two interesting magnitudes for my work, in particular the second one. In my work, I perform two small modifications of this framework to adapt their model to patent data. Figure 3.7 shows an example of an ongoing spells data framework.

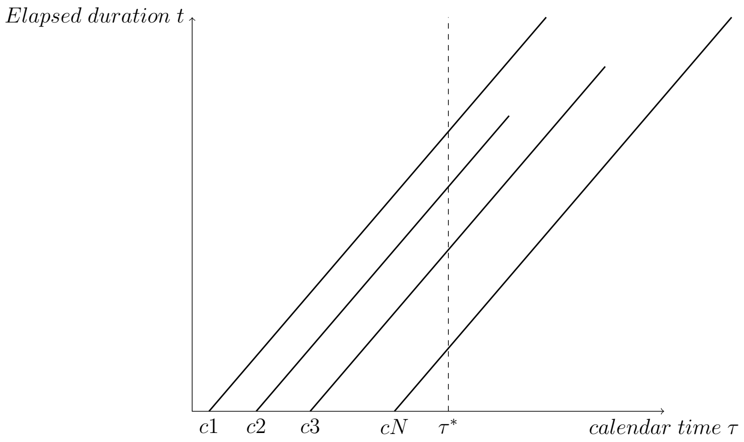


Figure 3.7: Lexis Diagram Ongoing Spells Data Framework

Before explaining the two modifications that I do to their analysis, I will remember the assumptions upon which their results and mine build, which are essential for interpretation.

Assumption 1 (Assignment)

$$S \perp\!\!\!\perp T(s)|(X,V) \text{ and } S \perp\!\!\!\perp V|X \tag{3.6}$$

This assumption is similar to the conditional independence assumption (CIA) but additionally conditioning on the unobservables V. It allows for the inflow cohorts to have systematically different distributions of (X,V). The second part of the assumption means that two different cohorts would have identical compositions of $V|X$.

Assumption 2 (No Anticipation)
For all $s \in (0,\infty)$ and for all $t \leq s$ and all X,V:

$$\Theta_{T(s)}(t|X,V) = \Theta_{T(\infty)}(t|X,V) \tag{3.7}$$

In their paper they assume that agents do not anticipate the policy reform (treatment), i.e. that the agents' behavior does not depend on the time remaining until treatment.

Assumption 3 (Multiplicative Unobserved Heterogeneity)

$$\theta_{T(s)}(t|X,V) = \theta^0_{T(s)}(t|X,V) \tag{3.8}$$

It means that the unobserved characteristics affect all hazard rates in the same manner, i.e. that the individual multiplicative effects on the hazard rate at t are homogeneous across units with different V.

In Figure 3.8 I present a direct application of the ongoing framework applied to my patent analysis but without further modifications implemented yet, where τ^{rc} is the right censoring time, 2018, and τ^* the moment of the policy change, 2008. The reason why I consider the moment of the policy change to be in 2008 and not 2016 (the year of the signature of the Kigali Amendment) is because since firms do participate in the policy meetings of the Montreal Protocol, there is a certain likelihood that some of them might have anticipated that event or an event of that sort some years before 2016. Since non anticipation of the policy is a key assumption for the implementation of the van den Bergh et al. (2020) approach, I decided to consider that the regulatory change happened in 2008 and to focus on the average treatment effects on the conditional survival probabilities, i.e. to consider the possible shocks from 2008 onwards as a delay effect of environmental policies affecting technologies of two different nature. The argument for considering that those technologies were considered of different nature (type) already in 2008 is supported by the forward citations analysis, which finds that the clean patents were significantly positively affected by the ongoing policy discussions, whereas the dirty ones were not significantly affected but slightly taking a negative trend in value.

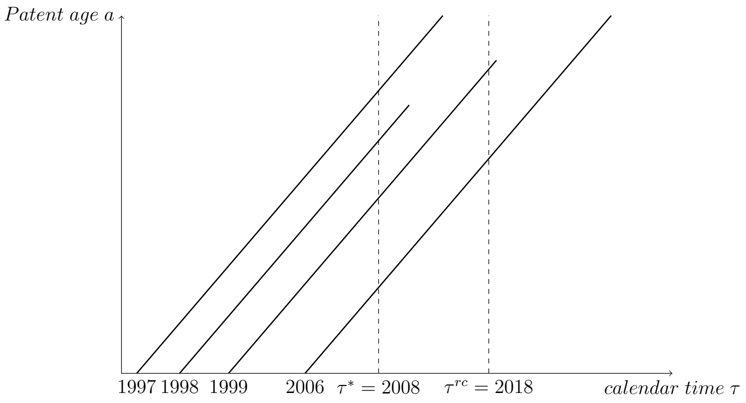


Figure 3.8: Lexis Diagram Ongoing Spells (patent framework in absolute years with right censoring)

The new average treatment effects that they define are the instantaneous causal effect of the treatment and the conditional survival probabilities. The instantaneous causal effect of the treatment, at the moment of the policy exposure is:

$$ATTS(s', s, t|X) = E[\theta_{T(s')}(t|X,V) - \theta_{T(s)}(t|X,V)|X, T(s') \geq t] \ with \ s' \leq t, s \tag{3.9}$$

They define the average treatment effects on conditional survival probabilities as:

$$\begin{aligned} ATTS(s', s, t|X) = E[Pr(T(s') > t + a|T(s') \geq t, X, V) \\ -Pr(T(s) > t + a|T(s) \geq t, X, V)|X, T(s') \geq t] \ with \ s' \leq s \ and \ a > 0 \end{aligned} \tag{3.10}$$

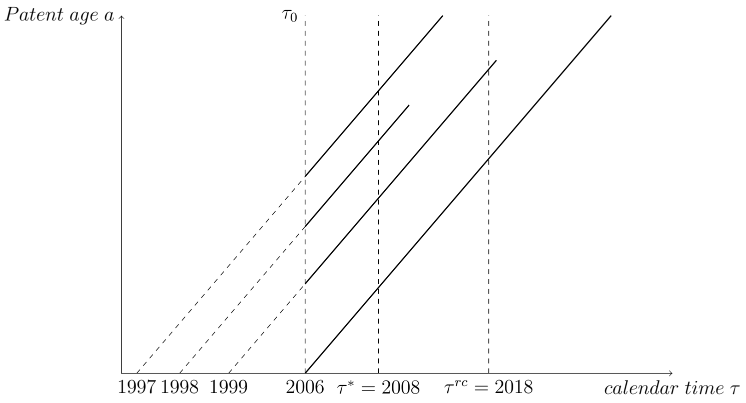


Figure 3.9: Lexis Diagram Ongoing Spells (patent framework in absolute years with left and right censoring)

They use the second-order boundary kernel estimator of Müller and Wang (1999) to estimate nonparametrically these effects. The aim of my duration analysis is to estimate those effects with the presented patent data. Nevertheless in order to be able to estimate them I need to perform two transformations of the data. The original data framework that I have is presented in Figure 3.8, where the first cohort is 1997, the last one is 2006, treatment year corresponds to 2008 and there is a right censoring in 2018. In order to be able to use their framework I need to transform first all my cohorts into a single cohort and aggregate them. This means that I will only keep and exploit renewal data to the right of the dashed line τ_0, as presented in Figure 3.9. For this, I will first drop all obsolete patents from my treatment and control groups until 2006 and recompute the patent age of the surviving ones from 2006 onwards such that 2006 becomes age 1 for all surviving patents from all cohorts. By doing this I aggregate my data to one single cohort but of course I add cohort dummies for the cohorts of origin. This results in the data framework presented in Figure 3.10 where the starting age is 1 at $\tau_0 = 2006$, the treated patents receive treatment in $\tau^* = 3$, i.e. at patent age 3 that corresponds to year 2008, and we have a right censoring at age $\tau^{rc} = 13$, which corresponds to 2018.

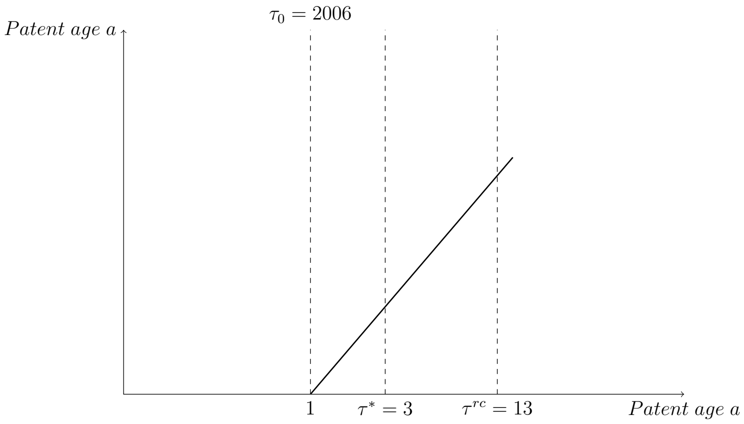


Figure 3.10: Lexis Diagram Ongoing Spells (patent framework in patent ages with left censoring, right censoring, and cross-cohorts aggregation)

In my framework I estimate now the instantaneous causal effect of the treatment at $\tau^* = 3$, i.e. in 2008 and the conditional survival probabilities from 2008 up to 2018. Since my regulation, the Kigali Amendment to the Montreat Protocol was signed in 2016, what is relevant for my analysis are the conditional survival probabilities (both the additive and multiplicative ones[11]). The reason for this is that through Assumption 2, I am assuming that the agents did not anticipate the Kigali Amendment before 2008, which is a reasonable assumption. Then, through the computation of the conditional survival probabilities from 2008 onwards, I aim at capturing any difference between the treatment and control groups from 2008 onwards, which could be interpreted as a delay effect of a treatment in 2008. The shock that I present in the next sections should be therefore interpreted bearing this in mind and as a delay effect from a difference in the nature of the technologies between treatment and control groups that could have affected patent value from 2008 onwards but not before. Therefore the formula of the instantaneous causal effect of the treatment at the moment of the policy exposure is the following (with $\tau^* = 3$):

$$ATTS(\tau^*, \infty, \tau^*|X) = E[\theta_{T(\tau^*)}(\tau^*|X,V) - \theta_{T(\infty)}(\tau^*|X,V)|X, T(\tau^*) \geq \tau^*] \; with \; \tau^* \leq \tau^*, \infty \tag{3.11}$$

The average treatment effects on conditional survival probabilities are the following

---

[11] For the formulas and derivation of the multiplicative treatment effects refer to van den Bergh et al. (2020).

(with $\tau^* = 3$ and a being the newly defined patent age):

$$\begin{aligned} ATTS(\tau^*, \infty, \tau^*|X) = E[Pr(T(\tau^*) > \tau^* + a|T(\tau^*) \geq \tau^*, X, V) \\ -Pr(T(\infty) > \tau^* + a|T(\infty) \geq \tau^*, X, V)|X, T(\tau^*) \geq \tau^*] \; with \; \tau^* \leq \infty \; and \; a > 0 \end{aligned} \tag{3.12}$$

Nonparametric Evidence

In this section I will present evidence stemming from three nonparametric duration analyses. The first two on the comparison of clean and dirty patents respectively against the control group, and the third one comparing renewal of dirty patents against renewal of clean technologies. For all analyses I use the following control variables, i.e., the five MCA dimensions, number of inventors, grant lag, number of applicants, family size, patent class by application year dummy, and cohort dummies.

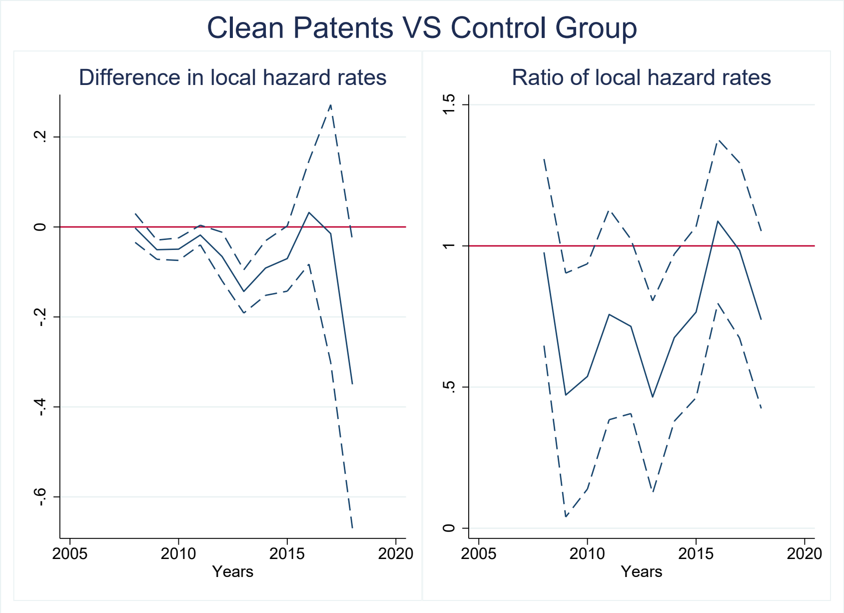


Figure 3.11: Nonparametric Duration Evidence (2008-2018): Clean Patents VS Control Group

Evidence on Clean Technologies In Figure 3.11 we can see the results from the nonparametric duration model, in particular the graphic on the left side represents the difference in local hazard rates and the right one their ratio. In all graphics (including Figures 3.12 and 3.13) the first point drawn corresponds to the instantaneous average treatment effect of the policy respectively in differences (left side) or ratios (right side). As mentioned in the previous subsection, we are not interested on the instantaneous average treatment effect, which happened in 2008, but on the average treatment effects on the conditional survival probabilities, which are the points drawn from 2008 onwards. Generally, the graphics should be interpreted in the following way, i.e., we are interested into significant differences either from 0, for the differences in local hazard rates (left graphic), or from 1 for the ratios (right graphic). It is important to notice that if in any graphic we have a positive significant difference, i.e. point estimate and 95% confidence intervals are above 0 (for differences) or above 1 (for ratios), then that point can be interpreted as a negative significant shock but from that moment onwards any further difference cannot be interpreted anymore. The reason for this is that we are losing subjects (patents) from our treatment group and therefore any shock afterwards could not be interpreted as causal independently of the nature of the policy.

For the causal interpretations of the results shown in this graphic and their numerical counterparts in Tables 3.12 and 3.13 of Appendix 3, it is essential to bear in mind the regulation that we are studying and the evidence regarding the impact of this regulation on dirty technologies. Namely, since we expect the impact of the Kigali Amendment to be positive on clean technologies, we would be therefore prone to interpret the first positive shocks observed in the graphics of Figure 3.11 (i.e., either below 0 or below 1) as the causal positive impact of the regulation on clean technologies. Nevertheless, both the first (2009-2010) and the second (2012-2013-2014) shocks are relatively early (the peak of the second shock is in 2013) to attribute them to the Kigali Amendment. In order to shed further light on this, I will later on analyze the behavior of dirty patents versus the control group (Figure 3.12) and also compare renewal of dirty versus clean patents (clean patents as control). The reason for doing these two further comparisons is that if we see that dirty patents also receive these two positive shocks then it means that they are likely to be related to the fact that these two types of technologies were substitutes to the HCFCs (previously regulated under the Montreal Protocol) and not due to the Kigali Amendment. This is confirmed by the HCFCs phase-down schedules presented in Appendix 4, where we can see the phase-down consumption (Figure 3.15) and production (Figure 3.16) schedules for HCFCs corresponding to the Non-Article 5 and Article 5 countries[12]. Interestingly, we observe that on January 1, 2010 there was a 75 percent reduction in both consumption and production of HCFCs for the Non-Article 5 parties, which would explain the positive shocks observed for both types of substances. Furthermore, on January 1, 2013 the production and consumption levels for HCFCs were frozen to the baseline of 2009-2010 for Article 5 parties and in January 1, 2015 they were reduced an additional 10 percent. These two measures concerning the HCFCs could explain why we observe positive shocks between 2012 and 2015 for the clean substances and the HFCs. More interestingly, we can see a positive shock in the differences' graphic of Figure 3.11 on the clean technologies in 2018. This significant positive shock on patent value is likely to be attributed to the Kigali Amendment, which happened in 2016, depending on the outcome of the comparisons just mentioned. In any case, since the shocks that we are observing are positive, we are not losing patents before 2018, so the interpretation of the shock of 2018 could still be causal.

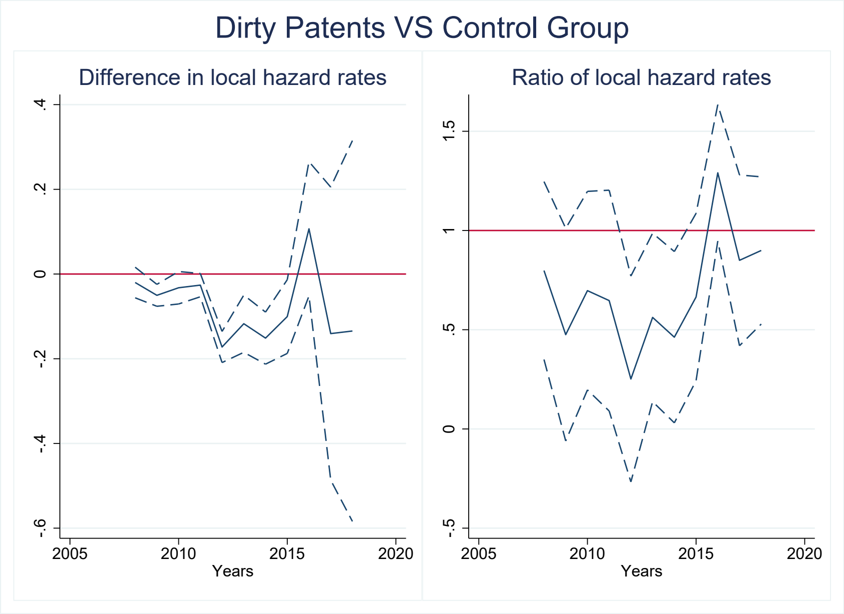


Figure 3.12: Nonparametric Duration Evidence (2008-2018): Dirty Patents VS Control Group

---

[12] The Montreal Protocol defined two types of countries: the so-called Non-Article 5 parties and the Article 5 parties, where Article 5 countries are defined as "Any Party that is a developing country and whose annual calculated level of consumption of the controlled substances in Annex A is less than 0.3 kilograms per capita on the date of the entry into force of the Protocol [...]."(UNEP, 2019).

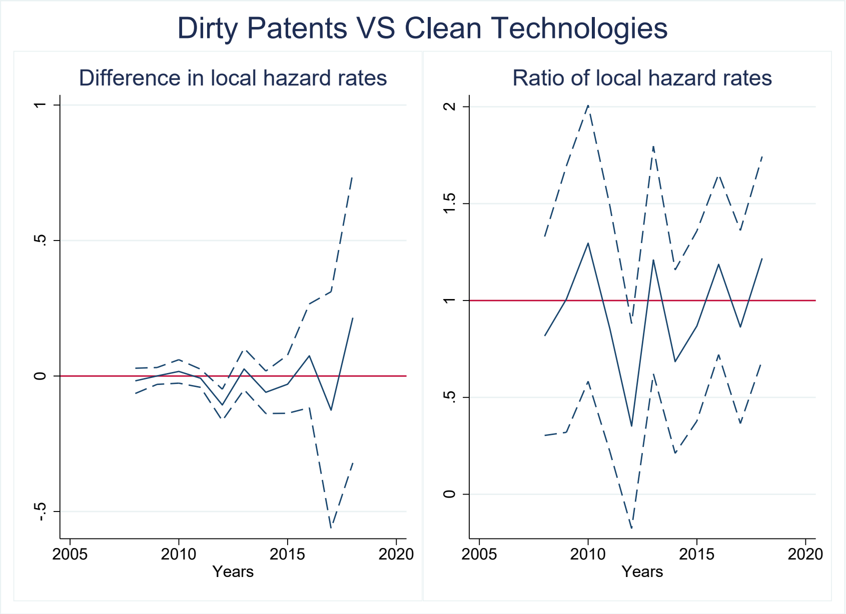


Figure 3.13: Nonparametric Duration Evidence (2008-2018): Dirty Patents VS Clean Technologies

Evidence on Dirty Technologies Turning to the evidence on dirty patents, I find two positive significant shocks. The first in 2009, and the second in 2012, 2013, 2014, and 2015, with a peak in 2012. Given that we would expect a negative shock on dirty technologies due to the Kigali Amendment, these shocks would be cumbersome in lack of a context. Now considering the framework of the Montreal Protocol, where HFCs were thought as replacement to the HCFCs, then it makes sense to observe a positive significant shock in their patent value when the market considered them to be clean. Furthermore, this would be in line with the evidence found on the clean substances, since as both types were substitutes for the HCFCs, both should have received these shocks in their patent value. This evidence stemming from the dirty patents helps us better understand the results from the clean patents' analysis. From the clean patents' analysis, we can now say that the clean shock received in 2018 can be causally attributed to the Kigali Amendment, since we do not observe such a shock in Figure 3.12 (numeric estimates can be found in Tables 3.15 and 3.16). Furthermore, regarding the results on the dirty technologies, we observe an almost significant negative shock in ratios (right graphic of Figure 3.12) in 2016, which we could guess that it could be attributed to the Kigali Amendment. Note, that in Figure

3.11 we do not see this shock as clearly and the variation that we observe is certainly very far from being significant.

Evidence on Dirty VS Clean Technologies Finally, I will compare the fate of dirty patents to the one of clean technologies. The reason for doing this is to try to test to some extent the robustness of the previous results. In Figure 3.13 we can see the nonparametric local hazard rates in differences and ratios. There are two things to notice on these graphics, first that in both of them we observe a positive shock in 2012, which corresponds to the peak of the positive shock on the dirty technologies previously mentioned. This confirms our rationale for considering the HFCs as clean substitutes of the HCFCs. Furthermore, a possible interpretation of this shock could be that they were the most cost efficient solution to the HCFCs' replacement. This would justify the need for a latter environmental regulation on the HFCs, since in the lack of this regulation the cleaner alternatives would be costlier, hence not the preferred solution. The second interesting point from Figure 3.13 comes from the widening of the confidence intervals of the differences' graphic. This would further point towards two shocks in opposite directions starting from 2016 onwards, which would confirm the almost significant negative shock on dirty patents in 2016 and the positive significant shock (at a 5 percent level) on clean technologies in 2018.

Before concluding this chapter, I would like to note that I have limited my analyses until 2018. The reason for this is that my renewal information ends in 2020 and evidence for 2019 is not clear, see Appendix 5. As it is difficult to assess whether the reason of the unclear results for 2019 (large confidence intervals for the last point estimate) stems from effects going into opposite directions or problems in estimating the last data point, I will extend this analysis with additional renewal years as soon as those are available.

3.6 Conclusion

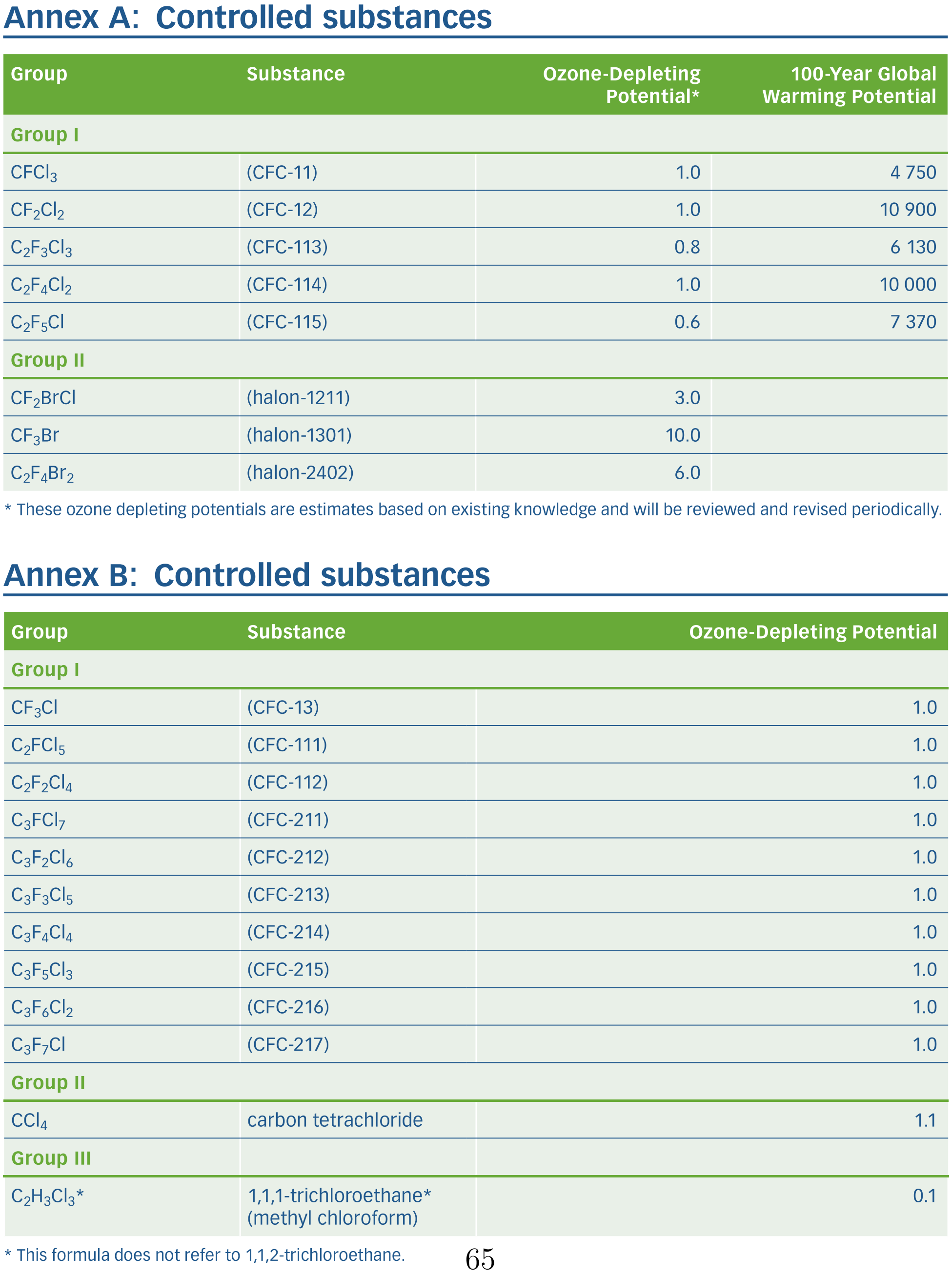
In this work, I study the impact of the Kigali Amendment to the Montreal Protocol on the timing and direction of technological change. To do this, I construct a unique dataset combining patents mentioning substances regulated under the Kigali Amendment and under the Montreal Protocol, and patents citing substances that could potentially replace them in refrigeration applications. Furthermore, I adapt the nonparametric duration model of van den Bergh et al. (2020) to the patent data framework, which allows me to study new average treatment effects, such as the average treatment effects on the conditional survival probabilities of clean and dirty patents affected by the Amendment to the Montreal Protocol. This allows me to explore a new dimension in the direction of technological change and the environment, that has been only studied indirectly so far in the literature, i.e., the timing of technological change. I find that the IEA first affects dirty patents negatively, with an almost significant negative effect (at a 5 percent level), and only later positively clean patents. This delay in the effect of the environmental regulation on the direction of technological change would be in line with the rationale suggested by Dechezleprêtre and Hémous (2022), claiming that dirty innovations would respond more to short-run market changes whereas clean innovations would depend more of long-run market incentives.

My work adds to the literature in several manners. First, I contribute to the literature on patent valuation developing a new approach to study the impact of a regulation on patent value proxied by patent renewal adapting the model of van den Bergh et al. (2020) to patent data. Second, I contribute to the innovation literature by constructing a unique dataset that includes patents on technologies that substitute each other. Third, I contribute to the literature on directed technological change and the environment by exploring the timing dimension for clean and dirty innovations, which was still scarcely studied. Finally, I contribute to the literature on IEAs and the direction of technological change by studying the impact of the Kigali Amendment on patent value.

3.7 Appendix 1: Lists of Substances

3.7.1 Appendix 1.1: Substances Regulated under the Kigali Amendment

Figure 3.14: Source: ”Handbook for the Montreal Protocol on Substances that Deplete the Ozone Layer” Annexes, Section 1.1., latest version available here (UNEP, 2019).



Annex A: Controlled substances

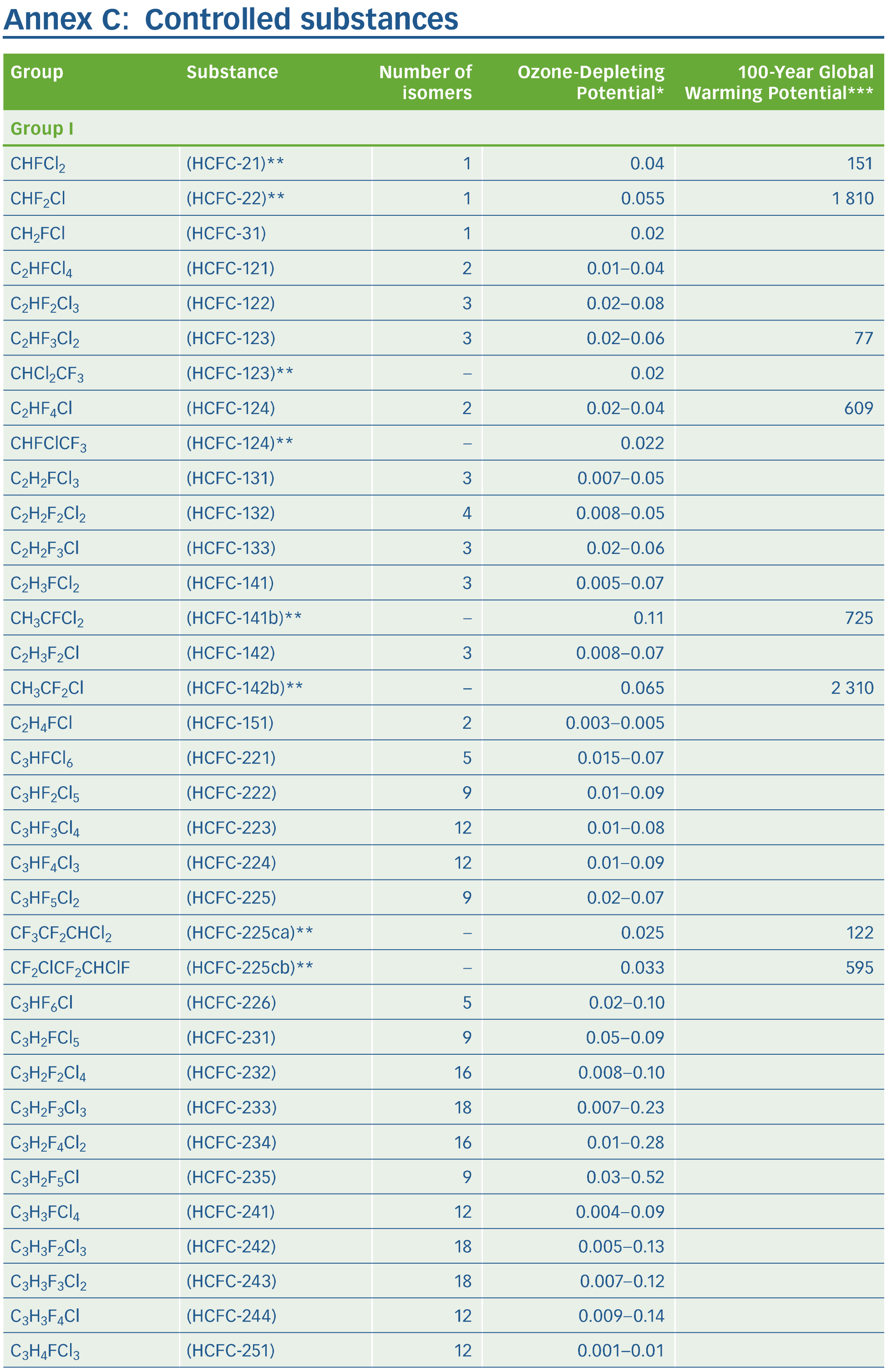
Group	Substance	Ozone-Depleting Potential*	100-Year Global Warming Potential
Group I			
$CFCl_3$	(CFC-11)	1.0	4 750
CF_2Cl_2	(CFC-12)	1.0	10 900
$C_2F_3Cl_3$	(CFC-113)	0.8	6 130
$C_2F_4Cl_2$	(CFC-114)	1.0	10 000
C_2F_5Cl	(CFC-115)	0.6	7 370
Group II			
CF_2BrCl	(halon-1211)	3.0	
CF_3Br	(halon-1301)	10.0	
$C_2F_4Br_2$	(halon-2402)	6.0	

* These ozone depleting potentials are estimates based on existing knowledge and will be reviewed and revised periodically.

Annex B: Controlled substances

Group	Substance	Ozone-Depleting Potential
Group I		
CF_3Cl	(CFC-13)	1.0
C_2FCl_5	(CFC-111)	1.0
$C_2F_2Cl_4$	(CFC-112)	1.0
C_3FCl_7	(CFC-211)	1.0
$C_3F_2Cl_6$	(CFC-212)	1.0
$C_3F_3Cl_5$	(CFC-213)	1.0
$C_3F_4Cl_4$	(CFC-214)	1.0
$C_3F_5Cl_3$	(CFC-215)	1.0
$C_3F_6Cl_2$	(CFC-216)	1.0
C_3F_7Cl	(CFC-217)	1.0
Group II		
CCl_4	carbon tetrachloride	1.1
Group III		
$C_2H_3Cl_3$*	1,1,1-trichloroethane* (methyl chloroform)	0.1

* This formula does not refer to 1,1,2-trichloroethane.



Annex C: Controlled substances

Group	Substance	Number of isomers	Ozone-Depleting Potential*	100-Year Global Warming Potential***
Group I				
$CHFCl_2$	(HCFC-21)**	1	0.04	151
CHF_2Cl	(HCFC-22)**	1	0.055	1 810
CH_2FCl	(HCFC-31)	1	0.02	
C_2HFCl_4	(HCFC-121)	2	0.01–0.04	
$C_2HF_2Cl_3$	(HCFC-122)	3	0.02–0.08	
$C_2HF_3Cl_2$	(HCFC-123)	3	0.02–0.06	77
$CHCl_2CF_3$	(HCFC-123)**	–	0.02	
C_2HF_4Cl	(HCFC-124)	2	0.02–0.04	609
$CHFClCF_3$	(HCFC-124)**	–	0.022	
$C_2H_2FCl_3$	(HCFC-131)	3	0.007–0.05	
$C_2H_2F_2Cl_2$	(HCFC-132)	4	0.008–0.05	
$C_2H_2F_3Cl$	(HCFC-133)	3	0.02–0.06	
$C_2H_3FCl_2$	(HCFC-141)	3	0.005–0.07	
CH_3CFCl_2	(HCFC-141b)**	–	0.11	725
$C_2H_3F_2Cl$	(HCFC-142)	3	0.008–0.07	
CH_3CF_2Cl	(HCFC-142b)**	–	0.065	2 310
C_2H_4FCl	(HCFC-151)	2	0.003–0.005	
C_3HFCl_6	(HCFC-221)	5	0.015–0.07	
$C_3HF_2Cl_5$	(HCFC-222)	9	0.01–0.09	
$C_3HF_3Cl_4$	(HCFC-223)	12	0.01–0.08	
$C_3HF_4Cl_3$	(HCFC-224)	12	0.01–0.09	
$C_3HF_5Cl_2$	(HCFC-225)	9	0.02–0.07	
$CF_3CF_2CHCl_2$	(HCFC-225ca)**	–	0.025	122
CF_2ClCF_2CHClF	(HCFC-225cb)**	–	0.033	595
C_3HF_6Cl	(HCFC-226)	5	0.02–0.10	
$C_3H_2FCl_5$	(HCFC-231)	9	0.05–0.09	
$C_3H_2F_2Cl_4$	(HCFC-232)	16	0.008–0.10	
$C_3H_2F_3Cl_3$	(HCFC-233)	18	0.007–0.23	
$C_3H_2F_4Cl_2$	(HCFC-234)	16	0.01–0.28	
$C_3H_2F_5Cl$	(HCFC-235)	9	0.03–0.52	
$C_3H_3FCl_4$	(HCFC-241)	12	0.004–0.09	
$C_3H_3F_2Cl_3$	(HCFC-242)	18	0.005–0.13	
$C_3H_3F_3Cl_2$	(HCFC-243)	18	0.007–0.12	
$C_3H_3F_4Cl$	(HCFC-244)	12	0.009–0.14	
$C_3H_4FCl_3$	(HCFC-251)	12	0.001–0.01	

Group	Substance	Number of isomers	Ozone-Depleting Potential*	100-Year Global Warming Potential***
$C_3H_4F_2Cl_2$	(HCFC-252)	16	0.005–0.04	
$C_3H_4F_3Cl$	(HCFC-253)	12	0.003–0.03	
$C_3H_5FCl_2$	(HCFC-261)	9	0.002–0.02	
$C_3H_5F_2Cl$	(HCFC-262)	9	0.002–0.02	
C_3H_6FCl	(HCFC-271)	5	0.001–0.03	

Group	Substance	Number of isomers	Ozone-Depleting Potential*
Group II			
$CHFBr_2$		1	1.00
CHF_2Br	(HBFC-22B1)	1	0.74
CH_2FBr		1	0.73
C_2HFBr_4		2	0.3–0.8
$C_2HF_2Br_3$		3	0.5–1.8
$C_2HF_3Br_2$		3	0.4–1.6
C_2HF_4Br		2	0.7–1.2
$C_2H_2FBr_3$		3	0.1–1.1
$C_2H_2F_2Br_2$		4	0.2–1.5
$C_2H_2F_3Br$		3	0.7–1.6
$C_2H_3FBr_2$		3	0.1–1.7
$C_2H_3F_2Br$		3	0.2–1.1
C_2H_4FBr		2	0.07–0.1
C_3HFBr_6		5	0.3–1.5
$C_3HF_2Br_5$		9	0.2–1.9
$C_3HF_3Br_4$		12	0.3–1.8
$C_3HF_4Br_3$		12	0.5–2.2
$C_3HF_5Br_2$		9	0.9–2.0
C_3HF_6Br		5	0.7–3.3
$C_3H_2FBr_5$		9	0.1–1.9
$C_3H_2F_2Br_4$		16	0.2–2.1
$C_3H_2F_3Br_3$		18	0.2–5.6
$C_3H_2F_4Br_2$		16	0.3–7.5
$C_3H_2F_5Br$		8	0.9–1.4
$C_3H_3FBr_4$		12	0.08–1.9
$C_3H_3F_2Br_3$		18	0.1–3.1
$C_3H_3F_3Br_2$		18	0.1–2.5
$C_3H_3F_4Br$		12	0.3–4.4
$C_3H_4FBr_3$		12	0.03–0.3
$C_3H_4F_2Br_2$		16	0.1–1.0

Group	Substance	Number of isomers	Ozone-Depleting Potential*
$C_3H_4F_3Br$		12	0.07–0.8
$C_3H_5FBr_2$		9	0.04–0.4
$C_3H_5F_2Br$		9	0.07–0.8
C_3H_6FBr		5	0.02–0.7
Group III			
CH_2BrCl	bromochloromethane	1	0.12

* Where a range of ODPs is indicated, the highest value in that range shall be used for the purposes of the Protocol. The ODPs listed as a single value have been determined from calculations based on laboratory measurements. Those listed as a range are based on estimates and are less certain. The range pertains to an isomeric group. The upper value is the estimate of the ODP of the isomer with the highest ODP, and the lower value is the estimate of the ODP of the isomer with the lowest ODP.
** Identifies the most commercially viable substances with ODP values listed against them to be used for the purposes of the Protocol.
*** For substances for which no GWP is indicated, the default value 0 applies until a GWP value is included by means of the procedure foreseen in paragraph 9 (a) (ii) of Article 2.

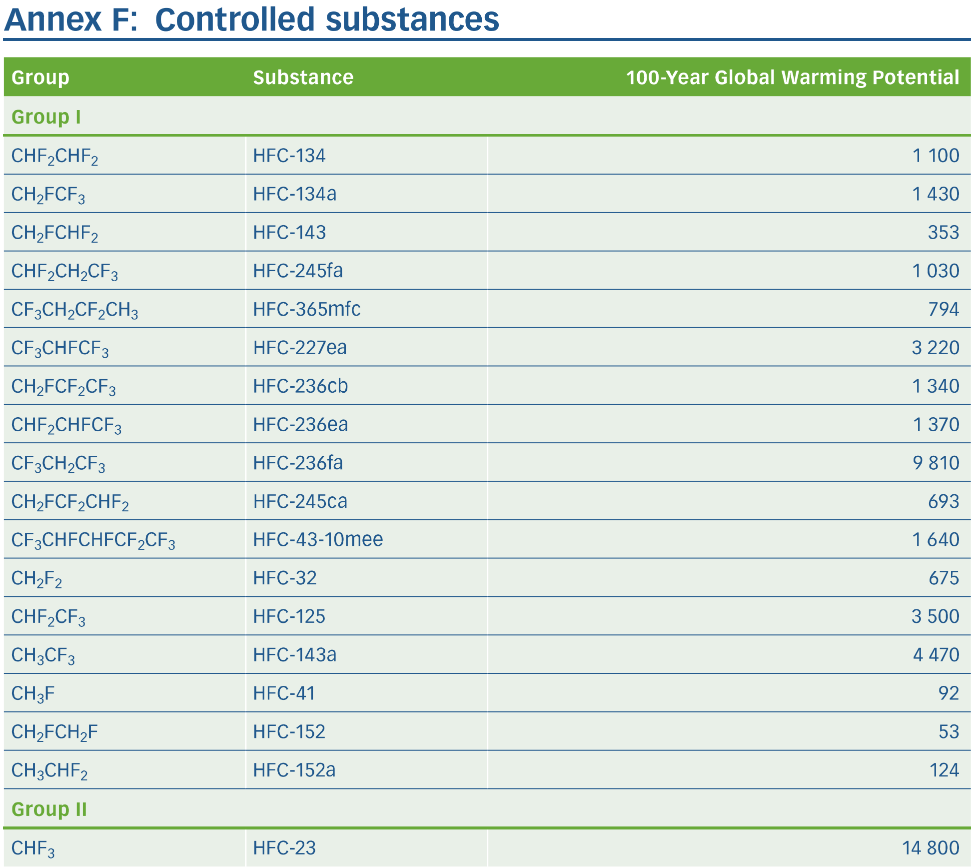
Annex D:* A list of products** containing controlled substances specified in Annex A

No.	Products	Customs code number
1	Automobile and truck air conditioning units (whether incorporated in vehicles or not)	....
2	Domestic and commercial refrigeration and air conditioning/heat pump equipment***	....
	e.g. Refrigerators	....
	Freezers	....
	Dehumidifiers	....
	Water coolers	....
	Ice machines	....
	Air conditioning and heat pump units	....
3	Aerosol products, except medical aerosols	....
4	Portable fire extinguisher	....
5	Insulation boards, panels and pipe covers	....
6	Pre-polymers	....

* This Annex was adopted by the Third Meeting of the Parties in Nairobi, 21 June 1991 as required by paragraph 3 of Article 4 of the Protocol.
** Though not when transported in consignments of personal or household effects or in similar non-commercial situations normally exempted from customs attention.
*** When containing controlled substances in Annex A as a refrigerant and/or in insulating material of the product.

Annex E: Controlled substances

Group	Substance	Ozone-Depleting Potential
Group I		
CH_3Br	methyl bromide	0.6



Annex F: Controlled substances

Group	Substance	100-Year Global Warming Potential
Group I		
CHF_2CHF_2	HFC-134	1 100
CH_2FCF_3	HFC-134a	1 430
CH_2FCHF_2	HFC-143	353
$CHF_2CH_2CF_3$	HFC-245fa	1 030
$CF_3CH_2CF_2CH_3$	HFC-365mfc	794
CF_3CHFCF_3	HFC-227ea	3 220
$CH_2FCF_2CF_3$	HFC-236cb	1 340
CHF_2CHFCF_3	HFC-236ea	1 370
$CF_3CH_2CF_3$	HFC-236fa	9 810
$CH_2FCF_2CHF_2$	HFC-245ca	693
$CF_3CHFCHFCF_2CF_3$	HFC-43-10mee	1 640
CH_2F_2	HFC-32	675
CHF_2CF_3	HFC-125	3 500
CH_3CF_3	HFC-143a	4 470
CH_3F	HFC-41	92
CH_2FCH_2F	HFC-152	53
CH_3CHF_2	HFC-152a	124
Group II		
CHF_3	HFC-23	14 800

3.7.2 Appendix 1.2: Substances in the ASHRAE Standard

ASHRAE Refrigerant Designations: tables from the ANSI/ASHRAE 34-2019 ”Designation and Safety Classification of Refrigerants” Standard, latest version available here (ASHRAE, 2019).

Table 3.6: ASHRAE Refrigerant Designations: tables separated by chemical family

Number	Chemical Name	Chemical Formula
	Methane Series	
11	trichlorofluoromethane	CCl3F
12	dichlorodifluoromethane	CCl2F2
12B1	bromochlorodifluoromethane	CBrClF2
13	chlorotrifluoromethane	CClF3
13B1	bromotrifluoromethane	CBrF3
13I1	trifluoroiodomethane	CF3I
14e	tetrafluoromethane (carbon tetrafluoride)	CF4
21	dichlorofluoromethane	CHCl2F
22	chlorodifluoromethane	CHClF2
23	trifluoromethane	CHF3
30	dichloromethane (methylene chloride)	CH2Cl2
31	chlorofluoromethane	CH2ClF
32	difluoromethane (methylene fluoride)	CH2F2
40	chloromethane (methyl chloride)	CH3Cl
41	fluoromethane (methyl fluoride)	CH3F
50	methane	CH4

Number	Chemical Name	Chemical Formula
	Ethane Series	
113	1,1,2-trichloro-1,2,2-trifluoroethane	CCl2FCClF2
114	1,2-dichloro-1,1,2,2-tetrafluoromethane	CClF2CClF2
115	chloropentafluoroethane	CClF2CF3
116	hexafluoroethane	CF3CF3
123	2,2-dichloro-1,1,1-trifluoroethane	CHCl2CF3
124	2-chloro-1,1,1,2-tetrafluoroethane	CHClFCF3
125	pentafluoroethane	CHF2CF3
134a	1,1,1,2-tetrafluoroethane	CH2FCF3
141b	1,1-dichloro-1-fluoroethane	CH3CCl2F
142b	1-chloro-1,1-difluoroethane	CH3CClF2
143a	1,1,1-trifluoroethane	CH3CF3
152a	1,1-difluoroethane	CH3CHF2
170	ethane	CH3CH3

Number	Chemical Name	Chemical Formula
	Ethers	
E170	Methoxymethane (dimethyl ether)	CH3OCH3

Number	Chemical Name	Chemical Formula
	Propane	
218	octafluoropropane	CF3CF2CF3
227ea	1,1,1,2,3,3,3-heptafluoropropane	CF3CHFCF3
236fa	1,1,1,3,3,3-hexafluoropropane	CF3CH2CF3
245fa	1,1,1,3,3-pentafluoropropane	CHF2CH2CF3
290	propane	CH3CH2CH3

Number	Chemical Name	Chemical Formula
	Cyclic Organic Compounds	
C318	octafluorocyclobutane	-(CF2)4-

Miscellaneous Organic Compounds		
Number	Chemical Name	Chemical Formula
hydrocarbons		
600	butane	CH3CH2CH2CH3 A3
600a	2-methylpropane (isobutane)	CH(CH3)2CH3 A3
601	pentane	CH3CH2CH2CH2CH3
601a	2-methylbutane (isopentane)	CH(CH3)2CH2CH3
oxygen compounds		
610	ethoxyethane (ethyl ether)	CH3CH2OCH2CH3
611	methyl formate	HCOOCH3
sulfur compounds		
620	(Reserved for future assignment)	

Number	Chemical Name	Chemical Formula
	Nitrogen Compounds	
630	methanamine (methyl amine)	CH3NH2
631	ethanamine (ethyl amine)	CH3CH2(NH2)

Number	Chemical Name	Chemical Formula
	Inorganic Compounds	
702	hydrogen	H2
704	helium	He
717	ammonia	NH3
718	water	H2O
720	neon	Ne
728	nitrogen	N2
732	oxygen	O2
740	argon	Ar
744	carbon dioxide	CO2
744A	nitrous oxide	N2O
764	sulfur dioxide	SO2

Number	Chemical Name	Chemical Formula
	Unsaturated Organic Compounds	
1130(E)	trans-1,2-dichloroethene	CHCl=CHCl
R-1132a	1,1-difluoroethylene	CF2=CH2
1150	ethene (ethylene)	CH2=CH2
R-1224yd(Z)	(Z)-1-chloro-2,3,3,3-tetrafluoropropene	CF3CF=CHCl
1233zd(E)	trans-1-chloro-3,3,3-trifluoro-1-propene	CF3CH=CHCl
1234yf	2,3,3,3-tetrafluoro-1-propene	CF3CF=CH2
1234ze(E)	trans-1,3,3,3-tetrafluoro-1-propene	CF3CH=CHF
1270	propene (propylene)	CH3CH=CH2
1336mzz(E)	trans-1,1,1,4,4,4-hexafluoro-2-butene	CF3CH=CHCF3
1336mzz(Z)	cis-1,1,1,4,4,4-hexaflouro-2-butene	CF3CHCHCF3

3.8 Appendix 2: Patent Classes

Section	IPC Subclasses
C	C09K, C08G, C08L, C11D, C07C, C08J, C07D, C07K, C07F, C10M, C02F, C22C, C12N, C08K
	C10N, C07J, C08F, C25D, C09D, C07H, C23C, C06B, C01B, C12Q, C23F, C04B, C12P, C09B
	C12M, C07B, C01F, C03C,C09J, C23G
F	F01K, F25B, F04B, F04C, F28F, F16N, F16D, F16K, F17C

Table 3.7: C and F IPC Subclasses from the Substances Regulated under the Kigali Amendment

Section	IPC Classes
C	C01, C02, C03, C04, C06, C07, C08, C09, C10, C11, C12, C22, C23, C25
F	F01, F04, F16, F17, F25, F28

Table 3.8: C and F IPC Classes for the Coarsened Exact Matching

3.9 Appendix 3: Descriptive Statistics and Estimates

3.9.1 Results from the Exact Matching

App. year	IPC	Control Group (T_0)	Dirty (T_1)	Clean (T_2)
1997	C07	476	17	10
1997	C08	301	17	39
1997	C09	142	6	7
1997	C23	60	4	3
1997	F17	9	2	1
1997	F25	20	3	1
1998	C01	42	1	5
1998	C07	539	14	4
1998	C08	266	12	38
1998	C09	128	2	7
1999	C07	606	19	5
1999	C08	363	16	93
1999	C09	155	3	7
1999	C12	925	8	1
1999	C23	84	2	1
1999	F04	118	1	2
1999	F17	19	1	2
1999	F25	36	5	3
2000	C04	107	1	1
2000	C07	762	18	10
2000	C08	427	15	65
2000	C09	184	4	13
2000	C10	20	7	1
2000	F25	51	6	2
2001	C01	62	1	5
2001	C07	933	36	12
2001	C08	501	33	76

App. year	IPC	Control Group (T_0)	Dirty (T_1)	Clean (T_2)
2001	C11	70	2	1
2001	C12	992	5	1
2001	C23	156	5	4
2001	F04	222	2	1
2001	F25	69	3	1
2002	C07	1069	41	10
2002	C08	513	31	79
2002	C09	242	5	25
2002	C23	171	1	6
2002	F04	231	1	1
2003	C07	1253	47	7
2003	C08	565	38	92
2003	C09	317	10	22
2003	C10	13	1	4
2003	C12	980	5	2
2003	C23	208	4	6
2004	C01	61	3	4
2004	C07	1284	68	9
2004	C08	646	40	84
2004	C09	352	8	13
2004	C10	15	2	7
2004	C23	225	1	5
2004	F25	90	1	1
2005	C01	67	2	2
2005	C07	1287	67	8
2005	C08	591	43	104
2005	C09	378	16	15
2005	C10	20	2	4
2005	C12	977	1	2
2005	C23	213	1	5

App. year	IPC	Control Group (T_0)	Dirty (T_1)	Clean (T_2)
2006	C07	1303	70	6
2006	C08	666	41	89
2006	C09	379	10	13
2006	C10	23	1	4
2006	C23	221	3	5

Table 3.9: Result from the Exact Matching

3.9.2 Estimates Panel Event Study

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim1	3.178***	0.434	7.317	0.000	2.327	4.030
Dim2	3.591***	0.361	9.953	0.000	2.883	4.298
Dim3	0.829	0.485	1.709	0.087	-0.122	1.779
Dim4	-2.407***	0.325	-7.412	0.000	-3.044	-1.771
Dim5	-2.871***	0.429	-6.689	0.000	-3.712	-2.030
Grant Lag	0.000	0.000	0.287	0.774	-0.000	0.000
Applicants	-0.362***	0.093	-3.894	0.000	-0.544	-0.180
Inventors	0.272***	0.016	17.157	0.000	0.241	0.303
Family Size	0.042***	0.003	14.875	0.000	0.036	0.048
Active	0.599***	0.078	7.657	0.000	0.446	0.752
App. year * IPC Class FE	0.018***	0.002	11.795	0.000	0.015	0.021
1998.year	0.000	.	.	.	0.000	0.000
1999.year	0.363	1.700	0.213	0.831	-2.969	3.695
2000.year	0.761	1.589	0.479	0.632	-2.354	3.875
2001.year	1.154	1.547	0.746	0.456	-1.878	4.185
2002.year	1.510	1.529	0.987	0.324	-1.488	4.507
2003.year	1.858	1.520	1.222	0.222	-1.122	4.838
2004.year	2.164	1.516	1.428	0.153	-0.806	5.135
2005.year	2.362	1.512	1.562	0.118	-0.602	5.326
2006.year	2.583	1.510	1.710	0.087	-0.377	5.543
2007.year	2.835	1.508	1.880	0.060	-0.120	5.791
2008.year	3.037*	1.507	2.015	0.044	0.082	5.991
2009.year	3.362*	1.507	2.231	0.026	0.409	6.315
2010.year	3.756*	1.506	2.494	0.013	0.805	6.708
2011.year	4.164**	1.506	2.765	0.006	1.213	7.115
2012.year	4.587**	1.505	3.047	0.002	1.637	7.538
2013.year	4.989***	1.505	3.315	0.001	2.039	7.939
2014.year	5.332***	1.505	3.543	0.000	2.382	8.282

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
2015.year	5.629***	1.505	3.740	0.000	2.679	8.579
2016.year	5.889***	1.505	3.912	0.000	2.939	8.839
2017.year	6.053***	1.505	4.021	0.000	3.103	9.003
Lead5	0.026	1.033	0.025	0.980	-1.999	2.051
Lead4	0.217	0.865	0.251	0.802	-1.479	1.912
Lead3	0.339	0.737	0.460	0.646	-1.106	1.784
Lead2	0.444	0.647	0.686	0.493	-0.825	1.712
Lead1	0.460	0.583	0.788	0.431	-0.684	1.603
Lag1	0.814	0.498	1.633	0.103	-0.163	1.791
Lag2	1.006*	0.473	2.129	0.033	0.080	1.933
Lag3	1.137*	0.456	2.491	0.013	0.242	2.031
Lag4	1.222**	0.444	2.754	0.006	0.352	2.091
Lag5	1.160**	0.429	2.705	0.007	0.319	2.000
Lag6	1.227**	0.422	2.906	0.004	0.400	2.055
Lag7	1.224**	0.414	2.957	0.003	0.413	2.034
Lag8	1.255**	0.409	3.067	0.002	0.453	2.057
Lag9	1.162**	0.404	2.875	0.004	0.370	1.954
Lag10	1.161**	0.403	2.880	0.004	0.371	1.951
_cons	-1.359	1.510	-0.900	0.368	-4.317	1.600

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 3.10: Panel Event Study Estimates of Clean Technologies

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim1	2.103***	0.434	4.840	0.000	1.251	2.954
Dim2	3.180***	0.366	8.683	0.000	2.462	3.898
Dim3	0.785	0.482	1.627	0.104	-0.160	1.729
Dim4	-2.676***	0.332	-8.058	0.000	-3.327	-2.025
Dim5	-3.170***	0.431	-7.353	0.000	-4.015	-2.325
Grant Lag	-0.000	0.000	-0.607	0.544	-0.000	0.000
Applicants	-0.514***	0.094	-5.443	0.000	-0.699	-0.329
Inventors	0.253***	0.016	15.813	0.000	0.221	0.284
Family Size	0.032***	0.003	11.694	0.000	0.027	0.037
Active	0.626***	0.079	7.929	0.000	0.471	0.780
App. year * IPC Class FE	0.017***	0.002	10.920	0.000	0.014	0.020
1998.year	0.000	.	.	.	0.000	0.000
1999.year	0.375	1.690	0.222	0.824	-2.937	3.688
2000.year	0.779	1.580	0.493	0.622	-2.318	3.875
2001.year	1.165	1.538	0.757	0.449	-1.850	4.179
2002.year	1.524	1.521	1.003	0.316	-1.456	4.505
2003.year	1.871	1.512	1.237	0.216	-1.092	4.834
2004.year	2.174	1.507	1.443	0.149	-0.779	5.127
2005.year	2.372	1.504	1.577	0.115	-0.576	5.319
2006.year	2.592	1.502	1.726	0.084	-0.351	5.535
2007.year	2.769	1.500	1.846	0.065	-0.171	5.708
2008.year	3.044*	1.499	2.031	0.042	0.106	5.981
2009.year	3.368*	1.498	2.248	0.025	0.432	6.304
2010.year	3.764*	1.497	2.514	0.012	0.829	6.699
2011.year	4.171**	1.497	2.786	0.005	1.236	7.105
2012.year	4.594**	1.497	3.069	0.002	1.660	7.527
2013.year	4.996***	1.497	3.338	0.001	2.062	7.929
2014.year	5.339***	1.497	3.568	0.000	2.406	8.272
2015.year	5.637***	1.497	3.767	0.000	2.704	8.571

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
2016.year	5.898***	1.497	3.941	0.000	2.964	8.831
2017.year	6.063***	1.497	4.051	0.000	3.130	8.997
Lead5	-0.461	1.541	-0.299	0.765	-3.481	2.559
Lead4	-0.751	1.216	-0.618	0.537	-3.135	1.633
Lead3	-0.651	1.049	-0.621	0.535	-2.707	1.405
Lead2	-0.724	0.950	-0.762	0.446	-2.585	1.137
Lead1	-0.780	0.855	-0.912	0.362	-2.457	0.896
Lag1	-0.793	0.718	-1.104	0.269	-2.200	0.614
Lag2	-0.739	0.666	-1.109	0.267	-2.044	0.566
Lag3	-0.648	0.632	-1.025	0.306	-1.887	0.591
Lag4	-0.738	0.603	-1.223	0.221	-1.920	0.445
Lag5	-0.961	0.577	-1.665	0.096	-2.092	0.170
Lag6	-0.966	0.560	-1.725	0.085	-2.063	0.131
Lag7	-0.903	0.550	-1.643	0.100	-1.981	0.174
Lag8	-0.945	0.535	-1.766	0.077	-1.994	0.104
Lag9	-1.016	0.530	-1.918	0.055	-2.055	0.022
Lag10	-1.024	0.530	-1.933	0.053	-2.062	0.014
_cons	-0.917	1.501	-0.611	0.541	-3.859	2.026

$*p < 0.05,\ **p < 0.01,\ ***p < 0.001$

Table 3.11: Panel Event Study Estimates of Dirty Technologies

3.9.3 Estimates Nonparametric Duration Model

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
2008	0.099	0.097	2.969	3.630	0.000	0.000
2009	0.096	0.045	3.052	4.514	0.000	0.000
2010	0.107	0.057	2.582	4.315	0.000	0.000
2011	0.074	0.056	3.597	5.408	0.000	0.000
2012	0.230	0.165	1.481	2.765	0.000	0.001
2013	0.268	0.124	1.549	3.146	0.000	0.000
2014	0.281	0.190	1.447	2.991	0.000	0.001
2015	0.300	0.229	1.692	2.601	0.000	0.001
2016	0.368	0.400	1.785	1.869	0.000	0.003
2017	0.936	0.921	0.797	0.797	0.001	0.020
2018	1.338	0.988	0.797	0.797	0.002	0.024

Table 3.12: Nonparametric Estimates Clean Patents VS Control Group (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
2008	-0.002	0.977	0.028	0.000	-0.034	0.030	0.647	1.308
2009	-0.051*	0.472*	0.049	0.000	-0.072	-0.029	0.040	0.904
2010	-0.049*	0.538*	0.041	0.000	-0.074	-0.024	0.139	0.937
2011	-0.018	0.757	0.036	0.000	-0.040	0.004	0.384	1.130
2012	-0.066*	0.715	0.025	0.001	-0.120	-0.012	0.406	1.024
2013	-0.143*	0.465*	0.030	0.001	-0.191	-0.095	0.124	0.806
2014	-0.091*	0.675*	0.023	0.001	-0.152	-0.031	0.379	0.971
2015	-0.070	0.765	0.024	0.001	-0.143	0.002	0.462	1.068
2016	0.032	1.088	0.022	0.003	-0.083	0.147	0.797	1.378
2017	-0.015	0.984	0.025	0.021	-0.301	0.272	0.674	1.295
2018	-0.350*	0.739	0.026	0.027	-0.670	-0.030	0.424	1.053

$*p < 0.05$

Table 3.13: Nonparametric Estimates Clean Patents VS Control Group (Hazard Rates' Differences and Ratios)

Variable	Description
Obc	Optimal Bandwidth Control Group
Obt	Optimal Bandwidth Treatment Group
aVc	Asymptotic Variance Control Group
aVt	Asymptotic Variance Treatment Group
aVr	Asymptotic Variance Ratio
aVd	Asymptotic Variance Difference
LB-Diff	Lower Bound Difference
UB-Diff	Upper Bound Difference
LB-Ratio	Lower Bound Ratio
UB-Ratio	Upper Bound Ratio

Table 3.14: Description of Variables from the Nonparametric Estimates

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
2008	0.099	0.079	2.969	4.155	0.000	0.000
2009	0.096	0.045	3.052	5.210	0.000	0.000
2010	0.107	0.074	2.582	3.794	0.000	0.000
2011	0.074	0.048	3.597	4.967	0.000	0.000
2012	0.230	0.058	1.481	4.818	0.000	0.000
2013	0.268	0.151	1.549	2.895	0.000	0.001
2014	0.281	0.130	1.447	3.459	0.000	0.001
2015	0.300	0.199	1.692	2.574	0.000	0.002
2016	0.368	0.474	1.785	1.895	0.000	0.006
2017	0.936	0.795	0.797	0.797	0.001	0.030
2018	1.338	1.203	0.797	0.797	0.002	0.050

Table 3.15: Nonparametric Estimates Dirty Patents VS Control Group (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
2008	-0.020	0.798	0.052	0.000	-0.056	0.016	0.350	1.246
2009	-0.050*	0.475	0.075	0.000	-0.076	-0.024	-0.061	1.011
2010	-0.032	0.697	0.065	0.000	-0.071	0.006	0.197	1.197
2011	-0.026	0.647	0.081	0.000	-0.054	0.001	0.091	1.203
2012	-0.172*	0.252*	0.070	0.000	-0.209	-0.136	-0.267	0.770
2013	-0.117*	0.562*	0.047	0.001	-0.185	-0.050	0.138	0.986
2014	-0.151*	0.462*	0.049	0.001	-0.213	-0.090	0.031	0.894
2015	-0.100*	0.665	0.046	0.002	-0.187	-0.013	0.243	1.086
2016	0.107	1.291	0.031	0.007	-0.052	0.265	0.947	1.634
2017	-0.141	0.850	0.048	0.031	-0.487	0.205	0.419	1.280
2018	-0.134	0.899	0.036	0.053	-0.584	0.315	0.529	1.270

$*p < 0.05$

Table 3.16: Nonparametric Estimates Dirty Patents VS Control Group (Hazard Rates' Differences and Ratios)

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
2008	0.097	0.079	3.630	4.155	0.000	0.000
2009	0.045	0.045	4.514	5.210	0.000	0.000
2010	0.057	0.074	4.315	3.794	0.000	0.000
2011	0.056	0.048	5.408	4.967	0.000	0.000
2012	0.165	0.058	2.765	4.818	0.001	0.000
2013	0.124	0.151	3.146	2.895	0.000	0.001
2014	0.190	0.130	2.991	3.459	0.001	0.001
2015	0.229	0.199	2.601	2.574	0.001	0.002
2016	0.400	0.474	1.869	1.895	0.003	0.006
2017	0.921	0.795	0.797	0.797	0.020	0.030
2018	0.988	1.203	0.797	0.797	0.024	0.050

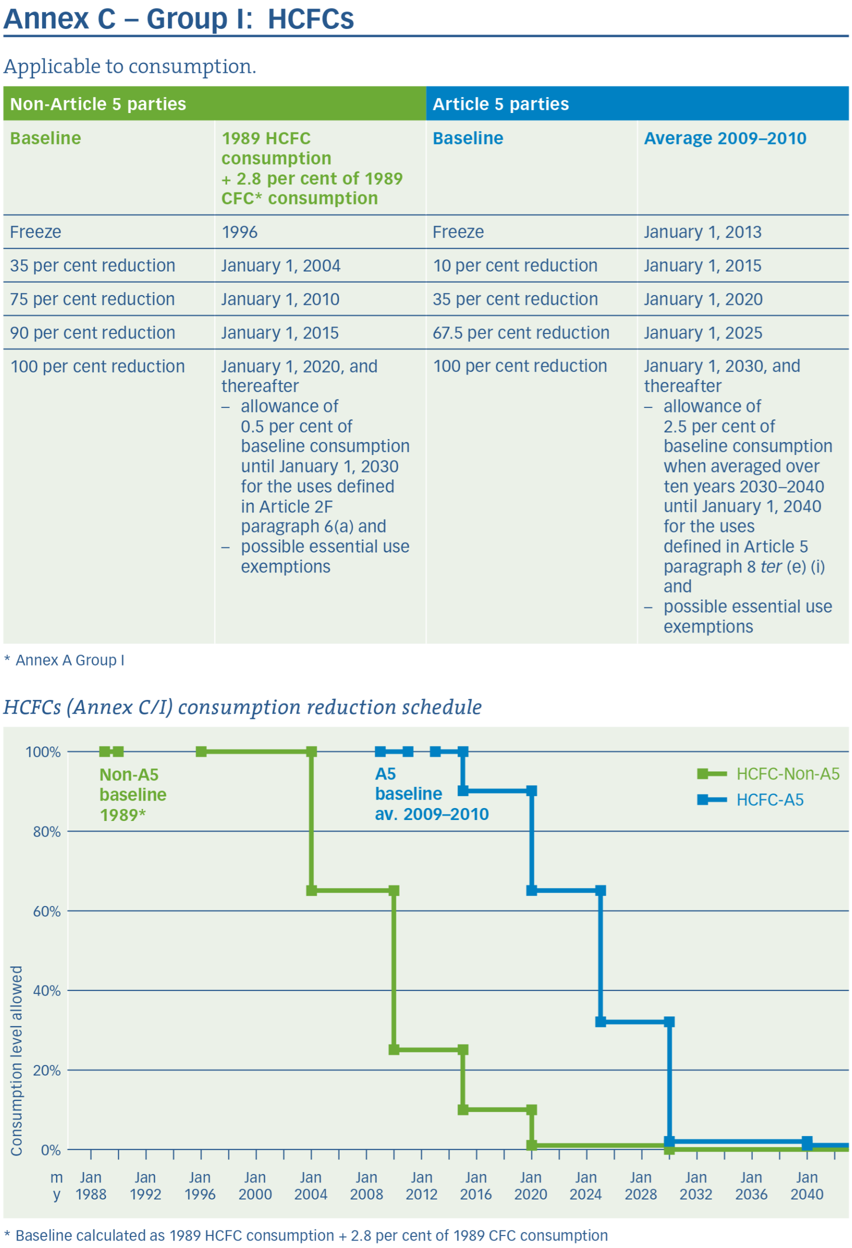
Table 3.17: Nonparametric Estimates Dirty VS Clean Patents (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
2008	-0.018	0.817	0.069	0.001	-0.064	0.029	0.304	1.330
2009	0.000	1.007	0.123	0.000	-0.031	0.031	0.320	1.694
2010	0.017	1.296	0.132	0.000	-0.026	0.060	0.583	2.009
2011	-0.008	0.854	0.105	0.000	-0.042	0.025	0.220	1.488
2012	-0.107*	0.352*	0.073	0.001	-0.165	-0.049	-0.177	0.881
2013	0.026	1.209	0.090	0.002	-0.050	0.102	0.622	1.797
2014	-0.060	0.685	0.058	0.002	-0.138	0.018	0.211	1.158
2015	-0.030	0.869	0.063	0.003	-0.138	0.077	0.378	1.359
2016	0.075	1.187	0.056	0.010	-0.117	0.266	0.721	1.652
2017	-0.126	0.863	0.065	0.050	-0.563	0.311	0.365	1.362
2018	0.215	1.218	0.072	0.075	-0.321	0.751	0.692	1.743

$*p < 0.05$

Table 3.18: Nonparametric Estimates Dirty VS Clean Patents (Hazard Rates' Differences and Ratios)

3.10 Appendix 4: Regulation Schedule



Annex C – Group I: HCFCs

Applicable to consumption.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	1996	Freeze	January 1, 2013
35 per cent reduction	January 1, 2004	10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline consumption until January 1, 2030 for the uses defined in Article 2F paragraph 6(a) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline consumption when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (i) and – possible essential use exemptions

* Annex A Group I

HCFCs (Annex C/I) consumption reduction schedule

* Baseline calculated as 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 3.15: HCFCs Phase-down Consumption Schedule.
Source: ”Handbook for the Montreal Protocol on Substances that Deplete the Ozone Layer”, Section 1.2., latest version available here (UNEP, 2019).

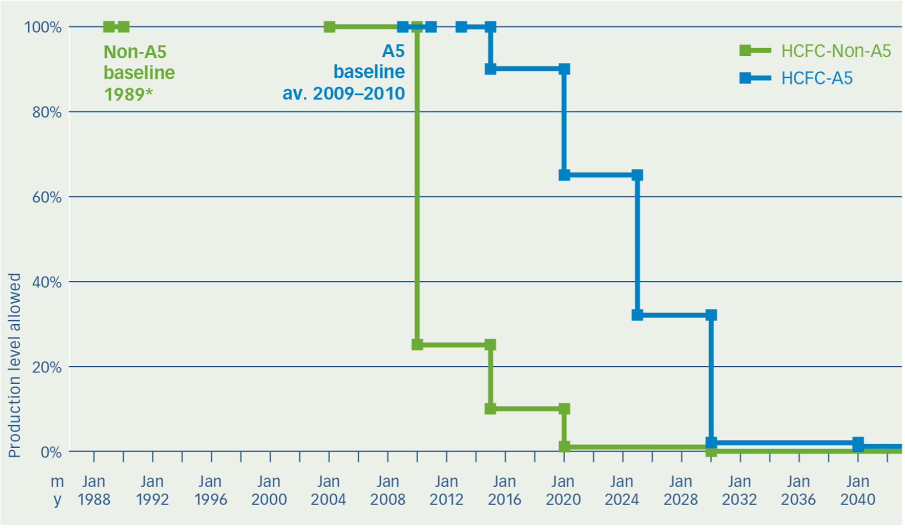
Annex C – Group I: HCFCs

Applicable to production.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**Average of 1989 HCFC production + 2.8 per cent of 1989 CFC* production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	January 1, 2004, at the baseline for production	Freeze	January 1, 2013
		10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline production until January 1, 2030 for the uses defined in Article 2F paragraph 6(b) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline production when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (ii) and – possible essential use exemptions

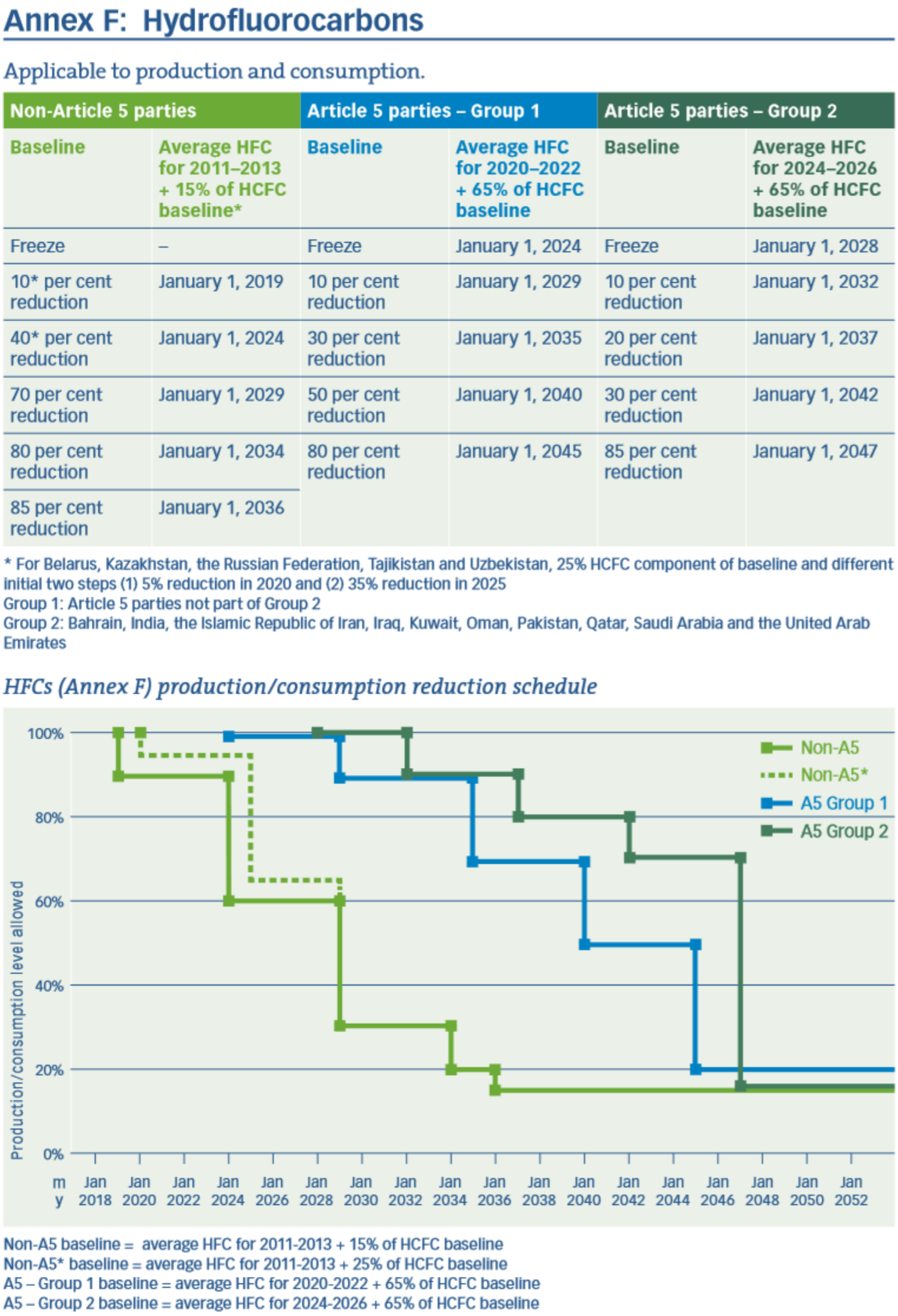
* Annex A Group I

HCFCs (Annex C/I) production reduction schedule



* Baseline calculated as average of 1989 HCFC production + 2.8 per cent of 1989 CFC production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 3.16: HCFCs Phase-down Production Schedule (UNEP, 2019)



Annex F: Hydrofluorocarbons

Applicable to production and consumption.

Non-Article 5 parties		Article 5 parties – Group 1		Article 5 parties – Group 2	
Baseline	**Average HFC for 2011–2013 + 15% of HCFC baseline***	**Baseline**	**Average HFC for 2020–2022 + 65% of HCFC baseline**	**Baseline**	**Average HFC for 2024–2026 + 65% of HCFC baseline**
Freeze	–	Freeze	January 1, 2024	Freeze	January 1, 2028
10* per cent reduction	January 1, 2019	10 per cent reduction	January 1, 2029	10 per cent reduction	January 1, 2032
40* per cent reduction	January 1, 2024	30 per cent reduction	January 1, 2035	20 per cent reduction	January 1, 2037
70 per cent reduction	January 1, 2029	50 per cent reduction	January 1, 2040	30 per cent reduction	January 1, 2042
80 per cent reduction	January 1, 2034	80 per cent reduction	January 1, 2045	85 per cent reduction	January 1, 2047
85 per cent reduction	January 1, 2036				

* For Belarus, Kazakhstan, the Russian Federation, Tajikistan and Uzbekistan, 25% HCFC component of baseline and different initial two steps (1) 5% reduction in 2020 and (2) 35% reduction in 2025

Group 1: Article 5 parties not part of Group 2

Group 2: Bahrain, India, the Islamic Republic of Iran, Iraq, Kuwait, Oman, Pakistan, Qatar, Saudi Arabia and the United Arab Emirates

HFCs (Annex F) production/consumption reduction schedule

Non-A5 baseline = average HFC for 2011-2013 + 15% of HCFC baseline
Non-A5* baseline = average HFC for 2011-2013 + 25% of HCFC baseline
A5 – Group 1 baseline = average HFC for 2020-2022 + 65% of HCFC baseline
A5 – Group 2 baseline = average HFC for 2024-2026 + 65% of HCFC baseline

Figure 3.17: HFCs Phase-down Production and Consumption Schedule (UNEP, 2019)

3.11 Appendix 5: Nonparametric Estimates 2008-2019

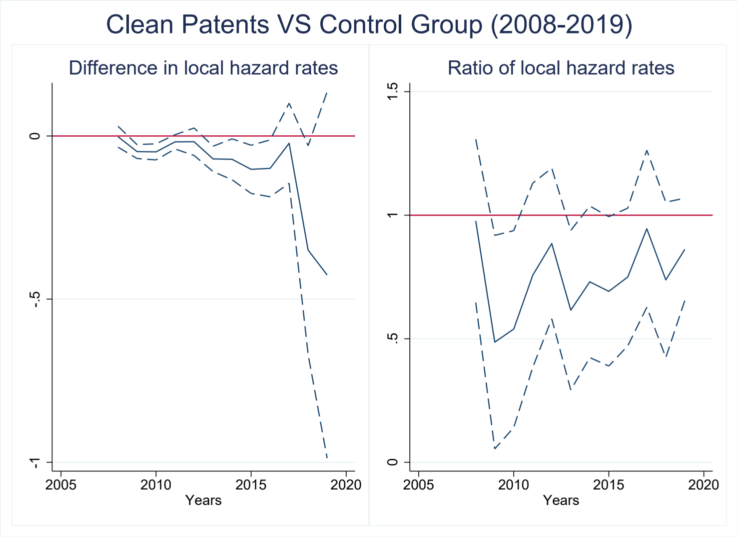


Figure 3.18: Nonparametric Duration Estimates (2008-2019): Clean Patents VS Control Group

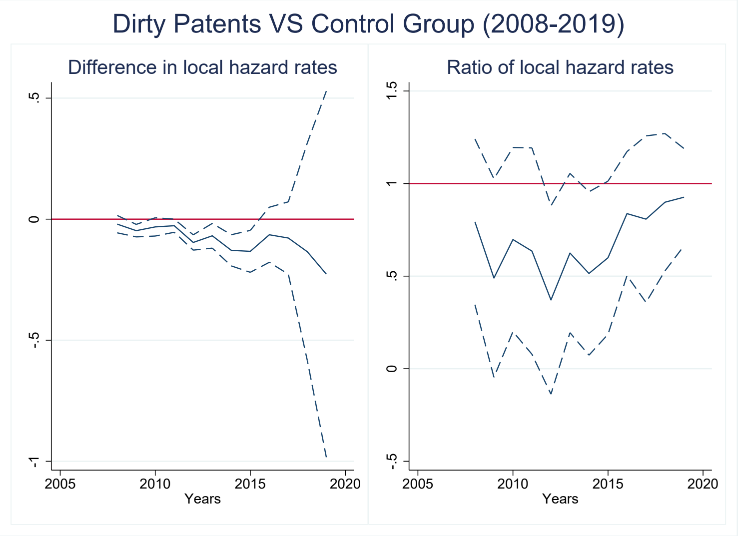


Figure 3.19: Nonparametric Duration Estimates (2008-2019): Dirty Patents VS Control Group

4 Patents as Options: Estimating Technological Gains and Losses from International Environmental Agreements*

4.1 Introduction

International environmental agreements (IEAs) are a key regulatory instrument for solving global environmental problems engendered by stock pollutants[1]. Nevertheless, the uncertainty related to the consequences of their signature makes them prone to long negotiations. This longer time scope makes it harder to quantify their impact, since stakeholders (i.e.: firms and countries) might anticipate their signature, reacting before their implementation, or if the negotiated terms are too lenient, deciding to postpone their reaction. Therefore, understanding and quantifying the economic implications of IEAs is a challenging but still essential task towards enabling future climate agreements.

In this paper I propose a new method to study the impact of regulations negotiated in IEAs on technologies. To achieve this, I take as a first approximation of the technological impact, the technological gains and losses an IEA generates in form of patent rights. Technological change measured as the publication of new ideas (e.g. patent applications) suffers from the lag between the decision to innovate and the actual publication of the innovation, which added to the slow and delayed nature of IEAs makes it even harder to back out the impact of IEAs on innovation. Instead, in order to disentangle the impact of an IEA on technological change, I use patent renewal, which as a yearly decision that patent holders make, does not suffer from this caveat. Therefore, exploiting patent renewal

---

*I would like to thank Victor Aguirregabiria, Bernhard Ganglmair, Timo Goeschl, Wolfgang Habla, François Laisney, Bettina Peters, Mar Reguant, Imke Reimers, John Rust, Carlos Serrano, Kenneth Simons, and Ulrich Wagner for their helpful feedback and comments. Furthermore, I would like to thank all participants to ZEW seminars, Econometric Society DSE 2018, MaCCI Annual Conferences 2020 and 2021, EAERE-ETH Winter School 2019, AURÖ 2019, MaCCI IO Day 2019, TECHNIS 2020, AERE 2020, Summer School on Data Algorithms for Science, Technology & Innovation Studies 2020, Mannheim Energy Conference 2021, IX IEB Symposium, and WIPE 2021. Lucas van Doorn provided excellent research assistance. The usual disclaimer applies.

[1] Stock pollutants are defined as those generating a negative externality through their accumulation in the environment (Phaneuf and Requate, 2017). This is the case of greenhouse gases like CO_2 but also of ozone-depleting substances (ODS), regulated under the Montreal Protocol.

variation, I estimate a model of patent renewal under uncertain exogenous environmental regulation, developed in Chapter 2.

In order to estimate my model, I use a unique self-constructed dataset[2] of European patents on substances regulated under an IEA, the Kigali Amendment to the Montreal Protocol, and their substitutes. IEAs often specify reduction targets for environmental harmful substances, which become binding environmental regulations in the signatory countries. In particular, I study the technological impact of the HFCs'[3] regulation under the Kigali Amendment. This pollutant-specific dataset on patent renewal decisions of clean and dirty patents allows me to estimate structural parameters of my patent renewal model and compute counterfactuals on the technological gains and losses associated to patent rights induced by the Amendment.

This chapter is structured in the following manner, first I shortly review the literature, second, I present the dataset used for estimation, summarize the theoretical modelling framework, and enumerate and explain the underlying assumptions of the models. Following this, I present the estimation results and discuss the goodness-of-fit. Finally, I close the chapter with a discussion of the caveats and measurement errors of the method and present the counterfactual results of the estimation.

4.2 Literature Review

This chapter stands upon three strands of the literature. First, on the literature of structural models in environmental economics. This literature started with the work of Ryan (2012) using a dynamic oligopoly model to estimate the welfare costs of changes in the Clean Air Act on the cement industry. Fabra and Reguant (2014) employ a structural estimation on optimal bidding in the electricity market to study how emissions costs are passed-through to electricity prices. Fowlie et al. (2014) building upon the work of Ryan

---

[2] Dugoua (2021) built a data set on U.S. patents and articles mentioning substances regulated under the Montreal Protocol.

[3] Hydrofluorocarbons (HFCs) are organic compounds containing hydrogen and fluorine atoms. HFCs have been widely used as substitutes for hydrochlorofluorocarbons (HCFCs), and chlorofluorocarbons (CFCs), which contain the chlorine atom responsible for the photo-induced reaction that depletes the ozone layer. HFCs do not harm the ozone layer but are powerful greenhouse gases. All three families of chemical compounds are regulated under the Montreal Protocol.

(2012) estimate the long-run consequences of a marked-based regulation of CO_2 emissions. Ito and Reguant (2016) quantify the welfare effects of arbitrage in a framework with sequential markets under imperfect competition and restricted entry in the framework of the Iberian electricity market. Wagner (2016), using a timing game in an oligopoly setting, estimates the sign and the magnitude of the strategic behavior of the parties to the Montreal Protocol in their ratification decision. Miravete et al. (2018) estimate an oligopoly model of horizontal differentiated goods applied to the Spanish automobile market and find that European carmakers profited from pro-diesel fuel taxes and lax NO_x emission policy to earn profits from diesel cars' sales. Grigolon et al. (2018) study the effect of fuel taxes versus product taxes in reducing fuel consumption estimating a random coefficients demand model with European car market data. Reynaert (2021) uses a structural model of consumer demand and firm behavior to study the welfare effect of the EU-wide emission standard on the car market. He finds that the regulation was not welfare improving. Finally, Blundell et al. (2020) estimate in a dynamic model of a plant and a regulator the effects on pollution damages of the dynamic enforcement policy used by the U.S. Environmental Protection Agency to enforce air regulations.

Second, my work builds upon the literature on optimal R&D policy under the existence of environmental externalities. This literature provides the theoretical intuitions of the forces driving the results shown in this paper. The work of Goeschl and Perino (2007) illustrates particularly well the technological dilemma faced by innovating firms under the Montreal Protocol. In particular, their modelling framework depicts in an accurate manner the interaction between the stock pollutants' nature of emissions and the lack of a backstop technology, which leads to sequential innovations. This innovation dilemma of undertaking R&D knowing that the outcome might not be a silver bullet to the environmental problem is further studied in their following work, Goeschl and Perino (2009). In their paper they model the uncertainty of clean innovations, which could result in either backstop technologies or engender a new pollution problem.

The third and last strand of the literature upon which this work stands is the literature on patent valuation of clean and dirty technologies. This literature is still relatively scarce. Hall and Helmers (2013) studied the characteristics of patents pledged under the "Eco-Patent Commons" and compare them to patents of the same firm or to patents in the same technologies. They find that pledged patents are of similar value to the ones of the pledging firm but of lower value compared to the patents in their technology class. Dechezleprêtre et al. (2021a; 2021b), employing the Tobin Q approach of Hall et al. (2005), compare the value of clean and dirty technologies and find that clean innovations are more valued than dirty ones. Finally, recently Langer et al. (2022), using the stock market approach of Kogan et al. (2017), study the impact of financial constraints on clean and dirty innovations. They find that clean innovations are more affected by financial constraints due to their perception as riskier assets.

4.3 Data, Equations, and Assumptions

In this section I will first shortly summarize the main datasets that I use for my method as well as the empirical evidence upon which it builds. Second, I describe the implementation of the method, explaining the equations and models used. Finally, I present the assumptions upon which my results build and discuss their viability.

4.3.1 Data

Estimation Dataset

In order to implement the method and quantify the monetary technological gains and losses engendered by the environmental regulation I use two sorts of data, i.e., patents with their renewal information and the corresponding renewal fees.

Patents The objective of this study is to estimate the technological gains and losses generated by an IEA using patent data. Therefore, I first need to identify the patents that might have won or lost value due to the Kigali Amendment as well as the set of comparable patents that should have not been directly affected by it. In particular, I need to identify patents citing substances that have been regulated by the Kigali Amendment, i.e., citing HFCs, so-called “dirty patents”, as well as clean patents. In order to define clean and dirty patents I focus my study on patents used in refrigeration. The reason for this is that substances that can be used as refrigerants are clearly defined as of the ANSI/ASHRAE

Standard 34-2019 (ASHRAE, 2019). There, all substances with refrigeration properties are listed, i.e., both the ones regulated under the Montreal Protocol (including the Kigali Amendment) and their potential clean substitutes. The exact construction of the dataset is presented in Chapter 3 and in this work I employ that same set of data. In particular, I use European patents renewed in Germany, applied between 1997 and 2006 belonging to the F and C IPC [4] sections. For further details on patent selection and the dataset, please refer to Chapter 3. The main descriptive statistics are reported in the Appendix 1 of the present chapter.

Renewal fees Besides patent data I gathered patent renewal fees from the Official Journal of the European Patent Office (EPO). The scope is from 1980 to 2020. Following Pakes (1986), since renewal fees were obtained in nominal domestic currency, I converted them to real domestic currency, using the country's own implicit G.D.P deflator and then transferred them to 1999 Euros, using the official exchange rates in 1999.

Empirical Evidence on the Existence of Positive and Negative Shocks on Patent Value

Before presenting a summary of the main equations and steps implemented in my method, I will present some results on the empirical evidence upon which my estimation approach builds. The empirical strategy of my method builds upon exploiting differences in renewal behavior between clean or dirty patents and the control group, and estimating different sets of parameters, which would allow us through a simulation approach to provide monetary estimates of the impact of that regulation. Nevertheless, this approach builds upon a cornerstone, namely on the existence of differences in renewal patterns between the two types of treated patents (clean and dirty) and those from the control group. Therefore, the aim of this subsection is to discuss the empirical evidence sustaining this exercise.

---

[4] IPC stands for International Patent Classification.

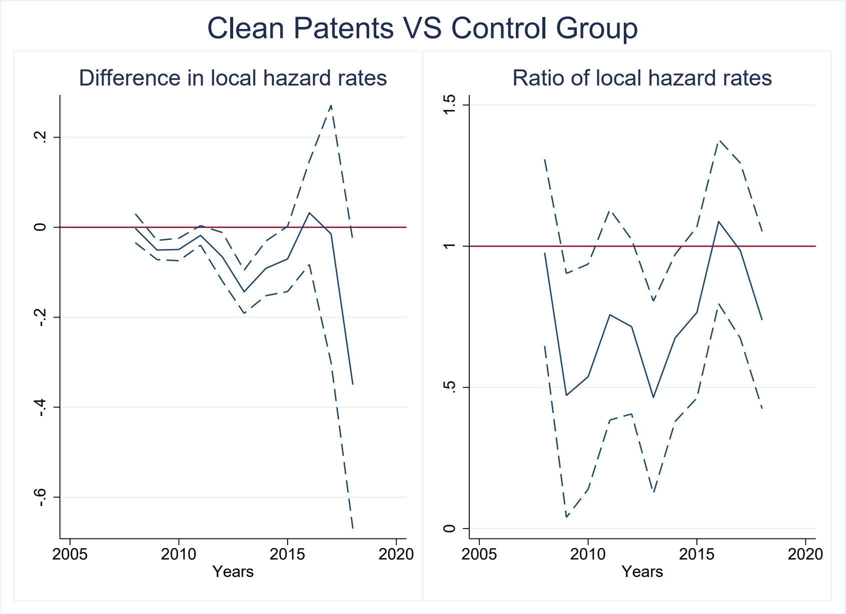


Figure 4.1: Nonparametric Duration Evidence (2008-2018): Clean Patents VS Control Group

To do this, I will build upon the results of Chapter 3, where I adapted the nonparametric duration model from van den Bergh et al. (2020). The adaptation that I performed allowed me to estimate two types of treatment effects, i.e., the instantaneous causal effect of the treatment at the moment of the policy change and the average treatment effects on conditional survival probabilities. The latter ones will be the most relevant for this analysis, since they would allow me to consider any significant difference in the local hazard rates as causal, provided that they are not preceded by a selection in renewal event, i.e., that we are not losing patents before that moment. I spare the reader the technical details, which are available in Chapter 3 and will present now the main results and framework from this analysis.

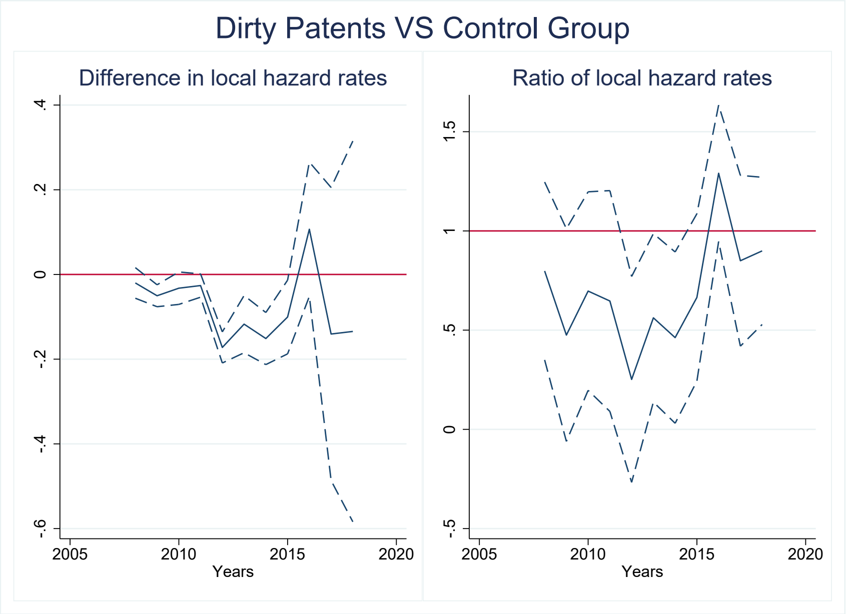


Figure 4.2: Nonparametric Duration Evidence (2008-2018): Dirty Patents VS Control Group

Regarding the framework of the analysis, I use patent renewal variation from the patent datasets presented in Chapter 3, whose main statistics are summarized in Appendix 1. I first recompute patent ages for all cohorts such that new age 1 corresponds to 2006 and drop patents elapsed before that age. Then I aggregate these recomputed duration data into a single cohort and add specific cohort dummies. Controlling additionally for five multiple correspondence analysis dimensions (Dim 1 to Dim 5), number of inventors, grant lag, number of applicants, family size, and including patent class by cohort year dummies, I perform a nonparametric estimation. Results for clean and dirty technologies are depicted in Figures 4.1 and 4.2. For both the analysis on clean technologies as well as for the analysis on dirty patents, I assume that treatment occurred in 2008, hence the instant causal effect would not be that relevant for us, and instead the average treatment effects on conditional survival probabilities would be at the center of our analysis. The reason for this is that since the Kigali Amendment was signed in 2016 it would allow us to capture any differences after 2008 and thereby observe if there was an anticipated reaction to the Amendment or if its effect was rather delayed. My analysis is limited until 2018 since my renewal information ends in 2020 and evidence for 2019 is not clear. As it is difficult to assess whether the reason of the unclear results for 2019 stems from effects going into opposite directions or problems in estimating the last data point, I will extend this analysis to additional renewal years as soon as those are available. Results from the nonparametric analysis until 2019 are available in Appendix 5 of Chapter 3.

Turning now to the main findings, I first observe a similar pattern in positive significant (at a 5 percent level) shocks for both types of technologies before 2015, which I attribute to both types of substances, i.e., HFCs and their clean substitutes, being HCFCs' substitutes. This is confirmed by the HCFCs' phase-down schedules presented in the Appendix 5, which show several reduction deadlines coinciding with those positive shocks. Further discussion of the shocks happening before 2015 is treated in Chapter 3. The foremost conclusion from these first observations for the present analysis is that there is no selection in renewal happening before 2016, i.e., we are not losing observations due to the existence of some negative significant shock. Taking this into account allows us to consider future negative shocks as causal. In particular, this is what happens for dirty patents in 2016 (Figure 4.2). In the graphic depicting the ratio of local hazard rates we observe an almost significant (at a 5 percent level) negative impact on the hazard rates. Likewise for clean technologies, we find a positive significant shock on the differences in hazard rates in 2018. These will be the two shocks whose monetary impact on the respective patent value of clean and dirty technologies I will estimate in this chapter.

4.3.2 Main Equations

In this section, I will present the sequential steps of the method, including the equations and models. As explained in Chapter 2, the method requires having three sets of comparable patents, one having been positively affected by the environmental regulation, a second having been affected negatively by the regulation (the treatment groups), and a last group that hasn't been affected by it (control group). Furthermore, it requires the existence of a positive and a negative shock on the patent value for the respective treatment groups, which I summarized in the previous subsection. Once these conditions are met, the method proceeds in two steps. First, I perform a structural estimation of a patent renewal model without environmental regulation for the control group patents. The parameter estimates from this first estimation will allow me to generate a synthetic control group from which I compute deviations in my second step. In particular, in the second step I realize a second structural estimation of a patent renewal model with environmental regulation, where I use the parameters from the control group estimation (first step) to generate the hazard rates of patents before and after being regulated. The difference in hazard rates itself is captured by the parameters governing the environmental regulation. In the next subsections I shortly present the different patent renewal models and their estimation procedures. Further extended details on the models and estimation techniques are presented in Chapter 2.

Synthetic Control Group: Patent Renewal Model without Environmental Regulation

The first step of my method is a structural estimation of a patent renewal model with the control group sample. The model is the modification of the Pakes (1986) done by Serrano (2018), where each period the patent holder decides whether to renew a patent or not. She takes this decision given the expected patent returns, current returns x_a and renewal fees c_a, as well as the expected sequence of renewal fees. Equation 4.1 shows the value function of a patent at a certain age a. Each period (age) a, the per period returns x_a get an age-specific stochastic shock g_a^i, which is independent of former returns x_a (equation 4.2). The random shock stems from a truncated distribution (equation 4.3), where returns might get to 0, when the technology becomes obsolete. This happens with probability $1-\gamma^i$. Otherwise, returns might either depreciate at a certain rate δ_i or increase if some new uses are found. This last characteristic is governed by σ_a^i (equation 4.4), which has an age specific component ϕ^{a-1}, capturing the fact that opportunities for gains are decreasing over time, and an age-independent characteristic σ^i.

$$V(x_a) = max\{0\,,\, x_a + \beta\, E[V(x_{a+1})|\Omega_a] - c_a\} \tag{4.1}$$

$$x_{a+1} = g_a^i x_a \tag{4.2}$$

$$F^{g^i}(g_a^i) = \begin{cases} 1-\gamma^i & if\ g_a^i = 0 \\ 1-\gamma^i + \gamma^i \left[1 - exp\left(\frac{-\delta_i}{\sigma_a^i}\right)\right] & if\ g_a^i = \delta_i \\ 1-\gamma^i + \gamma^i \left[1 - exp\left(\frac{-g_a^i}{\sigma_a^i}\right)\right] & if\ g_a^i > \delta_i \end{cases} \tag{4.3}$$

$$\sigma_a^i = \sigma^i \phi^{a-1} \tag{4.4}$$

$$\xi \sim N(\mu, \sigma_R^2) \tag{4.5}$$

$$x_{t,1} = exp(b_{C,t} D_t + \xi) \tag{4.6}$$

Employing a simulated method of moments approach, I estimate the vector of parameters governing the patent renewal process. Specifically, besides the already presented parameters, I also need to estimate the initial distribution of per period returns (equation 4.5). Initial returns stem from a log-normal distribution, with ξ being a random normally distributed shock of mean μ and standard deviation σ_R, where $b_{C,t}$ are cohort-specific dummies, which allow for the initial draw to be different across cohorts. I perform the estimation using empirical and simulated hazard rates for years 2016, 2017, 2018, and 2019. The reason for this is that since my shocks happen in 2016 and 2018, and they are the main objective of this exercise, it is reasonable to consider only differences from 2016 onwards to perform the second step, estimation. Specifically, in the second step I will realize a structural estimation, but also only for years 2016 to 2019. Hence, in my second step, what I aim at capturing will be deviations from the estimated first step hazard rates, that I simulate in the treatment groups' estimation. As a result from the first step estimation, I obtain the following vector of estimated parameters[5]: $w_C = (\gamma_i,\ \sigma^i,\ \phi^i,\ \delta_i,\ \mu,\ \sigma_R,\ b_{C,1},\ b_{C,2},\ b_{C,3},\ b_{C,4},\ b_{C,5},\ b_{C,6},\ b_{C,7},\ b_{C,8},\ b_{C,9},\ b_{C,10})$.

Treatment Groups: Patent Renewal Model with Environmental Regulation

In the second step I perform a structural estimation with the treatment groups, i.e., the dirty (T_1) and clean (T_2) patent samples. In particular, I develop now a model of patent renewal with uncertain environmental regulation. As presented in equation 4.7, this model is an extension of the previous and builds upon the model of patent renewal with the option to patent trade of Serrano (2018). Specifically, each period (age) a the patent owner decides whether to renew the patent or not given his current returns x_a, the returns she would get if the patent is affected by the environmental regulation y_a, and the information indicating whether the patent has been affected by the regulation or not. Besides this,

---

[5] Details on the weighting matrix are specified in Chapter 2.

he takes the decision taking into account the renewal fees and the probability of being regulated, which for a certain patent age a and cohort t is $p_{a,t}$. The expected returns from the patent holder will now depend on whether she has been regulated or not. Figure 4.3 shows the state evolution of the patent holder at each age and cohort.

$$V(x_a, y_a, \sigma_a) = max\{0\,,\; x_a + \beta\, E_{x,y,\sigma}[V(x_{a+1}, y_{a+1}, \sigma_{a+1})] - c_a\} \tag{4.7}$$

with $x_{a+1} = g_a^i x_a$

$$\begin{aligned} E_{x,y,\sigma}[V(x_{a+1}, y_{a+1},\sigma_{a+1})] =\; & p_{a,t}\; E_{x,y}[V(x_{a+1}, y_{a+1})] \\ & + (1-p_{a,t})\; E_{x,y,\sigma}[V(x_{a+1}, y_{a+1}, \sigma_{a+1})] \end{aligned} \tag{4.8}$$

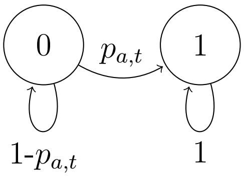


Figure 4.3: Evolution of environmental regulation

At the moment when the regulation is introduced then his per period returns are pre-multiplied by an exogenous shock g^e, which stems from two different CDFs, depending on the type of technology that the patent holder is renewing (these CDFs are derived applying Assumption 3 from a general functional form presented in equation 4.16). This regulatory shock is then multiplied by the random shock g_a^i explained in the previous section. In particular, if she has a clean technology she might receive a positive shock stemming from the CDF $F^{g^e,clean}(g^e)$ (equation 4.10), where his returns are increased. Conversely, if he owns a dirty technology, she might receive a negative shock stemming from the CDF $F^{g^e,dirty}(g^e)$ (equation 4.9), where with probability $1-\gamma^e_{dirty}$ his returns become obsolete.

$$F^{g^e,dirty}(g^e) = \begin{cases} 1-\gamma^e_{dirty} & if\ g^e = 0 \\ 1-\gamma^e_{dirty}+\gamma^e_{dirty} & if\ g^e = 1 \end{cases} \tag{4.9}$$

$$F^{g^e,clean}(g^e) = 1 - exp\left(\frac{-g^e}{\sigma^{e,clean}}\right) \quad with\ g^e \geq \delta^e_{clean} = 1 \tag{4.10}$$

Then, at the introduction of the regulation, i.e., when $\sigma_a = 1$ but $\sigma_{a-1} = 0$, patent returns evolve as following $x_{a+1} = g^i_a y_a$ with $y_a = g^e x_a$ such that the value function that the patent holder faces is the one of equation 4.11.

$$V(x_a, y_a) = max\{0\,,\, y_a + \beta\, E_x[V(x_{a+1})] - c_a\} \tag{4.11}$$

After the continuation of the regulation, i.e., when $\sigma_a = 1$ and $\sigma_{a-1} = 1$, patent returns evolve as following $x_{a+1} = g^i x_a$ and the value function of the agent is:

$$V(x_a) = max\{0\,,\, x_a + \beta\, E_x[V(x_{a+1})] - c_a\} \tag{4.12}$$

Given these models I use a simulated method of moment approach, where I assume all parameter that are not related to the environmental regulation to be those estimated with the control group, $\hat{\omega}_C$. This allows me to estimate the two shocks on patent value due to the environmental regulation ω_T, i.e., the clean one and the dirty shock (see equation 4.13). As mentioned in the first step, I realize this second structural estimation using only hazard rates for years 2016 up to 2019[6].

$$\omega_T = (\hat{\omega}_C, \gamma^e_{dirty}, \sigma^e_{clean}) = (\gamma^e_{dirty}, \sigma^e_{clean}) \tag{4.13}$$

4.3.3 Assumptions

In this subsection I will present the assumptions upon which my method builds.

Assumption 1

The probability of being regulated $p_{a,t}$ is weakly increasing over time, i.e. in a and t, such that:

---

[6] Details on the weighting matrix are specified in Chapter 2.

$$\begin{cases} p_{a-1,t} \leq \ p_{a,t} \\ p_{a,t-1} \leq \ p_{a,t} \end{cases} \tag{4.14}$$

A typical example of an environmental regulation fulfilling Assumption 1 would be one concerning stock pollutants. First, through the phase-down schedules, we can clearly see that this is fulfilled for the substances regulated under the Montreal Protocol (see phase-down schedules in Appendix 5). Second, since the HFCs were one of the stock pollutants targeted by the Kyoto Protocol (UNFCCC, 1997) then it is plausible to assume that their likelihood of being affected by a regulation is weakly increasing over time.

Assumption 2

Patent holders do not anticipate environmental regulation.

$$\begin{cases} E[p_{a+1,t}|\sigma_a = 0] = 0 \\ E[p_{a+1,t}|\sigma_a = 1] = 1 \end{cases} \tag{4.15}$$

This assumption is closely linked to the ex-ante empirical evidence that shows the existence of the positive and negative shocks. In Chapter 3, I find that there have been a positive and a negative shock on patent value for clean and dirty substances (Figure 4.1 and 4.2). This evidence builds upon Assumption 2 (of Chapter 3), saying that there has been no anticipation of those shocks by the patent holders. In the setting of Chapter 3, no anticipation means that patent holders did not anticipate the Kigali Amendments before 2008, i.e., that any deviation from that moment onwards could be attributed to the Kigali Amendment, unless otherwise justified. Under the setting of Chapter 3, I find that the negative shock happened in 2016 and the positive one in 2018. Therefore, in the framework of the structural analysis, I assume no anticipation of those shocks.

Assumption 3

Regarding the CDFs of positively and negatively affected patents, I assume that $\gamma^e_{dirty} < \gamma^e_{clean} \leq 1$, $\delta^e_{clean} = 1$, and $\sigma^e_{dirty} < \sigma^e_{clean}$. Furthermore I assume that some of these parameters have fixed values, i.e.: $\sigma^e_{dirty} = 0$, $\gamma^e_{clean} = 1$, and $\delta^e_{clean} = 1$.

This assumption allows us to simplify the general functional form of the external regulation shocks (equation 4.16). We would assume first two general form CDFs $F^{g^e,clean}(g^e)$ for the clean patents and $F^{g^e,dirty}(g^e)$ for the dirty ones having the form of equation 4.16, which we would simplify through Assumption 3 into the ones presented in equations 4.9 and 4.10. A way to understand this assumption is that clean patents, if affected by the environmental regulation, then they have gained in value. Symmetrically for dirty patents, if they have been affected, then they lost value.

$$F^{g^e}(g^e) = \begin{cases} 1 - \gamma^e & if\ g^e = 0 \\ 1 - \gamma^e + \gamma^e \left[1 - exp\left(\frac{-\delta_e}{\sigma^e}\right)\right] & if\ g^e = \delta_e \\ 1 - \gamma^e + \gamma^e \left[1 - exp\left(\frac{-g^e}{\sigma^e}\right)\right] & if\ g^e > \delta_e \end{cases} \tag{4.16}$$

Assumption 4

I assume that patents from my treatment groups ($T_1,\ T_2$) would have had a similar renewal pattern compared to the patents from the control group, had there been no regulation.

This implies that the parameters of the internal growth returns g^i are the same for regulated and non-regulated patents and that the cohort-specific initial draw of per period returns is also identic. This allows me to assume the estimated vector of parameters from my first step $\hat{\omega}^C$ for the second step and use the first step as a synthetic control group for the second structural estimation. The reasoning behind this assumption comes from the empirical evidence presented in Figures 4.1 and 4.2, where we can see that if the environmental regulation shocks had not existed then the renewal pattern of treatment group patents and control group ones would not have been significantly different from each other from 2016 onwards.

Assumption 5

I assume that the first step solution $\hat{\omega}^C$ must be able to accomodate the second step shock following the ex-ante provided evidence, i.e.:

$$\begin{cases} \gamma^e_{dirty} < 1 & if\ a\ negative\ significant\ shock\ exists \\ \sigma^e_{clean} > 0 & if\ a\ positive\ significant\ shock\ exists \end{cases}$$

The motivation for imposing Assumption 5 is closely related to the main purpose of this paper, namely, quantifying the monetary impact of an environmental regulation on patent value. A preliminary condition for the application of the method is that there has been an environmental regulation, which had an impact on patent value, proxied by patent renewal. Hence that the renewal rate of patents affected by the regulation was significantly different from that of non-affected similar patents (at some significance level provided by the researcher). I provide evidence in Chapter 3 that this has been the case for the Kigali Amendment with the dataset that I use. Since I will now simulate the datasets and estimate the parameters that generate those simulations, first the one of the non-regulated patents and then the one from the regulated ones, I need the parameters to follow the ex-ante empirical evidence. Namely, if we found a positive significant shock with the ex-ante analysis, then σ^e_{clean} must be strictly positive and γ^e_{dirty} strictly inferior to the unit.

Nevertheless, finding $\sigma^e_{clean} > 0$ or $\gamma^e_{dirty} < 1$ does not solely depend on the result from the second estimation, it also depends on the solution from the 1st step, w_C. The intuition for this is that the optimization algorithm for the first step will try to find an optimum that is able of explaining as much variation as possible with the vector of solution parameters. Since the problem that we are analyzing is of a cross-cohort nature, i.e. we are trying to estimate the hazard rates from different cohorts differing only by a dummy in the initial draw of per-period returns, the cross-cohort dummy is likely to capture only partially the cross-cohort differences. This means that the algorithm, in order to try to minimize the error of the first estimation, is likely to choose a set of parameters that would allow for many different possible shapes of the hazard rates. For example, by allowing for a high stochasticity of positive (σ_i, ϕ_i) and negative shocks (δ_i, γ_i). This would deliver a solution that would be an optimum for the first step, but without any further restriction it might lead to a situation where the second step is unable of capturing any difference from the simulated control group hazard rates because hazard rates of regulated (positive or negative) patents could have been just another realization of the stochastic parameters from the first step solution. We would therefore find in the second step no shocks although, the ex-ante evidence showed that they existed.

This is a challenge in my approach, since I try to replicate the evidence from a nonparametric model in a parametric setting. As it is shown in van den Bergh et al. (2020), a shock on the hazard rate will appear smaller in a parametric framework (e.g. proportional hazards model) than in a nonparametric one. So, it is likely that with the nonparametric model we can capture smaller shocks than with the structural estimation. To my knowledge, there is no clear solution for this problem and any solution would require the researcher to engage into a trade-off. Namely, accepting a lower quality first step solution that has a higher error in simulating the shapes of the cross-cohort hazard rates from the control group but that would still allow for the existence of the respective shocks following the ex-ante evidence. This is what is implied by Assumption 5. In the estimation shown in this chapter I haven't built in a restriction in the first step estimation, but I chose the best solution allowing for the existence of the second step shocks in line with the evidence from Chapter 3. In Appendix 4, I present the results of the first step global optimum, which does not fulfill Assumption 5 and I therefore reject. As commented above, comparing the estimated values with the ones presented in Table 4.1, we find a higher degree of stochasticity of the positive and negative shocks.

4.4 Estimation Results

4.4.1 Synthetic Control Group Estimates

I will now discuss the results from my two estimations, first from the synthetic control group estimates and then the ones from my treatment groups. In Table 4.2 I report the results from the first step structural estimation of the common parameters to the three patent groups, i.e., the two treatment groups (T_1, T_2), and the control group (T_0).

Compared to the parameter estimates of Serrano (2018), my non-obsolescence parameter γ_i is relatively high, pointing to a lower degree of obsolescence compared with his findings. Conversely my depreciation rate is much lower than the one he finds, pointing to higher losses over time. On the other side both my internal growth of returns σ_i are higher than his results, while the upside opportunities ϕ_i are lower than his. Regarding the mean of the lognormal initial returns distribution, my initial returns are higher while the standard deviations are similar. The cohort-specific dummies are difficult to compare since he does not use them.

Turning to the accuracy of the estimation my standard errors are very small, much smaller than the ones he finds. I compute the mean squared error (MSE) in a similar way as he does, i.e., performing the sum of the squared residuals of the difference between simulated and empirical moments divided by the number of moments (34). I find a MSE fifty percent smaller than the one he finds.

Table 4.1: Parameter Estimates (1st Estimation)

	Description (Parameter)	Estimate	s.e.
A.	Patent initial returns		
	Mean parameter of the lognormal initial distribution (μ)	11.0301	8.9115 e-15
	Std. deviation parameter of the lognormal initial distribution (σ_R)	1.7917	6.6837 e-16
	$b_{C,1}$	-0.9359	1.1139 e-16
	$b_{C,2}$	0.1518	1.1139 e-16
	$b_{C,3}$	-0.6175	3.3418 e-16
	$b_{C,4}$	-0.0297	0
	$b_{C,5}$	0.0262	3.4811 e-18
	$b_{C,6}$	-0.0056	0
	$b_{C,7}$	-0.2802	2.7849 e-16
	$b_{C,8}$	-0.4970	5.5697 e-17
	$b_{C,9}$	0.0479	0
	$b_{C,10}$	0.1650	1.3924 e-16
B.	Internal growth of returns		
	Depreciation factor (δ_i)	0.7618	2.2279 e-16
	Not obsolescence (γ_i)	0.9785	3.3418 e-16
	Internal growth of returns (σ_i)	0.6390	5.5697 e-16
	Upside opportunities (ϕ_i)	0.5481	4.4558 e-16
	MSE		1.5360 e-04

4.4.2 Treatment Groups Estimates

I estimate the second step doing three counterfactual scenarios based on the knowledge of the policy and the ex-ante evidence on the existence of a negative and a positive shock on patent renewal in 2016 and 2018 respectively (Chapter 3). In Scenario 1, I assume that $p_{a,t}$ turns from 0 to 1 in 2016 for all patents, i.e. for T_1 and T_2. In Scenario 2, I assume that $p_{a,t}$ for the dirty patents turns 1 in 2016, whereas $p_{a,t}$ for the clean substitutes becomes 1 in 2018. Finally, in Scenario 3, I allow for patents to be affected by the regulation at different years. This aims at capturing the fact that not all patents might have been affected at the same time and therefore the former scenarios might downward bias my estimates on the monetary impact. For this reason, in Scenario 3, I allow $p_{a,t}$ to evolve from 25% in 2016 to 100% in 2019 by 25% annual increases. Table 4.3 summarizes values of $p_{a,t}$ for the three scenarios and patent types. From the parameters of the distributions of interest, i.e. $F^{g^{e,dirty}}$ and $F^{g^{e,clean}}$, only γ^e_{dirty} has a direct interpretation[7]. This parameter refers to the additional non-obsolescence probability due to the environmental regulation. The estimated values are 1 for the first two scenarios, corresponding to a 0% additional obsolescence rate of the negatively affected patents due to the Kigali Amendment. Only the third scenario captures a tiny negative shock. This is in line with the nonparametric estimates from Chapter 3, where the negative shock from the causal nonparametric duration model was almost significant at 5 percent level. A possible explanation of these results might come from the different natures of the shocks, i.e., the additional obsolescence shock is a very radical shock since it reduces returns to zero such that marginal values rapidly generate large hazard rates. Therefore, when we employ Scenario 3, as the likelihood of the regulation is only 25% in 2016 it “de facto” reduces the size of the obsolescence impact in that year. A possible way to verify this rationale would be to replace the form of the negative shock and instead of an additional obsolescence rate use an additional depreciation rate δ^e, which will likely capture smaller shocks. This is particularly relevant for the negative impact as we have two limitations, first we try to capture an “almost” significant shock, and second, this shock was found using nonparametric methods (i.e., more sensitive) while we have a parametric approach.

Analyzing now estimates on the positive impact, I find interestingly a positive impact

---

[7] σ^e_{clean} requires some additional derivations in order to be able to interpret it. This is also the case for the set of parameters from the internal growth returns process.

different from zero in Scenarios 1 and 3. This is particularly striking, since nonparametric evidence on the positive impact pointed towards a shock in 2018, whereas my method does not capture it in 2018 and instead finds the stronger impact in 2016 followed by the differed impact over time of Scenario 3. A potential explanation of this results is aligned with the difference in the nature of the shock between an additional obsolescence shock γ^e and an additional depreciation rate shock δ^e. Namely, our positive shock σ^e is of a similar nature as δ^e, which means that a positive impact through σ^e is likely to have a delayed effect on the hazard rate. This rationale would explain why we find the largest positive impact in Scenario 1. If we now focus on the standard errors, as it was the case of the first estimation, they are very small. Regarding the MSE, which I compute in the same manner as described for the first step with the only difference that I now have 68 moments, my results are one order of magnitude larger than the ones of Serrano (2018). This is normal since I am adding two errors, the one from the second estimation and the one from using the synthetic control, as explained in Chapter 2. We will study now further measures of the goodness-of-fit, which might help us shed further light on our results.

Table 4.2: Parameter Estimates (2nd Estimation) for the three Scenarios

	Description (Parameter)	Estimate	s.e.
A.	Scenario 1		
	External not obsolescence ($\gamma^e_{dirty,1}$)	1.0000	0
	External growth of returns ($\sigma^e_{clean,1}$)	0.3815	1.6709 e-16
	MSE		0.0046
B.	Scenario 2		
	External not obsolescence ($\gamma^e_{dirty,2}$)	1.0000	0
	External growth of returns ($\sigma^e_{clean,2}$)	0	0
	MSE		0.0047
C.	Scenario 3		
	External not obsolescence ($\gamma^e_{dirty,3}$)	0.9997	1.1139 e-16
	External growth of returns ($\sigma^e_{clean,3}$)	0.2258	2.7849 e-17
	MSE		0.0046

Scenario		2015	2016	2017	2018	2019
1	$p_{a,t}$	0	1	1	1	1
2	$p_{a,t}^{dirty}$	0	1	1	1	1
	$p_{a,t}^{clean}$	0	0	0	1	1
3	$p_{a,t}$	0	0.25	0.50	0.75	1

Table 4.3: Scenarios for $p_{a,t}$

4.5 Goodness-of-Fit

In this section I will discuss the differences between empirical hazard rates and simulated moments for the two estimations and the three scenarios. I have depicted in Appendix 2 the different hazard rates for each cohort as well as their corresponding weights employed in the weighting matrices for each estimation. The legend of the goodness-of-fit plots is identic for all scenarios and cohorts, i.e., black color stands for control group, red for dirty patents, and blue for clean ones. Furthermore, dashed lines represent empirical hazard rates, full lines represent simulated ones, and dots weights. A general observation for all figures in Appendix 2 is that the simulated control group lines (full black lines) are always masked by simulated hazard rates for dirty technologies (full red lines). This is normal since, as reported in Table 4.2, I "de facto" find no negative impact, i.e., the tiny negative shock of Scenario 3 is not sufficient to appear in a graphical representation.

Starting with the hazard rates for the cohort of 1997 for all scenarios (Appendix 2.1), I only find a positive shock in Scenario 1. Furthermore, it is interesting to see that all empirical hazard rates for dirty technologies are smaller that the simulated ones from the control group (full black line and full red line), this explains why an additional negative impact could not be accommodated given the synthetic control. Additionally, we see empirical moments for clean technologies higher than those of dirty ones, which already indicates that one of the two shocks will be 0 if this is the case for the remaining cohorts. The rationale for this is that ideally for finding a positive and a negative impact, we would need to have black full and dashed lines in the middle, red full and dashed above the black lines and both blue lines below the black ones. If the red dashed line (empirical hazard rate of dirty patents) is below the black full line (simulated hazard rates for the control group) for most of the high-weighted cohorts (red dots), then it is impossible for this method to capture a negative impact, since it could only capture deviations above the full black line. The explanation regarding the ability of the model to capture positive shocks is symmetric to the one just mentioned.

Analyzing results for dirty technologies in Scenario 1 (Appendix 2.2.), we can see that the red dashed lines for cohorts with relatively high weights, e.g., values around 0.2, are often below the full black lines (which are the full red lines, as I explained above). This tells us that the model will struggle to find a negative impact and that the error gains from including one would not outweigh the losses hence leading to a no negative impact solution as the one found. Regarding results for the clean technologies, the situation is different. Now, we can see that for several cohorts having high weight values the blue dashed line is below the full black or red line, hence the model will try to accommodate a positive shock simulating the full blue line between both. High weighting values mean that relative to the whole sample and its cohort-technology composition[8], for those particular years of that cohort there were many observations.

Regarding Scenario 2 (Appendix 2.3), the graphical representation helps us better understand why we find no positive impact in this scenario. Before discussing the figures, it is important to remember that in Scenario 2 the positive impact happened in 2018, hence what would be relevant for the model would be those cohorts with high weights for clean patents (blue dots) for which in the years 2018 and 2019 the blue dashed line would be below the red or black full line. Looking at the graphics, we see that this is rarely the case and if it might be the case for some cohorts (e.g., 2000, 2001), it is not for many others (e.g., 1999, 2002, 2003, 2006). Since accommodating a shock would generate a positive deviation for all cohort in this scenario then the best solution is found with no positive impact.

Finally, turning to the results for Scenario 3 (Appendix 2.4), the increasing probability of being affected by the regulation complicates the interpretation of the results. The reason for this is that there are many effects occurring simultaneously. First, the shock might be accommodated differently across cohorts due to the initial differences in per period returns, hence the impact of the shock will not be the same for a same year in different cohorts (this would also happen in Scenario 1). Second, since the shock first leads to a reduction of the hazard rate it also leads to an increase in hazard rates with a certain delay,

---

[8] Further details on the construction of the weighting matrix of the second step are provided in Chapter 2.

which would also occur in the first scenario. Third and singular to Scenario 3, is that now the positive shock might occur twice for a same cohort but for different patents, which would modify the simulated hazard rates in an additional manner, likely generating more noise. This could be a possible explanation to the lower estimate in the third scenario, where the additional noise generated by the increasing treatment probability likely engaged in the trade-off of generating more error than reducing it, hence resulting in a lower estimate.

4.6 Robustness of Results, Caveats, and Measurement Error

After presenting the main results of the goodness-of-fit, I will now discuss the main caveats of this method, which have been partially mentioned in the previous section. Furthermore, I will present several robustness exercises, which could help certify the size of the estimates, which are related to the sensitivity of each step's estimates.

Nevertheless, and before discussing the different potential sensitivity analyses, I would like to discuss the main challenge and caveat of the current results. This refers to the number of moments, i.e. renewal years used to estimate the models. Since the environmental regulation that I am studying occurred in 2016, using a synthetic control group approach combined with a structural model forces me to limit the number of years used for estimation to those after the regulation. In particular, as the last available patent data version only provides information until 2020, which is a right-censoring year (last year), I can only perform my analysis until 2019, which means that I have at most 4 moments per cohort. This number of moments is very limited and constrains the identification of my structural estimations. In future versions of this work, I will extend my dataset to include further renewal years in order to tackle this issue. I will now discuss robustness tests related to the sensitivity of the estimates for each step.

First Step Estimation Sensitivity I start focusing on the sensitivity of the synthetic control group estimation. In order to discuss this, it is important to bear in mind the overarching goal of this method. Namely, estimating the technological monetary impact of an environmental regulation (the Kigali Amendment) on patent value. The approach that I propose in this work is to combine a synthetic control group method and structural estimations, where I use estimates from a first structural estimation to generate synthetic controls in the second estimation. Therefore, a key point regarding the robustness of the estimates is related to the quality of the first step estimates. Specifically, it is key to assess how much the size of the monetary impact depends on the quality of the first step estimation. This issue is common to other works using models to generate counterfactuals, such as Holland et al. (2016), where they use an integrated assessment model to assess health damages related to local pollutants' emissions. A main caveat of their approach is that their health damages estimates depend on some parameters of the integrated assessment model, hence they have to assess how other values would modify their estimates. In this line of thought, simulated methods of moments heavily depend on the weights assigned to each moment, which might lead to having some particular years heavily driving our results. Therefore, assessing the sensitivity of the first step estimates to particular moments in the spirit of Andrews et al. (2017) could help us bound the impact from this source of error.

Second Step Estimation Sensitivity Regarding the sensitivity of the second step estimation, there are several factors that might influence it. First and as just mentioned for the first step, checking the moment specific sensitivity as Andrews et al. (2017) could be a first straightforward robustness check. Second, as I have discussed in previous sections, the parametric form limits the ability of the method to capture positive and negative deviations. Yet, the objective remains that of capturing in the best possible manner the shown nonparametric shocks to be able to compute their monetary impact. Therefore, it will be needed to verify the robustness of the results to other shock forms, in particular for the negative impact, such as using an additional depreciation rate, δ^e, instead of an additional obsolescence shock, γ^e. Furthermore, since we have seen that the impact of the shock might be delayed, it could be relevant to verify the robustness of my results using other treatment combinations.

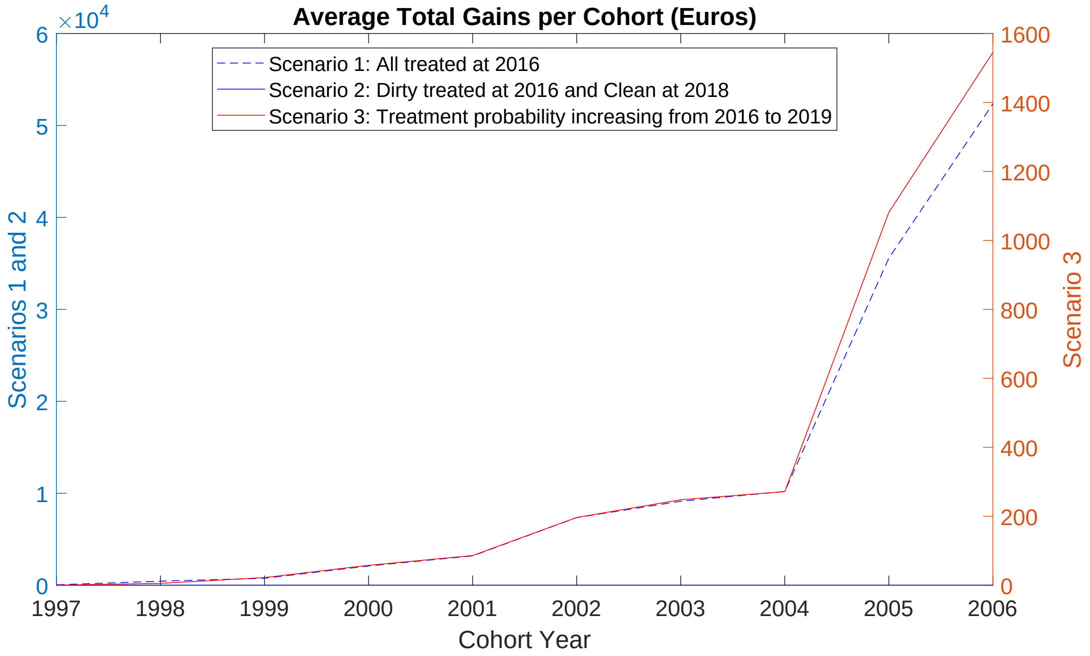


Figure 4.4: Average Total Gains by Cohort

4.7 Counterfactuals

In this section I will present the counterfactuals on the monetary impact engendered by the Kigali Amendment on patent value. For this, I use the parameter estimates exposed in Tables 4.1 and 4.2 and perform 10,000 simulations. I compute the average present discounted value (PDV) of the patents affected positively, negatively, and those non-regulated. Then I compare the PDVs of the regulated patents to the ones of the control group for each cohort. I compute differences in PDV only from the moment of the shock onwards and compute average total gains and losses using only patents that have survived until the shock event. I show results on the average total monetary gains in Figure 4.4. for the three scenarios. It is straightforward to see that gains for Scenario 2 are non-existent since there is no positive impact captured by our estimate. Then, as expected, gains for Scenario 1 (up to 50,000 Euro) are larger than for Scenario 3 (up to 1,600 Euro), which follows estimated values. If we turn now to the average total monetary losses depicted in Figure 4.5, we see that those are very small (up to 200 Euro) compared to the gains and that they only exist for the scenario where we found a negative impact, i.e., Scenario 3.

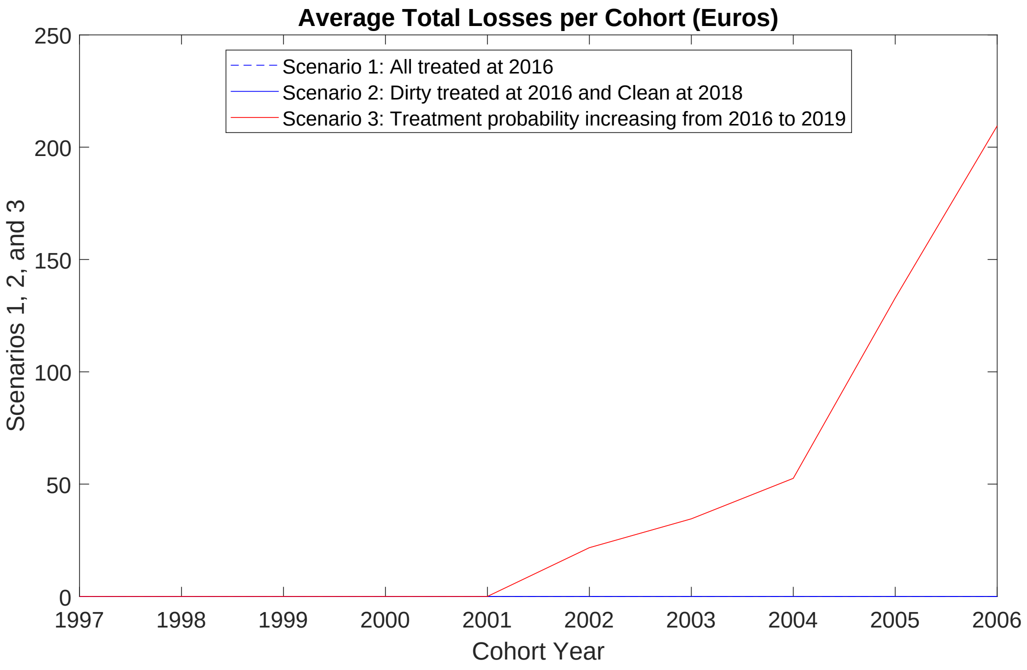


Figure 4.5: Average Total Losses by Cohort

4.8 Conclusion

In this chapter I propose a method to quantify the technological gains and losses engendered by an IEA, in particular the Kigali Amendment to the Montreal Protocol. For this I apply the patent renewal model under uncertain environmental regulation that I developed in Chapter 2 to quantify the monetary impact of the environmental regulation on patent value. With this structural model I estimate the monetary shocks on patent value triggered by the Kigali Amendment that I identified in Chapter 3. Using a counterfactual simulation, I find that average total gains depend on patent cohort and treatment years definition ranging by treatment type from 1,600 Euro up to 50,000 Euro. Conversely, I almost find no losses. Only in a scenario where treatment can occur at several periods, I find average total losses going up to 200 Euro. These results are in line with the rationale of the self-enforcing agreements' work by Barrett (1994), suggesting that the original Montreal

Protocol was successful because benefits outweighed costs. Although this work only considers technological costs and benefits proxied by patents, it supports his hypothesis on the original agreement. Of course, measurements on the environmental damages avoided and additional measures of economic benefits would help confirm this theory.

My method combines a synthetic control group approach and two structural estimations. As such, it has the caveats of both methods, i.e., the quality of my estimates strongly depends first, on the quality of the synthetic control group estimation, and second, on the weights of the different moments of my structural estimation. I discuss the goodness-of-fit and propose a series of tests and sensitivity analyses to verify the robustness of my results. With this work, I add to the literature in several ways. First, I contribute first to the literature on international environmental agreements by providing an approximation to the technological gains and losses engendered by the signature of the Kigali Amendment to the Montreal Protocol. As mentioned, technological gains and losses are only a partial proxy of the costs and benefits of an IEA, that would require, among others, avoided damages benefits etc. Nevertheless, it provides a flair for the underlying incentives of the signature of the Amendment. Second, this chapter contributes to the literature on structural models in environmental economics by estimating the first model including environmental regulation in patent renewal. Finally, it also contributes to the literature on IEAs and directed technological change by providing estimates of how an IEA directs innovation and affects clean and dirty technologies.

4.9 Appendix 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.008	0.080	−0.266	0.407
Dim 2		0.005	0.060	−0.543	0.237
Dim 3		−0.002	0.005	−0.033	0.026
Dim 4		0.003	0.025	−0.145	0.163
Dim 5		−0.023	0.051	−0.148	0.198
Grant Lag		2,294.896	987.860	468	5,685
Inventors		4.022	2.407	1	16
Applicants		1.097	0.316	1	4
Family Size		17.140	15.694	1	93
Sample Size	835				

Table 4.4: Descriptive statistics: Treatment Group T1

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.086	0.062	−0.168	0.413
Dim 2		−0.014	0.093	−0.614	0.486
Dim 3		−0.00000	0.008	−0.040	0.096
Dim 4		0.004	0.083	−0.874	0.431
Dim 5		0.006	0.060	−0.148	0.503
Grant Lag		2,278.194	996.228	582	6,572
Inventors		3.348	1.930	1	18
Applicants		1.077	0.312	1	4
Family Size		9.632	7.308	1	136
Sample Size	1,056				

Table 4.5: Descriptive statistics: Treatment Group T2

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		−0.009	0.085	−0.329	0.762
Dim 2		−0.001	0.071	−1.003	1.178
Dim 3		0.0002	0.077	−0.063	9.540
Dim 4		−0.001	0.078	−2.968	0.664
Dim 5		0.006	0.071	−0.230	1.161
Grant Lag		2,286.081	995.016	265	6,840
Inventors		3.472	2.197	1	31
Applicants		1.100	0.381	1	13
Family Size		12.713	11.005	1	269
Sample Size	23,204				

Table 4.6: Descriptive statistics: Control Group T0

4.10 Appendix 2: Goodness-of-Fit

4.10.1 Appendix 2.1: Cohort 1997 (All Scenarios)

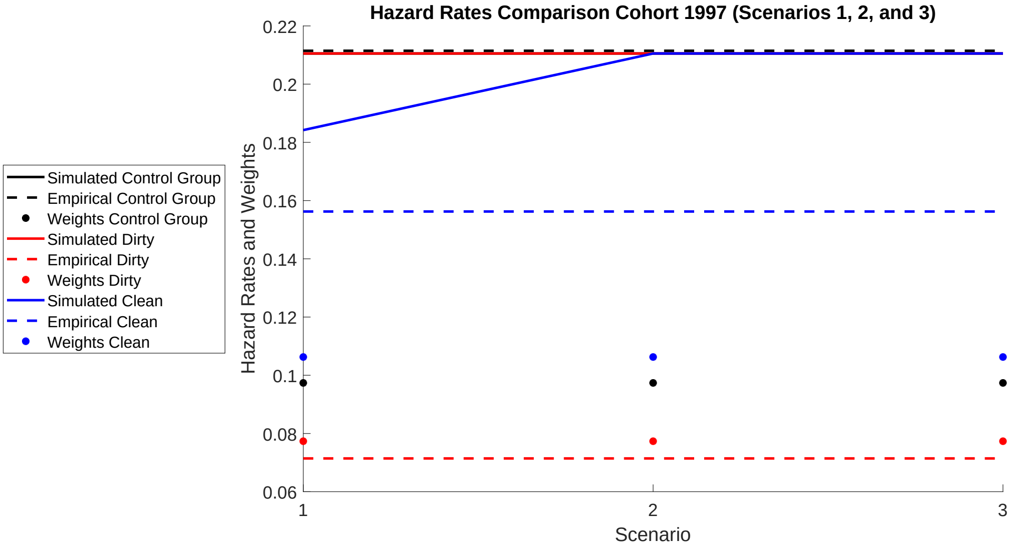
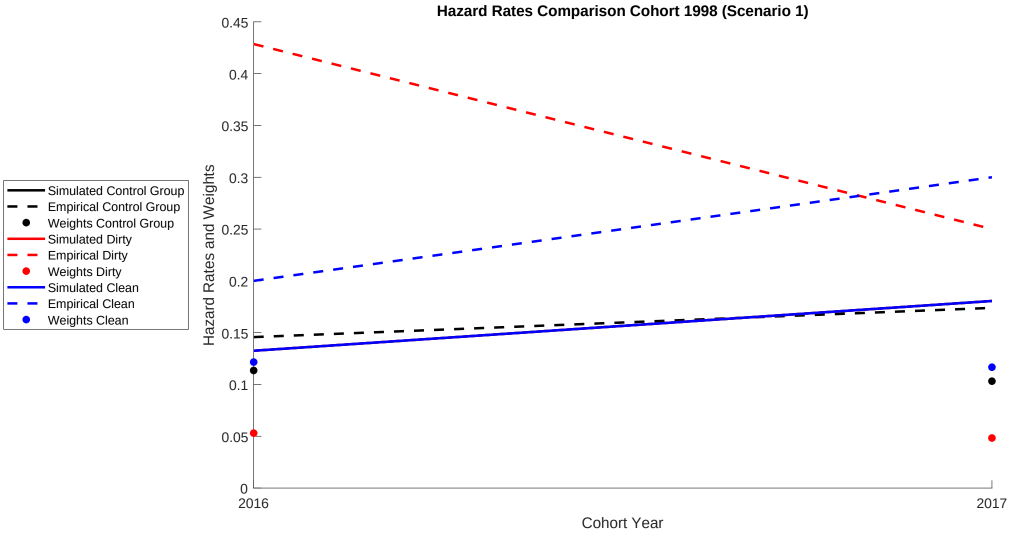
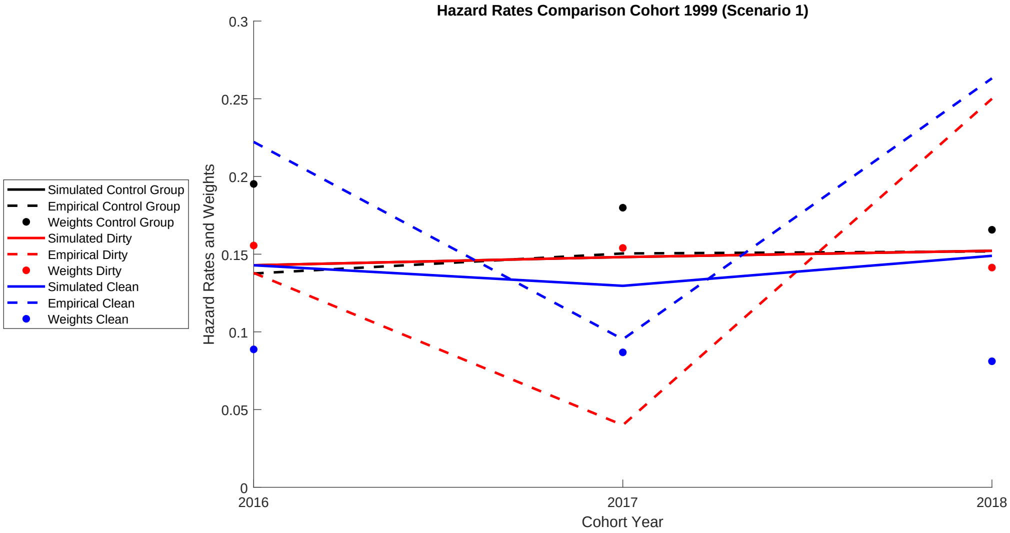
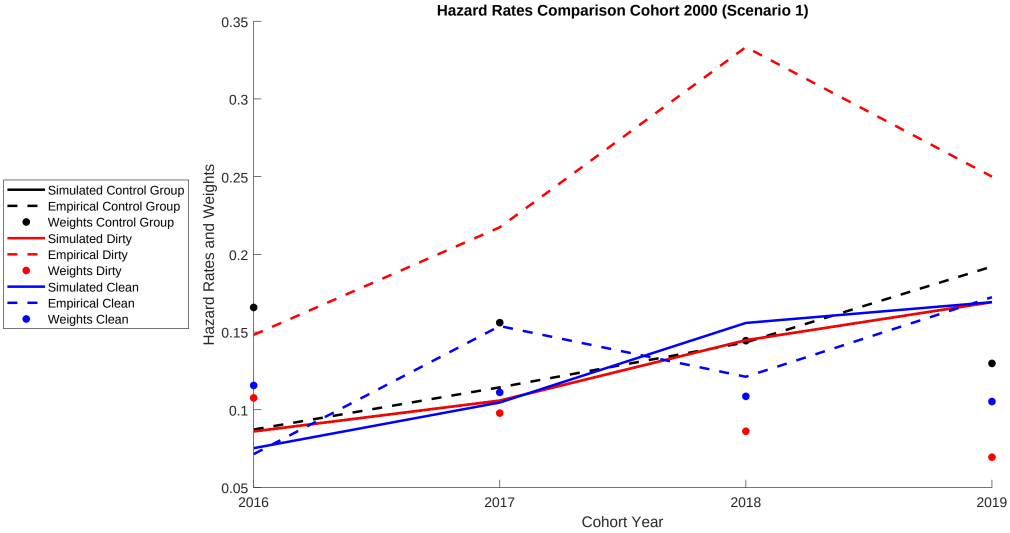


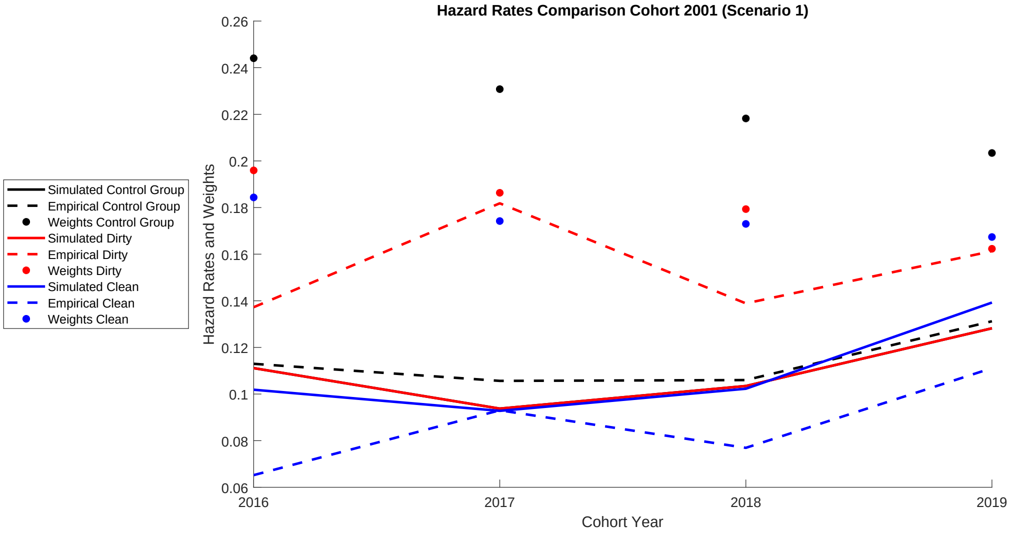
Figure 4.6: Goodness-of-Fit 1997 Cohort (All Scenarios, Year: 2016)

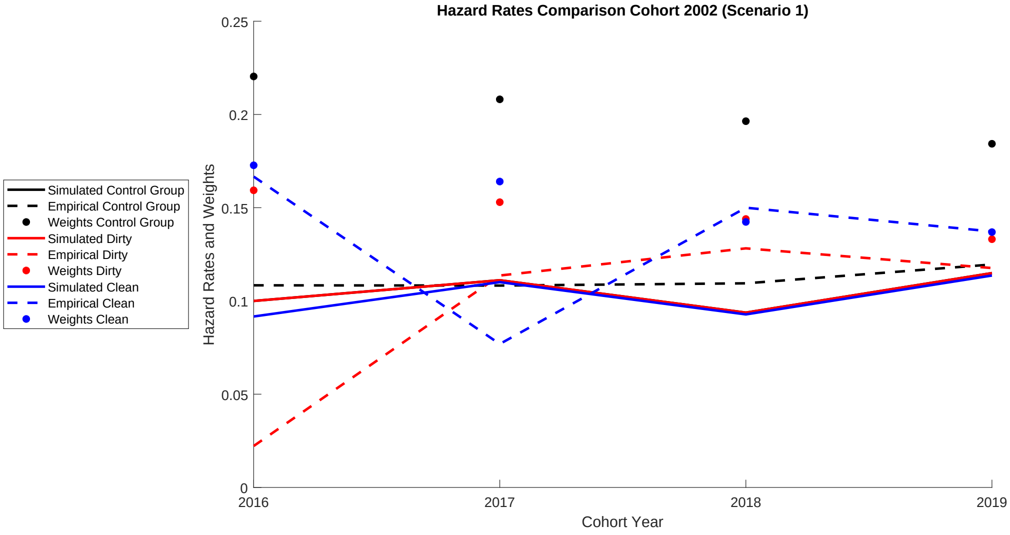
4.10.2 Appendix 2.2: Scenario 1

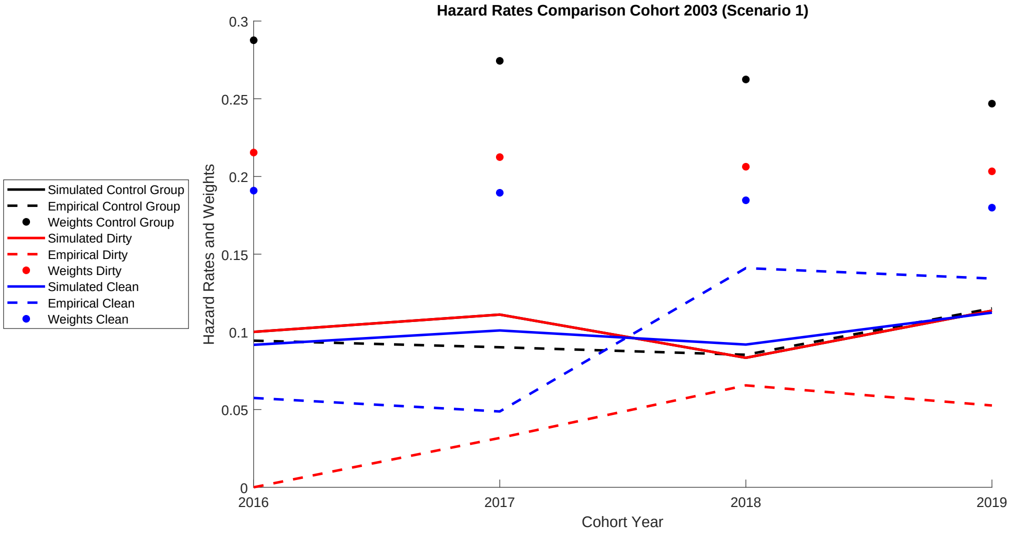


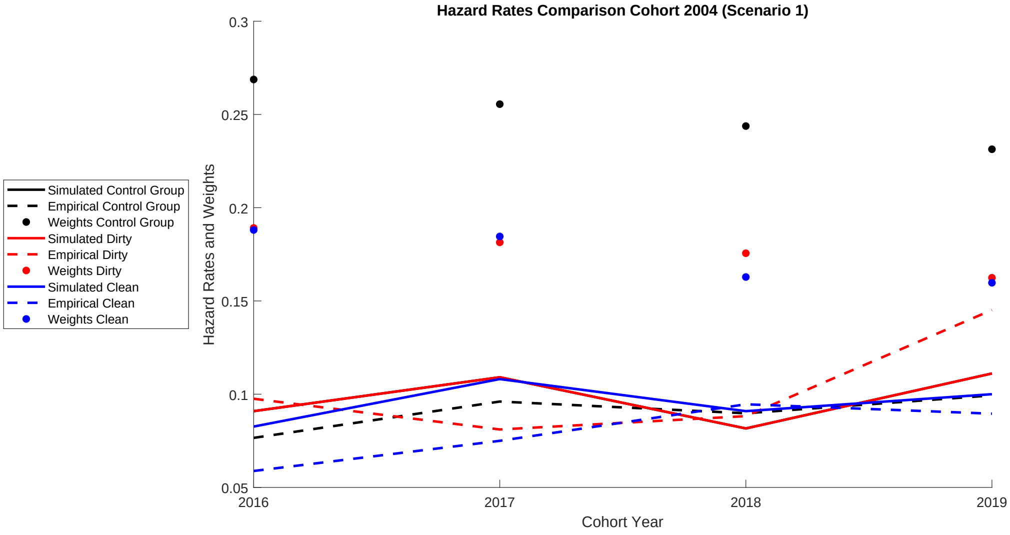

Hazard Rates Comparison Cohort 1999 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
Cohort Year

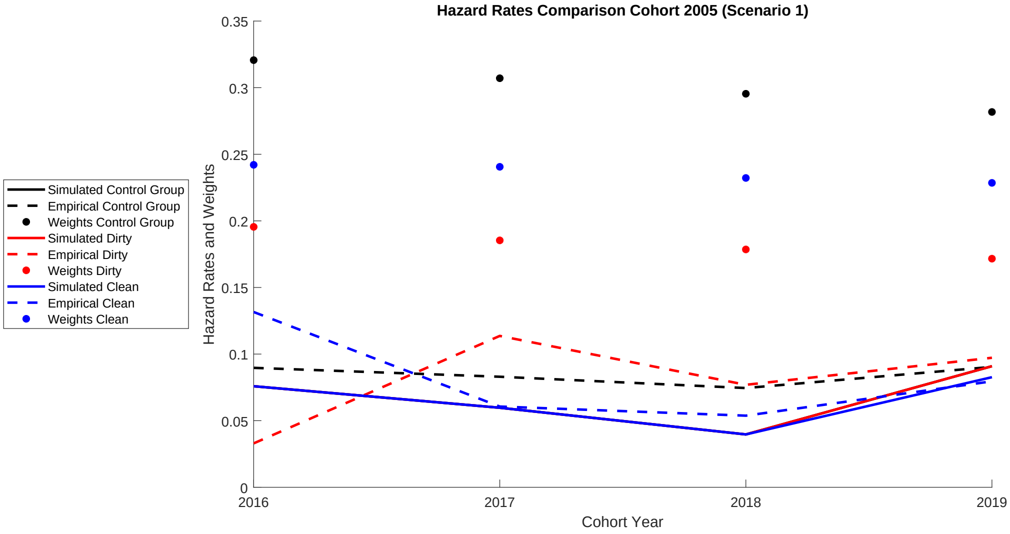

Hazard Rates Comparison Cohort 2000 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.05
0.1
0.15
0.2
0.25
0.3
0.35
2016
2017
2018
2019
Cohort Year

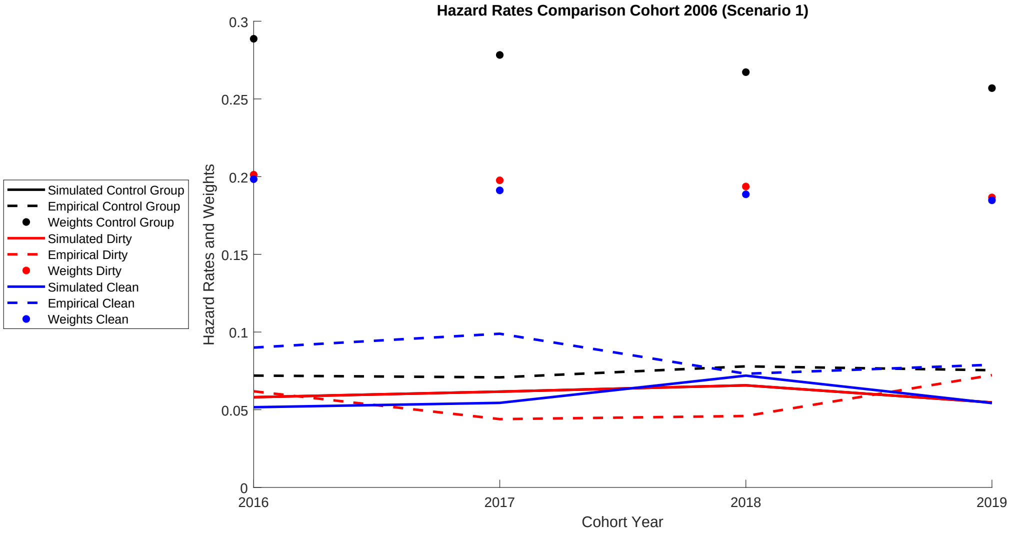

Hazard Rates Comparison Cohort 2001 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
2016
2017
2018
2019
Cohort Year


Hazard Rates Comparison Cohort 2002 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Cohort Year

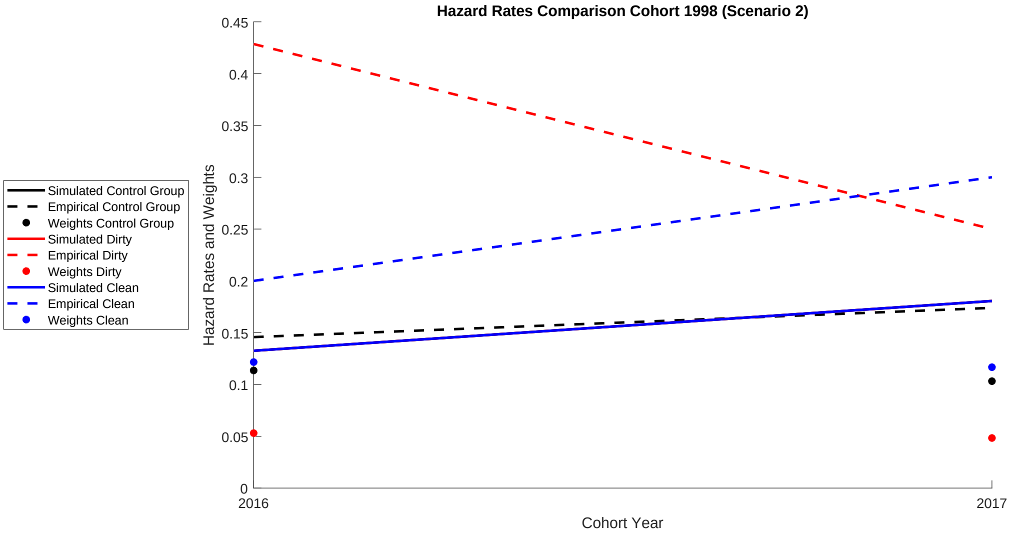

Hazard Rates Comparison Cohort 2003 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.3
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Cohort Year

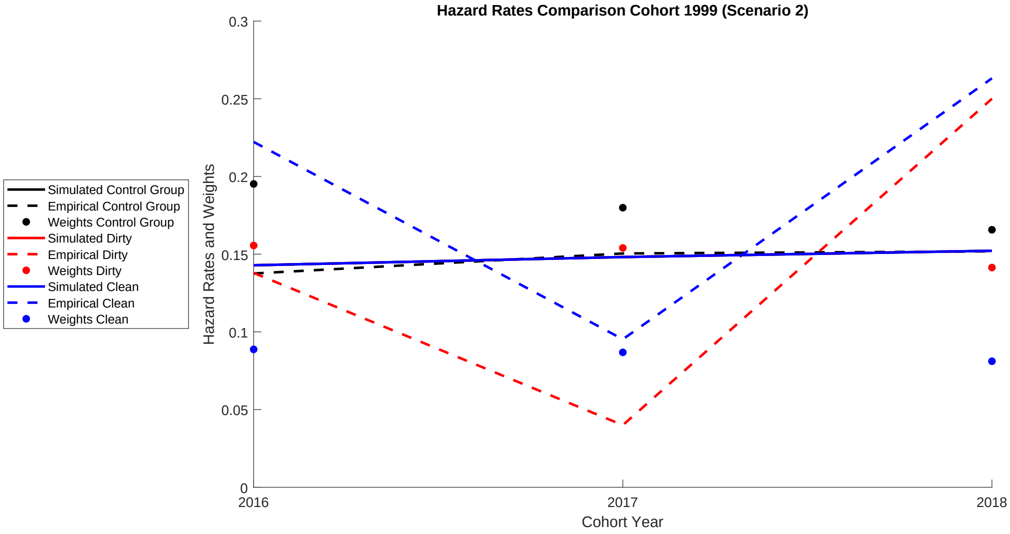

Hazard Rates Comparison Cohort 2004 (Scenario 1)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.3
0.25
0.2
0.15
0.1
0.05
2016
2017
2018
2019
Cohort Year

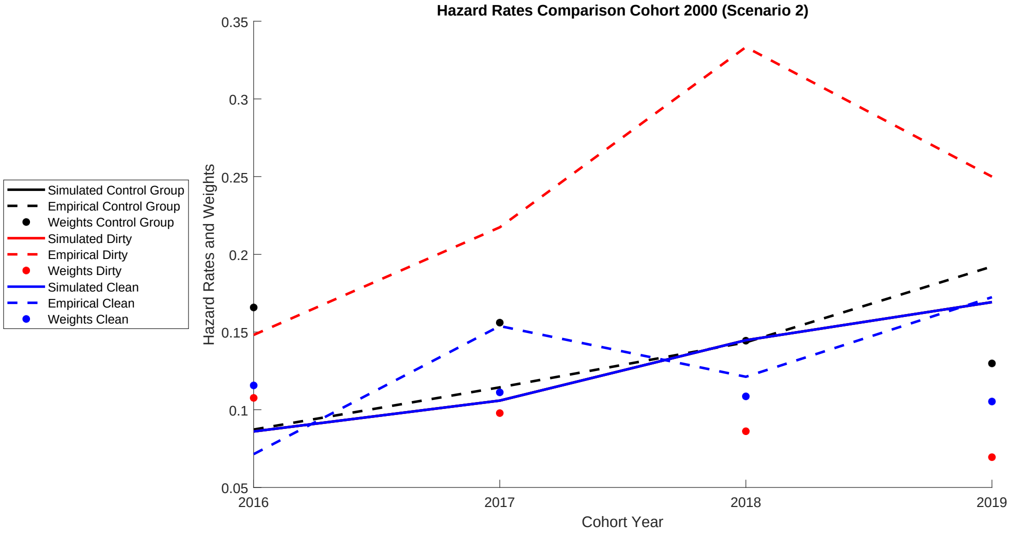

Hazard Rates Comparison Cohort 2005 (Scenario 1)
Hazard Rates and Weights
Cohort Year
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

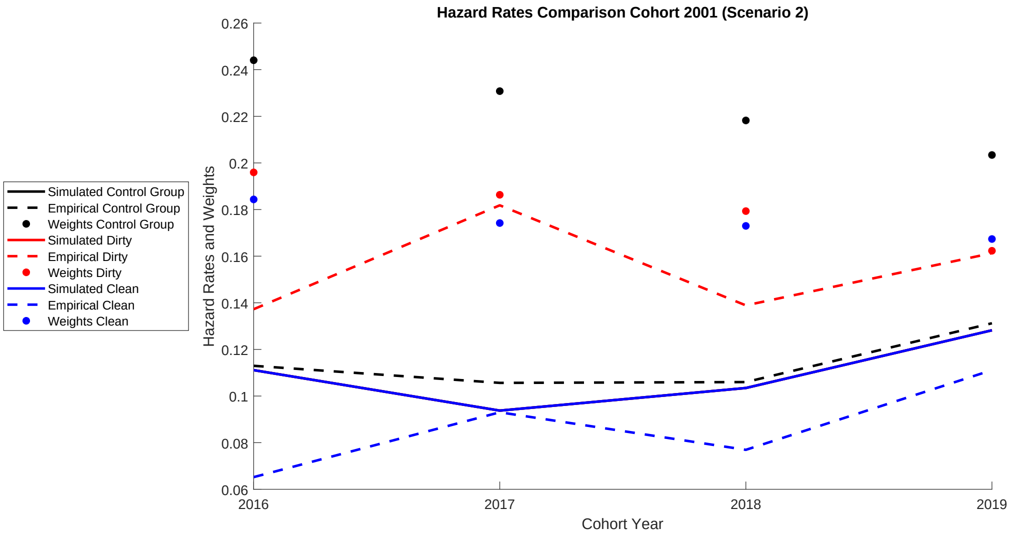

Hazard Rates Comparison Cohort 2006 (Scenario 1)
Hazard Rates and Weights
Cohort Year
0
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

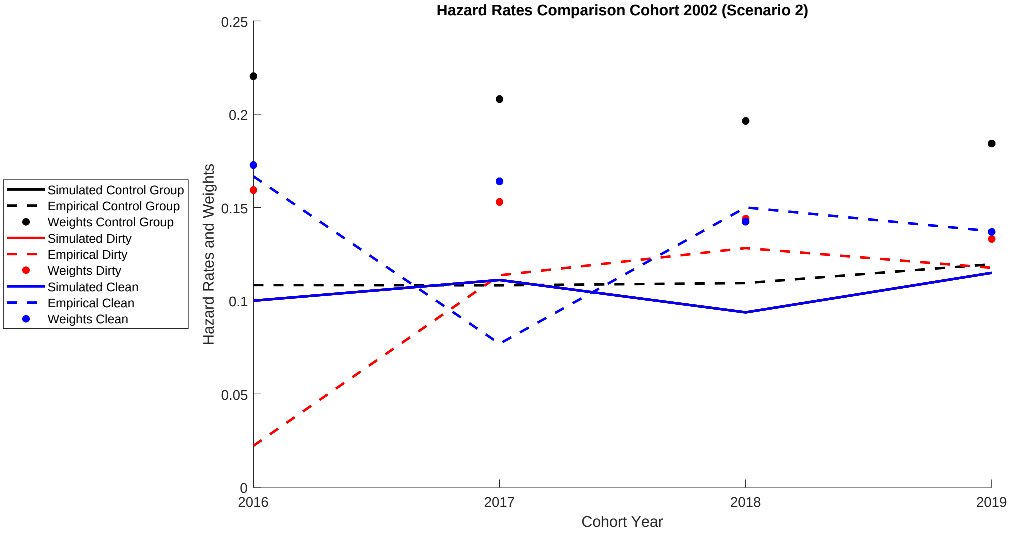
4.10.3 Appendix 2.3: Scenario 2

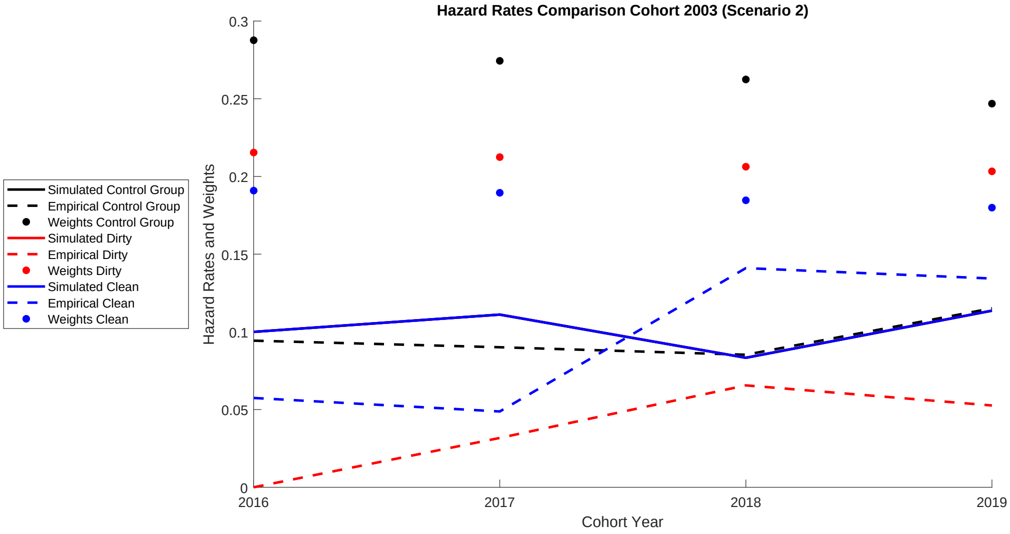


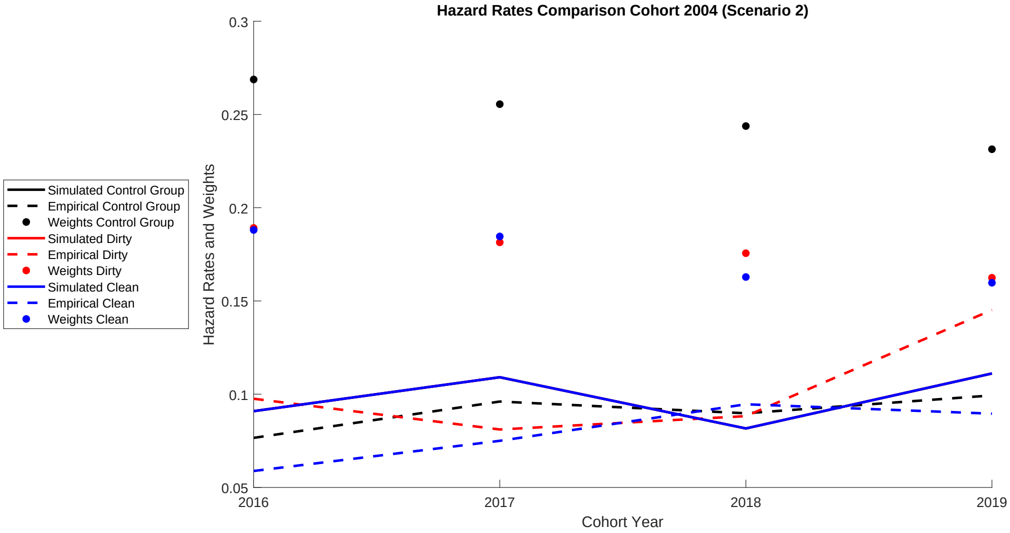

Hazard Rates Comparison Cohort 1999 (Scenario 2)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.3
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
Cohort Year

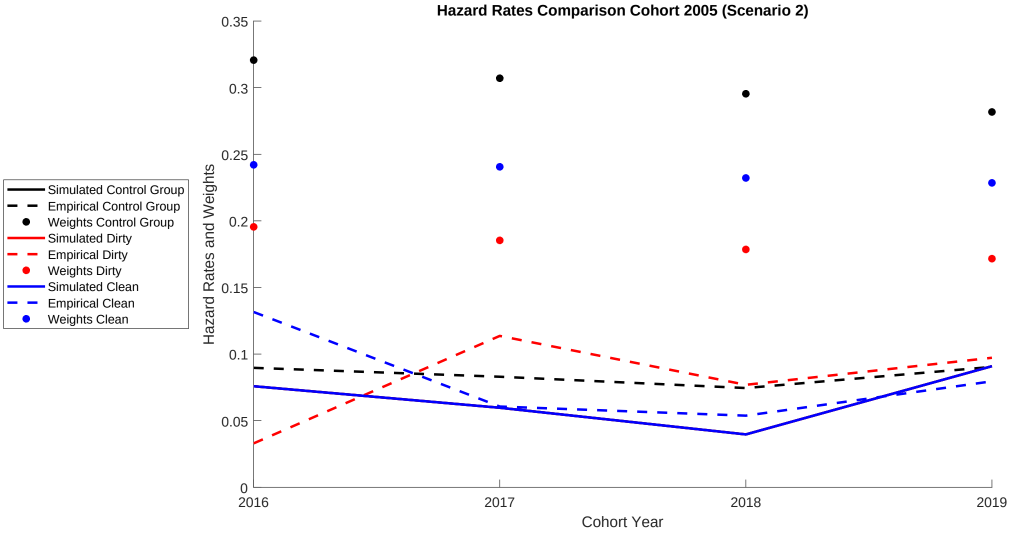

Hazard Rates Comparison Cohort 2000 (Scenario 2)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.35
0.3
0.25
0.2
0.15
0.1
0.05
2016
2017
2018
2019
Cohort Year

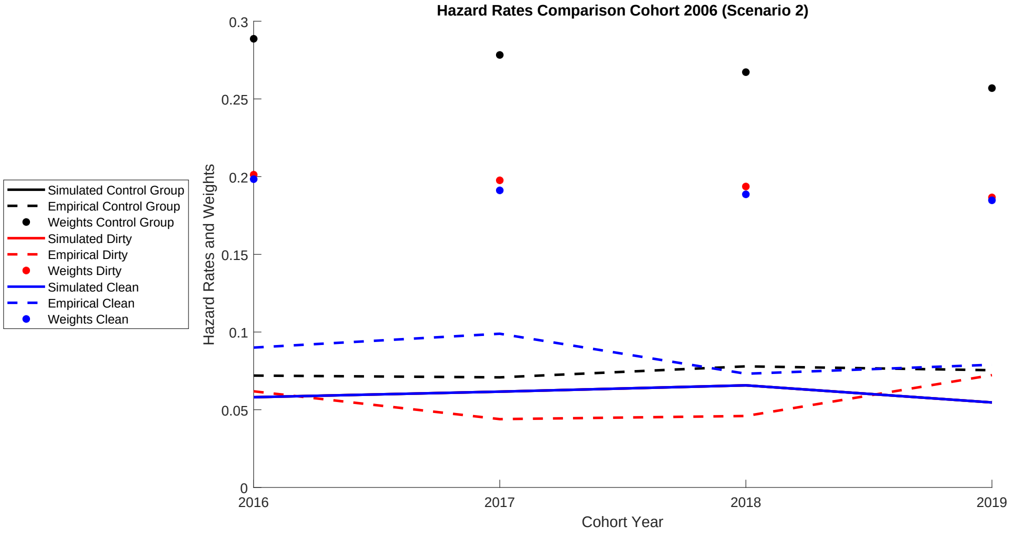

Hazard Rates Comparison Cohort 2001 (Scenario 2)
Hazard Rates and Weights
Cohort Year
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean


Hazard Rates Comparison Cohort 2002 (Scenario 2)
Hazard Rates and Weights
Cohort Year
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

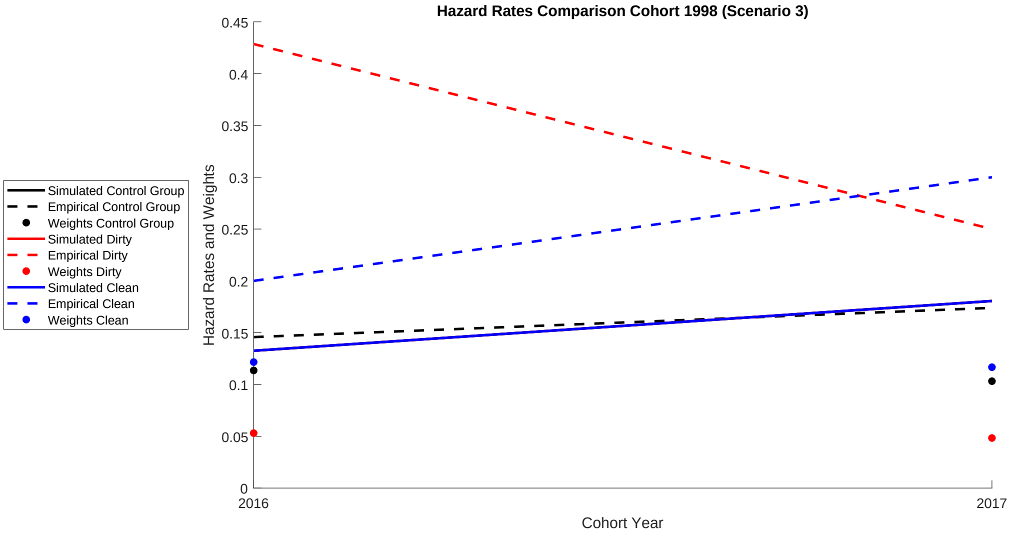

Hazard Rates Comparison Cohort 2003 (Scenario 2)
Hazard Rates and Weights
Cohort Year
0
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

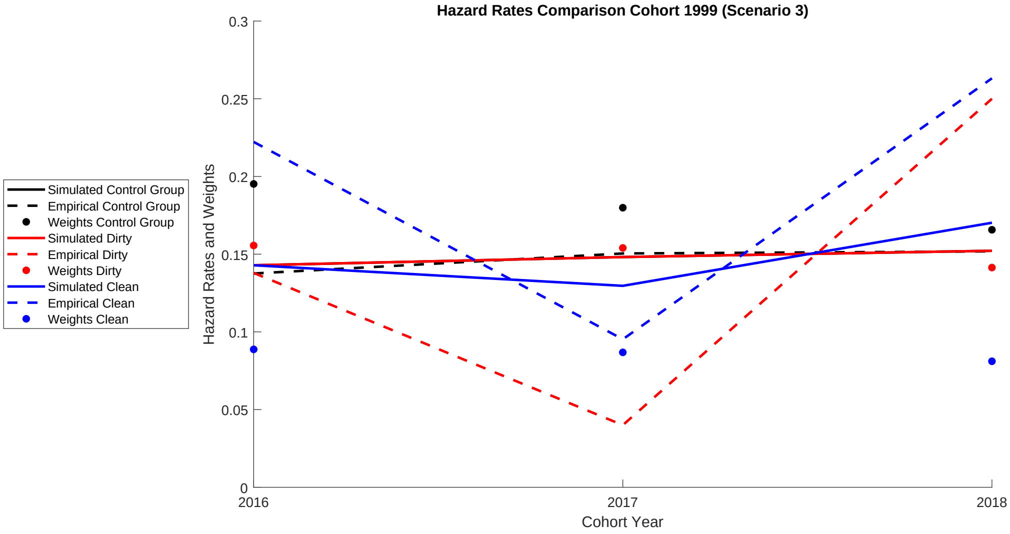

Hazard Rates Comparison Cohort 2004 (Scenario 2)
Hazard Rates and Weights
Cohort Year
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

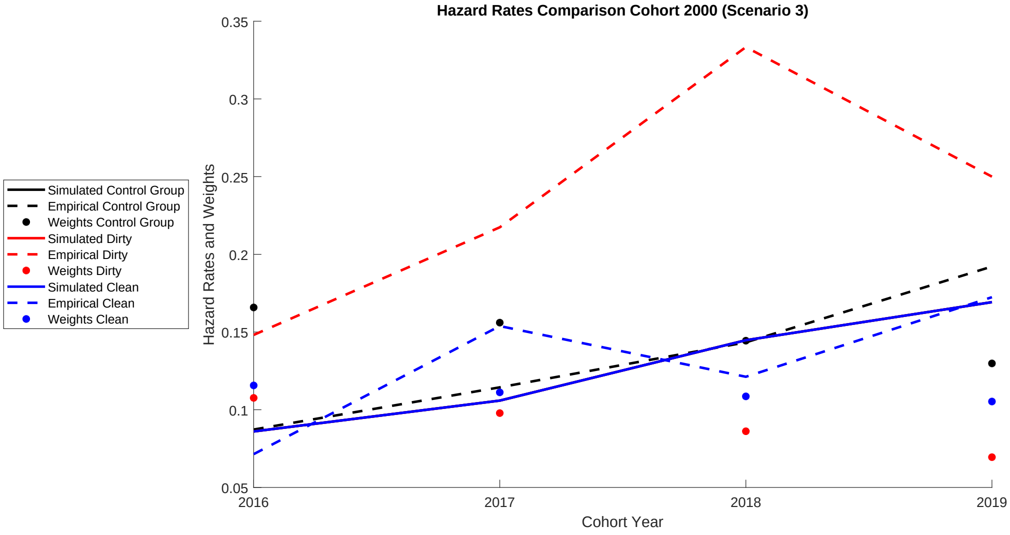

Hazard Rates Comparison Cohort 2005 (Scenario 2)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Cohort Year

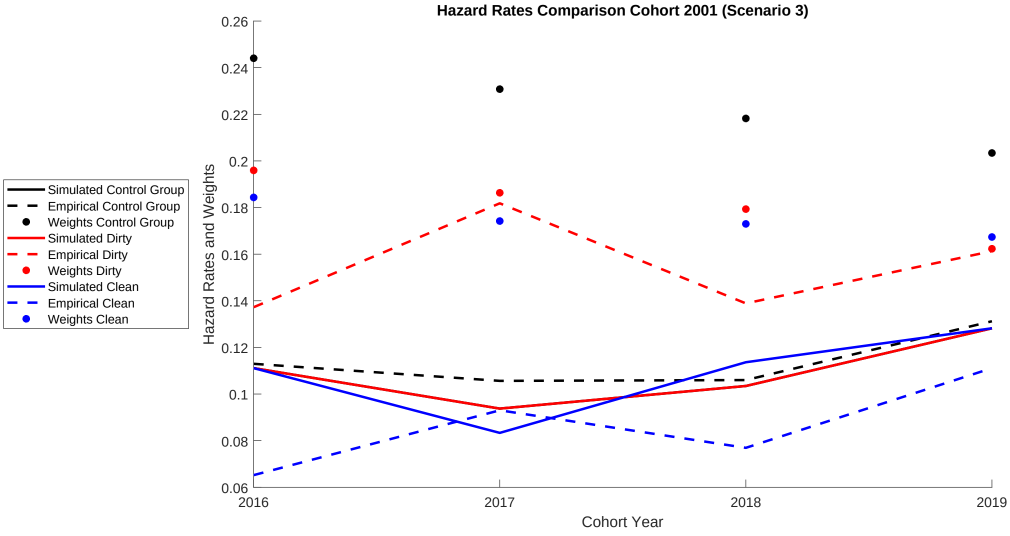

Hazard Rates Comparison Cohort 2006 (Scenario 2)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.3
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Cohort Year

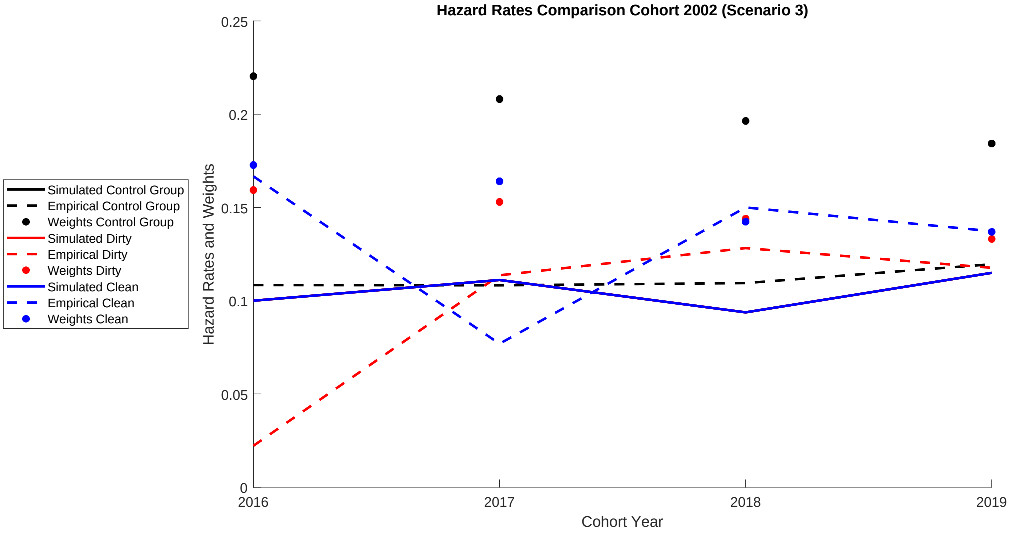
4.10.4 Appendix 2.4: Scenario 3

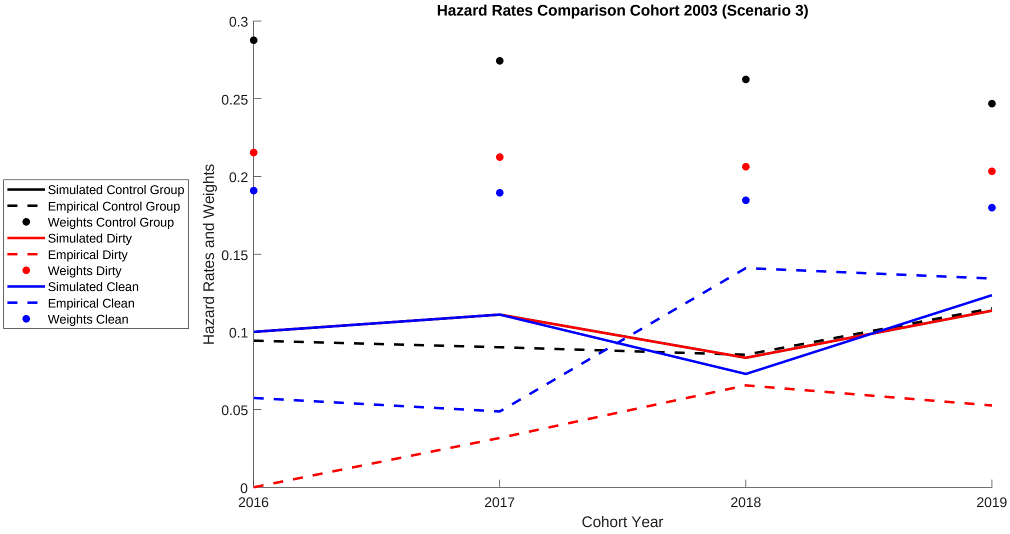


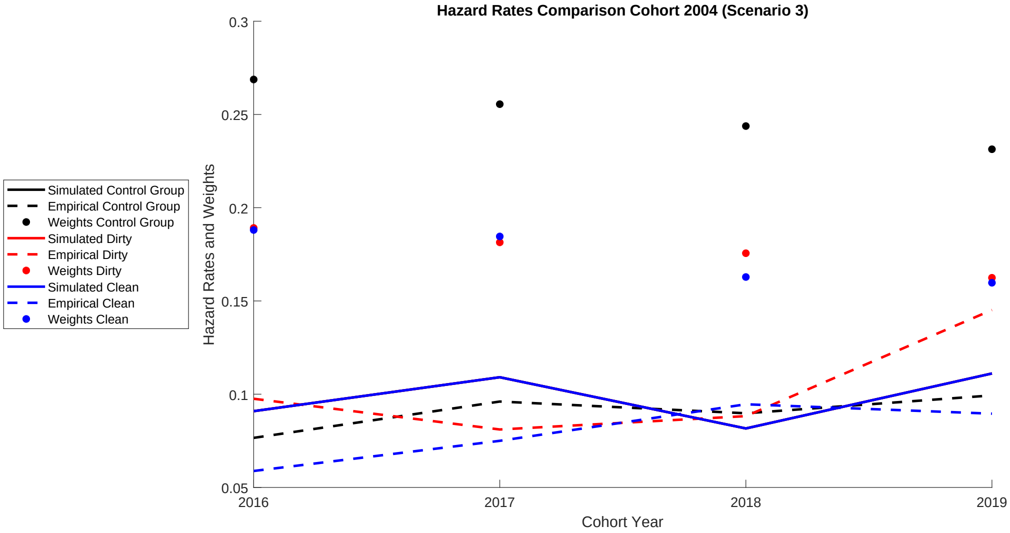

Hazard Rates Comparison Cohort 1999 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.3
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
Cohort Year

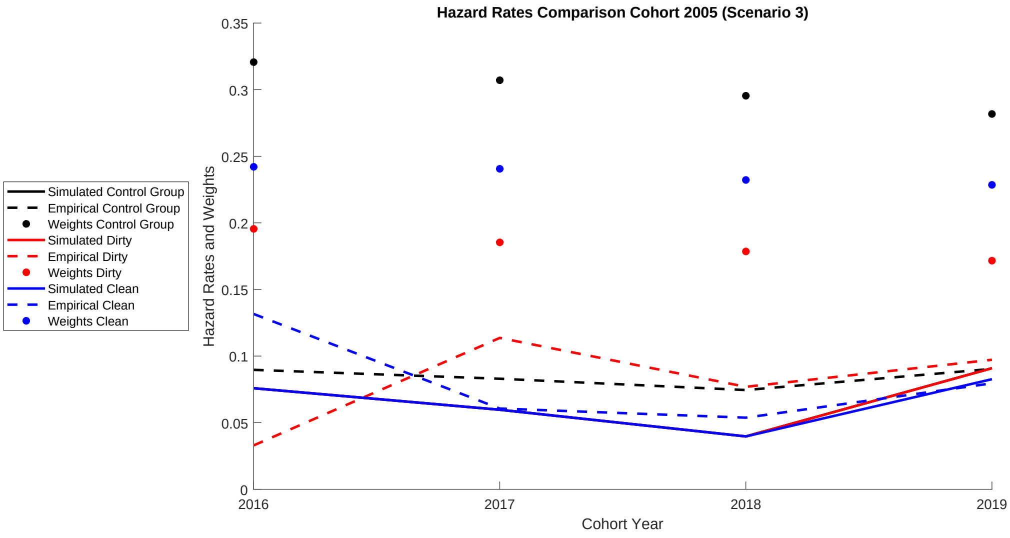

Hazard Rates Comparison Cohort 2000 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.35
0.3
0.25
0.2
0.15
0.1
0.05
2016
2017
2018
2019
Cohort Year

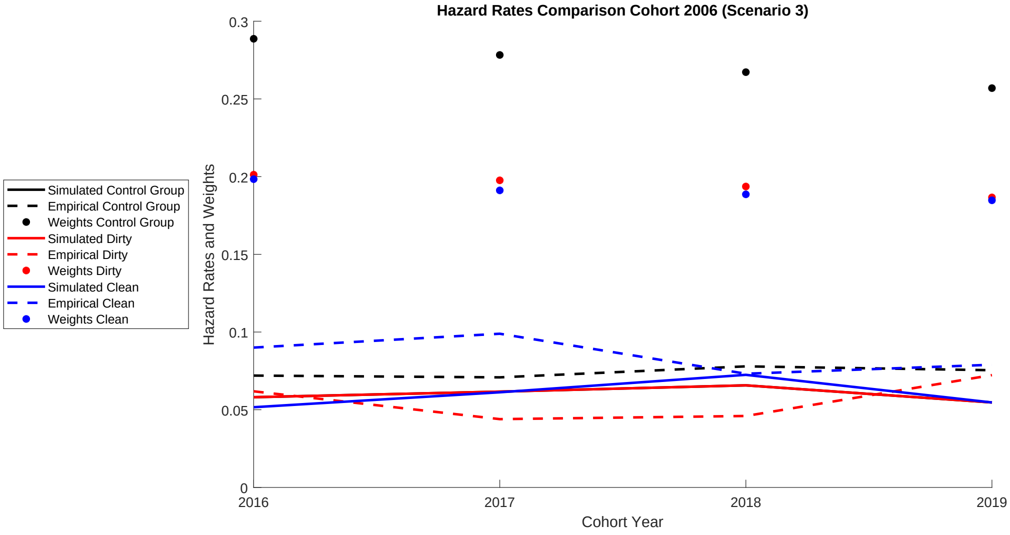

Hazard Rates Comparison Cohort 2001 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
2016
2017
2018
2019
Cohort Year


Hazard Rates Comparison Cohort 2002 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.25
0.2
0.15
0.1
0.05
0
2016
2017
2018
2019
Cohort Year


Hazard Rates Comparison Cohort 2003 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Cohort Year


Hazard Rates Comparison Cohort 2004 (Scenario 3)
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean
Hazard Rates and Weights
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Cohort Year


Hazard Rates Comparison Cohort 2005 (Scenario 3)
Hazard Rates and Weights
Cohort Year
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean


Hazard Rates Comparison Cohort 2006 (Scenario 3)
Hazard Rates and Weights
Cohort Year
0
0.05
0.1
0.15
0.2
0.25
0.3
2016
2017
2018
2019
Simulated Control Group
Empirical Control Group
Weights Control Group
Simulated Dirty
Empirical Dirty
Weights Dirty
Simulated Clean
Empirical Clean
Weights Clean

4.11 Appendix 3: Technical Specifications of the Estimation

In this Appendix, I shortly specify the technical details for both estimations:

- Cohorts: 1997-2006
- Renewal Years: 2016-2019

Algorithms employed:

1) Particle Swarm:
   Swarm Size: 1000, Function Tolerance: 1e-20, Minimum Neighbors Fraction: 1, Self-adjustment Weight: 1.9, Maximum Iterations: 400. Convergence achieved through relative change in objective value being less than function tolerance.

2) Simulated Annealing:
   Using as starting point the solution from the Particle Swarm, I perform a bounded simulated annealing with the following specifications: Function Tolerance: 1e-6, Maximum Function Evaluations: 900000.

3) Nelder-Mead:
   For the computation of the standard errors I use the bounded Nelder-Mead transformation performed by John D'Errico (D'Errico, 2022), with the following specifications: Number of Bootstraps: 150, Tolerance X: 10e-20, Function Tolerance: 10e-20, Maximum Function Evaluations: 100000.

4.12 Appendix 4: Global Optimum First Step

	Description (Parameter)	Estimate
A.	Patent initial returns	
	Mean parameter of the lognormal initial distribution (μ)	10.18
	Std. deviation parameter of the lognormal initial distribution (σ_R)	1.95
	$b_{C,1}$	-0.5000
	$b_{C,2}$	-0.4906
	$b_{C,3}$	-0.4567
	$b_{C,4}$	-0.4853
	$b_{C,5}$	-0.4884
	$b_{C,6}$	-0.4851
	$b_{C,7}$	-0.0806
	$b_{C,8}$	-0.1911
	$b_{C,9}$	-0.4888
	$b_{C,10}$	-0.3319
B.	Internal growth of returns	
	Depreciation factor (δ_i)	0.7724
	Not obsolescence (γ_i)	0.9664
	Internal growth of returns (σ_i)	1.000
	Upside opportunities (ϕ_i)	0.7157

Table 4.7: Parameter Estimates (First Step)

4.13 Appendix 5: Regulation Schedule

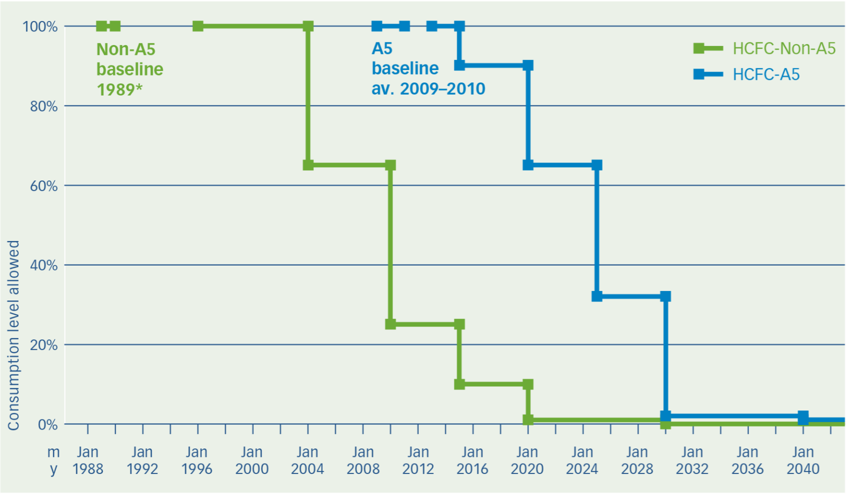
Annex C – Group I: HCFCs

Applicable to consumption.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	1996	Freeze	January 1, 2013
35 per cent reduction	January 1, 2004	10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline consumption until January 1, 2030 for the uses defined in Article 2F paragraph 6(a) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline consumption when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (i) and – possible essential use exemptions

* Annex A Group I

HCFCs (Annex C/I) consumption reduction schedule



* Baseline calculated as 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 4.7: HCFCs Phase-down Consumption Schedule.
Source: "Handbook for the Montreal Protocol on Substances that Deplete the Ozone Layer", Section 1.2., latest version available here (UNEP, 2019).

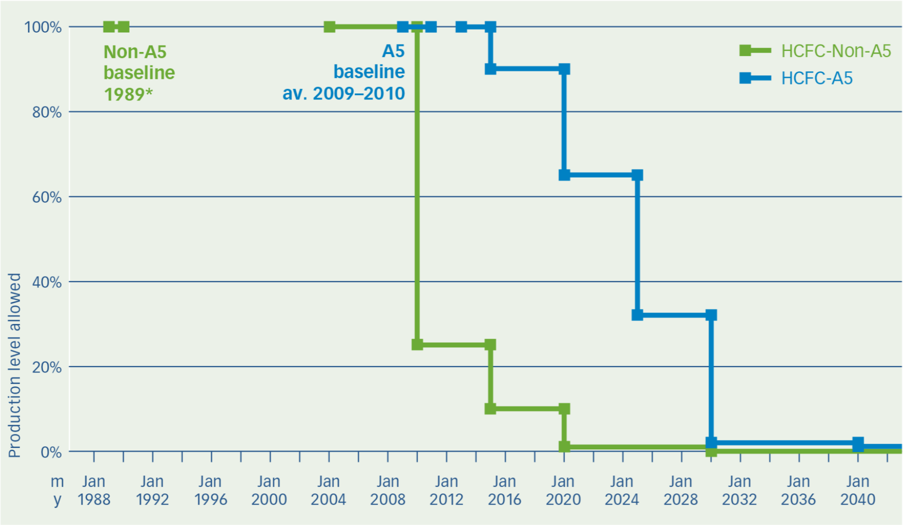
Annex C – Group I: HCFCs

Applicable to production.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**Average of 1989 HCFC production + 2.8 per cent of 1989 CFC* production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	January 1, 2004, at the baseline for production	Freeze	January 1, 2013
		10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline production until January 1, 2030 for the uses defined in Article 2F paragraph 6(b) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline production when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (ii) and – possible essential use exemptions

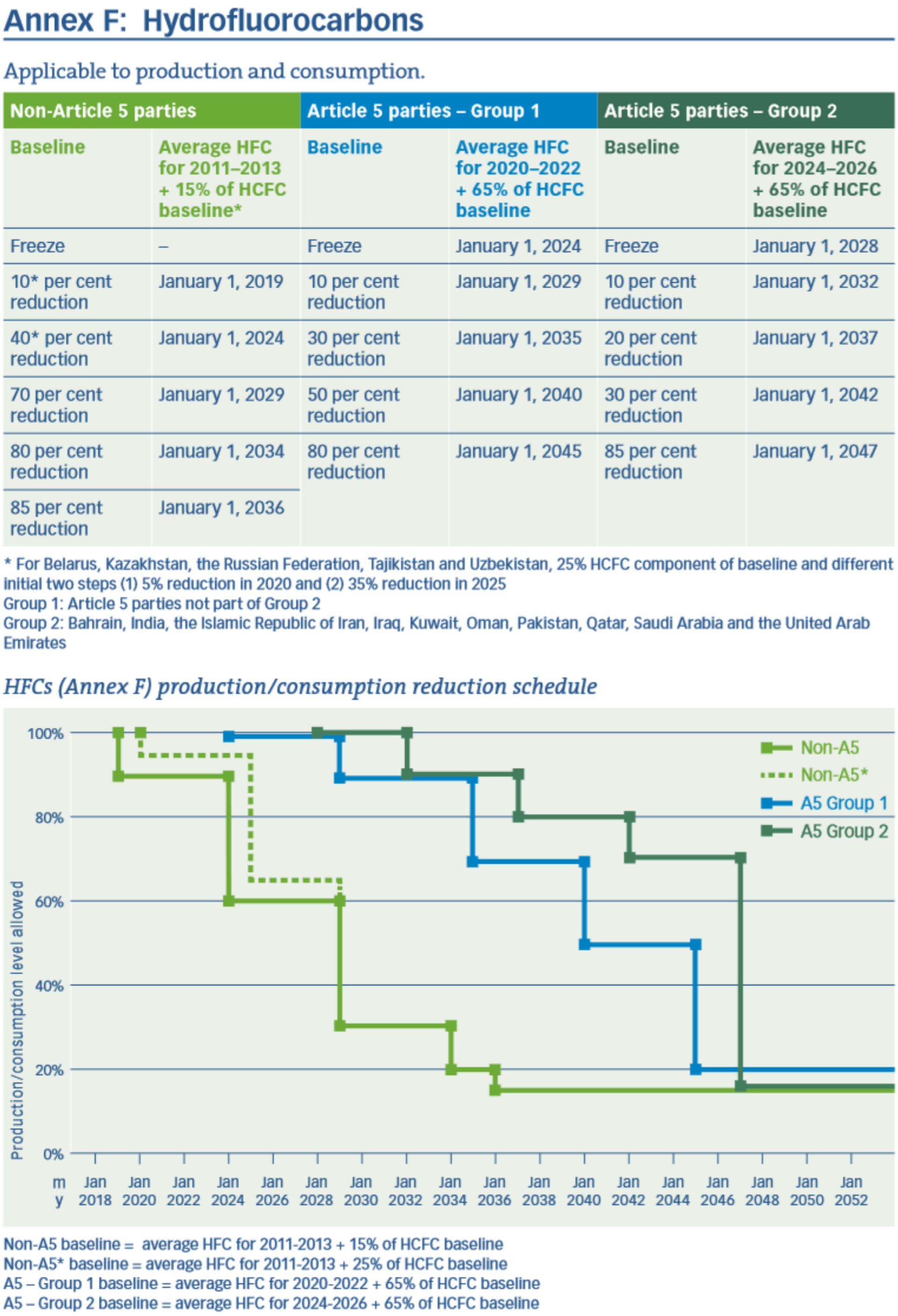
* Annex A Group I

HCFCs (Annex C/I) production reduction schedule



* Baseline calculated as average of 1989 HCFC production + 2.8 per cent of 1989 CFC production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 4.8: HCFCs Phase-down Production Schedule (UNEP, 2019)



Annex F: Hydrofluorocarbons

Applicable to production and consumption.

Non-Article 5 parties		Article 5 parties – Group 1		Article 5 parties – Group 2	
Baseline	**Average HFC for 2011–2013 + 15% of HCFC baseline***	**Baseline**	**Average HFC for 2020–2022 + 65% of HCFC baseline**	**Baseline**	**Average HFC for 2024–2026 + 65% of HCFC baseline**
Freeze	–	Freeze	January 1, 2024	Freeze	January 1, 2028
10* per cent reduction	January 1, 2019	10 per cent reduction	January 1, 2029	10 per cent reduction	January 1, 2032
40* per cent reduction	January 1, 2024	30 per cent reduction	January 1, 2035	20 per cent reduction	January 1, 2037
70 per cent reduction	January 1, 2029	50 per cent reduction	January 1, 2040	30 per cent reduction	January 1, 2042
80 per cent reduction	January 1, 2034	80 per cent reduction	January 1, 2045	85 per cent reduction	January 1, 2047
85 per cent reduction	January 1, 2036				

* For Belarus, Kazakhstan, the Russian Federation, Tajikistan and Uzbekistan, 25% HCFC component of baseline and different initial two steps (1) 5% reduction in 2020 and (2) 35% reduction in 2025

Group 1: Article 5 parties not part of Group 2

Group 2: Bahrain, India, the Islamic Republic of Iran, Iraq, Kuwait, Oman, Pakistan, Qatar, Saudi Arabia and the United Arab Emirates

HFCs (Annex F) production/consumption reduction schedule

Non-A5 baseline = average HFC for 2011-2013 + 15% of HCFC baseline
Non-A5* baseline = average HFC for 2011-2013 + 25% of HCFC baseline
A5 – Group 1 baseline = average HFC for 2020-2022 + 65% of HCFC baseline
A5 – Group 2 baseline = average HFC for 2024-2026 + 65% of HCFC baseline

Figure 4.9: HFCs Phase-down Production and Consumption Schedule (UNEP, 2019)

5 Analyzing Technological Costs and Benefits from the Montreal Protocol: Evidence from Patent Renewal*

5.1 Introduction

The Montreal Protocol of the Substances that Deplete the Ozone Layer (Montreal Protocol) aimed at phasing-down and phasing-out the so-called ozone-depleting substances (ODSs). Signed in 1987 and enforced in 1989, it is commonly seen as the most successful international environmental agreement (IEA) achieved so far. The drivers behind that success, however, are still not clear and have been the topic of discussions since early 1990s. There are two main hypotheses regarding its success. First, that the agreement was not very costly, and costs outweighed the benefits (Barrett, 1994). Second, that technologies were already available, and that the industry had started already moving (Sunstein, 2007). This second hypothesis, however, contradicts a statement by the U.S. chief negotiator at the Montreal Protocol, Richard Elliot Benedick, who said that the Protocol made the industry move in directions that would have been unexpected some years before (Benedick, 1998). Dugoua (2021), recently provided evidence supporting that the Protocol induced innovation in clean technologies and shows with a model of global collective goods that the agreement is best seen as a series of successive pledges increasing in stringency. Furthermore, her results would support the claims of Benedick (1998). In this paper, I aim at shedding further light to these questions by taking a different approach. To achieve this goal, I use a novel approach that combines a unique self-curated dataset of patents citing the ODSs and their substitutes. Furthermore, I use a new econometric method for studying shocks on the private value of patents developed in Chapter 3, and use a different identification strategy to the ones used in previous studies.

In particular, my identification strategy focuses on the impact of the Montreal Protocol and subsequent amendments to the value of R&D assets (patents) that had been applied

---

*I would like to thank Timo Goeschl and Wolfgang Habla for preliminary discussions on this chapter. Furthermore, I am grateful to Ulrich Wagner for discussions on the Montreal Protocol during my time at ZEW that indirectly benefited this work. The usual disclaimer applies.

either long-before the Protocol or just-before the Protocol was signed. Specifically, I define two periods, a first period before negotiations on the Protocol had started (1979-1983) and a second period during negotiations on an international agreement on ODSs (1984-1987). Then I study the impact of the Montreal Protocol and the following amendments on the hazard rate of clean and dirty patents applied in those two periods. This allows me to disentangle the role of the industry in achieving the Protocol and helps me shed further light on the different hypotheses behind the success of the Protocol.

The rationale behind my approach is that in the first period, one can assume that the industry had no expectations yet on the realization of a future agreement, such that if the agreement would have been exogenous it should have been experienced as such by the patent holders. Namely, dirty technology holders would have received a negative shock on the value of their patent assets and clean technology owners a positive one. Conversely, the second period started around the Vienna Convention for the Protection of the Ozone Layer (1985), which was the steppingstone upon which the Montreal Protocol was achieved. As such, one can assume that firms likely had a certain degree of information regarding the probability of a future agreement, i.e., some expectations on its realization. Therefore, one can hypothesize that if the agreement and its subsequent amendments were exogenous to those firms, then their impact should have been similar to the one we would expect firms having in the first period. If the impact differs then we could hypothesize that they adapted their innovation behavior to their expectations.

This chapter is structured in the following manner. In sections 2 and 3 I review the literature and present the environmental regulation that I study. In section 4, I present the dataset construction as well as the definition of treatment and control groups. Afterwards, in section 5, I describe the empirical analyses performed, first presenting empirical evidence stemming before the beginning of the discussions on the Montreal Protocol (1979-1983) and then evidence stemming from the period whilst discussions on an international environmental agreement were ongoing (1984-1987). Within each section I provide first descriptive statistics of the datasets, then present evidence from a panel event study, and finally nonparametric evidence from a duration model. I close this chapter summarizing my results in section 6.

5.2 Literature Review

This chapter stands upon three strands of the literature. First, the literature studying the ozone regulation and the Montreal Protocol. This literature started with the work of Barrett (1994) on self-enforcing agreements, where international environmental agreements are modeled as a non-cooperative game between countries. The Montreal Protocol and in particular the participation of the U.S. in the Protocol is interpreted in that framework, i.e., that the benefits from implementing the Protocol compared to its costs associated would have made the U.S. implement the negotiated measures independently of the agreement. Murdoch and Sandler (1997) further studied the reduction of chlorofluorocarbons (CFCs) as the voluntary provision of a public good and sustain that the initial emission reduction pledges were the outcome from the voluntary public good provision and not from cooperation. Beron et al. (2003) develop a probit model to study the decision of countries regarding whether to ratify the Montreal Protocol or not. Their findings suggest that countries ratified the Protocol without taking the behavior of other countries into account, in particular they reject free riding as a reason for not ratifying the agreement. Aufhammer et al. (2005) model the strategic behavior of countries prior to signing an IEA. Within the framework of a two player Nash-Cournot game they find evidence that the strategic anticipation behavior of the countries resulted in an increase of global CFC production. Goeschl and Perino (2007) developed a model of optimal R&D with stock pollutants, where technologies are not perfect backstops and find that innovation is sequential. Their model provides the intuition of the innovation challenge faced by agents within the framework of the Montreal Protocol. Wagner (2009) further studies the results of Murdoch and Sandler (1997) and questions their findings using UNEP emissions data reported by countries instead of their heavily imputed emissions dataset from the World Resources Institute that overstated emissions reduction and influenced their conclusions. This article was replied by the formers in Murdoch and Sandler (2009). More recently, Wagner (2016) estimates in a dynamic structural model the sign and magnitude of the strategic behavior of the countries in the ratification procedure of the Montreal Protocol. Finally, Dugoua (2021) using a synthetic control method approach finds that the Montreal Protocol induced innovation.

The second strand of the literature refers to the works on directed technological change and international environmental agreements, consisting of two main papers. First, the seminal work of Dekkers et al. (2012) scrutinizing the impact of an IEA on clean innovation exploiting the difference between "mother" innovations and family patents. They find that the Helsinki and Oslo protocols induced inventive activities and the diffusion of knowledge. Second, Dugoua (2021), as already mentioned, finds evidence of the impact of the Montreal Protocol on clean innovation using patents and scientific articles and finds that the Protocol induced clean inventive activities.

The last strand of the literature refers to the value of clean and dirty patents. First, Hall and Helmers (2013) study a pledge on clean innovations, the so-called "Eco-Patent Commons". For this they compare the value of the pledged patents to other patents from the same multinational or from the same technology field. They find that although the value of the pledged patents is similar to others from the same firm, they have a lower value compared to those of their technology field. Recently, Dechezleprêtre et al. (2021a; 2021b), using the stock-market approach of Hall et al. (2005) find that clean innovations are higher valued than dirty ones, while Langer et al. (2022) employing the Kogan et al. (2017) patent valuation method find that clean innovations suffer from financial constraints. In particular, they find that the economic crisis of 2010, which imposed severe financial constraints, affected negatively the relative share of clean versus dirty innovations.

5.3 Overview of the Regulation: The Montreal Protocol

The Montreal Protocol was signed in 1987 and entered into force in 1989. Signing parties agreed to implement phase-down and phase-out schedules for reducing emissions of ozone-depleting substances (the full list can be found in Appendix 3). In the following years, subsequent amendments were signed extending the list of regulated substances and tightening the phase-down schedules of the original treaty. The main family of pollutants regulated under the Montreal Protocol are the so-called chlorofluorocarbons (CFCs), which are molecules having particular thermodynamic and chemical properties making them suitable for a large set of applications such as aerosols, working fluids in refrigeration and air conditioning devices (RAC) (i.e., fridges, freezers, etc.), and foams' blowing agents. Their large use made their phase-out be a considerable challenge for the industry such that alternative substances had to be developed, and devices adapted to other potential chemicals. One family of replacement chemicals employed as replacement for CFCs were hydrochlorofluorocarbons (HCFCs), which are substances with similar thermodynamic properties but with a smaller ozone depleting potential than CFCs (see Appendix 1.1). Besides HCFCs, the so-called hydrofluorocarbons (HFCs) were also used as replacement, since they are not ODSs but their global warming potential is much higher than that of CO_2 (see Appendix 1.1).

5.4 Data

5.4.1 Dataset Construction

The dataset used for the analysis of this paper is a subset of the original dataset described in Chapter 3 on patents citing substances regulated under the Montreal Protocol and their clean substitutes in the refrigeration sector. In Chapter 3 using the lists of regulated substances provided in the Handbook of the Montreal Protocol (UNEP, 2019) and the list of refrigerants, as of defined by ANSI/ASHRAE [1] Standard 34-2019 (ASHRAE, 2019) (see Appendix of this Chapter 1.1 and 1.2), I select all European patents renewed in Germany citing the listed substances. This dataset focuses on patents citing the following types of substances, i.e., chlorofluorocarbons (CFCs), hydrochlorofluorocarbons (HCFCs), hydrofluorocarbons (HFCs), other ozone-depleting substances (ODS) regulated by the Montreal Protocol, non-patented chemicals with refrigerant properties[2], and hydrofluoroolefins (HFOs).

Treatment and Control Groups

Since the aim of this paper is to further shed light on the impact of the Montreal Protocol on patent value, then treatment group selection will be different from that of Chapter 3. In particular, as we are interested in the impact of the original Protocol, we will focus primarily on patents citing the first family of chemicals regulated under the IEA, i.e.,

---

[1] ANSI stands for the "American National Standards Institute" and ASHRAE refers to the "American Society of Heating, Refrigerating and Air-Conditioning Engineers".

[2] Following the ASHRAE (2009) definition: "Natural refrigerants occur in nature's biological and chemical cycles without human intervention. These materials include ammonia, carbon dioxide, natural hydrocarbons, water and air".

the CFCs. Besides patents citing the original pollutants, we will be also interested in patents citing their substitutes. Given that we want to study the original Protocol, then we will consider as "clean" substitutes patents citing HCFCs, HFCs, HFOs, or non-patented chemicals. I will now define the treatment and control groups of the analysis.

First, I define as T_I the group of patents citing CFCs, i.e., as patents citing substances from Annex A and Annex B of Appendix 1.1 also included in the ASHRAE list of Appendix 1.2. Then as T_{II}, those patents citing any of the clean substitutes mentioned above, i.e., any substance from the ASHRAE list of Appendix 1.2 not included in Annex A or Annex B of Appendix 1.1. Finally, I define T_{III} as those patents citing any other substance regulated under the Montreal Protocol, i.e., listed in Appendix 1.1, not included in either T_I or T_{II}. Those three patent groups can be represented in a Venn diagram, see Figure 5.1. In order to define the control group, I use the patents from T_I. Namely, I first define a vector with the IPC[3] subclasses of the patents from T_I belonging to either F or C sections[4] (see Table 5.8 in Appendix 2), and then I consider as control group all patents from those IPC subclasses that do not belong to T_I, T_{II}, or T_{III}.

As one can observe in the Venn diagram (Figure 5.1), the three sets of treated patents (T_I, T_{II}, and T_{III}) intersect each other. The rationale for this is that technologies were developed to be able to work with different types of chemicals, i.e., pollutants and their substitutes. This includes not only the mechanical components of refrigeration devices such as compressors or valves, but also additional chemicals used in those devices such as lubricants or additives. Since patents citing both types of substances could generate noise in my analysis, I decide to keep only those citing single sorts of substances. Therefore, I redefine the treatment groups as following. T_1 is the group of patents citing solely CFCs, i.e., $T_1 = T_I \backslash ((T_I \cap T_{II}) \cup (T_I \cap T_{III}))$. T_2 is the group of patents mentioning only their substitutes, i.e., $T_2 = T_{II} \backslash ((T_I \cap T_{II}) \cup (T_{II} \cap T_{III}))$. The control group contains all patents from the IPC subclasses of the patents from T_I netted out of the patents of T_I, T_{II}, or T_{III}. Before presenting the empirical analysis, I will describe two further steps in the data selection process and explain the timeframe of my analysis.

---

[3] IPC stands for International Patent Classification.

[4] C section includes Chemistry and Metallurgy, and F section includes Mechanical engineering, lighting, heating, weapons, and blasting.

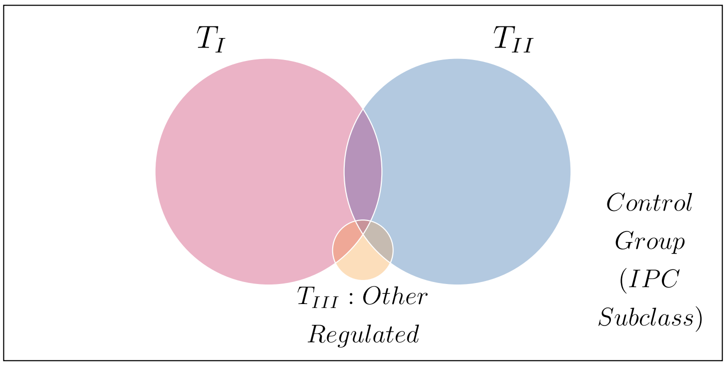


Figure 5.1: Treatment and Control Groups

Multiple Correspondence Analysis and Coarsened Exact Matching After having defined the treatment and control groups, I will now perform an additional step for further capturing the unobserved technological heterogeneity of the different patents' samples. In particular, I exploit that patents are co-classified into several IPC subclasses[5] for disentangling the technological space to which the invention belongs. With this purpose I perform a multiple correspondence analysis of the co-classified IPC subclass dummies into 5 dimensions. This will allow me later in my empirical analysis to further control for technological similarities between two patents. The second and final step before describing the timeframe of the analysis is a coarsened exact matching. Specifically, in order to increase the comparability of the three different groups (T_1, T_2, and control group), I implement a coarsened exact matching at the application year and patent class level. I impose an additional constraint on the matching, i.e., I only keep the matched "bins" where there are at least one observation of T_1 and one of T_2 (in Table 5.9 of Appendix 2 I present the matched IPC classes). The result from this matching for the period described in the next paragraph constitutes the final dataset of my analysis (Table 5.10 in Appendix 2 presents the matched bins of the whole dataset, i.e., not constrained to the cohorts of analysis).

Cohorts of analysis Since I aim at scrutinizing the consequences of the signature, enforcement, and of the early amendments to the Montreal Protocol, I will focus on European patents renewed in Germany applied for years between 1979 and 1987 (bearing in mind

---

[5] A patent is assigned an "F" IPC subclass and additional IPC subclasses, which I call the "co-classified" IPC subclasses. The list of co-classified IPC subclasses can be of hundreds for a single patent.

that the Protocol was signed in 1987). The reason for focusing on patents applied for before the Montreal Protocol was signed is that I want to analyze the fate of the existing R&D assets (proxied by patents) after the signature of the Protocol. Later on, I will split my analysis in two, first focusing on patents applied for “before discussions” on the Montreal Protocol had started, i.e. those patents applied between 1979 and 1983, and then on those “during discussions” on the Montreal Protocol, i.e., those having application dates between 1984 and 1987. The decision to split the sample and the analysis in two is because the Montreal Protocol was preceded by the Vienna Convention for the Protection of the Ozone Layer, which started in March 1985 and was the steppingstone towards achieving the Montreal Protocol. For this reason, I consider that from the Vienna Convention onwards (I take one year lead that I consider as of “preparation” of the conference) countries and industries could foresee and make assumptions of an IEA on ozone depleting substances. As a consequence, one can hypothesize that the patenting behavior of firms (R&D strategy) between 1984 and 1987 is not naïve to the Montreal Protocol. We will study this hypothesis later on in the empirical analysis. Conversely, one can hypothesize that patents applied for between 1979 and 1983 are early enough to the Montreal Protocol such that patent holders could not guess at the application date that in 1987 the Montreal Protocol would be signed. The comparison of the impact of the Montreal Protocol on the value of those two sorts of patents, proxied by forward citations and patent renewal would allow us to further shed light on the different hypotheses regarding the rationale of the Protocol’s drivers. In the next section I will present evidence on the impact of the IEA on patent value, first for the dataset ”before discussions” on the Montreal Protocol (1979-1983) and then for the one ”during discussions” on the Montreal Protocol (1984-1987).

5.5 Empirical Analysis of the Impact of the Environmental Regulation on Patent Value

In this section I present the empirical analysis of the impact of the Montreal Protocol on patent value. My analysis is divided in two parts referring to two different periods and datasets. In the first part, I study the time before official discussions on Montreal Protocol had started, which I define from 1979 to 1983. Afterwards I scrutinize the period during which discussions on the Montreal Protocol happened, which I define from 1984 until 1987. The reference point for splitting the two analyses is the Vienna Convention, which happened in 1985, but whose effect might have already started before, hence I start the second period in 1984. Each one of the analyses has three parts. First, I provide some descriptive statistics of the data sample related with patent value and technological similarity. Second, I study the impact of the Protocol on patent value using forward citations as a proxy for patent value. Finally, I scrutinize the impact on patent value using nonparametric duration techniques for my two types of patents. For the duration analysis I exploit patent renewal as a proxy for patent value and use the adaptation of the van den Bergh et al. (2020) approach that I developed in Chapter 3.

5.5.1 Evidence Before Discussions on the Montreal Protocol (1979-1983)

Concerns about the potential threat that CFCs represented for the ozone layer started in 1974 with the evidence provided by Molina and Rowland (1974). This research milestone sparked worries that soon led to political action. In Germany, for instance, already in 1975 the German Federal Government started gathering further evidence on the effects of the CFCs on the atmosphere and in 1977 there was a commitment to cut the quantity of CFCs used in aerosols by 1979. Yet, since the CFCs and other ODSs were used on a global scale, international action was essential and there was still a long way to go until reaching global pledges. As I present in Appendix 6, in a retranscription of a report from the German Environmental Agency (UBA, 2017), between 1974 and the Vienna Convention (1985) there were already some events on the ozone regulation. Those events and regulations were, however, limited to either some specific uses or some CFCs. The most relevant ones affecting Germany in the period 1974-1985, and in particular the refrigeration sector, were the resolution from the Council of the European Community in 1978 that prevented the increase in production of CFC-11 and CFC-12, and the agreement of the Council in 1980 on freezing their production. Given this information, we can conclude that during the period from 1974 until 1985 there were strong concerns on the threats that CFCs represented for the ozone layer. Furthermore, we can also conclude that national and international action had already started at a sector level and that some industry players in certain countries were already aware of the problem caused by ODSs. Yet, that some countries and sectors had started actions doesn't mean that stakeholders, such as countries or firms, could imagine that a pledge at a world level was likely to happen. Taking this into account, in this part of the paper I will analyze how the signature of the Montreal Protocol affected the patent value of European patents applied between 1979 and 1983, which were renewed in Germany.

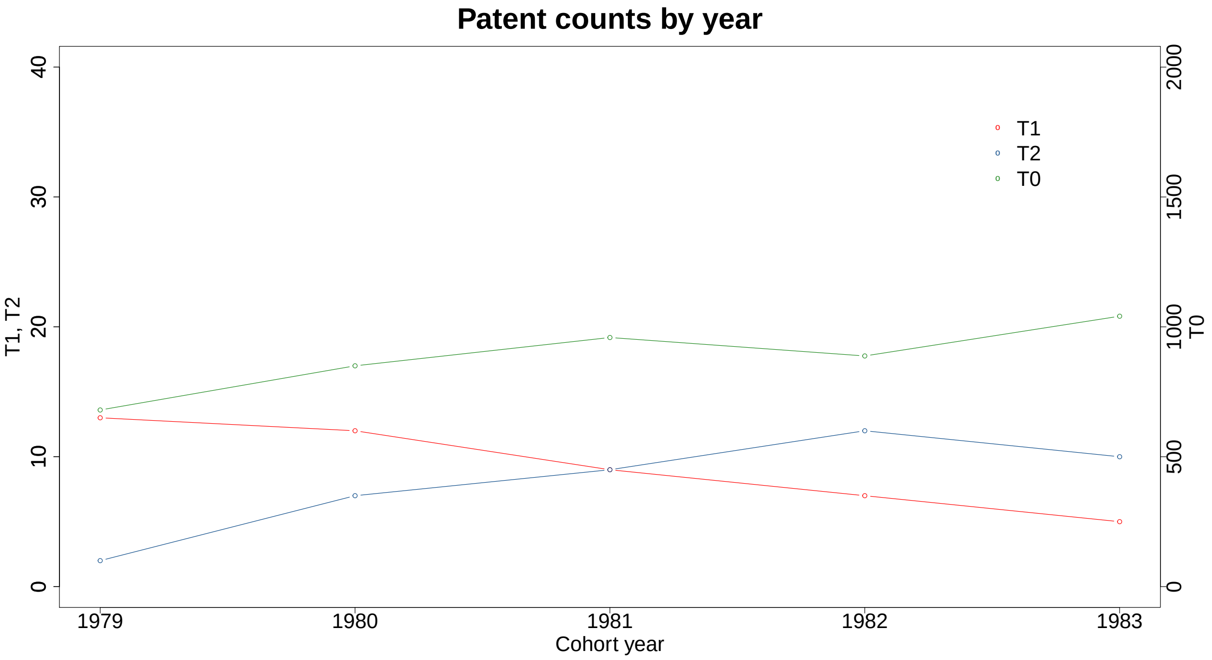


Figure 5.2: Patent counts by cohort year 1979-1983

Descriptive Statistics

In Tables 5.1 to 5.3 I present descriptive statistics from the three data samples T_1, T_2, and control group T_0. I provide values of different proxies of ex-ante patent value such as number of inventors, number of applicants, family size, and grant lag, as well as five proxies for technological space resemblance stemming from the multiple correspondence analysis (MCA). First of all, it is noteworthy mention the difference in sample sizes between treatment groups and control group. In line with the finding from Dugoua (2021), there were not many patents in the sector, either mentioning dirty substances (CFCs) or their

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.041	0.026	−0.008	0.112
Dim 2		0.0004	0.005	−0.016	0.008
Dim 3		0.006	0.061	−0.163	0.157
Dim 4		−0.003	0.005	−0.022	0.005
Dim 5		−0.005	0.022	−0.060	0.051
Grant Lag		1,308.971	437.124	586	2,511
Inventors		2.914	1.560	1	7
Applicants		1.000	0.000	1	1
Family Size		7.629	3.598	4	19
Sample Size	35				

Table 5.1: Descriptive Statistics 1979-1983: Treatment Group T_1

substitutes (T_2). Given that sample sizes are about 35 patents each, this clearly limits the interpretation of the estimates from this analysis. Nonetheless, even if only as descriptive evidence, it could help shed further light on the impact of the Protocol on patent value. Extending the analysis to further countries might help overcome this clear shortcoming.

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.048	0.035	−0.012	0.158
Dim 2		0.00003	0.004	−0.008	0.009
Dim 3		0.012	0.048	−0.081	0.125
Dim 4		0.002	0.014	−0.010	0.074
Dim 5		−0.007	0.018	−0.060	0.025
Grant Lag		1,373.294	460.387	714	3,005
Inventors		2.735	1.310	1	5
Applicants		1.000	0.000	1	1
Family Size		6.206	4.305	3	24
Sample Size	34				

Table 5.2: Descriptive Statistics 1979-1983: Treatment Group T_2

Besides the sample size discussion, it is interesting to notice that the three samples have similar number of applicants, inventors, and grant lags, which are three known measures of ex-ante patent value. Regarding the pre-grant patent value measure, only family size seems to be slightly larger for the control group sample than for my treatment group ones.

Concerning the technological space, we can see that treatment groups (T_1, T_2) have very close values of MCA dimensions 1 and 2. Furthermore, T_1 and control group have also similar values of dimension 4. In general differences across the three samples are not large, which would speak for a similar technological space across samples.

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.012	0.060	−0.331	0.412
Dim 2		−0.002	0.005	−0.021	0.039
Dim 3		−0.017	0.064	−0.193	0.744
Dim 4		−0.005	0.008	−0.049	0.226
Dim 5		0.004	0.033	−0.332	1.327
Grant Lag		1,284.201	460.826	499	4,965
Inventors		2.699	1.539	1	16
Applicants		1.035	0.212	1	4
Family Size		8.916	7.277	2	79
Sample Size	3,365				

Table 5.3: Descriptive Statistics 1979-1983: Control Group T_0

Regarding technological distribution, proxied by the "F" or primary IPC class, I present in Figure 5.2 the figures for my three samples. It is straightforward to notice that treatment groups (T_1, T_2) have very close distributions, with patents from the C08 class dominating[6]. Conversely patents from control group seem rather be stemming from the C07 class[7]. Regarding the distribution of patents by cohort, it is interesting to see that the number of patents from T_1 (dirty patents) decreases over time. Likewise, it is also noteworthy mentioning that patents from T_2 (clean patents) have similar cohort count patterns as those from the control group, slightly diverging in 1983, where the number of clean patents decreases.

Forward Citations Evidence

I will now present evidence stemming from a panel event study on the impact of the Montreal Protocol on patent value, proxied by forward citations. I consider that the event date is 1987, which corresponds to the signature of the Protocol. In my study, both for

---

[6] C08 stands for "Organic Macromolecular Compounds; Their Preparation or Chemical Working-up; Compositions based Thereon".

[7] C07 stands for "Organic Chemistry".

my clean and dirty technologies' analyses, I include 3 leads and 13 lags. Furthermore, I control for the five MCA dimensions, grant lag, number of applicants, number of inventors, family size, a dummy indicating whether the patent is still active, application year by IPC subclass fixed effects, and I also include year fixed effects. I use the panel event study implementation of Clarke and Tapia-Schythe (2021).

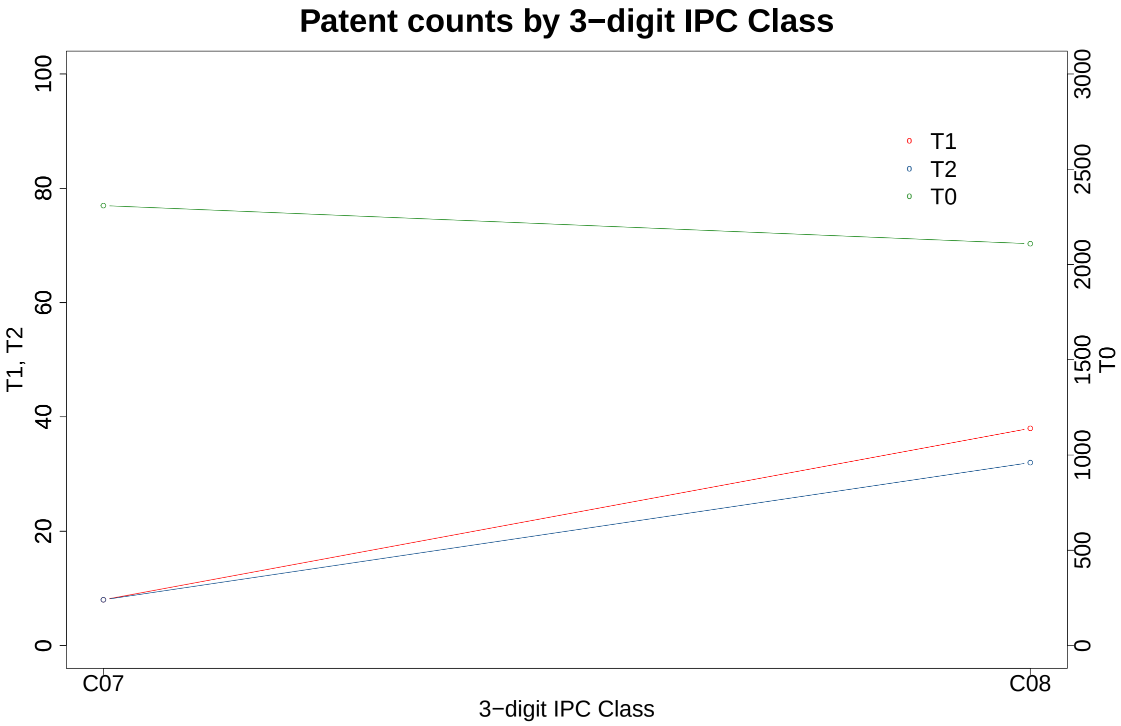


Figure 5.3: Patent counts by 3-digit IPC Class 1979-1983

Evidence on Clean Technologies I consider first, evidence for clean technologies, i.e., comparing T_2 to the control group patents. I implement the panel event study presented in equation 5.1. As shown in Figure 5.4, this analysis delivers no significant negative nor positive effects. Nevertheless, the size of the confidence intervals is considerably large compared, for instance, to that from the analysis of Chapter 3. This could be attributed to both the limited sample size and the small magnitude of the effects. As already mentioned, increasing sample size by extending this analysis to other countries would benefit the analysis in general terms and could potentially help disentangle this question. Even if the effects are not significant, it is still possible to observe a positive trend in forward citations. This would be in line with what we would expect happening. As the Montreal Protocol imposed phase-down schedules for CFCs (see Appendix 3), it is intuitive to think that the value of clean substitutes to those substances would increase, although evidence is here not significant at a 5 percent level.

$$y_{it} = \alpha + \sum_{j=1}^{13} \beta_j (Lag\ j)_{it} + \sum_{k=2}^{4} \beta_k (Lead\ k)_{it} + \lambda_t + X'_{it}\Gamma + \epsilon_{it} \tag{5.1}$$

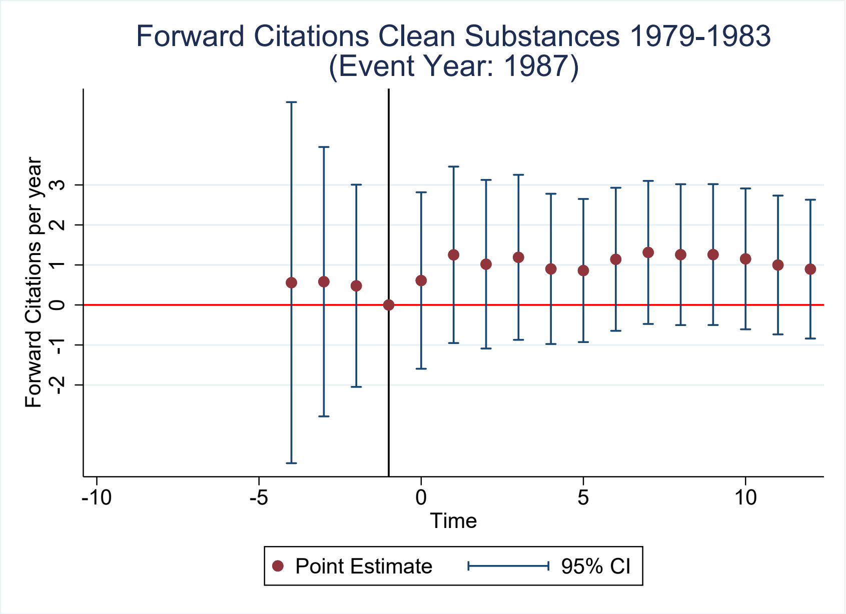


Figure 5.4: Panel Event Study Evidence of the Impact of the Montreal Protocol on Clean Technologies (baseline: 1987)

I report estimates from this analysis in Table 5.11 of Appendix 4.1. It is interesting to note that all controls are significant at 0.1 percent level except dimension 5 from the MCA analysis, which is significant at a 1 percent level and the subclass-application year interaction, which is significant at a 5 percent level. Besides this, all year fixed effects are significantly positive at 0.1 percentage level from 1990 onwards, while year fixed effects for 1987 and 1988 are significantly positive at 5 percent level and that of 1989 is significantly positive at 1 percent. The fact that year fixed effects are significantly positive, but the lags are not, could point towards an overall impact of the Montreal Protocol on innovation, for both clean and control group patents, since year fixed effects before 1987 are not significant. It could, however, also be attributed to the fact that forward citations are likely to be increasing over time. We could further study this through the panel event study on dirty technologies.

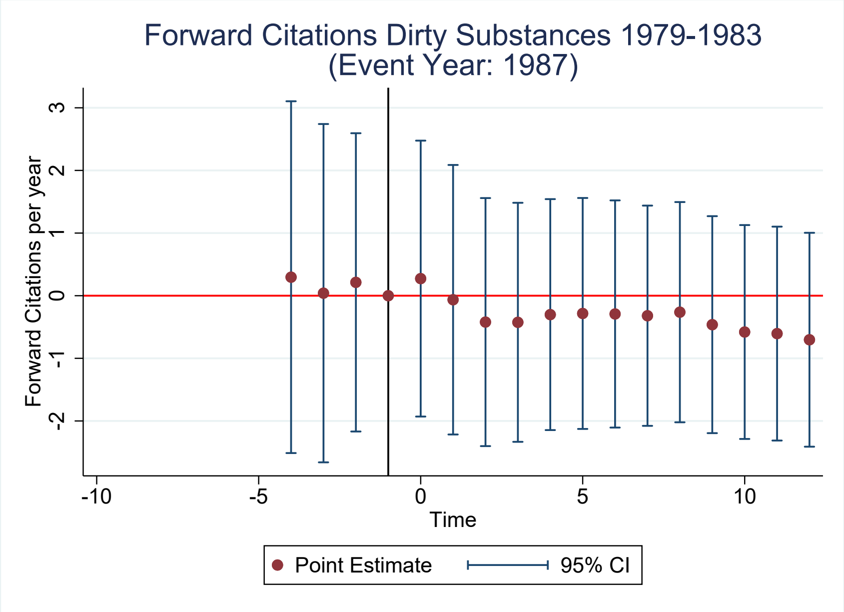


Figure 5.5: Panel Event Study Evidence of the Impact of the Montreal Protocol on Dirty Technologies (baseline: 1987)

Evidence on Dirty Technologies Turning now to the analysis on dirty technologies, also following equation 5.1, I find again no significant (at a 5 percent level) positive nor negative impact of the Montreal Protocol on patent value proxied by forward citations (see Figure 5.5). It is possible, however, to distinguish a negative trend in the lags, which would confirm the expected rationale on the impact of an environmental regulation on dirty technologies. As for the evidence on clean technologies, confidence intervals are very large for the first lags and slightly decreasing for the latter. Similarly to the previous analysis, this could be due to either the lack of the effect or also due to the small sample size available for estimation.

If we analyze estimates reported in Table 5.12 of Appendix 4.1, we see that results on controls and year fixed effects are almost identic to the ones from the first regression. The sign, significance, and size of coefficients for the ex-ante control variables are the same as for the regression on clean technologies. Only dimension 4 from the MCA is now significant at 1 percent level instead of at 0.1 percent. Reported year fixed effects have same sign, significance levels and sizes. This result points out that treatment samples are similar in their comparison to the control group referring to the characteristics responsible for additional forward citations that I control for. Besides this, the increasing trend in significance and size of the year fixed effects remains the same as for the clean technologies but their interpretation is still difficult due to the nature of the variable (forward citations).

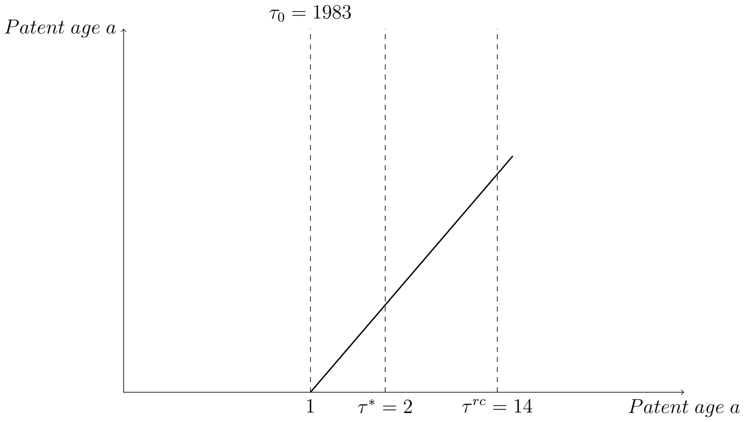


Figure 5.6: Lexis Diagram Ongoing Spells for Cohorts from 1979 to 1983 (patent framework in patent ages with left censoring, right censoring, and cross-cohorts aggregation)

Patent Renewal Evidence

After the first and rather preliminary evidence from the panel event study, I will now try to further disentangle the impact of the Montreal Protocol on patent value analyzing another dimension related with it, i.e., patent renewal. For the study of patent renewal, I will use a duration analysis framework. In particular, I implement the adaptation of the van den Bergh et al. (2020) nonparametric duration model that I have presented in Chapter 3. As presented in Figure 5.6, I first redefine patent ages for the different cohorts such that the new first renewal year corresponds to $\tau_0 = 1983$. For this I drop patents that have not survived until that year. Afterwards, I consider that the moment of the policy change is in 1984 (age $\tau^* = 2$) and analyze the average treatment effects on the conditional survival probabilities until 1996 (age $\tau^{rc} = 14$). This would help us capture any differences between treatment and control groups in the renewal pattern that could be attributed to an event occurring from 1984 onwards. The reason for taking this approach is that the event of interest is the signature of the Montreal Protocol in 1987. Nevertheless, since the Vienna Convention, which was the enabler of the Protocol, took place in 1985, the effects of the Montreal Protocol might have been slightly anticipated. Likewise, since the Protocol was only enforced in 1989, its effects might have been delayed. Therefore, an approach that could allow us to take into account those anticipation and delay effects is key to shed light on the impact of the Montreal Protocol on patent value.

Evidence on Clean Technologies I start studying the impact of the signature of the Montreal Protocol on the renewal of clean patents (T_2). To do this, I use the duration framework described before and add further controls. Specifically, I control for the five dimensions of the MCA, number of inventors, number of applicants, family size, patent class by application year dummy, and cohort dummies. I present the estimated average treatment effects on the conditional survival probabilities from 1984 until 1996. Before describing the graphical results, I will shortly comment on the estimates that I report in Tables 5.15 and 5.16 of Appendix 5.1. Particularly relevant are results of Table 5.16, since we find that many years do not report any estimates, which is the case for (1985, 1986, 1987, 1988, and 1990). If we look at results from Table 5.15, we can see in the hazard rate estimation for treatment and control groups that the missing results stem principally from the treatment group hazard rate estimation, although the algorithm also seems not to be able to compute results of 1986 for the control group. I hypothesize that the reason of this caveat is the lack of variation, which in the case of the treatment group could come from the small sample size. Further explorative evidence is needed to further disentangle the reasons behind this caveat and will be performed in future versions of this paper. Taking this into account and bearing in mind that the reduced sample size limits the causal interpretation of the results, I will now discuss the findings.

In order to interpret the results I will assume that there is no selection in renewal during the periods for which I don't have estimates on ratios and differences of hazard rates. Taking this into account, I find that there have been three positive significant shocks on the differences in hazard rates at the 5 percent level. The first one in 1984, which would be the instantaneous average treatment effect of the hazard rate (since I assume that the change in policy regime happened in 1984), the second in 1989, and the last one in 1992. If we want to be able to interpret these results it is important to bear in mind the regulatory changes related to ODSs happening in Germany during that period.

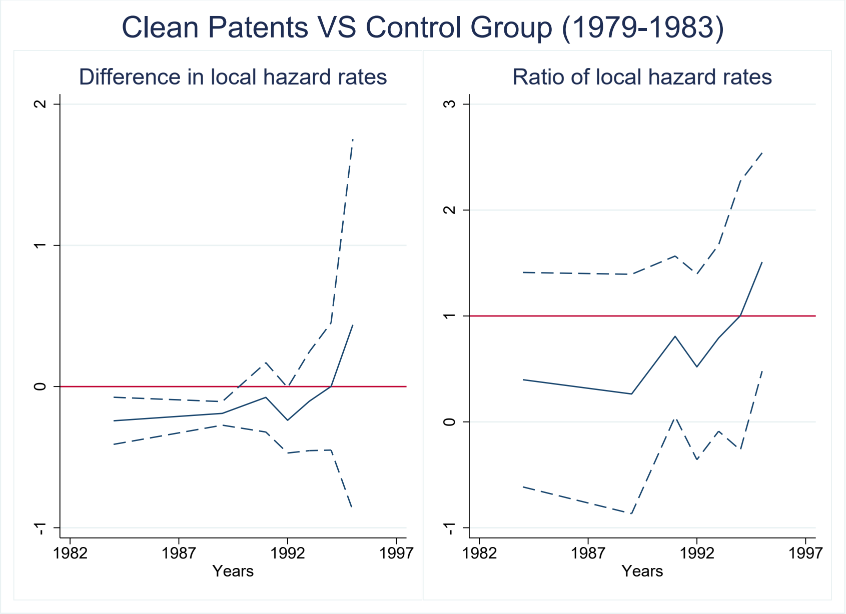


Figure 5.7: Nonparametric Duration Evidence: Clean Patents VS Control Group 1979-1983

The reasons behind those shocks are potentially multiple. Since it is very difficult to disentangle the exact origin of each shock without additional sectoral data such as exports, market sizes, etc., or interviews with industry experts or policymakers, I will limit my analysis to an exposition of the possible origin for each shock. Given that my dataset focuses on Germany, I use two main sources for the possible origin of the shocks, i.e., the Montreal Protocol phase-down schedules presented in Appendix 3, and the regulatory changes on ODSs in Germany summarized in Table 5.24 of Appendix 6. Regarding the shock of 1984, in the table summing the ozone-related regulations in Germany we only find the Vienna Convention signed in 1985. It doesn't make sense to find an event in the Montreal Protocol phase-down schedules of Appendix 3, since those happened after the enforcement of the Protocol itself in 1989. Concerning the second shock, in 1989, interpretation is a bit blurrier since in 1988 the European Council agreed on a regulation on some CFCs and halons, limiting their import, production and use (see Table 5.24 Appendix 6 (UBA, 2017)). At the same time, in 1988, Germany ratified the Montreal Protocol, which was enforced in 1989 (UBA, 2017). Under the Protocol, already in 1989 Annex A/I CFCs (see Appendix 3) saw their production and consumption frozen in Non-article 5 parties[8], i.e., in industrialized countries. Since this second reason was likely a larger incentive for innovators for revising positively the value of their clean R&D assets than the former, I will take it as the reason for this second positive shock. Finally, we observe a last positive significant (at a 5 percent level) shock in 1992. Again, several reasons might potentially explain this shock. Focusing first on potential regulations implemented in Germany, we see in Table 5.24 that in 1991 there was an ordinance on the prohibition of CFCs and halons in Germany, that completely phased-out these substances in every area of use by 1995 (UBA, 2017). Furthermore, in 1991 the resolutions from the London Amendments of the 2^{nd} conference of the parties to the Montreal Protocol were implemented. Those Amendments tightened the phase-out schedule for production and use of CFCs by 2000 and included further substances to the Protocol (UBA, 2017). Besides this, in 1992 during the 4^{th} conference of the parties to the Montreal Protocol, the phase-down schedules of halons and CFCs became stricter, and parties decided to forbid manufacturing of CFCs by 1996 (UBA, 2017). Interestingly, HCFCs, which were considered so far as “clean” substitutes become also regulated under the Montreal Protocol, but at that moment it is decided that their production would be banned from 2020 onwards (UBA, 2017). In my analysis, HCFCs belong to T_2. If we now search in the phase-down schedules of Appendix 3, only the 20% reduction of Annex B/I CFCs in 1993 could explain the existence of a positive shock. Taking all the possible reasons into account it seems that the larger potential effect might have been the 4^{th} conference of the parties to the Montreal Protocol in Copenhagen. Although some patent holders of patents citing CFC-substitutes, e.g. HCFCs, also receive the information that HCFCs will be banned in from 2020 onwards, as the patents that I

---

[8] Under the Montreal Protocol countries were classified into Article 5 and Non-Article 5 countries, where Article 5 countries are defined as “Any Party that is a developing country and whose annual calculated level of consumption of the controlled substances in Annex A is less than 0.3 kilograms per capita on the date of the entry into force of the Protocol [...].”(UNEP, 2019).

analyze now were applied between 1979 and 1983. It is reasonable to assume that this won't affect negatively to their renewal behavior.

From the analysis on clean technologies, bearing in mind the limitations and caveats of the nonparametric estimation, I find that the Vienna Convention, the enforcement of the Montreal Protocol and the Copenhagen Amendment had positive impacts on the value of clean technologies. Furthermore, this evidence points out towards supporting the Sunstein (2007) argument that clean substitutes were already available before the Protocol, which facilitated achieving the agreement.

Evidence on Dirty Technologies I present now nonparametric duration model evidence on the impact of the Montreal Protocol on dirty technologies. In this paragraph my analysis will be symmetric to the one on clean technologies with the only difference that I consider now as treatment patents those from T_1, i.e., the ones citing CFCs. I show graphical results from the estimation in Figure 5.8 and present the corresponding estimates in Tables 5.18 and 5.19 of Appendix 5. Before discussing the graphic results, it is important to note that we encounter in this estimation the same problems as for the one on clean technologies. Namely, that the algorithm is unable to compute estimates for one hazard rate of the control group (again 1986), and four hazard rates from the treatment group (now 1986, 1987, 1988, and 1995). The hypothesis on the reason for this caveat is the same as in the previous analysis and will require further study and robustness checks to confirm the results deduced from this analysis. Assuming, as for the clean patents' study, that there has been no selection in renewal for the years for which we cannot compute the estimates, i.e., that we are not losing observations, I will present the shocks that I find.

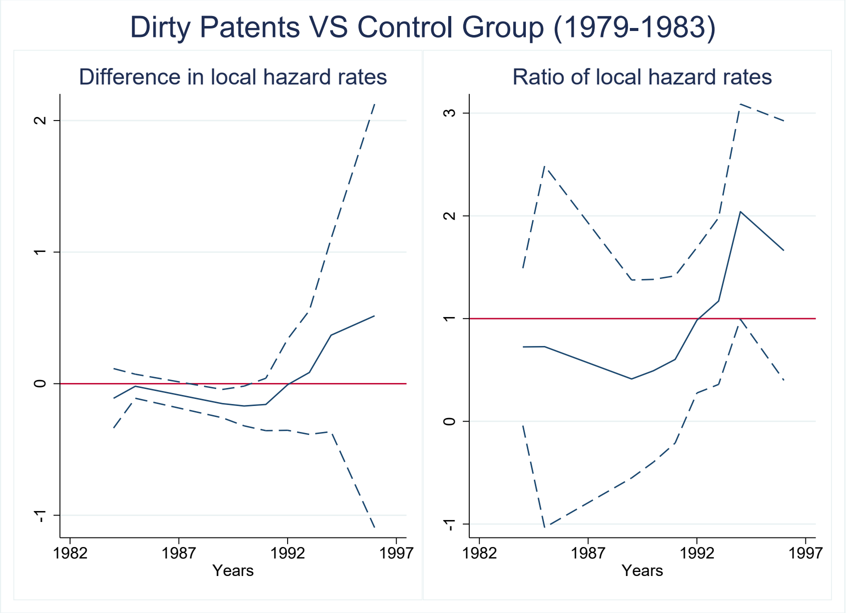


Figure 5.8: Nonparametric Duration Evidence: Dirty Patents VS Control Group 1979-1983

As we can graphically see in Figure 5.8 and further confirm in Table 5.19, I find two positive shocks in differences significant at a 5 percent level, one in 1989 and one in 1990. Furthermore, I find an almost negative significant (at a 5 percent level) shock in ratios in 1994. First of all let's discuss the positive shocks, which seem to be the most counterintuitive ones. In 1989, as we had seen for clean technologies, the most likely largest shock on technologies related to the Montreal Protocol that could have happened is the enforcement of the Protocol, which led to the establishment of the phase-down schedules for Non-Article 5 countries regarding the Annex A/I CFCs (see Appendix 3) (UBA, 2017). This is unexpected, since it seems that the enforcement of the Montreal Protocol and the official implementation of the phase-down schedules might have had a positive impact on the value of European patents applied for between 1979 and 1983 that were renewed in Germany citing CFCs. This result is very interesting since it would provide evidence supporting the argument from Barrett (1994), i.e., that IEA's benefits outweighed cost, which seems to be also true for dirty technology holders, and that it would be an additional reason for explaining why the IEA was successful. Of course, given that we cannot compute estimates for the years between 1986 and 1988, included, this result should be taken carefully, and further descriptive evidence should be analyzed for confirming it, among others, increasing sample size. Regarding this, the broad confidence intervals in the ratio estimation might be misleading since the point estimates for those years could not be estimated for the treatment group. Interestingly, the results on the negative almost significant (at a 5 percent level) shock from 1994 support the hypothesis on the positive shocks. In particular, if there has been no selection in patent renewal for the treatment group patents before 1994, then it seems that the dirty patents applied between 1979 and 1983 were only impacted negatively by 1994. After the signature and enforcement of the Protocol, countries decided to tighten the phase-down schedule, e.g., in 1990 during the London conference of the parties as explained for clean technologies, such that the 75% reduction schedule for CFCs of both Annex A/I and Annex B/I is in 1994 (see Appendix 3). Since this was a major regulatory milestone for CFCs, it might have been the reason behind the negative shock. It is nonetheless interesting to note that the event is still not significant (at a 5 percent level), so it could support the rationale of Dugoua (2021) that the Montreal Protocol was an agreement where benefits outweighed costs (Barrett, 1994) but that it enabled future stricter commitments.

To conclude this analysis on the evidence on R&D assets stemming before the signature and enforcement of the Montreal Protocol, I summarize my main findings and take-aways. From the evidence on clean technologies, I find that the successive conferences of the parties from the Montreal Protocol and their related tightening of the CFCs phase-down schedules had a positive impact on the value of clean innovations. This main finding on clean technologies is in line with the expected rationale on the impact of environmental regulations on environmentally friendly innovations. Furthermore, since the cohorts of analysis are selected to be before discussions on the Montreal Protocol had started, then these positive impacts would support the argument of Sunstein (2007), claiming that clean technologies were already available before the signature of the Protocol. Conversely, the results from the analysis on dirty technologies are challenging the expected results and instead provide first evidence on the rationale supported by Barrett (1994) claiming that the Montreal Protocol was easy to achieve because benefits outweighed costs. In particular, I find that the IEA had a positive impact on the value of existing dirty technologies. Furthermore, my findings also support the rationale suggested by Dugoua (2021), that builds upon the Barrett (1994) argument, claiming that the Montreal Protocol was signed because benefits outweighed costs (Barrett, 1994) but that it enabled future more stringent regulations. The negative and almost significant effect (at a 5 percent level) on dirty technologies in 1994 together with the positive shocks in 1989 would support these arguments. These results need, however, to be further confirmed with additional evidence increasing the sample size of the analysis by potentially extending it to other countries and providing further descriptive evidence justifying that the caveats encountered do not falsify my results.

5.5.2 Evidence During Discussions on the Montreal Protocol (1984-1987)

After having studied the impact of the Montreal Protocol on the value of R&D assets existing before discussions on the Montreal Protocol were at stage, I study the impact of the Protocol on patents applied during the time while the Protocol was being prepared, i.e., between 1984 and 1987. To do this, I consider the Vienna Convention (1985) as the steppingstone that enabled the Montreal Protocol (1987). In order to take into account a possible anticipation to the Vienna Convention I also include in my analysis patents applied for in 1984. In the next section I present some descriptive statistics of my dataset. Afterwards, I will proceed to symmetric analyses to the ones performed for the data sample from 1979 to 1983, i.e., first a forward citations panel event study and then a nonparametric duration model. The motivation for this second analysis using patents from this later period is to seek confirmation (or to refute) the findings from the first period. Namely, that the Montreal Protocol was a successful international environmental agreement because it successively increased the stringency of the regulations first offering an agreement where benefits outweighed costs (Barrett, 1994), which would enable future stricter regulations, rationale suggested by Dugoua (2021). Furthermore, this second analysis also aims at shedding further light on the Sunstein (2007) hypothesis sustaining that replacement technologies were already available at the moment of the agreement.

Descriptive Statistics

Before starting the empirical analysis, I will provide some descriptive statistics of the dataset that I use. In Tables 5.4 to 5.6 we can see some statistics from the main characteristics of the patents analyzed. Specifically, I provide means from the five dimensions of the multiple correspondence analysis, grant lags, number of inventors, number of applicants, and family size. The first and most striking difference compared to the previous analysis lies in the sample sizes. If in the previous empirical analysis treatment group samples (T_1, T_2) were similar, we notice now a large difference between them. The sample of patents mentioning clean substitutes almost doubles that of those citing pollutants. This could already point out to a selection mechanism in what is decided to be patented, which goes in line with the decreasing number of CFCs' patents in the first sample. If we now focus on the other characteristics, we find that three samples have similar grant lags, number of inventors, and number of applicants. Only regarding family sizes we observe slight differences, with patents from the control group having on average the largest family size, followed by patents citing dirty substances (T_1), and those citing clean substitutes (T_2). This is interesting since on the one hand it points towards lower ex-ante value of clean innovations, but on the other hand it might just show that clean innovations stand upon "smaller shoulders". This could mean that they have a smaller ex-ante value, that they are developed by different types of innovators, or that the innovation targets a smaller market. If we now turn to the proxies of the technological space, i.e., the five dimensions of the MCA, I find in general that differences between the three samples are not large, although this is particularly true for dimension 4 comparing dirty patents and the control group, and for dimensions 2, 3, and 4 between treatment groups.

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.037	0.047	−0.080	0.171
Dim 2		−0.0001	0.005	−0.011	0.011
Dim 3		0.012	0.067	−0.116	0.220
Dim 4		−0.001	0.007	−0.018	0.014
Dim 5		−0.007	0.025	−0.083	0.036
Grant lag		1,622.235	728.169	777	4,716
Inventors		2.853	1.579	1	7
Applicants		1.000	0.000	1	1
Family Size		7.382	4.645	4	26
Sample Size	34				

Table 5.4: Descriptive Statistics 1984-1987: Treatment Group T_1

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.053	0.037	−0.109	0.160
Dim 2		0.001	0.004	−0.015	0.013
Dim 3		0.027	0.060	−0.155	0.234
Dim 4		0.009	0.038	−0.019	0.184
Dim 5		−0.004	0.056	−0.096	0.363
Grant Lag		1,610.472	476.459	869	2,940
Inventors		2.321	1.173	1	5
Applicants		1.038	0.275	1	3
Family Size		6.245	3.075	3	24
Sample Size	53				

Table 5.5: Descriptive Statistics 1984-1987: Treatment Group T_2

Statistic	N	Mean	St. Dev.	Min	Max
Dim 1		0.011	0.071	−0.429	0.250
Dim 2		−0.001	0.033	−0.020	2.110
Dim 3		−0.005	0.072	−0.200	1.110
Dim 4		−0.003	0.017	−0.057	0.520
Dim 5		0.001	0.044	−0.214	1.549
Grant Lag		1,668.617	562.855	575	6,543
Inventors		2.767	1.613	1	16
Applicants		1.043	0.229	1	4
Family Size		8.839	6.181	2	50
Sample Size	4,195				

Table 5.6: Descriptive Statistics 1984-1987: Control Group T_0

Turning now to the technology class distribution across the three samples, as depicted in Figure 5.9. I find similar IPC class distributions for treatment group patents (T_1, T_2). It is noteworthy mention that the main IPC class for those patents remains C08, followed by C07, as in the previous analysis. Now, however, we can also find patents from other classes, i.e., C09, C10, and C23[9]. Regarding control group patents, as in the first analysis, C07 is the predominant class and is followed by C08. Focusing now on the distribution of patents across cohorts, as presented in Figure 5.10, we can see that the three sorts of patents follow a similar shape in numbers of patents from each cohort. In general the peak year is 1985, while the number of patents seems to decrease from 1986 onwards.

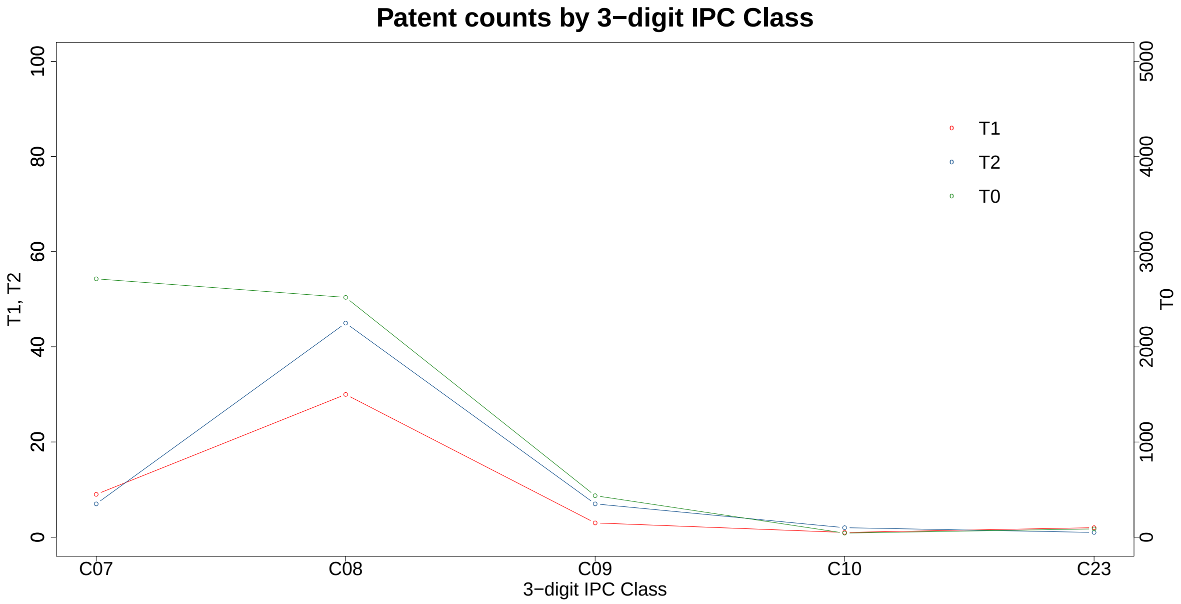


Figure 5.9: Patent counts by 3-digit IPC Class 1984-1987

---

[9] C09 stands for “Dyes; Paints; Polishes; Natural Resins; Adhesives; Compositions not otherwise provided for; Applications of materials not otherwise provided for”, C10 corresponds to “Petroleum, gas or coke industries; Technical gases containing carbon monoxide; Fuels; Lubricants; Peat”, and C23 includes “Coating metallic material; Coating material with metallic material; Chemical surface treatment; Diffusion treatment of metallic material; Coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general; Inhibiting corrosion of metallic material or incrustation in general”.

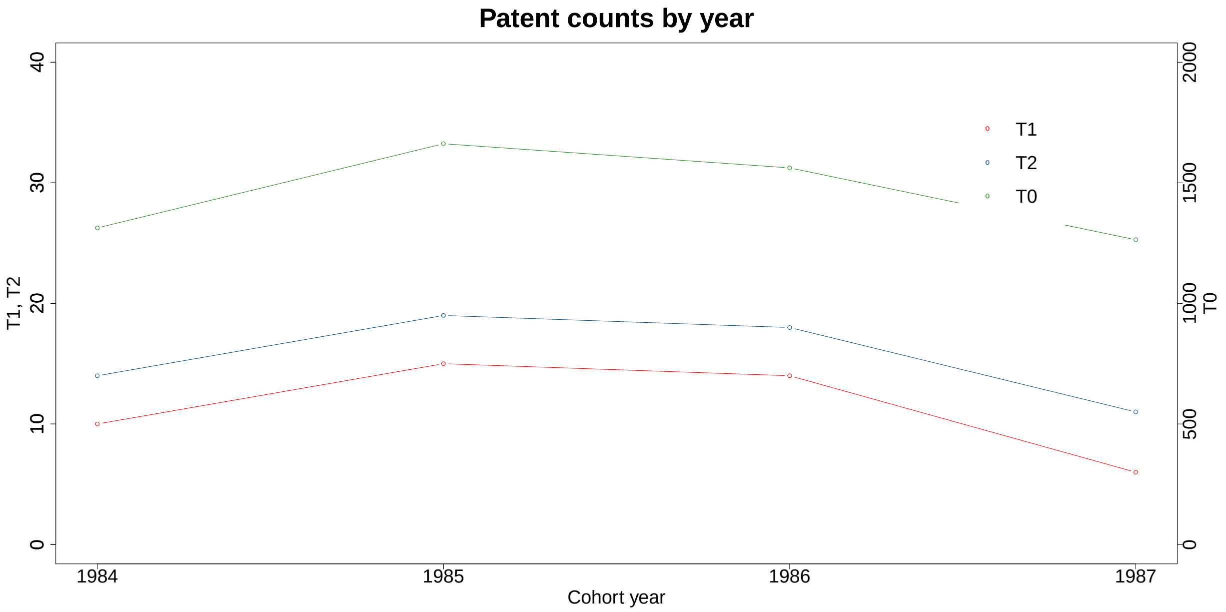


Figure 5.10: Patent counts by cohort year 1984-1987

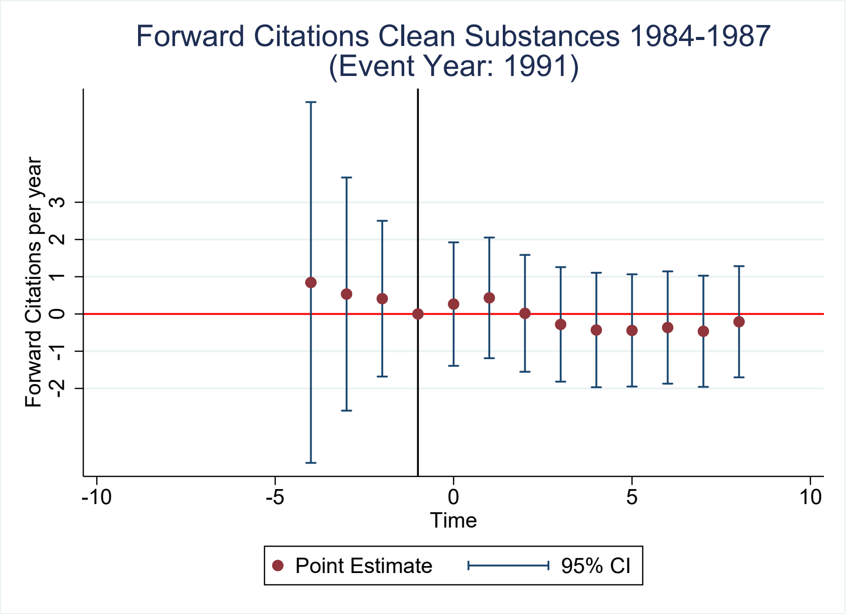


Figure 5.11: Panel Event Study Evidence of the Impact of the Montreal Protocol on Clean Technologies 1984-1987 (baseline: 1991)

Forward Citations Evidence

In this section I present the empirical evidence stemming from a similar panel event study to the one described in the first analysis. As for the first evidence, I employ as the dependent variable the number of forward citations received by the patent, which I explain with the following controls: grant lag, number of inventors, number of applicants, a dummy indicating whether a patent is still active, family size, and the five dimensions from the MCA. Furthermore, as in the first regressions, I include application year by IPC class fixed effects and year fixed effects. The general form of the regression is presented in equation 5.2, where for both, the clean and the dirty technologies analyses, I include three leads and 9 lags. Apart from this, it is noteworthy mentioning that I use now 1991 as the event year. The reason for this is twofold, first that since I focus on patents being applied for between 1984 and 1987, I cannot analyze an event immediately close to the last cohort, since I will likely have few observations, i.e., many zeros, which will difficult drawing conclusions from the results. Second and foremost, that the goal of this analysis is to shed further light on whether the Montreal Protocol was successful because it successively increased the stringency of the pledges, departing from a starting point where clean technologies might have been already available (Sunstein, 2007; Dugoua, 2021).

Evidence on Clean Technologies Now, I present the panel event study evidence from clean technologies. Since the cohort years that I exploit for my study are very close to the signature of the Montreal Protocol, I cannot analyze the event of the signature itself nor the enforcement. Instead, I will focus on the impact of the main first amendments to the Montreal Protocol on patent value. As depicted in Figure 5.11, I find no positive impact in 1991 nor a negative one, but instead I find a negative trend in forward citations. This would point towards a decreasing value of the analyzed clean technologies, but results are not significant (at a 5 percent level). A possible explanation for this could be that the sustainability of the initial substitutes (above all HCFCs) started to be questioned, principally in 1992 during the Copenhagen conference (UBA, 2017). The duration analysis as well as the panel event study evidence on dirty technologies might help us shed further light on the rationale. Regarding the estimates on controls used for the regression, results differ from the ones in the first analysis. As shown in Table 5.13 of Appendix 4.2, now some coefficients of the control variables are not significant. In particular, two dimensions of the MCA, dimension 2 and dimension 5 are not significant even at the 5 percent level, and dimension 4 is significant at a 5 percent whereas the remaining ones are significant at a 0.1 percent. This is particularly interesting compared to the first analysis, where all dimensions were significant for clean and dirty technologies at least at a 1 percent level. Furthermore, we also see that now the number of inventors is not significant, and that the IPC subclass application year interaction is significant at a 0.1 percent level, while in the previous study it achieved only a 5-percentage significance. This result and its difference compared to the first analyses points toward an increase in the patent technology heterogeneity in this new period, which was initially already suggested by the IPC class distribution. Particularly striking is the non-significance of the number of inventors. A possible explanation of this is that the sample analyzed is more homogeneous on the type of innovators and that differences that would otherwise be captured by this variable are now taken into account by the number of applicants. Besides this, year fixed effects are increasing in coefficient over time and the significance pattern is close to the one of the first analysis. The rationale for this is, as before, difficult to interpret since forward citations are themselves generally increasing over time.

$$y_{it} = \alpha + \sum_{j=1}^{9} \beta_j (Lag\ j)_{it} + \sum_{k=2}^{4} \beta_k (Lead\ k)_{it} + \lambda_t + X'_{it}\Gamma + \epsilon_{it} \tag{5.2}$$

Evidence on Dirty Technologies Performing a similar analysis on dirty technologies I find likewise no negative nor positive significant effects (at a 5 percent level). Furthermore, as depicted in Figure 5.12, we observed point estimates consistently aligning with the zero-effect line. This evidence is difficult to interpret as in the case of the clean substances and for the first analysis, since samples sizes are small and confidence intervals are large. Nevertheless, if these results would be true, then it would point out towards dirty technologies following a similar forward citations' pattern as that of the control group and that of the clean substitutes. If we now focus on the coefficient estimates for the control variables, we find similar results as for the clean substances. As reported in Table 5.14 of Appendix 4.2, similarly to the clean technologies' analysis dimensions 2 and 5 of the MCA are not significant and dimension 4 is only significant at a 5 percent level, whereas the remaining ones are at a 0.1 percentage level. Furthermore, I find the same non-significance result regarding the number of inventors, a similar decrease in significance level regarding the IPC class application year interaction, and an identic pattern for the year fixed effects as the one of the clean technologies. The reasoning behind these findings should be the same as for the clean treatment group.

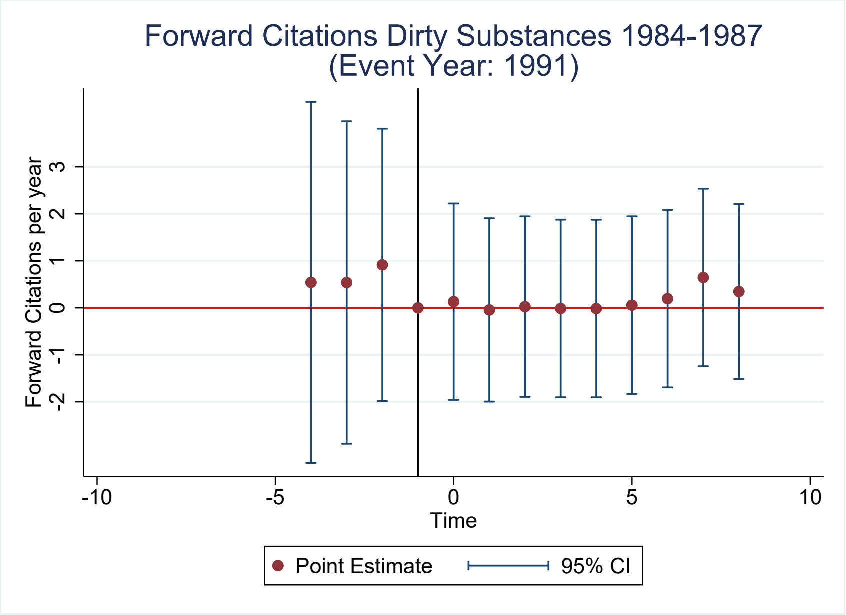


Figure 5.12: Panel Event Study Evidence of the Impact of the Montreal Protocol on Dirty Technologies 1984-1987 (baseline: 1991)

Patent Renewal Evidence

In this section I present evidence on the impact of the Montreal Protocol and the subsequent amendments on patent value, proxied by patent renewal. As for the analysis of the first period I use the adaptation to patent data performed in Chapter 3 of the nonparametric duration model developed by van den Bergh et al. (2020). In Figure 5.13, I present the Lexis diagram of the duration analysis that I perform in this section. In particular, I aggregate cohorts' data, drop observations of patents elapsed before $\tau_0 = 1987$ and consider thereon as the new starting patent age. I assume that the change in policy regime happened in $\tau^* = 2$, i.e., 1988, and will be interested into the average treatment effects on the conditional survival probabilities, which would allow me to capture the differences in hazard rates between treatment and control occurred between the treatment event $\tau^* = 2$ and the right censoring $\tau^{rc} = 12$ (1998). As in the first analysis, after the first negative significant shock on the hazard rates, later positive or negative significant shocks cannot be interpreted since we have a selection in renewal between the two groups, i.e., we are losing observations. I will now present the results first for clean technologies and afterwards for patents citing dirty pollutants. For both analyses I control for the five dimensions of the multiple correspondence analysis, number of inventors, grant lags, number of applicants, family size, patent class by application year dummy, and cohort dummies.

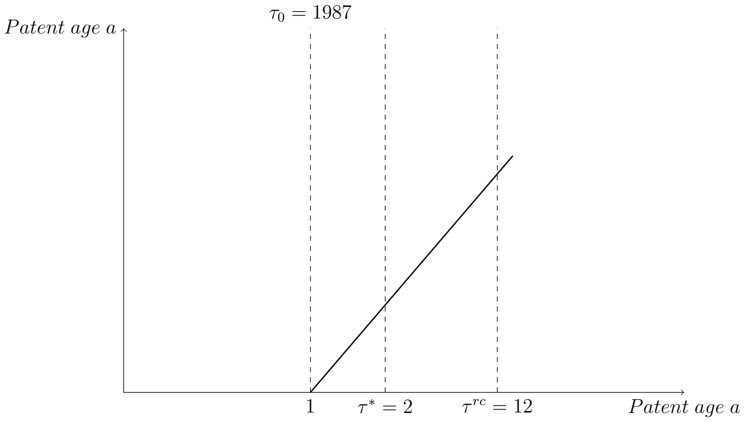


Figure 5.13: Lexis Diagram Ongoing Spells for Cohorts from 1984 to 1987 (patent framework in patent ages with left censoring, right censoring, and cross-cohorts aggregation)

Evidence on Clean Technologies The objective of the nonparametric duration analysis on clean technologies is to study the impact of the Montreal Protocol and its successive Amendments on the value of clean technologies. Point estimates from this analysis together with their 95% confidence intervals are presented in Figure 5.14. From the graphic representation of the effects, we can see at first glance that there seem to be three positive significant (at a 5 percent level) shocks in differences in years 1992, 1993, and 1996, and that there are also three negative significant (at a 5 percent level) shocks in ratios in years 1989, 1991, and 1998. This is confirmed in Tables 5.20 and 5.21 of Appendix

5.2, where I report estimation results. Nevertheless, before engaging in the discussion of the results, it is noteworthy comment two points from this estimation exercise. First, that as for the analysis on the first period, samples sizes are small and further reduced since I drop observations of patents not renewed up to 1987. This point limits in general the causal interpretation of the results, for which I would rather claim to be of descriptive and preliminary nature. Second, that as in the first period analysis, due to the limited variation and number of observations for the treatment group, some hazard rates could not be computed. This is not the case anymore for the control group but remains for years 1988 and 1994 in the treatment group. As in the first period analysis, I will assume for the interpretation of results that in those years there has been no shock that has brought selection in renewal.

Turning now to the interpretation of the effects, we need to be cautious. In the right graphic we observe early on a negative significant (at a 5 percent level) shock, in 1989, which limits any causal interpretation of the remaining shocks as it has generated an early selection in renewal. First of all, this shock is somehow counterintuitive, since we would expect the Montreal Protocol to have a positive effect on the value of clean technologies instead of a negative one. It is also noteworthy mention that the effect in differences is also almost significant (at a 5 percent level) in 1989, which adds further evidence to this shock. Since nor from the timeline on the ozone regulation in Germany (UBA, 2017) (Appendix 6) nor from the phase-down schedules of Appendix 3 (UNEP, 2019), we can find an explanation to this shock, we might rather turn to the differences in periods of analysis. In this section, we are analyzing patents applied during 1984 and 1987, i.e., during the time while the discussions on the Montreal Protocol were taking place. A negative impact on clean technologies might only have two reasons, first that discussions on a future ozone regulation generated an overinvestment in clean technologies such that the resulting agreement, with its phase-out schedules, was too lenient for clean technology producers. This would have resulted in a drop in the expectations' horizon for recovering their investment, which might have generated the negative impact. This would be in line with the positive shock on dirty technologies found for patents applied between 1979 and 1983. Since it would mean that the initial agreement was too lenient, hence easy to achieve and that benefits outweighed costs, also in terms of technologies, supporting Barrett (1994). Second, that some patents citing clean substances were “de facto” dirty patents but that my selection method was unable to identify. On the second reason, extending the analysis to more countries would allow verify the robustness of the results and perform leave-one-out robustness checks by leaving alternatively different clean substitutes out of the regression.

For the interpretation of the remaining shocks after 1989, we should bear in mind that we are referring to a selection of the initial sample of patents citing clean substances and that our analysis would be always conditional on not having been affected by the previous shock. Taking this into account, I find that there is a negative significant (at a 5 percent level) shock in 1991 followed by two positive significant shocks in 1992 and 1993 (at a 5 percent). In 1991 the London conference resolutions were implemented (UBA, 2017), which represented a further tightening of the phase-down schedule for CFCs. This second negative shock might further point either towards a misclassification of clean patents what were actually referring to a dirty technology or, as before, to a deception regarding the stringency of the environmental regulation. The positive significant (at a 5 percent) shocks of 1992 and 1993 are in line with the evidence from the first analysis and would suggest that the subsample composition at that moment would be of similar technology type as of the one from the first period. The interpretation of the remaining shocks is speculative, but the positive significant (at a 5 percent) shock of 1996 coincides with the 100% reduction date for the CFCs and with the freeze in HCFCs' consumption for Non-Article 5 countries (Appendix 3). Given that the shock is positive, we could think of being due to the CFCs' phase-out, but this is just speculative. The negative shock in 1998 is difficult to assess and would require, as this overall analysis, of extending the data sample for performing further robustness regressions.

To conclude with the analysis on clean technologies, we found similar results as for the clean technologies in the first period, i.e., a positive shock in the tightening of the CFCs' phase-down around 1992-1993. Nevertheless, we found also two negative shocks that are counterintuitive and could either support the Barrett (1994) argument stating that the original Protocol had more benefits than costs. In this sense the Protocol and the early Amendments would have had a negative impact on the value of clean technologies because there might have been an overinvestment in them, this might be true since the period of analysis is the time while the Protocol was discussed, i.e., expectations might have been high. At the same time, I might be capturing some patents that I misclassify as "clean" while instead they are dirty patents. Regarding this last point extending the analysis to more countries might help us shed further light.

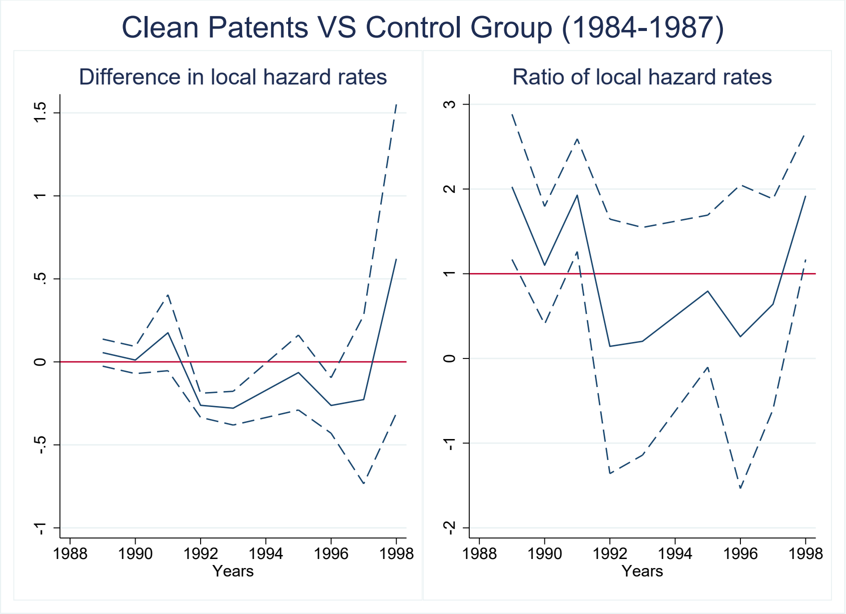


Figure 5.14: Nonparametric Duration Evidence: Clean Patents VS Control Group 1984-1987

Evidence on Dirty Technologies Focusing now on the analysis on dirty technologies, I will first give an overview of the graphical results, and later comment on exact estimates and their interpretation. In Figure 5.15 we can see the representation of the point estimates and their 95% confidence intervals. From a first inspection, we observe an almost significant negative impact in ratios in 1990, an almost positive significant shock in differences in 1994 and a negative significant shock in ratios in 1997. Looking now at the reported estimates in Tables 5.22 and 5.23 of Appendix 5.2, we see, first, a similar pattern in missing coefficients as for the clean estimates. As before, the algorithm manages to compute estimates for the control group but fails for 3 ages of the treatment group. Given the small sample size of the dirty patents and the dropped observations before 1987, the insufficient variation is likely responsible for this. This matter needs to be further scrutinized to understand exactly the origin of the missing estimates. Similarly to the previous duration analyses, I will assume that the reason is the insufficient variation and therefore that there has been no selection in renewal during those periods. This problem happens in 1988, 1989, and 1998.

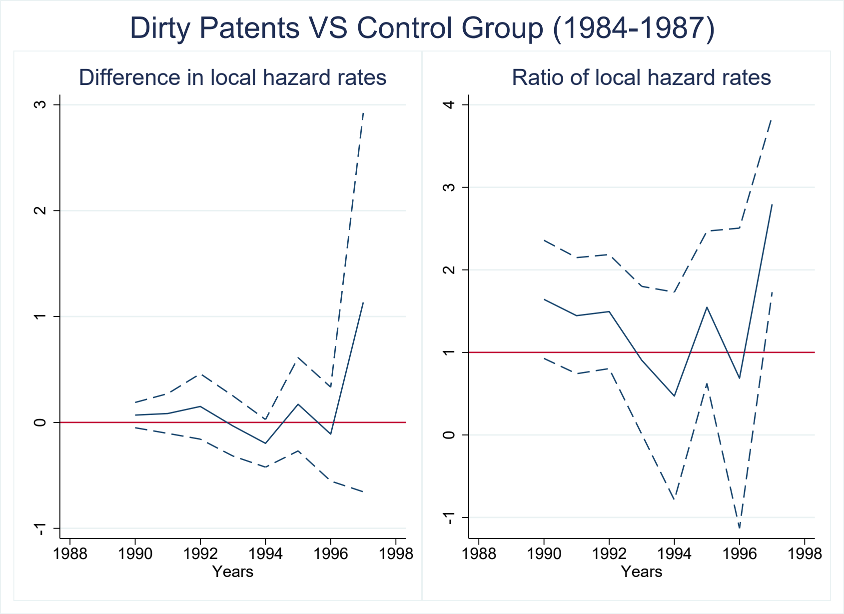


Figure 5.15: Nonparametric Duration Evidence: Dirty Patents VS Control Group 1984-1987

Further scrutinizing estimates from Table 5.23, our first impressions are confirmed, and we find indeed almost significant shocks in 1990 and 1994 as well as a significant negative shock in 1997 (at a 5 percent). These results are interesting, even more if we compare them with our former analyses. The almost significant negative shock of 1990 could be related with the London conference and the accelerated phased-down schedule for CFCs. This almost negative shock would confirm our hypotheses for the analysis on clean technologies, i.e., that the shock was related to the London conference and that the effect found in clean technologies might have been due to hybrid technologies. Turning now to the almost significant positive shock of 1994, which coincides with the 75% reduction deadline for CFCs. It could be proof of further evidence that the method that I used for classifying patent into clean and dirty technologies is not perfect and is an approximation. Specifically, it is likely that some clean patents might have cited some "CFCs" in their corpus and I tagged them as dirty while they were clean and vice versa. Alternatively, it could be that dirty patents of the first period (1979-1983) versus those of the second period

(1984-1987) belonged to two different technology generations. While the first generation was developed before the Protocol's discussions, hence it was impacted negatively by the 75% reduction deadline for the CFCs in 1994, the second was developed with the possibility of an agreement in mind. Therefore, this second generation might have already taken into account the possibility of having those types of deadlines. Further scrutinizing the last, and only significant, shock of this analysis, we find a negative significant effect in 1997. This effect almost coincides with the 100% reduction of CFCs, which was scheduled in 1996, and with the freeze of HCFC consumption for Non-Article 5 countries (UBA, 2017). This last shock confirms the hypothesis mentioned before that some CFC technologies were developed having the agreement in mind and therefore were impacted negatively with the 100% CFC reduction deadline, i.e., one could think of low consumption CFC devices or processes. In the analysis on clean technologies, I also find a significant negative effect (at a 5 percent) in a close period (1998), which might have happened either due to the existence of hybrid technologies or due to misclassification reasons. Since the size and significance of the effects for the shock in the dirty technologies is larger than the one for the clean patents around 1997-1998, I attribute the shock to the CFC consumption and production phase-out.

Summing up the analysis on dirty technologies, evidence further points towards the Sunstein (2007) hypothesis, even more if we compare the results with those of clean and dirty technologies from the first period. Yet, further evidence will be needed to confirm these results and extending the analysis to additional countries might help us further disentangle between the different hypotheses.

5.6 Conclusion

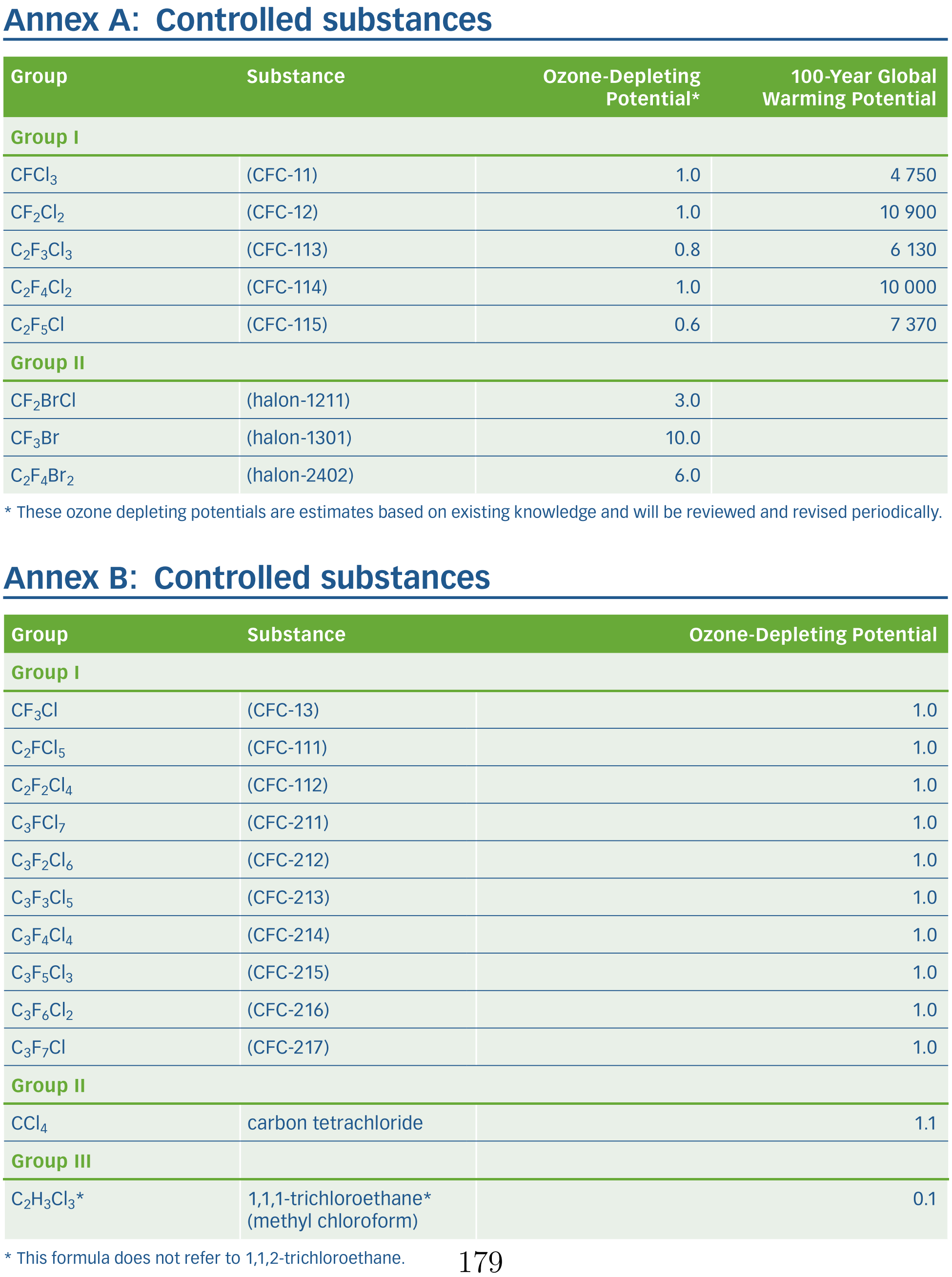
In this paper I study the impact of the Montreal Protocol and its successive amendments on the value of clean and dirty patents. For achieving this, I combine a unique dataset of patents citing substances regulated under the Protocol and their substitutes used in refrigeration, a novel nonparametric technique that I adapted in Chapter 3 to estimate shocks on patent value, and a different identification approach exploiting the fate of R&D assets developed in two different periods before the signature of the Protocol. In particular, I study patent renewal patterns for clean and dirty European patents renewed in Germany applied either long before the signature of the Protocol or few years before the Protocol. This difference allows me to consider the first time period as a time “before discussions on the Montreal Protocol had started” and the second period as a time when “discussion on the Montreal Protocol were on-going”. I use as a difference and turning point the Vienna Convention for the Protection of the Ozone Layer (1985). This empirical setting allows me to shed further light on the different hypotheses regarding the origin of the success of the Protocol such as the ones argued by Barrett (1994), Benedick (1998), Sunstein (2007), and Dugoua (2021). Specially, my findings support the hypotheses of Barrett (1994) stating that the agreement was achieved because benefits outweighed costs, Sunstein (2007) claiming that substitute technologies were already available, and Dugoua (2021) arguing that the Montreal Protocol was a first step having relatively lenient pledges that enabled future stricter agreements. The main outcome from my analysis, however, is that it seems that firms were not completely naïve, nor had not anticipated nor started innovating before the agreement. This result would contradict the argument of Benedick (1998) but not the findings of Dugoua (2021) stating that the agreement induced innovation.

My analysis has strong caveats and limitations, the main one being the small sample size of my treatment groups for the two periods, which not only limits the interpretation of my results but also prevents me from being able to provide estimates for all years within my periods of analysis. To further assess the robustness of my results this analysis would strongly benefit from being extended to more countries. This chapter adds to the literature on several ways. First, it contributes to the literature on IEAs and the Montreal Protocol by providing evidence for different hypotheses regarding the origin of the IEA. Second, it provides new evidence on the impact of the Montreal Protocol on the direction of technological change using a novel dataset. Third, it exploits a new variation in patent data not used so far to study the Montreal Protocol and implements a novel identification strategy not exploited so far in the study of this IEA.

5.7 Appendix 1: Lists of Substances

5.7.1 Appendix 1.1: Substances Regulated under the Kigali Amendment

Figure 5.16: Source: "Handbook for the Montreal Protocol on Substances that Deplete the Ozone Layer" Annexes, Section 1.1., latest version available here (UNEP, 2019).



Annex A: Controlled substances

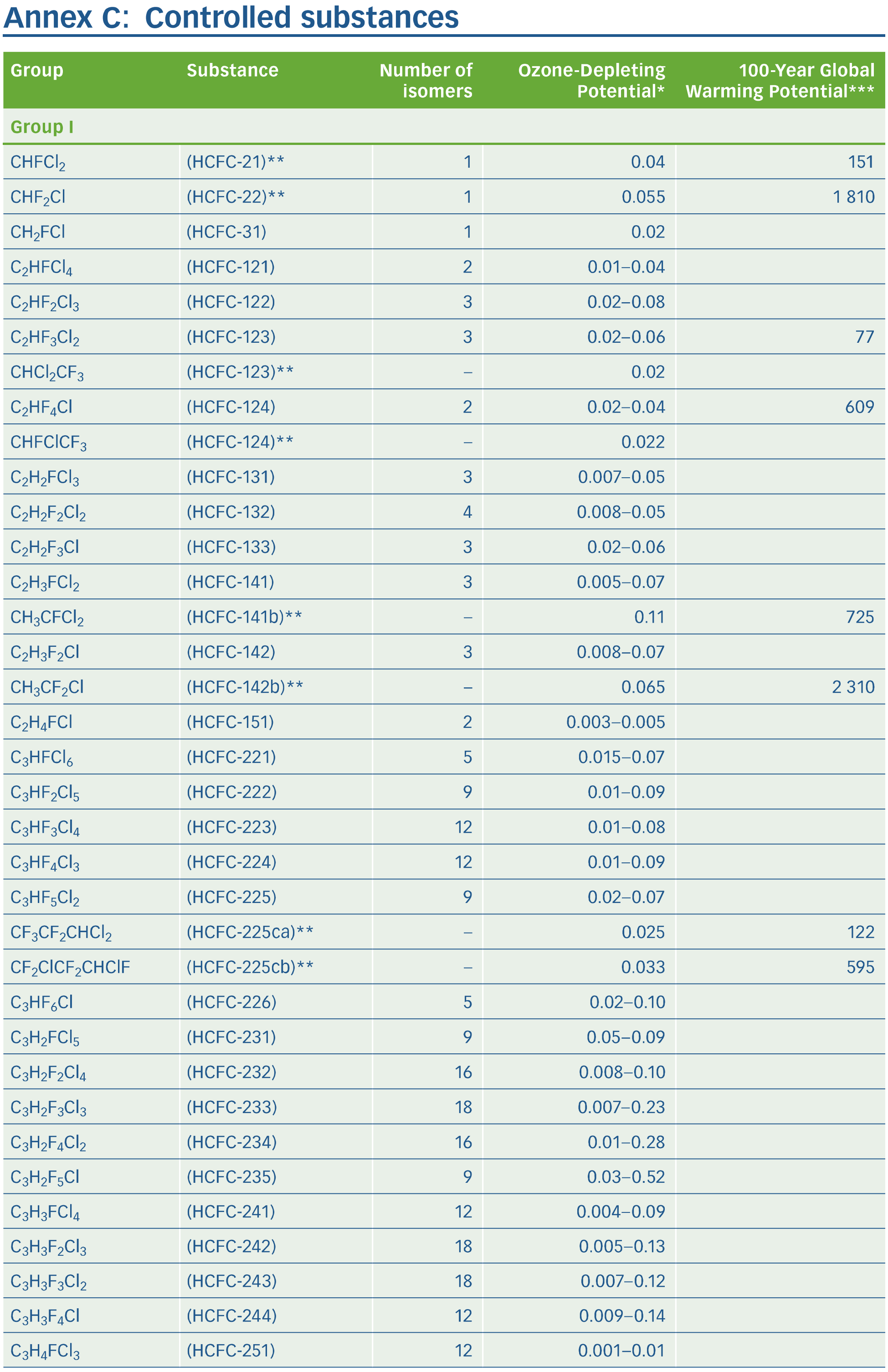
Group	Substance	Ozone-Depleting Potential*	100-Year Global Warming Potential
Group I			
$CFCl_3$	(CFC-11)	1.0	4 750
CF_2Cl_2	(CFC-12)	1.0	10 900
$C_2F_3Cl_3$	(CFC-113)	0.8	6 130
$C_2F_4Cl_2$	(CFC-114)	1.0	10 000
C_2F_5Cl	(CFC-115)	0.6	7 370
Group II			
CF_2BrCl	(halon-1211)	3.0	
CF_3Br	(halon-1301)	10.0	
$C_2F_4Br_2$	(halon-2402)	6.0	

* These ozone depleting potentials are estimates based on existing knowledge and will be reviewed and revised periodically.

Annex B: Controlled substances

Group	Substance	Ozone-Depleting Potential
Group I		
CF_3Cl	(CFC-13)	1.0
C_2FCl_5	(CFC-111)	1.0
$C_2F_2Cl_4$	(CFC-112)	1.0
C_3FCl_7	(CFC-211)	1.0
$C_3F_2Cl_6$	(CFC-212)	1.0
$C_3F_3Cl_5$	(CFC-213)	1.0
$C_3F_4Cl_4$	(CFC-214)	1.0
$C_3F_5Cl_3$	(CFC-215)	1.0
$C_3F_6Cl_2$	(CFC-216)	1.0
C_3F_7Cl	(CFC-217)	1.0
Group II		
CCl_4	carbon tetrachloride	1.1
Group III		
$C_2H_3Cl_3$*	1,1,1-trichloroethane* (methyl chloroform)	0.1

* This formula does not refer to 1,1,2-trichloroethane.



Annex C: Controlled substances

Group	Substance	Number of isomers	Ozone-Depleting Potential*	100-Year Global Warming Potential***
Group I				
$CHFCl_2$	(HCFC-21)**	1	0.04	151
CHF_2Cl	(HCFC-22)**	1	0.055	1 810
CH_2FCl	(HCFC-31)	1	0.02	
C_2HFCl_4	(HCFC-121)	2	0.01–0.04	
$C_2HF_2Cl_3$	(HCFC-122)	3	0.02–0.08	
$C_2HF_3Cl_2$	(HCFC-123)	3	0.02–0.06	77
$CHCl_2CF_3$	(HCFC-123)**	–	0.02	
C_2HF_4Cl	(HCFC-124)	2	0.02–0.04	609
$CHFClCF_3$	(HCFC-124)**	–	0.022	
$C_2H_2FCl_3$	(HCFC-131)	3	0.007–0.05	
$C_2H_2F_2Cl_2$	(HCFC-132)	4	0.008–0.05	
$C_2H_2F_3Cl$	(HCFC-133)	3	0.02–0.06	
$C_2H_3FCl_2$	(HCFC-141)	3	0.005–0.07	
CH_3CFCl_2	(HCFC-141b)**	–	0.11	725
$C_2H_3F_2Cl$	(HCFC-142)	3	0.008–0.07	
CH_3CF_2Cl	(HCFC-142b)**	–	0.065	2 310
C_2H_4FCl	(HCFC-151)	2	0.003–0.005	
C_3HFCl_6	(HCFC-221)	5	0.015–0.07	
$C_3HF_2Cl_5$	(HCFC-222)	9	0.01–0.09	
$C_3HF_3Cl_4$	(HCFC-223)	12	0.01–0.08	
$C_3HF_4Cl_3$	(HCFC-224)	12	0.01–0.09	
$C_3HF_5Cl_2$	(HCFC-225)	9	0.02–0.07	
$CF_3CF_2CHCl_2$	(HCFC-225ca)**	–	0.025	122
CF_2ClCF_2CHClF	(HCFC-225cb)**	–	0.033	595
C_3HF_6Cl	(HCFC-226)	5	0.02–0.10	
$C_3H_2FCl_5$	(HCFC-231)	9	0.05–0.09	
$C_3H_2F_2Cl_4$	(HCFC-232)	16	0.008–0.10	
$C_3H_2F_3Cl_3$	(HCFC-233)	18	0.007–0.23	
$C_3H_2F_4Cl_2$	(HCFC-234)	16	0.01–0.28	
$C_3H_2F_5Cl$	(HCFC-235)	9	0.03–0.52	
$C_3H_3FCl_4$	(HCFC-241)	12	0.004–0.09	
$C_3H_3F_2Cl_3$	(HCFC-242)	18	0.005–0.13	
$C_3H_3F_3Cl_2$	(HCFC-243)	18	0.007–0.12	
$C_3H_3F_4Cl$	(HCFC-244)	12	0.009–0.14	
$C_3H_4FCl_3$	(HCFC-251)	12	0.001–0.01	

Group	Substance	Number of isomers	Ozone-Depleting Potential*	100-Year Global Warming Potential***
$C_3H_4F_2Cl_2$	(HCFC-252)	16	0.005–0.04	
$C_3H_4F_3Cl$	(HCFC-253)	12	0.003–0.03	
$C_3H_5FCl_2$	(HCFC-261)	9	0.002–0.02	
$C_3H_5F_2Cl$	(HCFC-262)	9	0.002–0.02	
C_3H_6FCl	(HCFC-271)	5	0.001–0.03	

Group	Substance	Number of isomers	Ozone-Depleting Potential*
Group II			
$CHFBr_2$		1	1.00
CHF_2Br	(HBFC-22B1)	1	0.74
CH_2FBr		1	0.73
C_2HFBr_4		2	0.3–0.8
$C_2HF_2Br_3$		3	0.5–1.8
$C_2HF_3Br_2$		3	0.4–1.6
C_2HF_4Br		2	0.7–1.2
$C_2H_2FBr_3$		3	0.1–1.1
$C_2H_2F_2Br_2$		4	0.2–1.5
$C_2H_2F_3Br$		3	0.7–1.6
$C_2H_3FBr_2$		3	0.1–1.7
$C_2H_3F_2Br$		3	0.2–1.1
C_2H_4FBr		2	0.07–0.1
C_3HFBr_6		5	0.3–1.5
$C_3HF_2Br_5$		9	0.2–1.9
$C_3HF_3Br_4$		12	0.3–1.8
$C_3HF_4Br_3$		12	0.5–2.2
$C_3HF_5Br_2$		9	0.9–2.0
C_3HF_6Br		5	0.7–3.3
$C_3H_2FBr_5$		9	0.1–1.9
$C_3H_2F_2Br_4$		16	0.2–2.1
$C_3H_2F_3Br_3$		18	0.2–5.6
$C_3H_2F_4Br_2$		16	0.3–7.5
$C_3H_2F_5Br$		8	0.9–1.4
$C_3H_3FBr_4$		12	0.08–1.9
$C_3H_3F_2Br_3$		18	0.1–3.1
$C_3H_3F_3Br_2$		18	0.1–2.5
$C_3H_3F_4Br$		12	0.3–4.4
$C_3H_4FBr_3$		12	0.03–0.3
$C_3H_4F_2Br_2$		16	0.1–1.0

Group	Substance	Number of isomers	Ozone-Depleting Potential*
$C_3H_4F_3Br$		12	0.07–0.8
$C_3H_5FBr_2$		9	0.04–0.4
$C_3H_5F_2Br$		9	0.07–0.8
C_3H_6FBr		5	0.02–0.7
Group III			
CH_2BrCl	bromochloromethane	1	0.12

* Where a range of ODPs is indicated, the highest value in that range shall be used for the purposes of the Protocol. The ODPs listed as a single value have been determined from calculations based on laboratory measurements. Those listed as a range are based on estimates and are less certain. The range pertains to an isomeric group. The upper value is the estimate of the ODP of the isomer with the highest ODP, and the lower value is the estimate of the ODP of the isomer with the lowest ODP.
** Identifies the most commercially viable substances with ODP values listed against them to be used for the purposes of the Protocol.
*** For substances for which no GWP is indicated, the default value 0 applies until a GWP value is included by means of the procedure foreseen in paragraph 9 (a) (ii) of Article 2.

Annex D:* A list of products** containing controlled substances specified in Annex A

No.	Products	Customs code number
1	Automobile and truck air conditioning units (whether incorporated in vehicles or not)	....
2	Domestic and commercial refrigeration and air conditioning/heat pump equipment***	....
	e.g. Refrigerators	....
	Freezers	....
	Dehumidifiers	....
	Water coolers	....
	Ice machines	....
	Air conditioning and heat pump units	....
3	Aerosol products, except medical aerosols	....
4	Portable fire extinguisher	....
5	Insulation boards, panels and pipe covers	....
6	Pre-polymers	....

* This Annex was adopted by the Third Meeting of the Parties in Nairobi, 21 June 1991 as required by paragraph 3 of Article 4 of the Protocol.
** Though not when transported in consignments of personal or household effects or in similar non-commercial situations normally exempted from customs attention.
*** When containing controlled substances in Annex A as a refrigerant and/or in insulating material of the product.

Annex E: Controlled substances

Group	Substance	Ozone-Depleting Potential
Group I		
CH_3Br	methyl bromide	0.6

Annex F: Controlled substances

Group	Substance	100-Year Global Warming Potential
Group I		
CHF_2CHF_2	HFC-134	1 100
CH_2FCF_3	HFC-134a	1 430
CH_2FCHF_2	HFC-143	353
$CHF_2CH_2CF_3$	HFC-245fa	1 030
$CF_3CH_2CF_2CH_3$	HFC-365mfc	794
CF_3CHFCF_3	HFC-227ea	3 220
$CH_2FCF_2CF_3$	HFC-236cb	1 340
CHF_2CHFCF_3	HFC-236ea	1 370
$CF_3CH_2CF_3$	HFC-236fa	9 810
$CH_2FCF_2CHF_2$	HFC-245ca	693
$CF_3CHFCHFCF_2CF_3$	HFC-43-10mee	1 640
CH_2F_2	HFC-32	675
CHF_2CF_3	HFC-125	3 500
CH_3CF_3	HFC-143a	4 470
CH_3F	HFC-41	92
CH_2FCH_2F	HFC-152	53
CH_3CHF_2	HFC-152a	124
Group II		
CHF_3	HFC-23	14 800

5.7.2 Appendix 1.2: Substances in the ASHRAE Standard

ASHRAE Refrigerant Designations: tables from the ANSI/ASHRAE 34-2019 ”Designation and Safety Classification of Refrigerants” Standard, latest version available here (ASHRAE, 2019).

Table 5.7: ASHRAE Refrigerant Designations: tables separated by chemical family

Number	Chemical Name	Chemical Formula
	Methane Series	
11	trichlorofluoromethane	CCl3F
12	dichlorodifluoromethane	CCl2F2
12B1	bromochlorodifluoromethane	CBrClF2
13	chlorotrifluoromethane	CClF3
13B1	bromotrifluoromethane	CBrF3
13I1	trifluoroiodomethane	CF3I
14e	tetrafluoromethane (carbon tetrafluoride)	CF4
21	dichlorofluoromethane	CHCl2F
22	chlorodifluoromethane	CHClF2
23	trifluoromethane	CHF3
30	dichloromethane (methylene chloride)	CH2Cl2
31	chlorofluoromethane	CH2ClF
32	difluoromethane (methylene fluoride)	CH2F2
40	chloromethane (methyl chloride)	CH3Cl
41	fluoromethane (methyl fluoride)	CH3F
50	methane	CH4

Number	Chemical Name	Chemical Formula
	Ethane Series	
113	1,1,2-trichloro-1,2,2-trifluoroethane	CCl2FCClF2
114	1,2-dichloro-1,1,2,2-tetrafluoromethane	CClF2CClF2
115	chloropentafluoroethane	CClF2CF3
116	hexafluoroethane	CF3CF3
123	2,2-dichloro-1,1,1-trifluoroethane	CHCl2CF3
124	2-chloro-1,1,1,2-tetrafluoroethane	CHClFCF3
125	pentafluoroethane	CHF2CF3
134a	1,1,1,2-tetrafluoroethane	CH2FCF3
141b	1,1-dichloro-1-fluoroethane	CH3CCl2F
142b	1-chloro-1,1-difluoroethane	CH3CClF2
143a	1,1,1-trifluoroethane	CH3CF3
152a	1,1-difluoroethane	CH3CHF2
170	ethane	CH3CH3

Number	Chemical Name	Chemical Formula
	Ethers	
E170	Methoxymethane (dimethyl ether)	CH3OCH3

Number	Chemical Name	Chemical Formula
	Propane	
218	octafluoropropane	CF3CF2CF3
227ea	1,1,1,2,3,3,3-heptafluoropropane	CF3CHFCF3
236fa	1,1,1,3,3,3-hexafluoropropane	CF3CH2CF3
245fa	1,1,1,3,3-pentafluoropropane	CHF2CH2CF3
290	propane	CH3CH2CH3

Number	Chemical Name	Chemical Formula
	Cyclic Organic Compounds	
C318	octafluorocyclobutane	-(CF2)4-

Miscellaneous Organic Compounds		
Number	Chemical Name	Chemical Formula
hydrocarbons		
600	butane	CH3CH2CH2CH3 A3
600a	2-methylpropane (isobutane)	CH(CH3)2CH3 A3
601	pentane	CH3CH2CH2CH2CH3
601a	2-methylbutane (isopentane)	CH(CH3)2CH2CH3
oxygen compounds		
610	ethoxyethane (ethyl ether)	CH3CH2OCH2CH3
611	methyl formate	HCOOCH3
sulfur compounds		
620	(Reserved for future assignment)	

Number	Chemical Name	Chemical Formula
	Nitrogen Compounds	
630	methanamine (methyl amine)	CH3NH2
631	ethanamine (ethyl amine)	CH3CH2(NH2)

Number	Chemical Name	Chemical Formula
	Inorganic Compounds	
702	hydrogen	H2
704	helium	He
717	ammonia	NH3
718	water	H2O
720	neon	Ne
728	nitrogen	N2
732	oxygen	O2
740	argon	Ar
744	carbon dioxide	CO2
744A	nitrous oxide	N2O
764	sulfur dioxide	SO2

Number	Chemical Name	Chemical Formula
	Unsaturated Organic Compounds	
1130(E)	trans-1,2-dichloroethene	CHCl=CHCl
R-1132a	1,1-difluoroethylene	CF2=CH2
1150	ethene (ethylene)	CH2=CH2
R-1224yd(Z)	(Z)-1-chloro-2,3,3,3-tetrafluoropropene	CF3CF=CHCl
1233zd(E)	trans-1-chloro-3,3,3-trifluoro-1-propene	CF3CH=CHCl
1234yf	2,3,3,3-tetrafluoro-1-propene	CF3CF=CH2
1234ze(E)	trans-1,3,3,3-tetrafluoro-1-propene	CF3CH=CHF
1270	propene (propylene)	CH3CH=CH2
1336mzz(E)	trans-1,1,1,4,4,4-hexafluoro-2-butene	CF3CH=CHCF3
1336mzz(Z)	cis-1,1,1,4,4,4-hexaflouro-2-butene	CF3CHCHCF3

5.8 Appendix 2: Patent Classes

Section	IPC Subclasses
C	C07D, C01F, C08F, C23C, C09D, C09J, C07F, C07C, C07K, C12P, C12N, C08G, C09K, C23G
	C11D, C08L, C25B, C08J, C10M, C03C, C09B, C07B, C14C, C01B, C25D, C12S, C10L, C04B
	C12Q, C08B, C07H, C12L, C08K, C07J, C03B, C23F, C30B, C02F, C08C, C06D
F	F16J, F26B, F25B

Table 5.8: C and F IPC Subclasses from the Substances Regulated under the Montreal Protocol

Section	IPC Classes
C	C01, C02, C03, C04, C06, C07, C08, C09, C10, C11, C12, C14, C23, C25, C30
F	F16, F25, F26

Table 5.9: C and F IPC Classes for the Coarsened Exact Matching

App. year	IPC	Control Group (T_0)	Dirty (T_1)	Clean (T_2)
1979	C07	352	1	1
1979	C08	328	12	1
1980	C07	469	2	2
1980	C08	381	10	5
1981	C07	517	3	2
1981	C08	442	6	7
1982	C07	464	1	1
1982	C08	424	6	11
1983	C07	507	1	2
1983	C08	534	4	8
1984	C07	568	1	2
1984	C08	588	8	10
1984	C09	157	1	2
1985	C07	696	2	3
1985	C08	739	10	12
1985	C09	140	1	3
1985	C23	87	2	1
1986	C07	714	5	1
1986	C08	666	7	13
1986	C09	139	1	2
1986	C10	43	1	2
1987	C07	737	1	1
1987	C08	527	5	10
1988	C07	729	4	5
1988	C08	526	4	9
1988	C09	165	4	4
1989	C07	567	7	11
1989	C08	460	9	10
1989	C09	151	1	2
1990	C07	621	6	9

App. year	IPC	Control Group (T_0)	Dirty (T_1)	Clean (T_2)
1990	C08	521	16	19
1990	C09	194	2	4
1990	C10	51	1	8
1991	C07	384	9	11
1991	C08	513	14	14
1991	C10	17	1	5
1992	C07	410	14	13
1992	C08	481	13	21
1992	C09	163	2	6
1992	C10	21	1	1
1992	F25	14	2	2
1993	C07	421	24	15
1993	C08	377	27	29
1993	C09	108	3	13
1993	C10	14	2	9
1993	C12	387	2	2
1993	F25	19	3	3
1994	C01	38	1	1
1994	C04	68	1	1
1994	C07	412	18	22
1994	C08	379	25	40
1994	C09	112	1	3
1994	C12	428	3	1
1995	C07	403	29	22
1995	C08	313	21	46
1995	C09	95	2	3
1995	C12	517	4	2
1995	F25	19	1	2
1995	F26	15	1	3

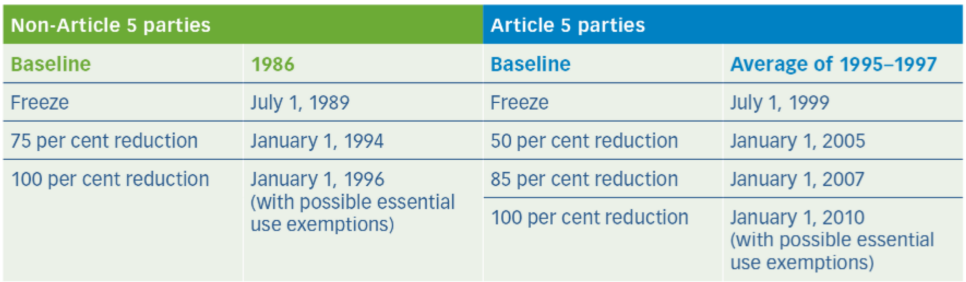
Table 5.10: Results from the Exact Matching

5.9 Appendix 3: Regulation Schedule

Figure 5.17: CFCs Annex A/I Phase-down Production and Consumption Schedule (UNEP, 2019) Latest version available here.

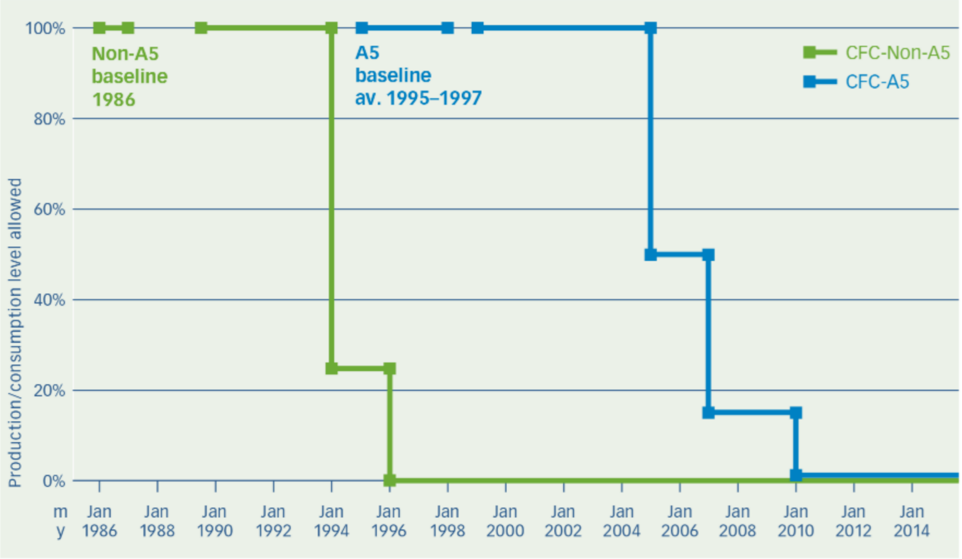
Annex A – Group I: Chlorofluorocarbons (CFC-11, CFC-12, CFC-113, CFC-114 and CFC-115)

Applicable to production and consumption.



Non-Article 5 parties		Article 5 parties	
Baseline	**1986**	**Baseline**	**Average of 1995–1997**
Freeze	July 1, 1989	Freeze	July 1, 1999
75 per cent reduction	January 1, 1994	50 per cent reduction	January 1, 2005
100 per cent reduction	January 1, 1996 (with possible essential use exemptions)	85 per cent reduction	January 1, 2007
		100 per cent reduction	January 1, 2010 (with possible essential use exemptions)

CFCs (Annex A/I) production/consumption reduction schedule



Annex B – Group I: Other fully halogenated CFCs (CFC-13, CFC-111, CFC-112, CFC-211, CFC-212, CFC-213, CFC-214, CFC-215, CFC-216, CFC-217)

Applicable to production and consumption.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**1989**	**Baseline**	**Average of 1998–2000**
20 per cent reduction	January 1, 1993	20 per cent reduction	January 1, 2003
75 per cent reduction	January 1, 1994	85 per cent reduction	January 1, 2007
100 per cent reduction	January 1, 1996 (with possible essential use exemptions)	100 per cent reduction	January 1, 2010 (with possible essential use exemptions)

Other CFCs (Annex B/I) production/consumption reduction schedule

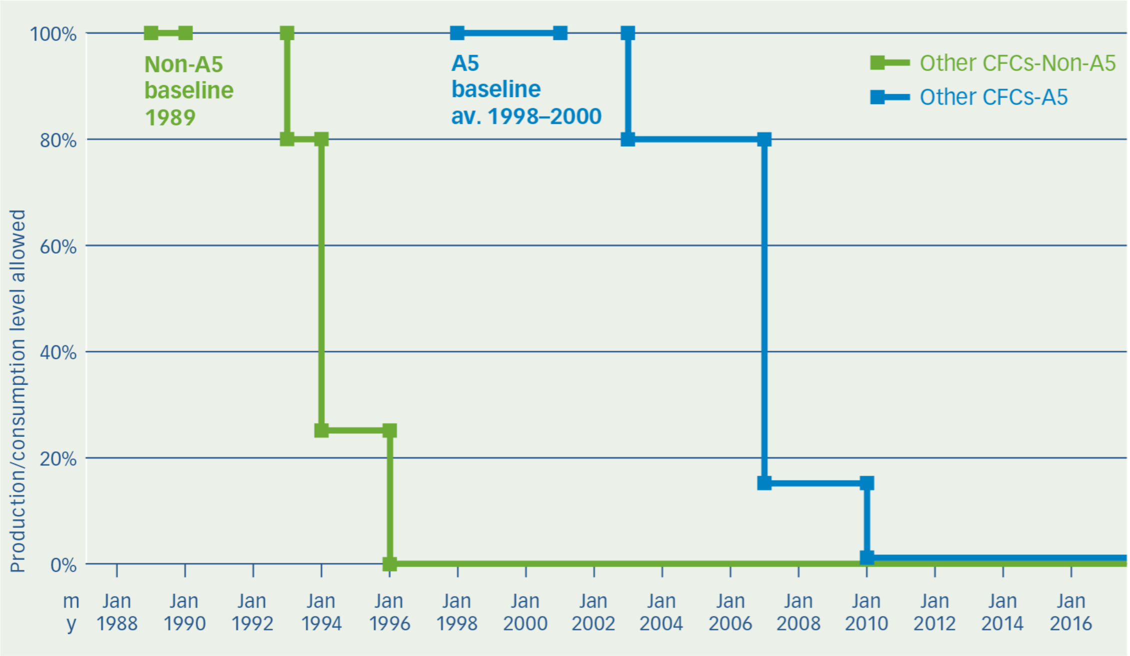


Figure 5.18: CFCs Annex B/I Phase-down Production and Consumption Schedule (UNEP, 2019)

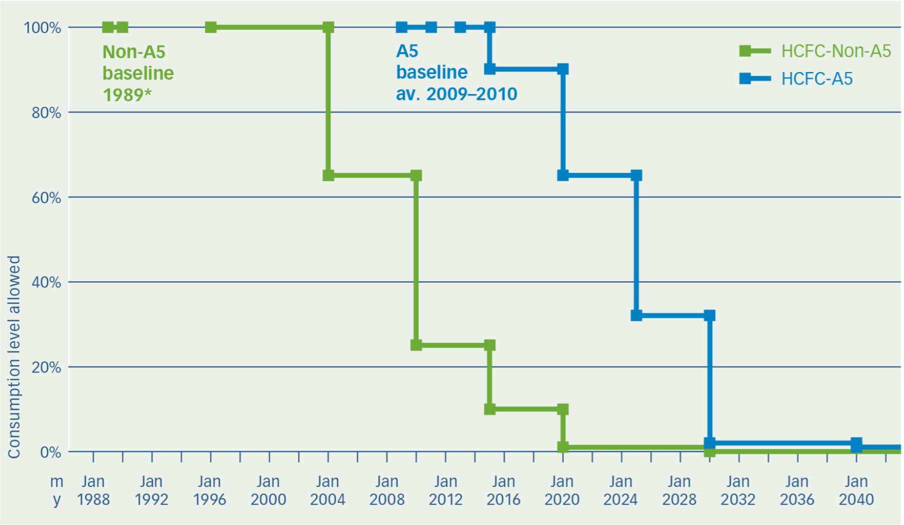
Annex C – Group I: HCFCs

Applicable to consumption.

Non-Article 5 parties		**Article 5 parties**	
Baseline	**1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	1996	Freeze	January 1, 2013
35 per cent reduction	January 1, 2004	10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline consumption until January 1, 2030 for the uses defined in Article 2F paragraph 6(a) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline consumption when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (i) and – possible essential use exemptions

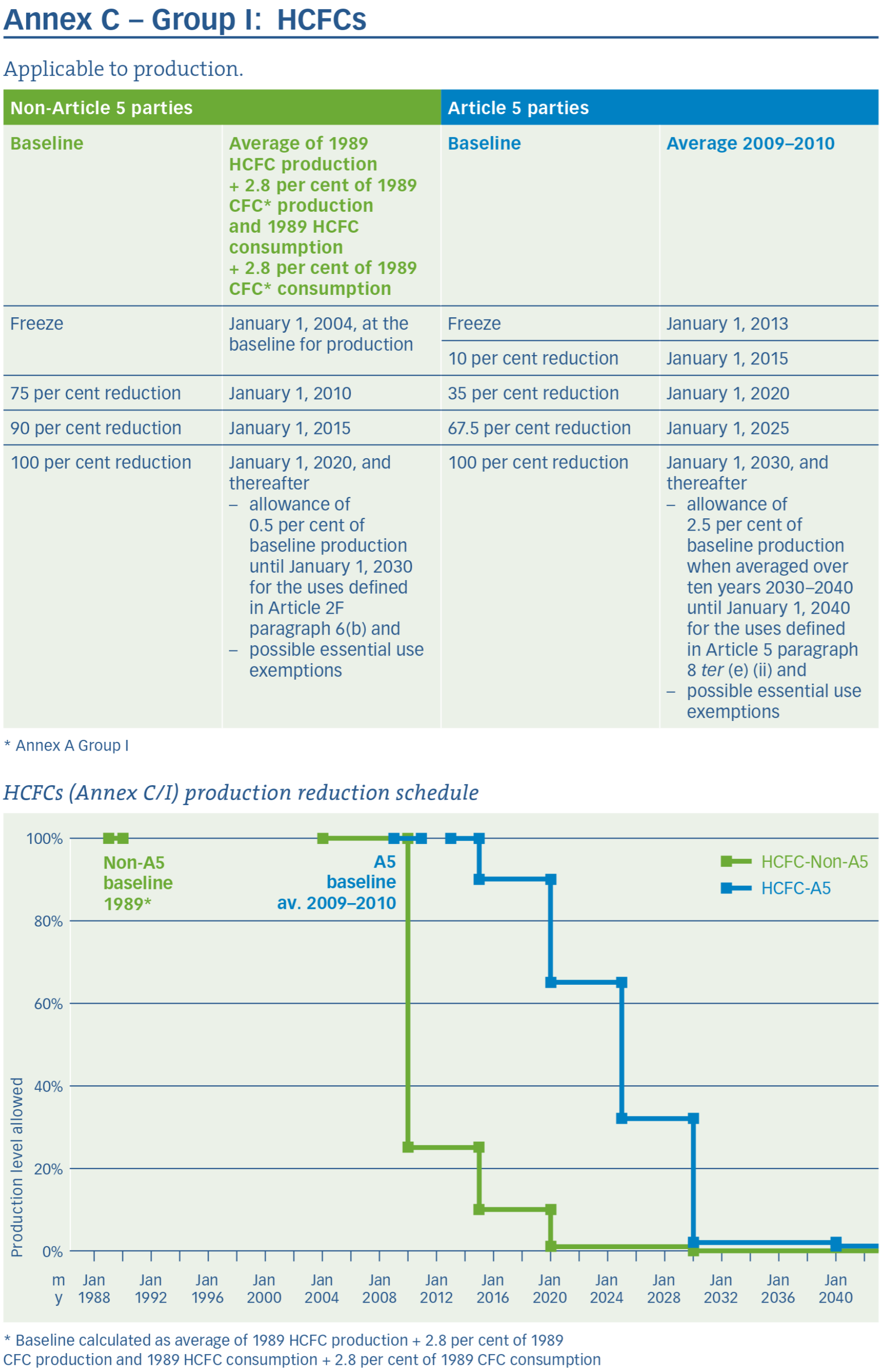
* Annex A Group I

HCFCs (Annex C/I) consumption reduction schedule



* Baseline calculated as 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 5.19: HCFCs Phase-down Consumption Schedule (UNEP, 2019)



Annex C – Group I: HCFCs

Applicable to production.

Non-Article 5 parties		Article 5 parties	
Baseline	**Average of 1989 HCFC production + 2.8 per cent of 1989 CFC* production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC* consumption**	**Baseline**	**Average 2009–2010**
Freeze	January 1, 2004, at the baseline for production	Freeze	January 1, 2013
		10 per cent reduction	January 1, 2015
75 per cent reduction	January 1, 2010	35 per cent reduction	January 1, 2020
90 per cent reduction	January 1, 2015	67.5 per cent reduction	January 1, 2025
100 per cent reduction	January 1, 2020, and thereafter – allowance of 0.5 per cent of baseline production until January 1, 2030 for the uses defined in Article 2F paragraph 6(b) and – possible essential use exemptions	100 per cent reduction	January 1, 2030, and thereafter – allowance of 2.5 per cent of baseline production when averaged over ten years 2030–2040 until January 1, 2040 for the uses defined in Article 5 paragraph 8 *ter* (e) (ii) and – possible essential use exemptions

* Annex A Group I

HCFCs (Annex C/I) production reduction schedule

* Baseline calculated as average of 1989 HCFC production + 2.8 per cent of 1989 CFC production and 1989 HCFC consumption + 2.8 per cent of 1989 CFC consumption

Figure 5.20: HCFCs Phase-down Production Schedule (UNEP, 2019)

5.10 Appendix 4: Panel Event Study Evidence

5.10.1 Appendix 4.1: Pre-Montreal Negotiations (1979-1983)

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim 1	-7.667***	0.514	-14.924	0.000	-8.674	-6.660
Dim 2	-58.515***	14.330	-4.083	0.000	-86.602	-30.429
Dim 3	9.279***	1.197	7.750	0.000	6.933	11.626
Dim 4	-14.103**	4.403	-3.203	0.001	-22.733	-5.473
Dim 5	2.420**	0.903	2.680	0.007	0.650	4.191
Grant Lag	0.001***	0.000	20.550	0.000	0.001	0.001
Applicants	0.387***	0.116	3.344	0.001	0.160	0.613
Inventors	0.071***	0.016	4.532	0.000	0.040	0.102
Family Size	0.121***	0.004	33.764	0.000	0.114	0.128
Active	1.373***	0.057	24.015	0.000	1.261	1.485
App. year*	-0.005*	0.002	-2.202	0.028	-0.010	-0.001
IPC Class FE						
1980.year	0.000	.	.	.	0.000	0.000
1981.year	0.102	0.793	0.128	0.898	-1.453	1.656
1982.year	0.148	0.738	0.200	0.841	-1.298	1.593
1983.year	0.349	0.721	0.484	0.628	-1.064	1.762
1984.year	0.572	0.714	0.802	0.423	-0.827	1.972
1985.year	0.957	0.710	1.348	0.178	-0.435	2.349
1986.year	1.178	0.708	1.664	0.096	-0.209	2.566
1987.year	1.437*	0.707	2.033	0.042	0.051	2.822
1988.year	1.794*	0.706	2.541	0.011	0.410	3.178
1989.year	2.165**	0.706	3.067	0.002	0.781	3.548
1990.year	2.547***	0.705	3.611	0.000	1.165	3.930
1991.year	2.930***	0.705	4.155	0.000	1.548	4.312
1992.year	3.304***	0.705	4.685	0.000	1.921	4.686
1993.year	3.683***	0.705	5.223	0.000	2.301	5.065
1994.year	4.015***	0.705	5.693	0.000	2.633	5.397

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
1995.year	4.325***	0.705	6.132	0.000	2.942	5.707
1996.year	4.630***	0.705	6.563	0.000	3.247	6.013
1997.year	4.919***	0.706	6.972	0.000	3.536	6.302
1998.year	5.156***	0.706	7.307	0.000	3.773	6.539
1999.year	5.447***	0.706	7.717	0.000	4.063	6.830
Lead3	0.557	2.302	0.242	0.809	-3.956	5.069
Lead2	0.581	1.718	0.339	0.735	-2.785	3.948
Lead1	0.479	1.290	0.371	0.711	-2.049	3.006
Lag1	0.610	1.125	0.542	0.588	-1.595	2.816
Lag2	1.253	1.125	1.114	0.265	-0.952	3.458
Lag3	1.018	1.075	0.947	0.343	-1.089	3.125
Lag4	1.190	1.052	1.131	0.258	-0.872	3.253
Lag5	0.901	0.958	0.941	0.347	-0.977	2.779
Lag6	0.860	0.912	0.943	0.346	-0.928	2.649
Lag7	1.141	0.912	1.251	0.211	-0.647	2.929
Lag8	1.312	0.912	1.439	0.150	-0.476	3.100
Lag9	1.258	0.898	1.400	0.162	-0.503	3.018
Lag10	1.259	0.898	1.402	0.161	-0.502	3.020
Lag11	1.152	0.898	1.282	0.200	-0.609	2.912
Lag12	0.999	0.885	1.129	0.259	-0.736	2.734
Lag13	0.895	0.885	1.012	0.312	-0.839	2.630
_cons	-2.871***	0.718	-4.000	0.000	-4.278	-1.464

$*p < 0.05, \; **p < 0.01, \; ***p < 0.001$

Table 5.11: Panel Event Study Estimates of Clean Technologies 1979-1983

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim 1	-7.621***	0.513	-14.848	0.000	-8.627	-6.615
Dim 2	-55.240***	14.275	-3.870	0.000	-83.220	-27.260
Dim 3	8.984***	1.193	7.528	0.000	6.645	11.322
Dim 4	-14.531**	4.502	-3.228	0.001	-23.355	-5.706
Dim 5	2.443**	0.903	2.705	0.007	0.673	4.213
Grant Lag	0.001***	0.000	20.997	0.000	0.001	0.001
Applicants	0.383***	0.116	3.312	0.001	0.156	0.609
Inventors	0.081***	0.016	5.149	0.000	0.050	0.111
Family Size	0.120***	0.004	33.573	0.000	0.113	0.127
Active	1.353***	0.057	23.723	0.000	1.241	1.465
App. year*	-0.005*	0.002	-2.056	0.040	-0.009	-0.000
IPC Class FE						
1980.year	0.000	.	.	.	0.000	0.000
1981.year	0.098	0.792	0.124	0.902	-1.454	1.650
1982.year	0.141	0.737	0.191	0.848	-1.303	1.585
1983.year	0.342	0.720	0.475	0.635	-1.069	1.753
1984.year	0.565	0.713	0.792	0.428	-0.833	1.963
1985.year	0.946	0.709	1.335	0.182	-0.444	2.336
1986.year	1.167	0.707	1.651	0.099	-0.218	2.553
1987.year	1.426*	0.706	2.019	0.043	0.042	2.809
1988.year	1.783*	0.705	2.529	0.011	0.401	3.166
1989.year	2.154**	0.705	3.056	0.002	0.772	3.535
1990.year	2.535***	0.704	3.598	0.000	1.154	3.916
1991.year	2.916***	0.704	4.140	0.000	1.536	4.296
1992.year	3.288***	0.704	4.669	0.000	1.908	4.668
1993.year	3.666***	0.704	5.205	0.000	2.285	5.046
1994.year	3.996***	0.704	5.674	0.000	2.616	5.377
1995.year	4.305***	0.704	6.112	0.000	2.924	5.686
1996.year	4.609***	0.705	6.542	0.000	3.228	5.990
1997.year	4.897***	0.705	6.951	0.000	3.516	6.279

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
1998.year	5.133***	0.705	7.284	0.000	3.752	6.514
1999.year	5.423***	0.705	7.693	0.000	4.041	6.805
Lead3	0.296	1.433	0.207	0.836	-2.512	3.105
Lead2	0.040	1.378	0.029	0.977	-2.661	2.741
Lead1	0.213	1.215	0.175	0.861	-2.168	2.594
Lag1	0.273	1.124	0.243	0.808	-1.930	2.476
Lag2	-0.064	1.098	-0.059	0.953	-2.216	2.087
Lag3	-0.421	1.010	-0.417	0.677	-2.401	1.559
Lag4	-0.425	0.974	-0.436	0.663	-2.333	1.484
Lag5	-0.302	0.941	-0.321	0.748	-2.146	1.542
Lag6	-0.283	0.941	-0.301	0.763	-2.127	1.560
Lag7	-0.292	0.925	-0.315	0.753	-2.105	1.522
Lag8	-0.320	0.897	-0.356	0.722	-2.078	1.439
Lag9	-0.263	0.897	-0.293	0.769	-2.021	1.495
Lag10	-0.462	0.884	-0.523	0.601	-2.194	1.270
Lag11	-0.579	0.871	-0.665	0.506	-2.287	1.128
Lag12	-0.605	0.871	-0.694	0.487	-2.312	1.102
Lag13	-0.703	0.871	-0.807	0.420	-2.411	1.004
_cons	-2.895***	0.717	-4.038	0.000	-4.300	-1.490

$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 5.12: Panel Event Study Estimates of Dirty Technologies 1979-1983

5.10.2 Appendix 4.2: During-Montreal Negotiations (1984-1987)

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim 1	-9.892***	0.439	-22.549	0.000	-10.752	-9.032
Dim 2	-1.505	0.819	-1.837	0.066	-3.110	0.100
Dim 3	4.120***	0.442	9.331	0.000	3.254	4.985
Dim 4	-4.029*	1.613	-2.498	0.012	-7.190	-0.868
Dim 5	-0.381	0.640	-0.596	0.551	-1.636	0.874
Grant Lag	0.001***	0.000	12.272	0.000	0.001	0.001
Applicants	0.872***	0.114	7.633	0.000	0.648	1.096
Inventors	0.014	0.017	0.795	0.426	-0.020	0.047
Family Size	0.119***	0.005	25.646	0.000	0.109	0.128
Active	1.497***	0.068	22.154	0.000	1.364	1.629
App- year*	0.008***	0.002	3.594	0.000	0.004	0.013
IPC Class FE						
1985.year	0.000	.	.	.	0.000	0.000
1986.year	0.234	0.846	0.276	0.783	-1.425	1.892
1987.year	0.438	0.805	0.545	0.586	-1.139	2.016
1988.year	0.787	0.793	0.993	0.321	-0.767	2.341
1989.year	1.135	0.788	1.440	0.150	-0.410	2.680
1990.year	1.648*	0.786	2.096	0.036	0.107	3.188
1991.year	2.235**	0.785	2.846	0.004	0.696	3.774
1992.year	2.810***	0.785	3.581	0.000	1.272	4.348
1993.year	3.375***	0.785	4.302	0.000	1.837	4.913
1994.year	3.915***	0.785	4.990	0.000	2.377	5.452
1995.year	4.385***	0.785	5.589	0.000	2.847	5.923
1996.year	4.844***	0.785	6.174	0.000	3.306	6.382
1997.year	5.295***	0.785	6.748	0.000	3.757	6.833
1998.year	5.709***	0.785	7.275	0.000	4.171	7.247
1999.year	6.076***	0.785	7.742	0.000	4.538	7.614
Lead3	0.845	2.472	0.342	0.732	-4.000	5.690
Lead2	0.535	1.597	0.335	0.738	-2.596	3.665

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Lead1	0.411	1.067	0.385	0.700	-1.681	2.502
Lag1	0.265	0.846	0.313	0.754	-1.393	1.923
Lag2	0.432	0.827	0.523	0.601	-1.188	2.053
Lag3	0.016	0.801	0.020	0.984	-1.553	1.586
Lag4	-0.280	0.784	-0.357	0.721	-1.818	1.257
Lag5	-0.430	0.784	-0.549	0.583	-1.968	1.107
Lag6	-0.442	0.769	-0.575	0.566	-1.949	1.066
Lag7	-0.364	0.769	-0.474	0.636	-1.872	1.143
Lag8	-0.464	0.762	-0.610	0.542	-1.958	1.029
Lag9	-0.209	0.762	-0.274	0.784	-1.702	1.284
_cons	-3.402***	0.797	-4.270	0.000	-4.963	-1.840

$*p < 0.05,\ **p < 0.01,\ ***p < 0.001$

Table 5.13: Panel Event Study Estimates of Clean Technologies 1984-1987

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Dim 1	-9.781***	0.439	-22.265	0.000	-10.642	-8.920
Dim 2	-1.519	0.820	-1.853	0.064	-3.126	0.088
Dim 3	4.018***	0.444	9.050	0.000	3.148	4.888
Dim 4	-3.684*	1.666	-2.211	0.027	-6.949	-0.419
Dim 5	-0.377	0.648	-0.582	0.560	-1.646	0.892
Grant Lag	0.001***	0.000	12.305	0.000	0.001	0.001
Applicants	0.827***	0.115	7.169	0.000	0.601	1.053
Inventors	0.018	0.017	1.072	0.284	-0.015	0.052
Family Size	0.120***	0.005	26.028	0.000	0.111	0.129
Active	1.509***	0.068	22.239	0.000	1.376	1.642
App. year*	0.008***	0.002	3.432	0.001	0.003	0.012
IPC Class FE						
1985.year	0.000	.	.	.	0.000	0.000
1986.year	0.234	0.847	0.276	0.783	-1.426	1.894
1987.year	0.439	0.806	0.545	0.586	-1.140	2.018
1988.year	0.787	0.794	0.991	0.322	-0.769	2.342
1989.year	1.134	0.789	1.438	0.151	-0.412	2.681
1990.year	1.642*	0.787	2.087	0.037	0.100	3.184
1991.year	2.234**	0.786	2.843	0.004	0.694	3.775
1992.year	2.810***	0.785	3.577	0.000	1.270	4.350
1993.year	3.376***	0.785	4.299	0.000	1.837	4.915
1994.year	3.917***	0.785	4.988	0.000	2.378	5.456
1995.year	4.388***	0.785	5.588	0.000	2.849	5.927
1996.year	4.848***	0.785	6.173	0.000	3.308	6.387
1997.year	5.300***	0.785	6.748	0.000	3.760	6.839
1998.year	5.714***	0.785	7.275	0.000	4.175	7.254
1999.year	6.081***	0.786	7.741	0.000	4.542	7.621
Lead3	0.542	1.960	0.277	0.782	-3.299	4.384
Lead2	0.539	1.750	0.308	0.758	-2.891	3.969
Lead1	0.915	1.479	0.619	0.536	-1.983	3.813

Variable	Coeff.	S.E.	t	p-val	Min 95% C.I.	Max 95% C.I.
Lag1	0.132	1.066	0.124	0.901	-1.956	2.221
Lag2	-0.044	0.995	-0.044	0.965	-1.994	1.906
Lag3	0.027	0.979	0.028	0.978	-1.892	1.946
Lag4	-0.013	0.964	-0.013	0.989	-1.903	1.877
Lag5	-0.014	0.964	-0.014	0.988	-1.903	1.876
Lag6	0.057	0.964	0.060	0.953	-1.832	1.947
Lag7	0.197	0.964	0.204	0.838	-1.692	2.086
Lag8	0.647	0.964	0.671	0.502	-1.243	2.536
Lag9	0.348	0.950	0.367	0.714	-1.513	2.209
_cons	-3.392***	0.798	-4.252	0.000	-4.955	-1.828

$*p < 0.05,\ **p < 0.01,\ ***p < 0.001$

Table 5.14: Panel Event Study Estimates of Dirty Technologies 1984-1987

5.11 Appendix 5: Duration Analysis Estimates

5.11.1 Appendix 5.1: Pre-Montreal Negotiations (1979-1983)

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
1984	0.403	0.160	1.520	3.299	0.000	0.007
1985	0.071	.	1.718	.	0.000	.
1986	.	.	.	.	.	.
1987	-0.006	.	6.463	.	0.000	.
1988	0.021	.	2.706	.	0.000	.
1989	0.258	0.068	1.520	6.859	0.000	0.002
1990	0.334	.	1.520	.	0.000	.
1991	0.397	0.321	1.520	3.497	0.001	0.015
1992	0.497	0.258	1.520	3.893	0.001	0.013
1993	0.498	0.395	1.520	2.904	0.001	0.031
1994	0.354	0.355	1.915	1.915	0.001	0.052
1995	0.858	1.295	0.927	0.927	0.003	0.447
1996	0.779	.	0.927	.	0.003	.

Table 5.15: Nonparametric Estimates Clean Patents VS Control Group 1979-1983 (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
1984	-0.242*	0.398	0.267	0.007	-0.409	-0.076	-0.615	1.411
1985	.	.	.	.	.	.	.	.
1986	.	.	.	.	.	.	.	.
1987	.	.	.	.	.	.	.	.
1988	.	.	.	.	.	.	.	.
1989	-0.190*	0.264	0.333	0.002	-0.273	-0.106	-0.867	1.394
1990	.	.	.	.	.	.	.	.
1991	-0.076	0.808	0.150	0.016	-0.322	0.169	0.049	1.566
1992	-0.239*	0.519	0.200	0.014	-0.471	-0.007	-0.357	1.396
1993	-0.104	0.792	0.202	0.032	-0.454	0.247	-0.088	1.672
1994	0.001	1.003	0.419	0.053	-0.450	0.452	-0.266	2.273
1995	0.437	1.510	0.277	0.450	-0.878	1.753	0.479	2.541
1996	.	.	.	.	.	.	.	.

$*p < 0.05$

Table 5.16: Nonparametric Estimates Clean Patents VS Control Group 1979-1983 (Hazard Rates' Differences and Ratios)

Variable	Description
Obc	Optimal Bandwidth Control Group
Obt	Optimal Bandwidth Treatment Group
aVc	Asymptotic Variance Control Group
aVt	Asymptotic Variance Treatment Group
aVr	Asymptotic Variance Ratio
aVd	Asymptotic Variance Difference
LB-Diff	Lower Bound Difference
UB-Diff	Upper Bound Difference
LB-Ratio	Lower Bound Ratio
UB-Ratio	Upper Bound Ratio

Table 5.17: Description of Variables from the Nonparametric Estimates

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
1984	0.403	0.292	1.520	3.102	0.000	0.013
1985	0.071	0.051	1.718	3.893	0.000	0.002
1986	.	.	.	.	.	.
1987	-0.006	.	6.463	.	0.000	.
1988	0.021	.	2.706	.	0.000	.
1989	0.258	0.106	1.520	6.463	0.000	0.003
1990	0.334	0.164	1.520	5.277	0.000	0.006
1991	0.397	0.239	1.520	4.881	0.001	0.010
1992	0.497	0.489	1.520	3.497	0.001	0.031
1993	0.498	0.583	1.520	2.904	0.001	0.057
1994	0.354	0.723	1.915	1.915	0.001	0.139
1995	0.858	.	0.927	.	0.003	.
1996	0.779	1.295	0.927	0.927	0.003	0.671

Table 5.18: Nonparametric Estimates Dirty Patents VS Control Group 1979-1983 (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
1984	-0.111	0.724	0.153	0.013	-0.337	0.115	-0.042	1.490
1985	-0.019	0.727	0.807	0.002	-0.111	0.072	-1.034	2.488
1986	.	.	.	.	.	.	.	.
1987	.	.	.	.	.	.	.	.
1988	.	.	.	.	.	.	.	.
1989	-0.151*	0.413	0.241	0.003	-0.259	-0.044	-0.551	1.376
1990	-0.169*	0.492	0.206	0.006	-0.320	-0.018	-0.397	1.382
1991	-0.158	0.603	0.172	0.010	-0.357	0.041	-0.211	1.417
1992	-0.008	0.984	0.130	0.031	-0.354	0.339	0.276	1.692
1993	0.085	1.171	0.171	0.058	-0.385	0.556	0.360	1.983
1994	0.369	2.041	0.285	0.140	-0.364	1.102	0.994	3.088
1995	.	.	.	.	.	.	.	.
1996	0.516	1.662	0.415	0.674	-1.094	2.125	0.399	2.925

$*p < 0.05$

Table 5.19: Nonparametric Estimates Dirty Patents VS Control Group 1979-1983 (Hazard Rates' Differences and Ratios)

5.11.2 Appendix 5.2: During-Montreal Negotiations (1984-1987)

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
1988	0.001	.	7.650	.	0.000	.
1989	0.054	0.110	1.718	5.870	0.000	0.002
1990	0.108	0.119	1.718	6.859	0.000	0.002
1991	0.189	0.364	1.718	2.706	0.000	0.013
1992	0.305	0.044	1.520	4.684	0.000	0.001
1993	0.350	0.071	1.520	3.695	0.000	0.002
1994	0.374	.	1.520	.	0.000	.
1995	0.314	0.249	1.520	2.508	0.000	0.013
1996	0.354	0.091	1.718	1.915	0.000	0.007
1997	0.632	0.405	0.927	0.927	0.001	0.066
1998	0.674	1.295	0.927	0.927	0.002	0.224

Table 5.20: Nonparametric Estimates Clean Patents VS Control Group 1984-1987 (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
1988	.	.	.	.	.	.	.	.
1989	0.056	2.026*	0.191	0.002	-0.026	0.137	1.169	2.883
1990	0.011	1.100	0.126	0.002	-0.071	0.092	0.406	1.795
1991	0.175	1.927*	0.115	0.014	-0.053	0.404	1.262	2.593
1992	-0.262*	0.143	0.587	0.001	-0.334	-0.189	-1.359	1.645
1993	-0.279*	0.203	0.470	0.003	-0.381	-0.177	-1.142	1.547
1994	.	.	.	.	.	.	.	.
1995	-0.064	0.795	0.210	0.013	-0.290	0.161	-0.103	1.692
1996	-0.263*	0.257	0.837	0.007	-0.430	-0.095	-1.536	2.050
1997	-0.227	0.641	0.402	0.067	-0.734	0.280	-0.601	1.883
1998	0.621	1.921*	0.147	0.225	-0.310	1.551	1.168	2.673

$*p < 0.05$

Table 5.21: Nonparametric Estimates Clean Patents VS Control Group 1984-1987 (Hazard Rates' Differences and Ratios)

Year	Haz. Rate Control	Haz. Rate Treatment	Obc	Obt	aVc	aVt
1988	0.001	.	7.650	.	0.000	.
1989	0.054	.	1.718	.	0.000	.
1990	0.108	0.177	1.718	6.859	0.000	0.004
1991	0.189	0.273	1.718	4.684	0.000	0.009
1992	0.305	0.456	1.520	3.299	0.000	0.025
1993	0.350	0.317	1.520	3.497	0.000	0.021
1994	0.374	0.176	1.520	3.893	0.000	0.013
1995	0.314	0.485	1.520	2.904	0.000	0.050
1996	0.354	0.243	1.718	1.915	0.000	0.051
1997	0.632	1.766	0.927	0.927	0.001	0.832
1998	0.674	.	0.927	.	0.002	.

Table 5.22: Nonparametric Estimates Dirty Patents VS Control Group 1984-1987 (Hazard Rates)

Year	Diff	Ratio	aVr	aVd	LB-Diff	UB-Diff	LB-Ratio	UB-Ratio
1988	.	.	.	.	.	.	.	.
1989	.	.	.	.	.	.	.	.
1990	0.069	1.643	0.133	0.004	-0.050	0.189	0.927	2.358
1991	0.084	1.445	0.129	0.009	-0.103	0.272	0.742	2.148
1992	0.151	1.495	0.124	0.025	-0.158	0.460	0.804	2.185
1993	-0.033	0.905	0.209	0.021	-0.317	0.251	0.010	1.800
1994	-0.198	0.471	0.413	0.013	-0.422	0.027	-0.788	1.730
1995	0.172	1.547	0.222	0.051	-0.269	0.612	0.625	2.470
1996	-0.111	0.687	0.861	0.051	-0.554	0.333	-1.131	2.506
1997	1.134	2.795*	0.295	0.833	-0.655	2.923	1.730	3.861
1998	.	.	.	.	.	.	.	.

$*p < 0.05$

Table 5.23: Nonparametric Estimates Dirty Patents VS Control Group 1984-1987 (Hazard Rates' Differences and Ratios)

5.12 Appendix 6: Timeline of Ozone Regulation in Germany

Year	Event
1974	Scientists Rowland and Molina highlight the risk to the ozone layer due to CFCs for the first time.
1975	The German federal government conducts some initial studies on CFCs and supports more than 20 projects to explore the earth's atmosphere.
1977	Voluntary commitment by German industry to reduce the amount of CFCs used in aerosol cans to 30 % below the 1975 level by 1979.
(26/04-28/04)	The first international governmental conference on CFCs in Washington, DC calls for a reduction of CFC emissions, in particular from aerosols just as the second conference in Munich in 1978, which is organised by the German federal government.
1978	UBA Blue Angel ecolabel for CFC-free aerosol cans.
(30/05)	Resolution from the Council of the European Community on preventing increasing production of CFC-11 and CFC-12. Furthermore, industry is instructed to seek alternative products.
1980	The Council of the European Community agrees on freezing the production capacity of CFC-11 and CFC-12 as well as on a 30% reduction on the amount of CFCs used in aerosols.
1985	21 Nations sign the Vienna Convention. First international framework agreement to demand measures to protect the ozone layer (enforced in 1988).
Autumn	Evidence reported in Nature on the ”ozone hole”.
1986	Germany specifies binding limit values for equipment emitting CFCs.
1987	Adoption of the Montreal Protocol. Commitment to limit the production of 8 CFCs and halons. Parties aim to reduce the use of CFCs to half of the 1986 levels by 1999.
1988	Agreement of the European Council Regulation on certain chlorofluorocarbons and halons depleting the ozone layer, limiting their import, production, and use.
(16/12)	Germany ratifies the Montreal Protocol.

Year	Event
1990	2^{nd} conference of the Parties to the Montreal Protocol in London. Significant tightening by ending the production and use of CFCs by the year 2000. Inclusion of additional substances and support mechanisms.
1991	Implementation of the London resolutions of the Montreal Protocol, the European Regulation on ozone depleting substances (ODS).
	Ordinance on the Prohibition of CFCs and Halons, Germany legislates to completely phase out these ODS in almost every area of use by 1995 at the latest.
1992	4^{th} conference of the Parties to the Montreal Protocol in Copenhagen. Montreal Protocol becomes stricter: halons will no longer be manufactured or used by 1994 and CFCs by 1996, while HCFCs and methylbromide are also included in the Protocol with their production being banned from 2020 onwards.
1993	The new European Council Regulation to speed up the phasing-out of ODS (No 3952/92) enters into force. The production and imports of halons are banned from 1994, of CFCs from 1995, and of certain solvents from 1995/96 onwards.
1994	Revision and tightening of the European Council Regulation on ODS (now No 3093/94).
1997	9^{th} conference of the Parties to the Montreal Protocol. Amendment of the timetables for the phase-out of the production of ODS. Agreement on measures to prevent their trade on the black market.
1999	11^{th} conference of the Parties to the Montreal Protocol. Inclusion of bromomethane and trade restrictions for HCFCs.
2000	The European Regulation ODS (No 2037/2000) is enacted. It applies immediately in Germany and tightens certain rules.
2006	European regulation and directive to reduce the emissions of fluorinated greenhouse gases in refrigerators and air conditioning systems and other applications (No 842/2006 and 2006/40) are enacted. They include some prohibitions for HFC and SF_6 in certain applications.

Year	Event
2007	The German federal government agrees to an integrated climate and energy programme (IEKP). Point 23 includes steps to reduce HFC emissions and to support refrigeration systems which use natural refrigerants.
2008	A Chemicals Climate Protection Ordinance is enacted in Germany for the first time. This supplements the European F-gas Regulation and also contains limit values for specific refrigerant losses in stationary systems.
2009	The European Regulation on ODS No 1005/2009 replaces and tightens regulation enacted in the year 2000. It applies immediately in Germany.
2014	The new European F-gas Regulation (No 517/2014) with further bans and the step-by-step placing on the market limits ("phase-down") of hydrofluorocarbons (HFC) is agreed. By 2030, the quantity of HFCs on sale should be reduced to one fifth of the current quantity.
2016	28^{th} conference of the Parties to the Montreal Protocol in Kigali. HFCs are included in the Montreal Protocol as their use as a CFC replacement is rapidly increasing.
2017	Amendment of the German Chemicals Climate Protection Ordinance from 2008 according to the new European F-gas Regulation.
2018	According to the F-gas Regulation, the HFC quantity available on the market will go down to 63% of the initial quantity.
2020 Year	Refrigeration systems with HFC (GWP $>$ 2,500) are banned, as well as mobile household air conditioning units with HFC (GWP $>$ 150).

Table 5.24: Author's summarized retranscription of the graphical timeline from (UBA, 2017). Latest version available here.

Bibliography

Abadie, A., Diamond, A., and Hainmueller, J. (2010): “Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program.” In: *The Journal of the American Statistical Association* 105.490, pp. 493–505.

Abadie, A., and Gardeazabal, J. (2003): “The Economic Costs of Conflict: A Case Study of the Basque Country.” In: *The American Economic Review* 93.1, pp. 113–132.

Abrams, D. S., Akcigit, U., and Grennan, J. (2018): “Patent Value and Citations: Creative Destruction or Strategic Disruption?” In: *Working Paper*.

Abrell, J., Kosch, M., and Rausch, S. (2022): “How effective is carbon pricing?–A machine learning approach to policy evaluation.” In: *Journal of Environmental Economics and Management* 112, p. 102589.

Acemoglu, D. (1998): “Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality.” In: *The Quarterly Journal of Economics* 113.4, pp. 1055–1089.

– (2002): “Directed Technical Change.” In: *The Review of Economic Studies* 69.4, pp. 781–809.

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012): “The Environment and Directed Technical Change.” In: *The American Economic Review* 102.1, pp. 131–66.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., and Van Reenen, J. (2016): “Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry.” In: *Journal of Political Economy* 124.1, pp. 1–51.

Albert, M. B., Avery, D., Narin, F., and McAllister, P. (1991): “Direct validation of citation counts as indicators of industrially important patents.” In: *Research Policy* 20.3, pp. 251–259.

Andrews, I., Gentzkow, M., and Shapiro, J. M. (2017): “Measuring the Sensitivity of Parameter Estimates to Estimation Moments.” In: *The Quarterly Journal of Economics* 132.4, pp. 1553–1592.

ASHRAE (2019): *ANSI/ASHRAE 34-2019, Designation and Safety Classification of Refrigerants.*

Auffhammer, M., Morzuch, B. J., and Stranlund, J. K. (2005): “Production of Chlorofluorocarbons in Anticipation of the Montreal Protocol.” In: *Environmental and Resource Economics* 30, pp. 377–391.

Austin, D. H. (1993): “An Event-Study Approach to Measuring Innovative Output: The Case of Biotechnology.” In: *The American Economic Review* 83.2, pp. 253–258.

Barrett, S. (1994): “Self-enforcing International Environmental Agreements.” In: *Oxford Economic Papers* 54, pp. 325–338.

Benedick, R. E. (1998): *Ozone Diplomacy: New Directions in Safeguarding the Planet.* Harvard University Press.

Berg, G. J. van den, Bozio, A., and Costa Dias, M. (2020): “Policy discontinuity and duration outcomes.” In: *Quantitative Economics* 11.3, pp. 871–916.

Beron, K. J., Murdoch, J. C., and Vijverberg, W. P. M. (2003): “Why Cooperate? Public Goods, Economic Power, and the Montreal Protocol.” In: *The Review of Economics and Statistics* 85.2, pp. 286–297.

Bessen, J. (2008): “The value of U.S. patents by owner and patent characteristics.” In: *Research Policy* 37.5, pp. 932–945.

Blundell, W., Gowrisankaran, G., and Langer, A. (2020): “Escalation of Scrutiny: The Gains from Dynamic Enforcement of Environmental Regulations.” In: *The American Economic Review* 110.8, pp. 2558–85.

BMUV (Bundesministerium für Umwelt, Naturschutz, nukleare Sicherheit und Verbraucherschutz) (2021): *Federal Climate Change Act.*

Brunnermeier, S. B., and Cohen, M. A. (2003): “Determinants of environmental innovation in US manufacturing industries.” In: *Journal of Environmental Economics and Management* 45.2, pp. 278–293.

Burlig, F., Knittel, C., Rapson, D., Reguant, M., and Wolfram, C. (2020): “Machine Learning from Schools about Energy Efficiency.” In: *Journal of the Association of Environmental and Resource Economists* 7.6, pp. 1181–1217.

Calel, R., and Dechezleprêtre, A. (2016): “Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market.” In: *The Review of Economics and Statistics* 98.1, pp. 173–191.

Clarke, D., and Tapia-Schythe, K. (2021): “Implementing the panel event study.” In: *The Stata Journal* 21.4, pp. 853–884.

D'Errico, J. (2022): *fminsearchbnd, fminsearchcon (https://www.mathworks.com/matlab-central/fileexchange/8277-fminsearchbnd-fminsearchcon), MATLAB Central File Exchange. Retrieved July 21, 2022.*

Daylight (2020): *SMILES Tutorial.* URL: `https://www.daylight.com/meetings/summerschool98/course/dave/smiles-intro.html`.

Dechezleprêtre, A., and Hémous, D. (2022): "Directed Technical Change and Environmental Economics." In: *Working Paper.*

Dechezleprêtre, A., Muckley, C. B., and Neelakantan, P. (2021a): "Does the Market Value Clean Innovation? Evidence from US Listed Firms." In: *Applied Operations Research and Financial Modelling in Energy: Practical Applications and Implications*, pp. 225–261.

– (2021b): "Is firm-level clean or dirty innovation valued more?" In: *The European Journal of Finance* 27.1-2, pp. 31–61.

Dekker, T., Vollebergh, H. R. J., Vries, F. P. de, and Withagen, C. A. (2012): "Inciting Protocols." In: *Journal of Environmental Economics and Management* 64, pp. 45–67.

Deng, Y. (2007): "Private Value of European Patents." In: *European Economic Review* 51.7, pp. 1785–1812.

– (2011): "A dynamic stochastic analysis of international patent application and renewal processes." In: *International Journal of Industrial Organization* 29.6, pp. 766–777.

DOS (The United States Department of State) (2021): *U.S.-China Joint Statement Addressing the Climate Crisis.*

Dugoua, E. (2021): "Induced innovation and international environmental agreements: evidence from the ozone regime." In: *Working Paper.*

EU COMM (European Commission) (2021): *European Climate Law.*

Fabra, N., and Reguant, M. (2014): "Pass-Through of Emissions Costs in Electricity Markets." In: *The American Economic Review* 104.9, pp. 2872–2899.

Gambardella, A., Harhoff, D., and Verspagen, B. (2008): "The value of European patents." In: *European Management Review* 5.2, pp. 69–84.

Ganglmair, B., and Reimers, I. (2019): "Visibility of Technology and Cumulative Innovation: Evidence from Trade Secrets Laws." In: *Discussion Paper Series - CRC TR 224* 119.

Goeschl, T., and Perino, G. (2007): "Innovation without magic bullets: Stock pollution and R&D sequences." In: *Journal of Environmental Economics and Management* 54.2, pp. 146–161.

Goeschl, T., and Perino, G. (2009): "On backstops and boomerangs: Environmental R&D under technological uncertainty." In: *Energy Economics* 31.5, pp. 800–809.

Grigolon, L., Reynaert, M., and Verboven, F. (2018): "Consumer Valuation of Fuel Costs and Tax Policy: Evidence from the European Car Market." In: *American Economic Journal: Economic Policy* 10.3, pp. 193–225.

Griliches, Z. (1984): *R&D, Patents and Productivity.* Chicago: University of Chicago Press.

– (1990): "Patent Statistics as Economic Indicators: A Survey." In: *Journal of Economic Literature* 28.4, pp. 1661–1707.

Griliches, Z. (1981): "Market value, R&D, and patents." In: *Economics Letters* 7.2, pp. 183–187.

Hall, B., Jaffe, A., and Trajtenberg, M. (2001): "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." In: *NBER Working Paper* 8498.

Hall, B. H., and Helmers, C. (2013): "Innovation and diffusion of clean/green technology: Can patent commons help?" In: *Journal of Environmental Economics and Management* 66.1, pp. 33–51.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005): "Market Value and Patent Citations." In: *The RAND Journal of Economics* 36.1, pp. 16–38.

Harhoff, D., Narin, F., Scherer, F. M., and Vopel, K. (1999): "Citation Frequency and the Value of Patented Inventions." In: *The Review of Economics and Statistics* 81.3, pp. 511–515.

Harhoff, D., Scherer, F. M., and Vopel, K. (2003): "Citations, family size, opposition and the value of patent rights." In: *Research Policy* 32.8, pp. 1343–1363.

Heller, S. R., McNaught, A., Pletnev, I., Stein, S., and Tchekhovskoi, D. (2015): "InChI, the IUPAC International Chemical Identifier." In: *Journal of Cheminformatics* 7.1, p. 23.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016): "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors." In: *The American Economic Review* 106.12, pp. 3700–3729.

Ito, K., and Reguant, M. (2016): "Sequential Markets, Market Power, and Arbitrage." In: *The American Economic Review* 106.7, pp. 1921–1957.

IUPAC (2020): *The IUPAC International Chemical Identifier (InChI).* URL: `https://iupac.org/who-we-are/divisions/division-details/inchi/`.

Kim, S., Thiessen, P. A., Bolton, E. E., Chen, J., Fu, G., Gindulyte, A., Han, L., He, J., He, S., Shoemaker, B. A., Wang, J., Yu, B., Zhang, J., and Bryant, S. H. (2015): "PubChem Substance and Compound databases." In: *Nucleic Acids Research* 44.D1, pp. D1202–D1213.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017): "Technological Innovation, Resource Allocation, and Growth." In: *The Quarterly Journal of Economics* 132.2, pp. 665–712.

Langer, A., Lemoine, D., Martin, R., and Verhoeven, D. (2022): "The Private Value of Clean Energy Innovation." In: *Working Paper*.

Lanjouw, J. O., and Schankerman, M. (2004): "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators." In: *The Economic Journal* 114.495, pp. 441–465.

Lanjouw, J. O. (1998): "Patent Protection in the Shadow of Infringement: Simulation Estimations of Patent Value." In: *The Review of Economic Studies* 65.4, pp. 671–710.

Lanjouw, J. O., and Mody, A. (1996): "Innovation and the international diffusion of environmentally responsive technology." In: *Research Policy* 25.4, pp. 549–571.

Lerner, J. (1994): "The Importance of Patent Scope: An Empirical Analysis." In: *The RAND Journal of Economics* 25.2, pp. 319–333.

Miravete, E., Moral, M., and Thurk, J. (2018): "Fuel taxation, emissions policy, and competitive advantage in the diffusion of European diesel automobiles." In: *The RAND Journal of Economics* 49, pp. 504–540.

Molina, M. J., and Rowland, F. S. (1974): "Stratospheric sink for chlorofluoromethanes: chlorine atom-catalysed destruction of ozone." In: *Nature* 249.5460, pp. 810–812.

Muller, H.-G., and Wang, J.-L. (1994): "Hazard Rate Estimation under Random Censoring with Varying Kernels and Bandwidths." In: *Biometrics* 50.1, pp. 61–76.

Murdoch, J. C., and Sandler, T. (1997): "The Voluntary Provision of a Pure Public Good: The Case of Reduced CFC Emissions and the Montreal Protocol." In: *Journal of Public Economics* 63, pp. 331–349.

– (2009): "The Voluntary Provision of a Pure Public Good and the Montreal Protocol: Behavioral and Data Concerns." In: *Oxford Economic Papers* 61, pp. 197–200.

Newell, R. G., Jaffe, A. B., and Stavins, R. N. (1999): "The Induced Innovation Hypothesis and Energy-Saving Technological Change." In: *The Quarterly Journal of Economics* 114.3, pp. 941–975.

Nicholas, T. (2008): "Does Innovation Cause Stock Market Runups? Evidence from the Great Crash." In: *The American Economic Review* 98.4, pp. 1370–1396.

O'Boyle, N. M. (2012): "Towards a Universal SMILES representation - A standard method to generate canonical SMILES based on the InChI." eng. In: *Journal of cheminformatics* 4 (1), p. 22.

Pakes, A. (1985): "On Patents, R&D, and the Stock Market Rate of Return." In: *Journal of Political Economy* 93.2, pp. 390–409.

– (1986): "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks." In: *Econometrica* 54.4, pp. 755–784.

Pakes, A., and Schankerman, M. (1984): "The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources." In: *R&D, Patents, and Productivity.* National Bureau of Economic Research, Inc, pp. 73–88.

Pakes, A., Simpson, M., Judd, K., and Mansfield, E. (1989): "Patent Renewal Data." In: *Brookings Papers on Economic Activity. Microeconomics* 1989, pp. 331–410.

Phaneuf, D. J., and Requate, T. (2017): *A Course in Environmental Economics: Theory, Policy, and Practice.* Cambridge University Press.

Popp, D. (2002): "Induced Innovation and Energy Prices." In: *The American Economic Review* 92.1, pp. 160–180.

Putnam, J. (1996): "The Value of International Patent Rights." In: *PhD. Dissertation, Yale University.*

Reynaert, M. (2021): "Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Car Market." In: *The Review of Economic Studies* 88.1, pp. 454–488.

Ryan, S. P. (2012): "The Costs of Environmental Regulation in a Concentrated Industry." In: *Econometrica* 80.3, pp. 1019–1061.

Sassoon, D. (2009): "Island Nations Plead for Help from Obama on HFCs (June 23, 2009)." In: *Inside Climate News.*

Schankerman, M. (1998): "How Valuable is Patent Protection? Estimates by Technology Field." In: *The RAND Journal of Economics* 29.1, pp. 77–107.

Schankerman, M., and Pakes, A. (1986): “Estimates of the Value of Patent Rights in European Countries During the Post-1950 Period.” In: *The Economic Journal* 96.384, pp. 1052–1076.

Scherer, F. M. (1965): “Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions.” In: *The American Economic Review* 55.5, pp. 1097–1125.

Scherer, F. M., and Harhoff, D. (2000): “Technology policy for a world of skew-distributed outcomes.” In: *Research Policy* 29.4, pp. 559–566.

Schmookler, J. (1966): *Invention and Economic Growth.* Harvard University Press.

Serrano, C. J. (2005): “The Market for Intellectual Property: Evidence from the Transfer of Patents.” In: Job Market Paper.

– (2018): “Estimating the Gains from Trade in the Market for Patent Rights.” In: *International Economic Review* 59.4, pp. 1877–1904.

Shove, G. F. (1933): “The Theory of Wages. by J. R. Hicks.” In: *The Economic Journal* 43.171, pp. 460–472.

Squicciarini, M., Dernis, H., and Criscuolo, C. (2013): “Measuring Patent Quality.” In: URL: `https://www.oecd-ilibrary.org/content/paper/5k4522wkw1r8-en`.

Sullivan, R. J. (1994): “Estimates of the Value of Patent Rights in Great Britain and Ireland, 1852- 1876.” In: *Economica* 61.241, pp. 37–58.

Sun, X., and Ferris, T. (2018): “The Kigali Amendment’s and China’s Critical Roles in Evolving the Montreal Protocol.” In: *Natural Resources & Environment* 33.2.

Sunstein, C. R. (2007): “Of Montreal and Kyoto: A Tale of Two Protocols.” In: *Harvard Environmental Law Review* 31.1.

Trajtenberg, M. (1990): “A Penny for Your Quotes: Patent Citations and the Value of Innovations.” In: *The RAND Journal of Economics* 21.1, pp. 172–187.

UBA (Umweltbundesamt - German Environmental Agency) (1997): *1987-2017: 30th Anniversary of the Montreal Protocol (From the phase-out of CFCs to the phase-down of hydrofluorocarbons).*

UNEP (2019): *Handbook for the Montreal Protocol on Substances that Deplete the Ozone Layer.* Thirteenth edition (2019). UNEP.

UNFCCC (1997): *Kyoto Protocol to the United Nations Framework Convention on Climate Change.*

Wagner, U. J. (2009): “The Voluntary Provision of a Pure Public Good? Another Look at CFC Emissions and the Montreal Protocol.” In: *Oxford Economic Papers* 61, pp. 183–196.

– (2016): “Estimating Strategic Models of International Treaty Formation.” In: *The Review of Economic Studies* 83.4, pp. 1841–1778.